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A Novel Meta-Heuristic Optimization Algorithm to Determine Optimal Access Point and Generation of Distributed Generators for Maximizing Economic and Technical Benefits

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Abstract: This paper presents an intelligent meta-heuristic algorithm, named improved equilibrium optimizer (IEO), for addressing the optimization problem of multi-objective simultaneous integration of distributed generators at unity and optimal power factor in a distribution system. The main objective of this research is to consider the multi-objective function for minimizing total power loss, improving voltage deviation, and reducing integrated system operating costs with strict technical constraints. An improved equilibrium optimizer is an enhanced version of the equilibrium optimizer that can provide better performance, stability, and convergence characteristics than the original algorithm. For evaluating the effectiveness of the suggested method, the IEEE 69-bus radial distribution system is chosen as a test system, and simulation results from this method are also compared fairly with many previously existing methods for the same targets and constraints. Thanks to its ability to intelligently expand the search space and avoid local traps, the suggested method has become a robust stochastic optimization method in tackling complex optimization tasks.

Keywords: Meta-heuristic algorithm; Improved equilibrium optimizer; Voltage deviation; Total power loss; Distributed generator

1 Introduction

NOWADAYS, the penetration of distributed generators (DGs) into distribution systems (DSs) is increasingly popular in countries around the world [1, 2]. The multiple benefits of integrating DGs include reduced power loss, enhanced voltage profile, enhanced power quality, and guaranteed system reliability [3, 4]. However, if DG connection is not considered optimally, it can cause many negative problems such as overvoltage, large loss, increased operating cost, and reduced power quality [5]. Therefore, to avoid these unwanted problems, many researchers have taken different approaches to determining the appropriate penetration of DGs into the existing power grid. Like in [6, 7], researchers have presented using a classical particle swarm optimization (PSO) algorithm to find DGs' placement and sizing to minimize power loss in 26 and 33-bus DSs. The results demonstrated a significant loss reduction due to the suitable penetration from DGs. Besides, to increase the welfare in cutting branch power loss, the authors in [8] also applied this algorithm to search the simultaneous integration of DGs and distribution static compensator (DSTATCOM) in many different systems such as 12, 34 and 69 buses DSs. That study has also indicated that a great combination of DGs and DSTATCOM not only reduced branch losses but also improved voltage dips. Although PSO is a long-known method, its disadvantage is that it easily gets stuck in the local optimum in the high-dimensional zone. To solve this issue, [9] proposed a more aggressive method, called the cuckoo search optimization algorithm (CSA), for tackling the same problem as [8]. In that case, the best result from CSA is compared with PSO, so CSA's performance is better than that of PSO. Besides, some other researchers, such as [10, 11] have also

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applied another approach named artificial bee colony (ABC) algorithm to address two targets of minimizing (1) total energy cost through reducing branch power losses and (2) average voltage drop in the benchmark grids. Thanks to the reasonable integration of DGs in DSs, total losses have been sharply cut, leading to decreased energy costs and enhanced voltage drop. It shows the big benefits of connecting DGs in terms of economic and technical aspects. From another perspective, research [12] has considered an additional factor of total harmonic distortion (THD). In this case, harmonics are emitted from the inverter of DGs and nonlinear loads. Similarly, the gravitational search algorithm (GSA) is also used to find the best solution for penetrating DGs. Simulation results have shown that it effectively mitigates THD by 5%, according to IEEE Std. 51-1992. It is considered an advantage of connecting DGs in DSs. Additionally, to consider the multi-DGs at unity and optimal power factor (PF), [13] also proposed the efficient analytical (EA) for optimal installation of DGs to minimize losses in 33 and 69 buses DSs. This research proved that the benefits of the optimal power factor are better than those of the remaining case. Similarly, [14] also suggested the Kalman filter algorithm (KFA) for determining the connecting DGs into the practical distribution system in Seoul, Korea. KFA also demonstrated as a strong approach for loss reduction in that paper. In order to check the effectiveness of the meta-heuristic algorithm in a large system of 119 buses DS, the authors in [15] introduced an enhanced version of the artificial ecosystem-based optimization algorithm (EAEO) for determining DG allocations to minimize branch losses. Thanks to the successful improvement in the algorithm, the balance between exploitative and exploratory phases has been improved, leading to EAEO having better performance and more excellent convergence properties than the original algorithm (AEO). Besides, [16] also proposed a modified method called hybrid grey wolf optimizer (HGWO) for solving the same goal with [15]. A global optimum is identified, which is better than published methods in reducing line loss and voltage drop. Similarly, following that improvement trend, the authors in [18] also developed the search group algorithm (SGA). They launched a new method called enhanced SGA to cut active power loss and increase voltage capability in many systems such as 33, 69 and 118 buses DSs. ESGA also indicated excellent ability to solve complex meshes in this study. Another aspect to consider is protection coordination limits related to fault current from integrating synchronous-based DGs [19]. That paper has demonstrated the successful connection of DGs in DSs that satisfy the stated constraints. Moreover, other authors in [20] also focus on economic considerations such as investment and O&M costs, and fuel costs. The results have shown a significant cost reduction thanks to the appropriate integration of DGs in the microgrid system. It is also considered a good research paper for considering technical and economic benefits.

Most previous research only focused on the main objectives, such as loss minimization and voltage improvement. However, more is needed to consider a distribution system with connecting DGs. Therefore, in addition to the technical factors related to voltage and loss, it is necessary to consider the economic aspect. Determining a global solution that harmonizes technical and economic evaluation criteria is always encouraged. Besides, past studies often applied outdated algorithms, so the effectiveness of the found solutions is not guaranteed. Thus, introducing effective methods to apply to the optimization problem is also a key factor for maximizing welfare. In short, to limit the above problems, this research has several novel points, and the main contributions are summarized as follows:

- This research determines the optimal strategy for the simultaneous integration of DGs at unity and optimal power factor considering technical and economic aspects.
- The study applies the multi-objective function (MOF), which includes three single goals: minimizing total distribution line power loss, enhancing the system voltage deviation, and reducing the system operating cost, considering tight constraints.
- A novel algorithm called improved equilibrium optimizer (IEO) [21] has also been introduced to tackle the problem of optimally installing DGs in power networks. The optimal solutions from this method are compared with many published methods and implemented methods for testing the algorithm's performance.
- The impact of DG penetration on the power grid is discussed in detail to indicate the influence of different DG types in the same system.

The remaining content of this manuscript is organized as: Section No.2 is in charge of the objective function and constraints; Section No.3 mentions the applied method; Section No.4 discusses the collected results; Section 5 summarizes the primary points of the paper.

2 Problem formulation

2.1 Objective function

The final target of this work is to determine the best solution in terms of location and capacity of DGs in the system to maximum benefits considering the following objectives:

- *Power loss (TPL)*

Power loss in the branches is essential in evaluating the system's operating performance. Therefore, in this study, power loss reduction is considered one of the main objectives. The equation for calculating power loss is formulated as follows [16]:

$$PL = \sum_{l=1}^{N_L} I_l^2 R_l; \quad l = 1{:}\,N_L \tag{1}$$

Where R_l is the resistance of the l^{th} line and I_l is the line current. N_L denotes the number of lines in the network.

- *Voltage deviation (VD)*

Voltage deviation has a close relationship with bus voltage enhancement. Thus, minimizing this value will significantly improve the voltage profile, which is also considered one of this work's important goals. The formula for determining voltage deviation value can be presented by [15]:

$$VD = max|V_b - 1|; \quad b = 1{:}\,N_B \tag{2}$$

Where V_b denotes the voltage at the b^{th} bus, and N_b is the bus number.

- *Operating cost (OC)*

Cutting costs in operating the power network is an important factor that should be considered. In this case, the operating cost includes the loss of energy cost and the energy purchase cost from the public grid for the load demand. Thus, the mathematical equation for calculating this cost is described as:

$$OC = (C_1 \cdot PL) + (C_2 \cdot P^{Sub}) \tag{3}$$

Where P^{Sub} denotes the consumed power of the load demand provided by the main grid through the substation. N_d is the load's number. The cost coefficients for energy loss and load (C_1 and C_2) are 60 \$/MWh and 96 \$/MWh, respectively [22].

As mentioned above, in this research, the main objective is to consider the MOF for (1) minimizing power loss on branches, (2) enhancing voltage deviation, and (3) cutting operating costs through reducing electricity import costs from the main grid for losses and loads. Therefore, the MOF can be described in the mathematical equation as:

$$F_{Total}^{Obj} = \left(\omega_a \cdot \frac{PL}{PL_{base}}\right) + \left(\omega_b \cdot \frac{VD}{VD_{base}}\right) + \left(\omega_c \cdot \frac{OC}{OC_{base}}\right) \tag{4}$$

Where F_{Total}^{Obj} is the MOF's value, which should be minimized. PL, VD, and OC are defined as the total power loss, voltage deviation index, and operating cost after connecting distributed generators, and they can be determined by using Eq. (1), Eq. (2) and Eq. (3), respectively. Similarly, $PL_{base}, VD_{base,}$ and OC_{base} are the total power loss, voltage deviation index, and operating cost before integrating distributed generators (i.e. in the base system). These values can be calculated by applying the formulas in Eq. (1) to Eq. (3) with the condition of the original system.

Thanks to the proper connection of distributed generators (DGs) into the distribution system, the total power loss in the base system (PL_{base}) will be larger than the total power loss after connecting the DGs (PL). Therefore, $\frac{PL}{PL_{base}}$ will be varied in the range from 0 to 1. It is considered a great benefit in determining the penetration of DGs. Besides, as mentioned, one of the other benefits of integrating DGs is to mitigate the voltage deviation index, so the VD value, which is found by applying Eq. (2) after connecting DGs, will be better than the VD_{base} value of the original system (without DGs). Thus, the ratio of $\frac{VD}{VD_{base}}$ will also vary in the limit of 0 to 1. Similarly, in the initial system, the public grid is the sole source of energy supply for the entire distribution grid through the substation. Specifically, the public grid will provide power for total power losses and loads; hence, OC_{base} is considered as the cost paid to the electric company in the original system case, and it can also be calculated by applying Eq. (3). However, with the suitable penetration of DGs into the network, the cost of purchasing energy from the public grid will be significantly cut, leading to the decrease in OC value. Therefore, $\frac{OC}{OC_{base}}$ will only fluctuate in the range from 0 to 1.

The single-objective components are converted to the range [0, 1] as argued above to facilitate calculation and evaluation in MOF of Eq. (1). Additionally, the weighted sum method [23] is also considered for application to identify the best compromise solution in the MOF. In Eq. (4), $\omega_a, \omega_b,$ and ω_c are considered as the weighting factors of MOF, and these values should satisfy the following constraints:

$$\omega_a + \omega_b + \omega_c = 1 \ \& \ 0 \leq \omega_a, \omega_b, \omega_c \leq 1 \tag{5}$$

In this case, $\omega_a, \omega_b,$ and ω_c are factors that relate to power loss, voltage deviation, and operating cost, respectively, and their values depend on the level of importance of each component in MOF. Specifically, in this study, the power loss reduction is evaluated as the most important, followed by operating cost, and the lowest level of importance is voltage deviation. Therefore, ω_a receives the highest value of 0.5, ω_b gets the lowest value of 0.1, and the remaining value is ω_c of 0.4.

2.2 System constraints

The constraints for the optimization problem are described as follows:

- *Power flow equations*

The equations of power flow are expressed as Eqs. (6, 7) for injecting real power and reactive power at each bus during the optimization process [15].

$$P_b = \sum_{j=1}^{N_B} V_b V_j Y_{bj} \cos(\theta_{bj} - \delta_b + \delta_j);\ b = 2: N_B \quad (6)$$

$$Q_b = \sum_{j=1}^{N_B} V_b V_j Y_{bj} \sin(\theta_{bj} - \delta_b + \delta_j); \quad (7)$$

Where P_i and Q_i are the real power and reactive power injected at the b^{th} bus, V_b and V_j denote the b^{th} and j^{th} bus voltage, δ_b *and* δ_j denote the voltage angle and Y_{bj} and θ_{bj} are defined as the branch admittance and angle, respectively.

- *Voltage constraints*

Voltage amplitude at each bus should be kept at an acceptable limit of $\pm 5\%$ [18].

$$V_b^{min} \leq V_b \leq V_b^{max};\quad b = 1: N_B \quad (8)$$

Where V_b^{max} *and* V_b^{min} are the upper and lower bounds of the b^{th} bus voltage magnitude.

- *Current constraint*

The current on lines should not exceed the limit as [8].

$$I_l \leq I_l^{max};\quad l = 1: N_L \quad (9)$$

Where I_l and I_l^{max} are the l^{th} branch current and maximum current, respectively.

- *Capacity limits of each DG*

The generated power of each DG should be constrained within predefined limits as [24]:

$$P_{min,g}^{DG} \leq P_g^{DG} \leq P_{max,g}^{DG};\quad g = 1: N_G \quad (10)$$

Where P_g^{DG} is the power which is generated by the g^{th} DG; $P_{max,g}^{DG}$ and $P_{max,g}^{DG}$ are the upper and lower boundaries of power for the g^{th} DG, respectively; N_G denotes the number of connected DGs.

- *Total penetration limit of DGs*

To keep the balance between generation and consumption, the total generated power from DGs should not exceed the total load demand [15]

$$\sum_{g=1}^{N_G} P_g^{DG} \leq \left(\beta \cdot \sum_{lo=1}^{N_{lo}} P_{lo}\right);\ g = 1: N_G;\ lo = 1: N_{lo} \quad (11)$$

Where β is the percentage for maximum penetration of DGs; N_{lo} denotes the number of loads in the system.

3 Applied method for optimization problem

In this study, a powerful optimization algorithm called improved equilibrium optimizer (IEO) [21] is suggested for application to handle the problem of optimal installation of DGs with unity PF and optimal PF in DS. IEO is a recently upgraded version of EO [25], so it has many outstanding advantages over the original algorithm. In EO and IEO, each particle and its concentration are considered as searching agents for determining possible solutions. These agents update their concentration to expect to find a better quality solution. Each solution represents the internal concentration, and the adjusted variables in the solution are called the concentration parameters of the algorithm. The best balance of concentration and mass in the adjusted volume is considered the optimal trend. Overall, IEO is an effective method with a good balance of exploration and exploitation, so it is a practical algorithm for optimization problems. The process of applying IEO to the considering problem is presented in the below steps [21]:

Step 1: Insert the initial parameters for the algorithm, such as population size (N_n), trial run number (N_{tr}), and the number of control variables (N_v). Generate initial solutions randomly within upper and lower bounds (κ^{max} and κ^{min}) as Eq. (12).

$$\kappa_n = \kappa^{min} + rd \cdot (\kappa^{max} - \kappa^{min});\ n = 1: N_n \quad (12)$$

where κ_n is the initial generated solution and rd is the random number in the range [0, 1]. In this step, each solution includes a set of control variables, and each control variable is emitted within the predetermined allowable limits of (κ^{max} and κ^{min}).

Step 2: After all solutions are generated within the allowable limit, each solution will be calculated for quality assessment by using the fitness function such as Eq. (13):

$$Fitness_n = F_{Total,n}^{Obj} + \Delta Penalty_n \quad (13)$$

This fitness function includes two sub-functions: the objective and penalty functions. The objective function value of the n^{th} solution ($F_{Total,n}^{Obj}$) is determined by Eq. (4), and the penalty function value of the n^{th} solution ($\Delta Penalty_n$) can be found by Eq. (14):

$$\Delta Penalty_n = \left(\lambda . sum(\Delta V_{b,n})\right) + \left(\delta . sum(\Delta I_{l,n})\right) \quad (14)$$

where λ and δ are the penalty coefficients for bus voltage and branch current violations; ΔV and ΔI are the violation amount for bus voltage and branch current, respectively. These penalties can be determined by applying the rules [26]:

$$\Delta V_{b,n} = \begin{cases} (V^{max} - V_{b,n})^2 \ if\ V^{max} < V_{b,n};\ b = 1: N_B \\ (V^{min} - V_{b,n})^2 \ if\ V^{min} > V_{b,n} \\ 0 \quad else \end{cases} \quad (15)$$

$$\Delta I_{l,n} = \begin{cases} 0\ if\ I_{l,n}^{max} \geq I_{l,n};\ l = 1: N_L \\ (I_{l,n}^{max} - I_{l,n})^2\ else \end{cases} \quad (16)$$

Therefore, each proposed solution will be calculated and assigned its fitness value. Based on this fitness value, the quality of the solution will be determined.

Step 3: Based on the fitness value, the group of four best solutions in the current population ($\kappa_1^{best}, \kappa_2^{best}, \kappa_3^{best}$, and κ_4^{best}) are determined. Besides, one average solution (κ_{mean}) is also calculated.

Step 4: Calculate the exponential rate (*EXP*) by using Eq. (17):

$$EXP = \gamma_1 sign(\vartheta - 0.5)(e^{-h \cdot r} - 1) \quad (17)$$

Where γ_1 is the constant ($\gamma_1 = 2$); ϑ and r are the random integer number in the range [0, 1]; h is the coefficient that varies with each iteration, and it is defined as Eq. (18):

$$h = \left(1 - \frac{Ite}{Ite^{max}}\right)^{\gamma_2 \left(\frac{Ite}{Ite^{max}}\right)} \quad (18)$$

Where $\gamma_2$is a constant ($\gamma_1 = 1$), Ite and Ite^{max} are called as the current iteration and maximum iteration numbers.

Step 5: Determine the generation rate (*GEN*) by using Eq. (19):

$$GEN = EXP \cdot CtrlG \cdot (\kappa_n - r \cdot \kappa_s) \quad (19)$$

and
$$CtrlG = \begin{cases} \frac{\alpha_1}{2} \ if \ \alpha_2 \geq p \\ 0 \ else \end{cases} \quad (20)$$

where *CtrlG* is the control coefficient of *GEN*. p is the generation probability and is selected as 0.5 for a good balance. $\alpha_1, \alpha_{2,}$ and r are the numbers which are created randomly in [0, 1].

Step 6: Check the criteria for choosing a new solution generation equation by comparing the average fitness value ($Fitness_{mean}$) and the fitness value of the nth solution ($Fitness_n$) in the population. If $Fitness_{mean} > Fitness_n$, then Eq. (21) is applied to update new locations for each solution.

$$\kappa_n = \kappa_s + (\kappa_n - \kappa_s)EXP + \frac{GEN}{r}(1 - EXP) \quad (21)$$

where κ_s is the selected solution in the good solution group in step 3, κ_n is the *nth* current solution and r is the random integer number in the range [0, 1].

On the contrary, $Fitness_{mean} \leq Fitness_n$, then Eq. (22) is applied to generate new locations of each solution.

$$\kappa_n = \kappa_{Local}^{best} + \left(\kappa_n - \kappa_{Local}^{best}\right)ET + (\kappa_{r1} - \kappa_{r2}).\tau \quad (22)$$

κ_{Local}^{best} is the best solution for the population at the current iteration; κ_{r1} and κ_{r2} are randomly selected solutions in the good group. τ is an integer number randomly generated in the range [0, 1]. Using two update equations for producing new solutions in this step is to classify solutions into two groups including the good quality group and poor quality group based on the comparison results between $Fitness_{mean}$ and $Fitness_n$. Hence, the new solution generation equations are selected and applied appropriately to each solution group. This is considered a great improvement of IEO for avoiding local optimal traps and contributing to improving population quality.

Step 7: To ensure that each newly created solution always complies with the allowable limits of κ^{max} and κ^{min}, checking the variables in each created solution for violation is performed. If there is a violation, then it should be corrected according to the following rules. If the control variable value is outside the limit of κ^{max}, it is returned to the κ^{max} value and if the variable value is less than the κ^{min} value, it equals the κ^{min} value [21].

Step 8: After the adjustments for each solution have been implemented, Eq. (13) is applied to calculate the solution's fitness value. The solution with the best quality is also identified through fitness comparisons of solutions in the population.

Step 9: Check the condition to stop the iteration. If $Ite < Ite^{max}$, then go back to step 3. Otherwise, the global solution is shown.

Applying IEO to the optimization problem is briefly presented using the flowchart below [21].

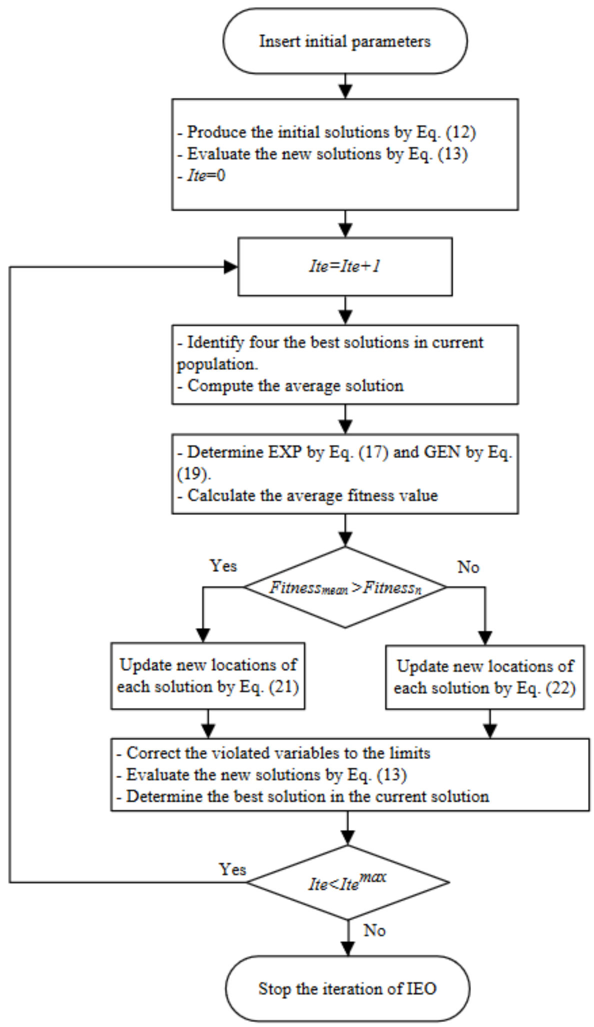

Fig. 1 The flowchart of IEO for addressing the optimization problem.

4 Simulation results

This work searches for the optimal solution for the simultaneous integration of three DGs with two cases: (1) DGs at unity PF and (2) DGs at optimal PF. In this simulation for EO and IEO, the number of independent test runs is 50, and the population is 40. The maximum iteration number is also taken to be 160 for case 1 and 200 for case 2, through survey to ensure convergence. The total penetration of DGs (β) is selected as 80%. Besides, the power for each DG is allowed to vary within the predetermined limit from 0 MW to 2.0 MW, and the location of each DG is from Bus 2 to Bus 69, as assumed. In this case, IEEE 69-bus DS is selected as a testing system. The data about this system is referenced as [21], and the network diagram is also plotted, as shown in Figure 2.

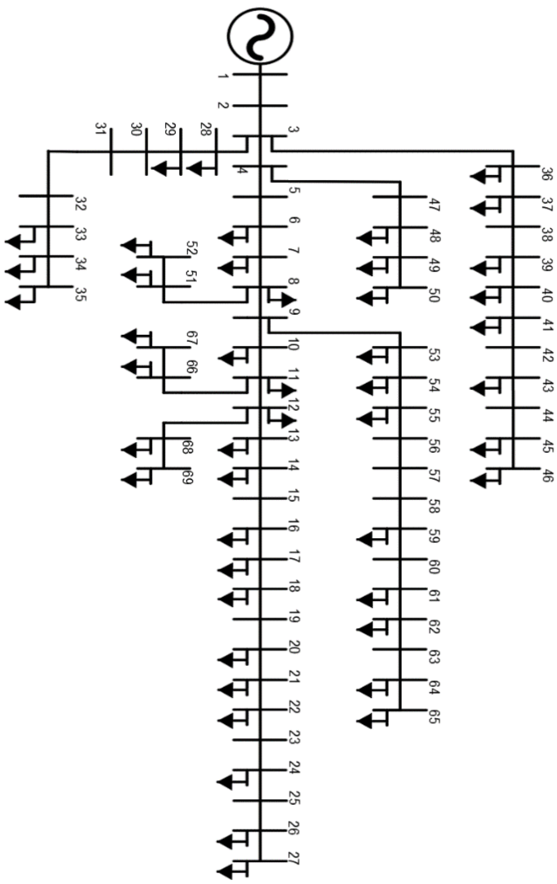

Fig. 2 IEEE 69-bus DS

4.1 Case 1: DGs with unity PF

As mentioned, this study finds the optimal integration solution of DGs in DS by applying optimization algorithms with multi-faceted consideration. This work implements the suggested algorithm (IEO) with the original algorithm (EO) with the same targets and constraints for fair comparison. Due to the stochastic characteristics of the nature-inspired meta-heuristic algorithms, 50 test runs are performed with the randomly generated initial population. The obtained results for the suggested algorithm (IEO) and the original algorithm (EO) are presented in Table 1.

Table 1 The summary of fitness values from methods at case 1

Implemented method	The best fitness	The average fitness
EO	0.2574	0.2588
IEO	0.2565	0.2576

The fitness of IEO is 0.2565, while it is 0.2574 for EO. It indicates that IEO can find a better-quality solution than its original algorithm. In other words, the improvements in IEO have been positive and brought about superior algorithm performance. Besides, the value of average fitness that represents the stability of the algorithms is also calculated, as shown in Table 1. The average value of the test runs by IEO (0.2576) is also lower than that by EO (0.2588). These numerical results have proven that the stability of IEO is better than EO in handling the optimization problem in this case. Therefore, it shows that IEO can find the optimal solution better than EO and has more stability than EO in solving the problem of installing DGs in DN. The best fitness value of IEO and EO is also compared with four other published methods, such as HSA [27], LSF-SA [28], MOBA [29], and BFOA [30], to demonstrate the effectiveness of the implemented methods, as plotted in Figure 3. The fitness value of IEO (0.2565) is also better than the published methods of HAS (0.4388), LSF-SA (0.3680), MOBA (0.3802), and BFOA (0.3678), respectively. These numerical results affirm that IEO is a stronger method than others in addressing the problem.

Furthermore, to consider the convergence characteristics of the suggested method, IEO is also compared with the original method, EO. As Figure 4 illustrates, most fitness points on the convergence curve of IEO are lower than EO. Improvements in IEO have contributed to avoiding the local optima better than EO in the convergence process for determining the globally optimal solution.

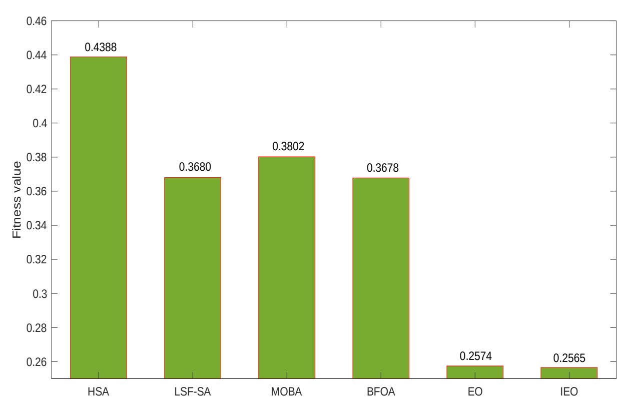

Fig. 3 The fitness value of methods with DGs at unity PF.

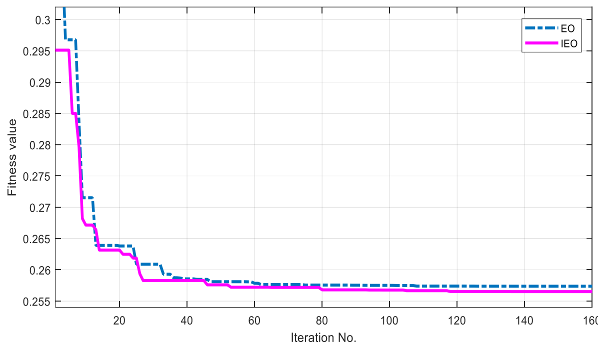

Fig. 4 Convergence curves of implemented methods.

Table 2 The optimal solution of methods for installing DGs at case 1

Method	Optimal installing DGs (Bus/ Capacity in MW)	PL (kW)	VD (p.u)	OC ($)
Base system	-	224.49	0.0910	378.45
HSA [27]	63/ 1.3024; 64/ 0.3690; 65/ 0.1018	86.32	0.0320	199.93
LSF-SA [28]	18/ 0.4204; 60/ 1.3311; 65/ 0.4298	76.92	0.0249	160.19
MOBA [29]	23/ 0.4000; 61/ 1.2000; 64/ 0.4000	73.37	0.0266	177.39
BFOA [30]	27/ 0.2954; 61/ 1.3451; 65/ 0.4476	74.98	0.0202	169.02
EO	67/ 0.6384; 18/ 0.4031; 61/ 2.0000	72.99	0.0119	77.38
IEO	11/ 0.6402; 18/ 0.4018; 61/ 1.9995	72.60	0.0119	77.35

As mentioned, this study considers MOF with three single objectives. The best solution for sitting and sizing DGs and single targets from the methods are presented in detail in Table 2. Specifically, for the first single objective function of reducing the total loss, the power loss (PL) has been significantly minimized from 224.49 kW to 72.60 kW, corresponding to a 67.66% loss reduction for using the optimal solution by the suggested method. Meanwhile, the found power loss of the remaining methods of HSA, LSF-SA, MOBA, BFOA, and EO is only in the range from 72.99 kW to 86.32 kW, corresponding to 61.55% to 67.49%. It has been proven that the optimal solution from IEO is better than other methods in cutting line loss. Besides, for the target of enhancing voltage deviation in DS, the value of EO and IEO is the same as 0.0119 p.u, and this value is smaller than HSA of 0.0320 p.u, LSF-SA of 0.0249 p.u, MOBA of 0.0266 p.u and BFOA of 0.0202 p.u. It confirms that the ability to improve the voltage deviation of EO and IEO is better than that of the other methods. Lastly, regarding the goal of cost minimization from importing electricity from the grid, by applying the optimal solution from IEO, the hourly cost has been sharply reduced from $378.45 to $77.35, equivalent to a 79.56% cost saving. Meanwhile, this cost percentage for the other methods varies from 47.17% to 79.55% compared to the base system. In short, the proposed solution of integrating DGs by IEO has more benefits than others in terms of loss minimization, power profile improvement, and operating cost reduction through purchasing electricity from the public grid.

4.2 Case 2: DGs with optimal PF

The suggested method (IEO) and three other methods, PSO, SFO, and EO, are implemented with the same target for comparing performance, stability, and convergence properties. Like case 1, 50 trial runs are also performed for meta-heuristic algorithms. The best fitness values from methods are also presented in Figure 5 and Table 3. They found that the fitness value of IEO (0.0941) is the lowest compared to PSO (0.0970), SFO (0.0953), and EO (0.0948). For this particular case, the smaller the fitness value, the higher the found solution quality, so it can be stated that the found solution from the suggested method of IEO is not only better than the original EO but also more effective than other methods such as PSO and SFO.

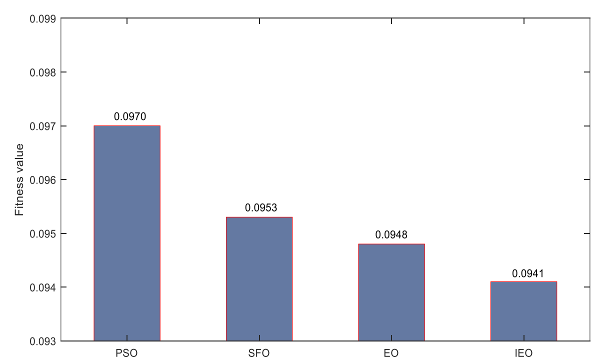

Fig. 5 The fitness value of methods with DGs at optimal PF

Table 3 The summary of fitness values from methods at case 2

Implemented method	The best fitness	The average fitness
PSO	0.0970	0.1075
SFO	0.0953	0.1061
EO	0.0948	0.1037
IEO	0.0941	0.1021

Besides, to demonstrate the outstanding stability of the suggested method, the average fitness value of 50 runs is calculated and presented in Table 3. In this case, the average fitness value of IEO is 0.1021. Meanwhile, these values are 0.1075, 0.1061, and 0.1037 for PSO, SFO and EO, respectively. The average fitness value of IEO is lower than that of EO and other methods. Therefore, it can be affirmed that the suggested method has better stability than others in addressing the optimization problem. Moreover, considering the convergence characteristics of IEO, the compared methods are also implemented. As plotted in Figure 6, most fitness points on the IEO convergence curve are lower than those of PSO, SFO, and EO. In other words, the convergence characteristics of the suggested method are greater than those of the original method and others throughout finding the optimal solution.

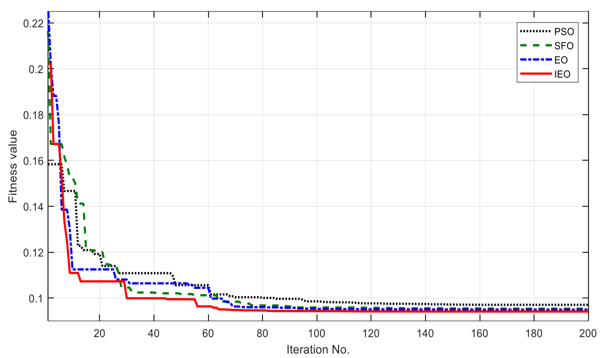

Fig. 6 Convergence curves of implemented methods

Table 4 The optimal solution of methods for installing DGs at case 2

Method	Optimal installing DGs (Bus/ Capacity in MW/ Optimal power factor)	PL (kW)	VD (p.u)	OC ($)
Base system	-	224.49	0.0910	378.45
PSO	18/ 0.4370/ 0.8332; 61/ 1.6733/ 0.8211; 09/ 0.9312/ 0.9023	5.90	0.0057	73.35
SFO	61/ 1.7168/ 0.8011; 50/ 0.7515/ 0.9859; 18/ 0.5732/ 0.8467	5.57	0.0049	73.33
EO	18/ 0.5915/ 0.8448; 50/ 0.6345/ 0.7001; 61/ 1.8115/ 0.8226	5.52	0.0042	73.71
IEO	17/ 0.5766/ 0.8367; 61/ 1.7887/ 0.8199; 50/ 0.6762/ 0.7959	5.24	0.0045	73.31

As presented in Table 4, the best solution for siting, sizing, and power factor of DGs from implemented methods and the single targets are also compared in detail. Specifically, for the first single target, by using the optimal solution of IEO, the total power loss (PL) is strongly reduced from 224.49 kW to 5.24 kW, corresponding to 97.67%. At the same time, this value is 97.37% for PSO, 97.52 for SFO, and 97.54% for EO. It indicates that the power loss reduction from the suggested method is better than that of the original algorithm and more significant than that of other methods. Moreover, the branch loss from the suggested method in this case is also compared with the case of DGs at unity PF. As plotted in Figure 7, power loss in all branches in the case of DGs at optimal PF is much lower than that of DGs at unity PF, leading the hourly loss saving up to 76.36 kW, corresponding to 92.78% compared to the case 1. For the goal of voltage deviation enhancement, the found value of IEO is 0.0045 p.u, which is worse than EO of 0.0042 p.u, but it is better than 0.0049 p.u of SFO and 0.0057 p.u of PSO. On the other hand, the voltage profile of this case is also compared with the DGs at unity PF. As plotted in Figure 8, the lowest bus voltage has been enhanced from 0.9090 p.u to 0.9955 p.u for case 2, and this value is also greater than case 1 of 0.9881 p.u. It shows the voltage benefit of determining optimal PF compared to unity PF. In addition, for the remaining target related to the hourly cost of purchasing energy from the public grid, the OC value from IEO ($73.31) can save up to 80.63% compared to the original network. It is also more economical than others, such as EO of 80.52%, PSO of $80.62, and SFO of 80.62%. This indicates that the welfare obtained from the suggested method is better than other methods in both technical and economic aspects. In summary, thanks to the suitable penetration of DGs in DS, line power loss is cut, voltage deviation is improved, and operating costs are cut significantly.

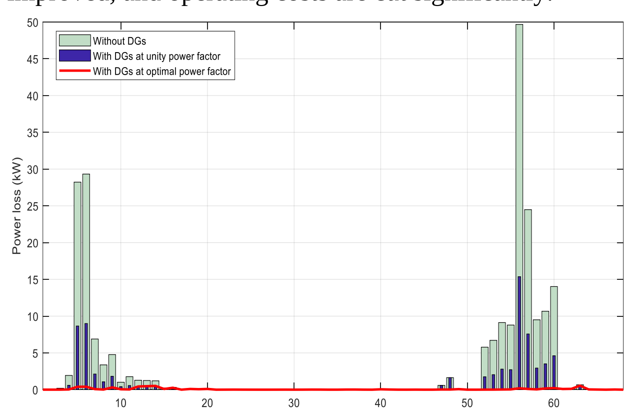

Fig. 7 Power loss at each line before and after connecting DGs

5 Conclusions

This work successfully determined the optimal solution for integrating DGs at the unity PF case and optimal PF case to minimize the multi-objective function's value using IEO, original EO, and other methods.

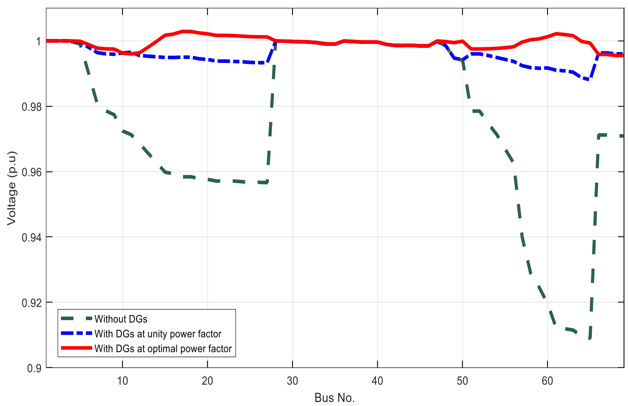

Fig. 8 The voltage at each bus before and after connecting DGs

The single objectives of MOF include branch power loss reduction, voltage deviation enhancement, and operating cost mitigation. The results from IEO also demonstrated its superiority compared to other methods such as HSA, LSF-SA, BOMA, BFOA, PSO, SFO, and EO for solving the considering problem. By using the optimal solution from IEO, the loss reduction is up to 67.66% and 97.67%, the weakest voltage is enhanced from 0.9090 p.u to 0.9881 p.u and 0.9955 p.u, and the operating cost saving is also reached 79.56% and 80.63% for case 1 and case 2, respectively. This shows that the benefits of integrating DGs with optimal PF are better than those of integrating DGs with unity PF. Furthermore, the suggested method (IEO) has also proven to be powerful for tackling various optimization problems in this study. In the future, this research will continue to consider the connection of wind and solar energy sources into the larger network, considering the uncertainty of wind speed and solar radiation. The study will also consider the impact of the penetration of charging stations and energy storage systems when integrated into the distribution grid.

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References

[1] A. Boukaroura, L. Slimani, and T. Bouktir, "Optimal placement and sizing of multiple renewable distributed generation units considering load variations via dragonfly optimization algorithm," *Iranian Journal of Electrical and Electronic Engineering*, vol. 16, no. 3, pp. 353-362, 2020.

[2] D. R. Prabha, T. Jayabarathi, R. Umamageswari, and S. Saranya, "Optimal location and sizing of distributed generation unit using intelligent water drop algorithm", *Sustainable Energy Technologies and Assessments*, vol. 11, pp. 106-113, 2015.

[3] E. S. Ali, S. M. Abd Elazim, and A. Y. Abdelaziz, "Ant Lion Optimization Algorithm for optimal location and sizing of renewable distributed generations", *Renewable Energy*, vol. 101, pp. 1311-1324, 2017.

[4] P. P. Biswas, R. Mallipeddi, P. N. Suganthan, and G.A. Amaratunga, "A multiobjective approach for optimal placement and sizing of distributed generators and capacitors in distribution network", *Applied soft computing*, vol. 60, pp. 268-280, 2017.

[5] B. Poornazaryan, P. Karimyan, G. B. Gharehpetian, and M. Abedi, "Optimal allocation and sizing of DG units considering voltage stability, losses and load variations", *International Journal of Electrical Power & Energy Systems* vol. 79, pp. 42-52, 2016.

[6] W. Phuangpornpitak, and K. Bhumkittipich, "Research Article Principle Optimal Placement and Sizing of Single Distributed Generation for Power Loss Reduction using Particle Swarm Optimization", *Research Journal of Applied Sciences, Engineering and Technology*, vol. 7, no. 6, pp. 1211-1216, 2014.

[7] T. Bouktir, and K. R. Guerriche, "Optimal allocation and sizing of distributed generation with particle swarm optimization algorithm for loss reduction," *Science and technology* vol. 6 no. 1, pp. 59-69, 2015.

[8] S. Devi, and M. Geethanjali, "Optimal location and sizing determination of Distributed Generation and DSTATCOM using Particle Swarm Optimization algorithm," *International Journal of Electrical Power & Energy Systems*, vol. 62, pp. 562-570, 2014.

[9] T. Yuvaraj, K. Ravi, and K. R. Devabalaji, "Optimal allocation of DG and DSTATCOM in radial distribution system using cuckoo search optimization algorithm," *Modelling and Simulation in Engineering*, vol. 12, no. 11, pp. 1-11, 2017.

[10] K. S. Ramudu, M. P. Lalitha, and P.S. Babu, "Optimal Placement of DG for Loss Reduction and Voltage Sag Mitigation in Radial Distribution Systems using ABC Algorithm," *International Journal on Electrical and Power Engineering*, vol. 5, no. 1, pp. 25-30, 2014.

[11] E. A. Al-Ammar, K. Farzana, A. Waqar, M. Aamir, A. U. Haq, M. Zahid, and M. Batool, "ABC algorithm based optimal sizing and placement of DGs in distribution networks considering multiple objectives," *Ain Shams Engineering Journal*, vol. 12, no. 1, pp. 697-708, 2021.

[12] A. F. A. Kadir, A. Mohamed, H. Shareef, M. C. Wanik, and A. A. Ibrahim, "Optimal sizing and

placement of distributed generation in distribution system considering losses and THDv using gravitational search algorithm," *Przeglad Elektrotechniczny*, vol. 4, pp. 132-136, 2013.
[13] K. Mahmoud, N. Yorino, and A. Ahmed, "Optimal distributed generation allocation in distribution systems for loss minimization," *IEEE Transactions on power systems*, vol. 31, *no.* 2, pp. 960-969, 2015.
[14] S. H. Lee, and J. W. Park, "Optimal placement and sizing of multiple DGs in a practical distribution system by considering power loss," *IEEE Transactions on Industry Applications*, vol. 49, no. 5, pp. 262-2270, 2013.
[15] A. Eid, S. Kamel, A. Korashy, and T. Khurshaid, "An enhanced artificial ecosystem-based optimization for optimal allocation of multiple distributed generations," *IEEE Access*, vol. 8, pp. 178493-178513, 2020.
[16] R. Sanjay, T. Jayabarathi, T. Raghunathan, V. Ramesh, and N. Mithulananthan, "Optimal allocation of distributed generation using hybrid grey wolf optimizer," *IEEE Access*, vol. *5*, pp. 14807-14818, 2017.
[17] K. Nekooei, M. M. Farsangi, H. Nezamabadi-Pour, and K. Y. Lee, "An improved multi-objective harmony search for optimal placement of DGs in distribution systems," *IEEE Transactions on smart grid*, vol. 4, no. 1, pp. 557-567, 2013.
[18] T. H. B. Huy, D. N. Vo, K. H. Truong, and T. T. Van, "Optimal Distributed Generation Placement in Radial Distribution Networks Using Enhanced Search Group Algorithm," *IEEE Access*, vol. 11, pp. 103288- 103305,2023.
[19] V. R. Pandi, H. H. Zeineldin, and W. Xiao, "Determining optimal location and size of distributed generation resources considering harmonic and protection coordination limits," *IEEE transactions on power systems*, vol. 28, no. 2, pp. 1245-1254, 2012.
[20] Z. Wang, B. Chen, J. Wang, J. Kim, and M. M. Begovic, "Robust optimization based optimal DG placement in microgrids," *IEEE Transactions on Smart Grid*, vol. 5, no. 5, pp. 2173-2182, 2014.
[21] T. D. Pham, T. T. Nguyen, and L. C. Kien, "An Improved equilibrium optimizer for optimal placement of distributed generators in distribution systems considering harmonic distortion limits," *Complexity*, vol. 2022, no. 4, pp. 1-23, 2022.
[22] T. D. Pham, H. D. Nguyen, and T. T. Nguyen, "Reduction of emission cost, loss cost and energy purchase cost for distribution systems with capacitors, photovoltaic distributed generators, and harmonics," *Indonesian Journal of Electrical Engineering and Informatics (IJEEI),* vol. 11, no. 1, pp. 36-49, 2023.
[23] G. W. Chang and N. C. Chinh, "Coyote optimization algorithm-based approach for strategic planning of photovoltaic distributed generation," *IEEE Access*, vol. 8, pp. 36180-36190, 2020.
[24] H. Shayeghi and M. Alilou, "Technical-economic management of smart home energy system in the presence of stochastic and seasonal behavior of PV and EV," *Journal of Energy Management and Technology*, vol. 6, no. 4, pp. 270-281, 2022.
[25] A. Faramarzi, M. Heidarinejad, B. Stephens, and S. Mirjalili, "Equilibrium optimizer: A novel optimization algorithm," *Knowledge-based systems*, vol. 191, pp. 105190, 2019.
[26] T. D. Pham, T. T. Nguyen and L. C. Kien, "Optimal Placement of Photovoltaic Distributed Generation Units in Radial Unbalanced Distribution Systems Using MATLAB and OpenDSS-Based Cosimulation and a Proposed Metaheuristic Algorithm", *International Transactions on Electrical Energy Systems*, vol. 2022, pp. 1-21, 2022.
[27] R. S. Rao, K. Ravindra, K. Satish, and S. V. L. Narasimham, "Power loss minimization in distribution system using network reconfiguration in the presence of distributed generation," *IEEE transactions on power systems*, vol. 28, no. 1, pp. 317-325, 2012.
[28] S. K. Injeti, and N. P. Kumar, "A novel approach to identify optimal access point and capacity of multiple DGs in a small, medium and large scale radial distribution systems," *International Journal of Electrical Power & Energy Systems*, vol. 45, no. 1, pp. 142-151, 2013.
[29] R. Prakash, B. Lokeshgupta, and S. Sivasubramani, "Multi-objective bat algorithm for optimal placement and sizing of DG," In *2018 20th National Power Systems Conference (NPSC)* 2018, pp. 1-6, December 2018.
[30] K. R. Devabalaji, and K. Ravi, "Optimal size and siting of multiple DG and DSTATCOM in radial distribution system using bacterial foraging optimization algorithm," *Ain Shams Engineering Journal*, vol. *7*, no. 3, pp. 959-971, 2016.

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