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Optimal Multi-Objective Design for Hybrid Renewable Energy System in Distribution System Considering Multi-Scenarios

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Abstract: This paper presents an effective approach for determining optimal integration of renewable energy distributed generator (RE-DGs) of solar farms (SFs) and wind farms (WFs) in IEEE 69-node power distribution network (PDN) with target of minimizing (1) the single objective function of total active power loss and (2) multi-objective function including a) total active power loss, b) total reactive power loss, c) the voltage deviation and d) imported energy from the main power gird. Intelligent and adaptive meta-heuristic optimization algorithm called bonobo optimizer (BO) is introduced to address optimization problem considering the changing four seasons of winter, spring, summer and autumn from both generation and consumption. The obtained results from BO show its outstanding performance in determining the suitable installation of SFs and WFs compared with many published methods and implemented methods for two cases of single and multi-objective functions.

Keywords: Solar farms; Wind farms; Bonobo optimizer; Total power loss; The voltage deviation.

Introduction

THE general trend of the world is to minimize the use of fossil fuels and encourage the penetration of renewable resources, especially wind energy and solar energy [1, 2]. According to Internatonal Renewable Energy Agency (IRENA), the shared global renewable energy to the world demand is predicted to increase from 25% in 2015 to 60% in 2030 and 85% in 2050 [3]. Receiving many benefits from the penetration of renewable energy distributed generation sources has strongly promoted the growth of these energy sources [4]. However, connecting RE-DGs without proper planning can cause many unwanted effects that are directly related to economic and technical factors [5]. Therefore, determining the appropriate penetration of RE-DGs is extremely necessary. Many researchers have proposed different approaches such as the mixed integer linear programming (MILP) [6], the mixed integer nonlinear programming (MINLP) [7, 8], artificial neural networks [9, 10], fuzzy logic control (FLC) [11, 12] and meta-heuristic algorithms [13-15] in determining the integration of distributed generation sources (DGs) in general and RE-DGs in particular in PDN. Among these groups, the meta-heuristic algorithm group has many superior advantages in solving many complex optimization problems with the large search spaces. Therefore, meta-heuristic algorithms have attracted much attention from researchers around the world for finding feasible solutions to address optimization problems related to the installation of distributed generators (DGs) in general into power grids. Specifically, the authors in [16, 17] applied genetic algorithm (GA) and hybrid algorithm of GA-particle optimization algorithm (GA-PSO) for minimizing total power loss on branches by connecting DGs. Although GA and GA-PSO are long-standing and popular method in solving various optimization problems, its biggest drawback is poor performance with uncertain convergence. Besides, [18, 19] have proposed more aggressive meta-heuristic algorithms such as artificial bee colony (ABC) and ant colony optimization (ACO) algorithms to improve profile voltage as well as reduce energy loss on transmission branches in different PDN thanks to the reasonable penetration of DGs. ACO and ABC are optimization algorithms that are inspired by the intelligent characteristics of animals on earth. Although these methods are widely used, they also have

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disadvantages of relatively slow convergence speed and easily falling into local optimal area, leading to poor performance. Additionally, the authors [20] also suggested another method called ant lion optimization algorithm (ALOA) for determining the location and capacity of RE-DGs such as SFs and WFs in IEEE PDN. This study also indicates the huge benefits of penetration from SFs and WFs in terms of environmental aspect as well as cost savings through loss reduction. With the same research object of renewable energy sources, [21] has further considered PDN with the existence of nonlinear loads. High penetration of these loads produces and injectes rich harmonic sources into the system, so consideration is given for minimizing related indicators such as total and individual harmonic distortions. That research also succeeded in reducing the total costs of grid operation as well as harmonic indicators while still ensuring that technical criteria were met by using the popular algorithm of particle swarm optimization (PSO). Similarly, [22] are also interested in the presence of nonlinear loads in PDN. These authors solved M-OF of loss reduction, harmonics reduction and voltage deviation with the penetration of renewable energy sources by applying biogeography-based optimization (BBO) in determining global solution. BBO is a powerful evolutionary algorithm but its effectiveness depends mainly on the control parameters, slow convergence speed and complex structure. Thus, it has not been widely used compared to other meta-heuristic methods. In addition to the above-mentioned goals, studies in [23] and [24] considered additional cost factors in the installation of DGRs and electric vehicle charging station (EVCS) such as investment and operational costs as the main targets. These research have also proven that total costs can be decreased significantly thanks to the proper connection of DGs in PDN.

Overall, the majority of published studies only focus on reducing branch power loss and improving node voltage as the primary tasks, and only a few researchers are interested in minimizing the total costs of installing and operating DGs. However, these are not enough in considering connection of DGs into PDN. Moreover, studies related to the penetration of renewable energy sources that consider for minimizing the imported energy from main grid have not yet received much attention, although this is also important in cutting the operational cost. On the other hand, past studies mostly searched for feasible solutions at peak load level or some load levels, and the found result may not be appropriate solution for all different load scenarios. Considering the time-varying of generation and demand will contribute to improving the quality of the optimal solution and shortening the difference between design and practical problems. Not only that, the mentioned studies used old algorithms with low efficiency and stability, leading to uncertain quality. Therefore, introducing an effective algorithms which can enhance the effectiveness in solving the various optimization problems is necessary. With the continuous development of computer science, in recent years, active meta-heuristic methods such as coyote optimization algorithm (COA) [25], bacterial foraging optimization algorithm (BFOA) [26], improved salp swarm algorithm (ISSA) [27], dragonfly algorithm (DA) [28], sewing training-based optimization (STBO) [29], walrus optimization algorithm (WaOA) [30], osprey optimization algorithm (OOA) [31], etc have also been developed for solving different problems. Among those algorithms, bonobo optimizer (BO) which is born based on the bonobos social behavior and breeding methods, has attracted a lot of attention because of its performance and stability in addressing real-world optimization problems [32].

Thus, this research suggests BO for determining the optimal installation of wind farms and solar farms in distribution network. The objective of the study is to consider all technical and economic aspects by simultaneous minimizing four sub-objectives including total active power loss, total reactive power loss, voltage deviation, and imported energy from main gird considering seasonal variations in load demand and grid-connected distributed generation sources. Real data of solar irradiance and wind speed for simulating SFs and WFs were taken from [33]. Therefore, in this work, 96 time segments (or data points) are averaged for 4 seasons in 1 year (365 days) are considered in this study and the 4 seasons (winter, spring, summer and fall) are represented by 4 days with each day consisting of 24 hours. Besides, IEEE reliability test system [4] that includes 96 time segments is used to simulate the time-varying load demand. The primary contributions of this research is listed as:

(1) An efficient algorithm named BO, is suggested for determining the optimal placement and penetration of renewable distributed generation sources including solar farms and wind farms in IEEE 69-node PDN considering time-varying demand and power generation. This can significantly improve the solution quality in addressing the optimization problem through applying the powerful method.
(2) The study comprehensively examines the related aspects of integrating RE-DGs into the distribution grid. Specifically, single-objective function (S-OF) and multi-objective function (M-OF) are applied to simultaneously minimize the technical and economic factors, and weighted sum method is also used for making the best compromise decision in this work. This is a reasonable and comprehensive consideration.

(3) Simulated data of output power of SFs and WFs as well as load demand are used in this study with seasonal variations during the year for 96 time periods. This contributes in enhancing the accuracy of the found optimal solution compared to reality.

The rest of this paper is included: The objective function and its constraints are given in Sect. 2. The introduced optimization algorithm is shown in Sect. 3. The simulation results and the discussions are presented in Sect. 4. Finally, a summary of whole work in Sect. 5.

Problem formulation

Determining the appropriate installation of SFs and WFs in PDN for maximizing welfare while still meeting technical criteria is a major challenge. As Figure 1 illustrates, distributed renewable energy sources are connected to the main power grid through power conversion devices for supplying electricity to the loads. The appropriate combination of distributed generation sources and main grid has created a flexible hybrid system with many excellent economic and technical benefits. Therefore, determining the right connectivity strategy that considers multiple aspects is essential. The detailed list of targets in M-OF for this work is mathematically presented as item 2.1.

1.1 Objective functions

Technical and economic benefits are considered as primary objectives in this research. Therefore, M-OF is selected to use in this research and presented in mathematical equations [14, 24]:

$$\textbf{\textit{Minimize}}\ OF = (\gamma_1 \cdot SF_1) + (\gamma_2 \cdot SF_2) + (\gamma_3 \cdot SF_3) + (\gamma_4 \cdot SF_4) \quad (1)$$

The components of M-OF can be determined by using the following equations:

$$SF_1 = \frac{PL^{RE\_DG}}{PL^{NoRE\_DG}} = \frac{\sum_{t=1}^{N^T}\sum_{h=1}^{N^H} I_{h,t,RE-DG}^2 R_h}{\sum_{t=1}^{N^T}\sum_{h=1}^{N^H} I_{h,t}^2 R_h} \quad (2)$$

$$SF_2 = \frac{QL^{RE\_DG}}{QL^{NoRE\_DG}} = \frac{\sum_{t=1}^{N^T}\sum_{h=1}^{N^H} I_{h,t,RE-DG}^2 X_h}{\sum_{t=1}^{N^T}\sum_{h=1}^{N^H} I_{h,t}^2 X_h} \quad (3)$$

$$SF_3 = \frac{VD^{RE\_DG}}{VD^{NoRE\_DG}} = \frac{\sum_{t=1}^{N^T}\sum_{s=1}^{N^S} |V_{Nom} - V_{s,t,RE-DG}|}{\sum_{t=1}^{N^T}\sum_{s=1}^{N^S} |V_{Nom} - V_{s,t}|} \quad (4)$$

$$SF_4 = \frac{IE^{RE\_DG}}{IE^{NoRE\_DG}} = \frac{\sum_{t=1}^{N^T} P_{t,RE\_DG}^{Sub}}{\sum_{t=1}^{N^T} P_t^{Sub}} \quad (5)$$

Obviously, like Eq. (2) to Eq. (5) described, the values of SF_1, SF_2, SF_3 and SF_4 only range from 0 to 1, in which, the smaller the value, the better. Additionally, the weighted sum method is also used for deciding the compromise output of M-OF as Eq. (1), where γ_1, γ_2, γ_3 and γ_4 are defined as weighting coefficients which involves the reduction of total active power loss, total reactive power loss, voltage deviation and imported energy from the main grid, respectively. These weighting coefficients should satisfy the constraint [17]:

$$\sum_{i=1}^{4} \gamma_i = 1;\ \gamma_i \in (0,1) \quad (6)$$

1.2 Constraints in this research

- Active power balance constraint [4]:

$$\sum_{h=1}^{N^H} P_{h,loss} + \sum_{d=1}^{N^D} P_{d,load} = \sum_{g=1}^{N^G} P_{g,RE\_DG} + P^{Sub} \quad (7)$$

- Reactive power balance constraint:

$$\sum_{l=1}^{N^H} Q_{l,loss} + \sum_{d=1}^{N^D} Q_{d,load} = \sum_{g=1}^{N^G} Q_{g,RE\_DG} + Q^{Sub} \quad (8)$$

- The line current constraint [23]:

$$I_h \le I_h^{Max};\ h = 1, \dots, N^H \quad (9)$$

- The node voltage constraint [18]:

$$|V_s^{Min}| \le |V_s| \le |V_s^{Max}|;\ s = 1, \dots, N^S \quad (10)$$

- The operational power factor constraint of inverter [33]

$$PF^{Min} \le PF_g \le PF^{Max};\ g = 1, \dots, N^G \quad (11)$$

- Installed power constraint of RE-DGs [10]

$$P_{RE\_DG}^{Min} \le P_g^{Rated} \le P_{RE\_DG}^{Max};\ g = 1, \dots, N^G \quad (12)$$

- Penetration constraint of RE-DGs [20]

$$\sum_{g=1}^{N^G} P_{g,RE\_DG} \le \sum_{l=1}^{N^H} P_{l,loss} + \sum_{d=1}^{N^D} P_{d,load} \quad (13)$$

The applied method for addressing optimization problem

In this work, a powerful method which named bonobo optimizer (BO), is suggested to find optimal solution for the installation of SFs and WFs in PDN considering the seasonal variation of distributed sources and loads. BO was developed by taking inspiration from the characteristic behaviors of bonobos, including social behavior and reproductive behavior, and the algorithm was first published by Das and Pratihar in 2019 [32]. BO is considered as an intelligent and adaptive meta-heuristic algorithm and has a mechanism to update the solution position after each iteration for enhancing the quality of the community.

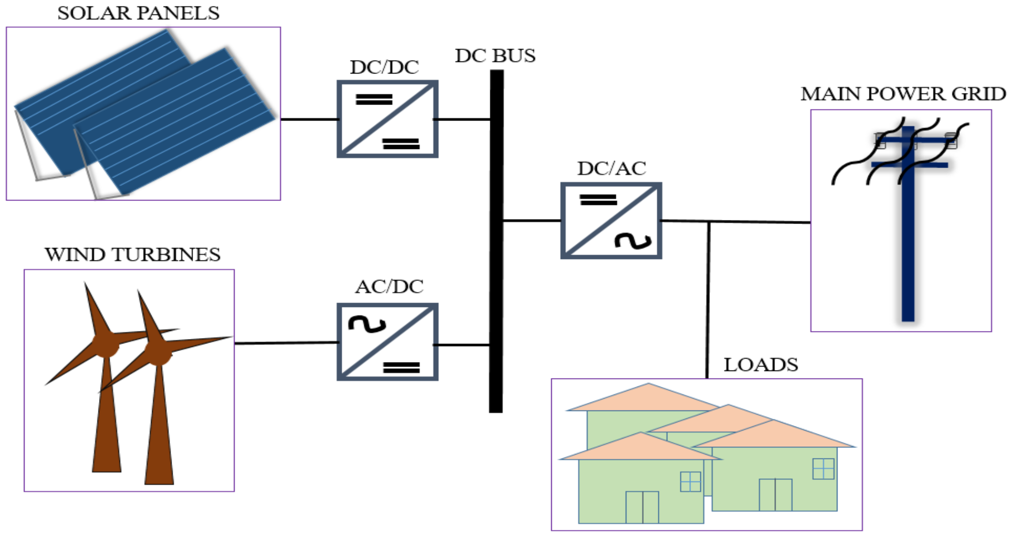

Fig 1. The power network integrates distribution generation of solar and wind energies

Not only that, bonobos also exhibit their special reproductive behavior with four strategies such as promiscuous, restricted mating, consortship, and extra-group mating [32]. All these behaviors of bonobos are modeled to address different optimization problems.

In this algorithm, each bonobo is represented for each optimal solution, in which bonobo with the best fitness value in the community is named alpha-bonobo (α^{bo}). After each iteration, the quality of α^{bo} is updated. The process of applying BO to address the optimization problem is implemented according to the following steps [34]:

Step 1: Initialization for parameters which are not defined by user.

Initial parameters for BO are generated such as positive phase count (PPC), negative phase count (NPC), directional probability (P_d), phase change (CP), extra-group mating probability (P_{xgm}), phase probability (P_ρ) and temporary sub-group size factor ($SGrp_{fact}$).

Step 2: Bonobo selection via fission fusion strategy.

In this stage, the community is separated into many temporary subgroups that subgroup's size cannot be determined precisely because it depends on stochastic generation. However, the maximum size of temporary subgroups ($SGrp_{temp}^{Max}$) can be defined by:

$$SGrp_{temp}^{Max} = \max(2, SGrp_{fact} \cdot N^N) \quad (14)$$

In the Eq. (14), N^N is the community size and $SGrp_{fact}$ should be an integer number. If its found result is not an integer number, the next integer number is considered.

Step 3: Generation of new bonobo by applying the mating strategies.

In this stage, the mating strategies are divided into two main groups including (1) the promiscuous and restrictive mating strategies group and (2) the consortship and extra-group mating strategies group. In the first strategies group, a randomly produced number (r_1) within (0, 1) is compared with the P_ρ for creating a new solution. If $P_\rho \geq r_1$ then a new solution of bonobo (bo_k^{new}) is generated by using (32):

$$bo_k^{new} = bo_k^n + \left[r_1 \cdot sc_1 \cdot \left(a_k^{bo} - bo_k^n\right)\right] + \left[(1 - r_1) \cdot sc_2 \cdot fl \cdot \left(bo_k^n - bo_k^p\right)\right] \quad (15)$$

Where fl is the flag which can get the value of 1 if the fitness value of bo_k^n is greater than bo_k^p and vice versa, -1 is assigned for fl; sc_1 and sc_2 are the sharing coefficients of alpha-bonobo and selected bonobo; a_k^{bo}, bo_k^p and bo_k^n are defined as the k^{th} control variables of alpha-bonobo, p^{th} bonobo and n^{th} bonobo, respectively. In the second strategies group, the P_{xgm} is updated through each loop and its value is compared to r_2 which is randomly generated in (0, 1).

If P_{xgm} >= r_2 then new solution generation is implemented by Eqs. (16-19):

$$bo_k^{new} = bo_k^n + \omega_1 \cdot \left({ctrl_{var}}_k^{max} - bo_k^n\right); k = 1, \dots, N^K \text{ and } n = 1, \dots, N^N \quad (16)$$

$$bo_k^{new} = bo_k^n - \omega_2 \cdot \left(-{ctrl_{var}}_k^{min} + bo_k^n\right); k = 1, \dots, N^K \text{ and } n = 1, \dots, N^N \quad (17)$$

$$bo_k^{new} = bo_k^n - \omega_1 \cdot \left(-{ctrl_{var}}_k^{min} + bo_k^n\right); k = 1, \dots, N^K \text{ and } n = 1, \dots, N^N \quad (18)$$

$bo_k^{new} = bo_k^n + \omega_2 \cdot \left({ctrl_{var}}_k^{max} - bo_k^n\right); k = 1, \dots,$ N^K and $n = 1, \dots, N^N$ (19)

In this case, Eqs. (16, 17, 18 & 19) are selected for producing the next generation if ($a_k^{bo} \geq bo_k^n$ and $P_\rho \geq r_3$), ($a_k^{bo} \geq bo_k^n$ and $P_\rho < r_3$), ($a_k^{bo} < bo_k^n$ and $P_\rho \geq r_3$), and ($a_k^{bo} < bo_k^n$ and $P_\rho < r_3$), respectively. Besides, ω_1 and ω_2 can be determined by using Eq. 20 and Eq. (21).

$$\omega_1 = e^A, \text{ where } A = r_4^2 + r_4 - 2/r_4 \quad (20)$$

$$\omega_2 = e^B, \text{ where } B = -r_4^2 + r_4 - 2/r_4 \quad (21)$$

In Eqs. (16-19), ${ctrl_{var}}_k^{max}$ and ${ctrl_{var}}_k^{min}$ are considered as the max and min limits of the control variables. r_3 and r_4 are random numbers in the range of (0, 1), where $r_4 \neq 0$.

If $P_{xgm} < r_2$ then new solution generation is implemented by applying Eq. (22).

$$bo_k^{new} = \begin{cases} bo_k^n + fl \cdot e^{-r_5} \cdot \left(bo_k^n - bo_k^p\right), if\ fl = 1\ or\ P_\rho \geq r_5, r_5 \in (0,1) \\ bo_k^p, otherwise \end{cases} \quad (22)$$

Step 4: Violated control variables correction.

After each new solution is released, the control variables (${ctrl_{var}}_k^{new}$) in each solution are checked and corrected if they have any violations according to the following rules

$$ {ctrl_{var}}_k^{new} = \begin{cases} {ctrl_{var}}_k^{min}, if\ {ctrl_{var}}_k^{new} < {ctrl_{var}}_k^{min} \\ {ctrl_{var}}_k^{max}, if\ {ctrl_{var}}_k^{new} > {ctrl_{var}}_k^{max}; k = 1, \dots, N^K \\ {ctrl_{var}}_k^{new},\ otherwise \end{cases} $$

(23)

Step 5: Evaluation for found solutions.

The fitness function is used to evaluate for the n^{th} generated solution by applying Eq. (24).

$$Fitness^n = OF^n + (\varphi_1 \cdot \Delta Volt^n + \varphi_2 \cdot \Delta Curt^n + \varphi_3 \cdot \Delta Pen^n);\ n = 1, \dots, N^n \quad (24)$$

Where OF^n is value of the multi-objective function at the n^{th} solution; φ_1, φ_2 and φ_3 are the penalty function coefficients; $\Delta Volt^n, \Delta Curt^n$ and ΔPen^n are respectively the penalty amounts of node voltage, current on branches and penetration of DGs.

Step 6: Comparison for remaining good quality solutions.

The solutions are compared by using the fitness function and the alpha-bonobo that has the best quality in the current community is determined through each iteration. Additionally, based on the quality of the current alpha-bonobo compared to the previous alpha-bonobo, the control parameters are updated.

Step 7: Iteration stopping.

The iteration process is repeated until the current iteration number reaches the maximum limit ($Iter_L = Iter^{max}$) and the best solution of the considering problem is also determined.

The process of implementing BO is also briefly illustrated in Figure 2.

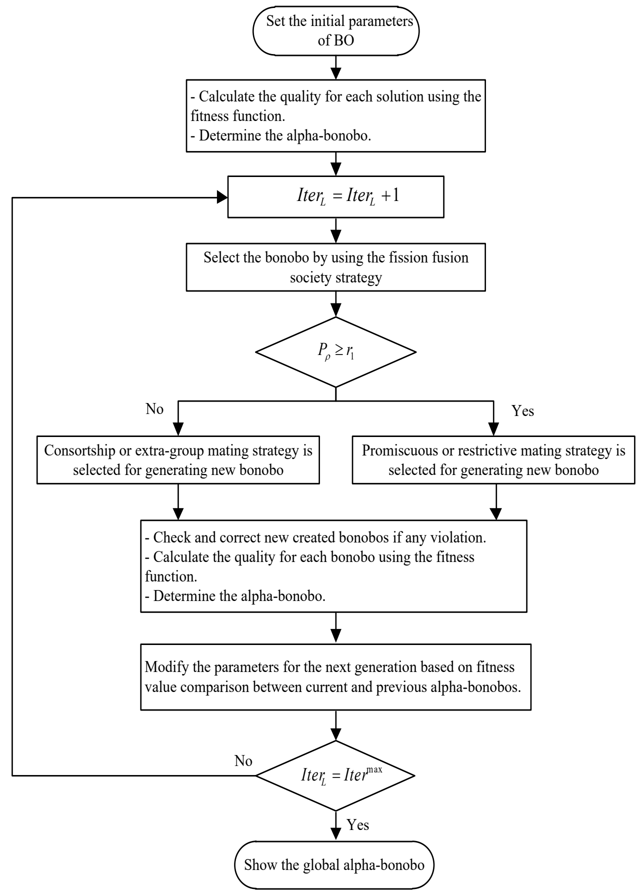

Fig 2. The flowchart of BO for finding the global solution

Discussion and simulation results

In this paper, bonobo optimizer is introduced to solve the optimization problem of installing distributed generation sources for S-OF and M-OF in IEEE 69-node PDN. Node and line data are collected for research from [20] and network configuration is also plotted as Figure 3. In this study, for implementing simulation of BO, GA, GA-PSO, ABC and SFS, the selected parameters are referenced from previous researches. Specifically, to simulating BO, the key parameters are signed such as $PPC = 0$, $NPC = 0$, $P_d = 0.5$, $CP = 0$, $P_\rho = 0.5$, $P_{xgm} = P_{init\_xgm}$ and $SGrp_{fact} = SGrp_{init\_fact}$. Where,

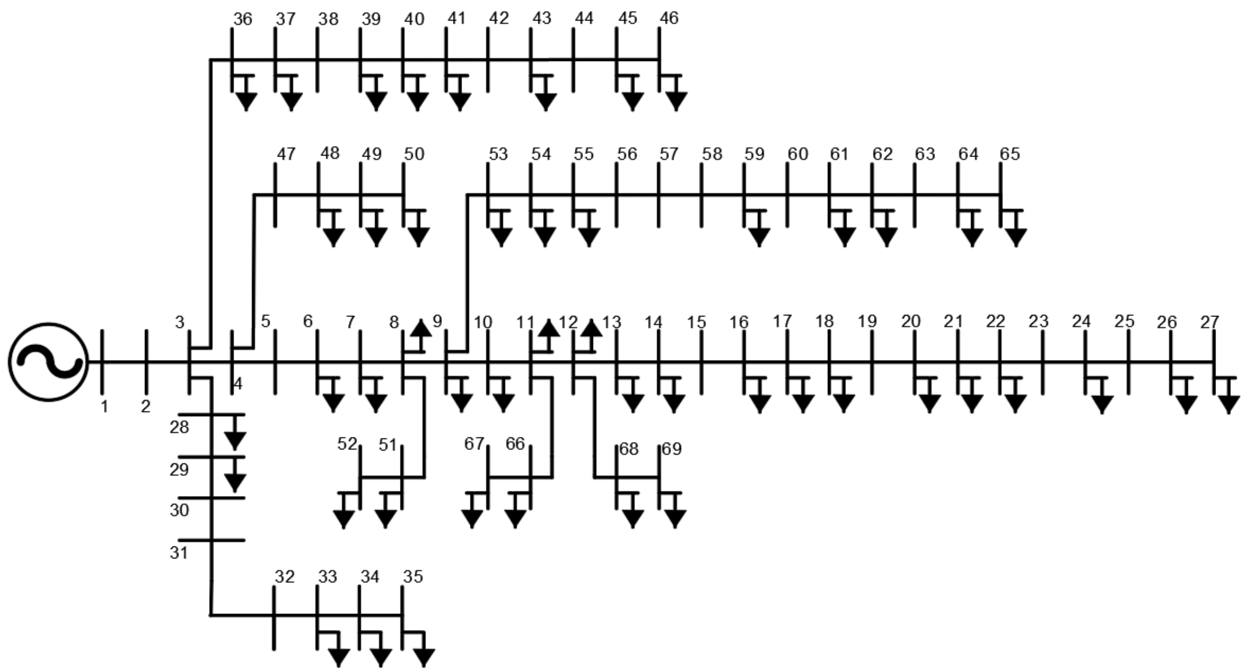

Fig 3. IEEE 69-node PDN

P_{init_xgm} and $SGrp_{init\_fact}$ are defined as the initial values of P_{xgm} and $SGrp_{fact}$, and they are clearly determined like presented [32]. For running GA, GA-PSO, SFS and ABC, the control parameters are taken from studies [16], [17], [36] and [19], respectively. Besides, due to the nature of meta-heuristic algorithms, the quality of the found optimal solution depends on the initial parameters such as population size and number of iterations. Therefore, in order to evaluate efficiency fairly, N^N and $Iter^{max}$ are surveyed to select appropriate values. Specifically, N^N is surveyed in the range from 20 to 50 (the selected step size is 10) and $Iter^{max}$ is also surveyed from 100 to 300 (the selected step size is 100). The obtained results from the survey showed that N^N and $Iter^{max}$ should be 30 and 200 for the implemented methods to ensure complete convergence.

1.3 Consideration of single objective function

In this specific scenario, the suggested method, BO, is used to solve the problem of optimal installation of three distributed generators for minimizing total power loss at the peak load level, and the obtained results are also compared with many published methods, as Table 1

As Table 1 indicated, with the primary target of minimizing total power loss, BO has found the most optimal solution compared to the six previously published methods. By applying the global solution of BO, total power loss is reduced significantly from 0.2245 MW to 69.204 kW, corresponding to a loss reduction of 69.18%. This value of BO is better than 68.74% of SGA [37], 68.75% of PSO [37], 69.07% of SFS [36], 68.37% of QOSIMBO-Q [38], 69.01% of KHA [39] and 68.10% of QOTLBO [40]. This shows that BO's solution is more positive than other methods in cutting total power loss of PDN in this case. Besides, thanks to the appropriate integration of DGs, the voltage profile is also strongly improved and all node voltages have also satisfied the constraint of (0.95, 1.05) p.u. Like Figure 4 plotted, the weakest node voltage has been enhanced from 0.909 p.u at node 65 to 0.978 p.u thanks to the application of optimal solution of the suggested method. Overall, determining the optimal integration of DGs not only brings great benefits in reducing total loss but also improving node voltage.

1.4 Consideration of the multi-objective function

In this specific case, a M-OF consisting of four single objectives is implemented and weighted sum method is also applied to determine the output of each proposed solution [17]. In that method, the weighting coefficients such as γ_1, γ_2, γ_3 and γ_4 are investigated to choose the suitable values for M-OF. The values of these coefficients are assigned based on the importance level of components in the objective function. In this study, the single objective component that involves reducing energy imports from the main power grid is the most important and the component which related to improving node voltage is considered the least important. Therefore, the search range for the value of γ_4 is (0.4, 0.6) and (0.1, 0.15) for γ_3, and the remaining range is (0.15, 0.25) for γ_1 and γ_2 as shown in Table 2.

Table 1. The optimal solution for installing DGs.

Method	Optimal solution of DGs	Total power loss	Loss reduction	Minimum voltage	Maximum voltage
SGA [37]	Node 17 – 0.4665 (MW) Node 61 – 1.6845 (MW) Node 53 – 0.5466 (MW)	70.175 (kW)	68.74%	0.9780 (p.u)	1.00 (p.u)
PSO [37]	Node 61 – 1.7812 (MW) Node 17 – 0.5312 (MW) Node 50 – 0.7202 (MW)	70.158 (kW)	68.75%	0.9779 (p.u)	1.00 (p.u)
SFS [36]	Node 11 – 0.5273 (MW) Node 18 – 0.3805 (MW) Node 61 – 1.7198 (MW)	69.428 (kW)	69.07%	0.9780 (p.u)	1.00 (p.u)
QOSIMBO-Q [38]	Node 09 – 0.8336 (MW) Node 18 – 0.4511 (MW) Node 61 – 1.5000 (MW)	71.0 (kW)	68.37%	0.9726 (p.u)	1.00 (p.u)
KHA [39]	Node 12 – 0.4962 (MW) Node 22 – 0.3113 (MW) Node 61 – 1.7354 (MW)	69.563 (kW)	69.01%	0.9779 (p.u)	1.00 (p.u)
QOTLBO [40]	Node 18 – 0.5334 (MW) Node 61 – 1.1986 (MW) Node 63 – 0.5672 (MW)	71.625 (kW)	68.10%	0.9782 (p.u)	1.00 (p.u)
BO	Node 18 – 0.3710 (MW) Node 11 – 0.5354 (MW) Node 61 – 1.7189 (MW)	69.204 (kW)	69.18%	0.9780 (p.u)	1.00 (p.u)

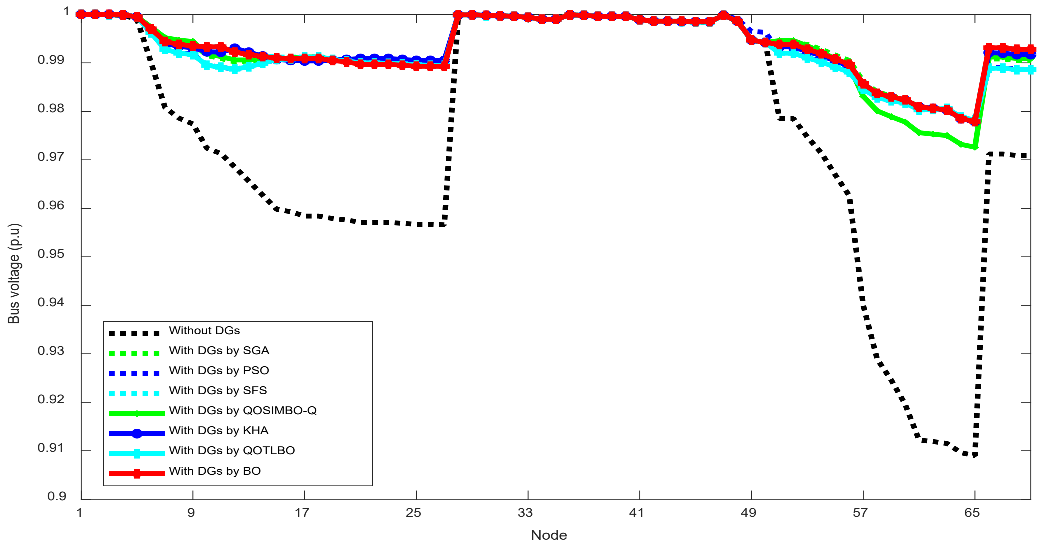

Fig 4. The voltage profile of suggested method and compared methods

Table 2. Figure 1Table 2 The survey for selecting the weighting coefficients in M-OF

Coefficients	γ_1	γ_2	γ_3	γ_4	$min\ (OF)$	$mean\ (OF)$	$max\ (OF)$
Scenario 1	0.2	0.2	0.1	0.5	0.07846	0.0871	0.1032
Scenario 2	0.15	0.15	0.1	0.6	0.06098	0.06734	0.08266
Scenario 3	0.2	0.2	0.15	0.45	0.081215	0.08838	0.10232
Scenario 4	0.25	0.25	0.1	0.4	0.09637	0.10523	0.15718

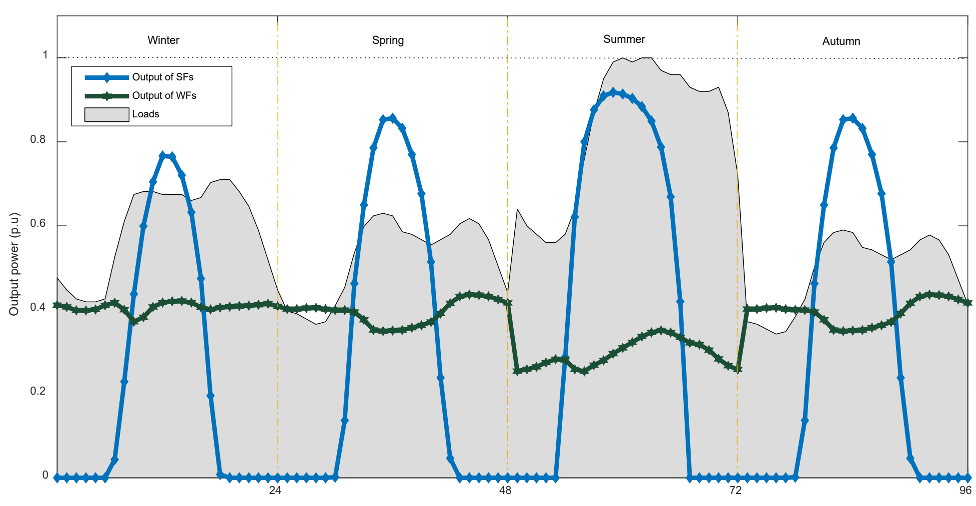

Fig 5. The output power curves in p.u of SFs, WFs and loads

To evaluate precision in determining the appropriate weighting coefficients, 40 test runs for four DGs are performed at the peak load with four pairs of weighting coefficients. The min, mean and max values of coefficients in M-OF are also collected for comparison in Table 2. Clearly, scenario 2 of ($\gamma_1 = 0.15$, $\gamma_2 = 0.15$, $\gamma_3 = 0.10$, and $\gamma_4 = 0.60$) has better values of OF than other scenarios, so the found weighting coefficients in the scenario 2 is chosen for this study.

As mentioned, this study considers the seasonal variation (winter, spring, summer, and autumn) from loads and output power of renewable energy generation sources. In this case, each season is represented by a day of 24 hours, and therefore, a total of 96 data points are considered in this work. The load data is referred from [4] and output power data of SFs and WFs are taken from [33]. These data are also illustrated as presented in Figure 5.

Due to the nature of stochastic algorithms, 40 test runs (N_{Run}) are simulated under the same conditions in this study. The best and average fitness values which demonstrate the efficiency and stability of each algorithm in the runs, are reported explicitly in Table 3.

Table 3. The obtained results from implemented method in 40 test runs

Applied methods	The best fitness	The average fitness	The fitness deviation
GA	0.2767	0.2831	0.0064
GA-PSO	0.2756	0.2797	0.0041
ABC	0.2743	0.2789	0.0046
SFS	0.2670	0.2713	0.0043
BO	0.2650	0.2679	0.0029

As shown in Table 3, the best and average fitness values of BO (0.2650 and 0.2679) are also better than GA (0.2767 and 0.2831), GA-PSO (0.2756 and 0.2797), ABC (0.2743 and 0.2789) and SFS (0.2670 and 0.2713). In addition, to demonstrate the stability of the methods, the deviation between the best fitness value and the average fitness value is also calculated. These values are 0.0064, 0.0041, 0.0046, 0.0043 and 0.0029 for GA, GA-PSO, ABC, SFS and BO, respectively. Clearly, the fitness deviation value from the suggested method is the smallest, leading to the best stability across multiple runs compared to others.

The best obtained results regarding the location and installed capacity of SFs and WFs of the implemented methods are described in Table 4. Clearly, BO found the best solution with the OF value of 0.2650 and it is lower than GA of 0.2767, GA-PSO of 0.2756, ABC of 0.2743 and SFS of 0.2670 after trial runs. In other words, the determined solution by BO is better than other methods in the case of considering this M-OF. Specifically, for the first and second single objective component that involves the reduction of active and reactive power losses (SF1 and SF2), the SF1 and SF2 values of BO (0.1346 and 0.1779) are lower than the other four methods such as GA (0.1576 and 0.1966), GA-PSO (0.1544 and 0.1928), ABC (0.1642 and 0.2021) and SFS (0.1485 and 0.1789), respectively. This indicates that active and reactive power loss reduction from BO's optimal solution is also better than others. Besides, for the third single target which is related to voltage (SF3), this value of BO is 0.2561 and it is much lower than 0.3067 of GA, 0.3075 of GA-PSO, 0.2630 of ABC but a little higher than SFS. This means that the voltage deviation of BO is better than GA, GA-PSO and ABC but worse than SFS, and this has to be a trade-off in considering M-OF. Finally, the single-objective component related to importing energy from the main power grid (SF4) is also compared. Obviously, this value of BO is 0.3209 and it is lower than 0.3216, 0.3214, 0.3217 and 0.3210 of GA, GA-PSO, ABC and SFS, respectively. In other words, the found solution by suggested method can reduce energy import better than remaining methods, and this is important in cutting electricity purchase cost from the main gird during operation. Overall, the results obtained for SF1, SF2, SF3 and SF4 from the implemented methods indicate that the suggested method is much more effective than others for solving the multi-objective problem of installing RE-DGs in PDN.

Furthermore, the convergence characteristics of the five implemented methods are also compared. To ensure complete convergence of the methods, the number of iterations are investigated and 200 iterations are selected for this optimization problem. As shown in Figure 6, the convergence curve of BO is also better than GA, GA-PSO, ABC and SFS.

Obviously, at the 48th iteration, BO has a tendency to achieve stable convergence and the best optimal solution in this case is determined at the 55th iteration. Meanwhile, GA, GA-PSO, ABC and SFS found their best optimal solutions at the 70th, 59th, 81st and 60th iterations, respectively. It is shown that the effective new solution generation mechanism of the suggested method has significantly contributed to improving the ability to avoid local optimal traps and promoting BO to achieve better convergence than other compared methods. In summary, BO is not only an efficient method in terms of performance but also has better convergence than other methods in solving the problem of optimizing the installation of distributed sources in PDN.

By applying the best solution from the suggested method (BO), the penetration of renewable energy distributed generation sources versus consumption demand is plotted as Figure 7.

Table 4. The obtained results from implemented method in 40 test runs

Item	SFs	WFs	SF_1	SF_2	SF_3	SF_4	OF
GA	Node 16 – 0.5263 (MW) Node 61 – 0.6279 (MW)	Node 61 – 2.3583 (MW) Node 55 – 0.8761 (MW)	0.1576	0.1966	0.3067	0.3216	0.2767
GA-PSO	Node 17 – 0.5241 (MW) Node 62 – 0.6305 (MW)	Node 53 – 0.7333 (MW) Node 61 – 2.5013 (MW)	0.1544	0.1928	0.3075	0.3214	0.2756
ABC	Node 15 – 0.2019 (MW) Node 67 – 0.9465 (MW)	Node 61 – 2.7867 (MW) Node 21 – 0.4530 (MW)	0.1642	0.2021	0.2630	0.3217	0.2743
SFS	Node 59 – 0.9591 (MW) Node 50 – 0.2000 (MW)	Node 61 – 2.4456 (MW) Node 17 – 0.7863 (MW)	0.1485	0.1789	0.2533	0.3210	0.2670
BO	Node 12 – 0.5165 (MW) Node 61 – 0.6383 (MW)	Node 17 – 0.7137 (MW) Node 61 – 2.5193 (MW)	0.1346	0.1779	0.2561	0.3209	0.2650

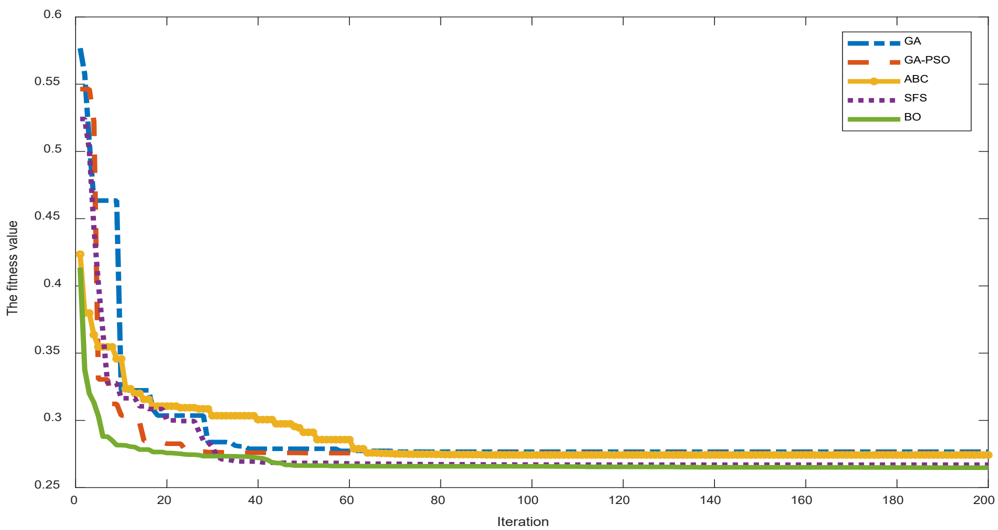

Fig 6. Convergence properties of GA, GA-PSO, ABC, SFS and BO

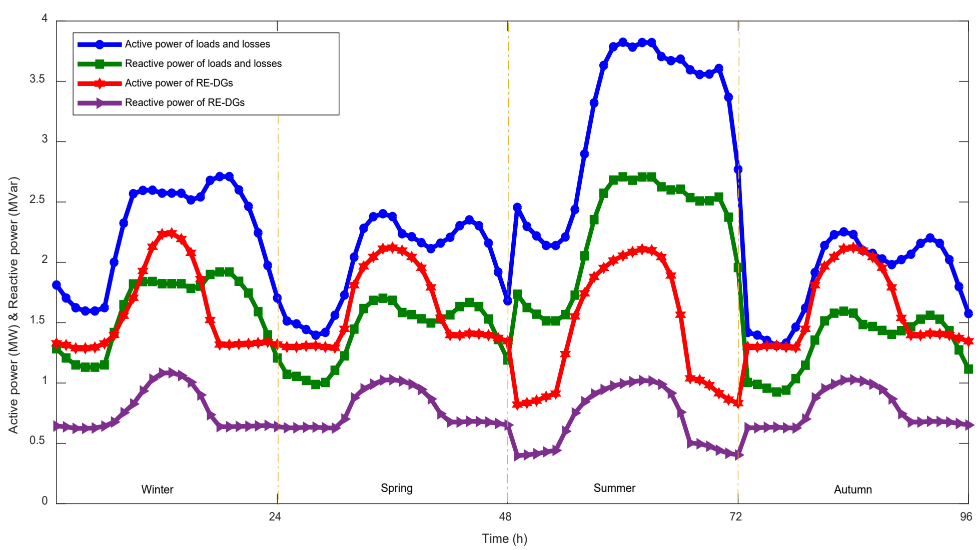

Fig 7. The penetration by RE-DGs in the considering periods

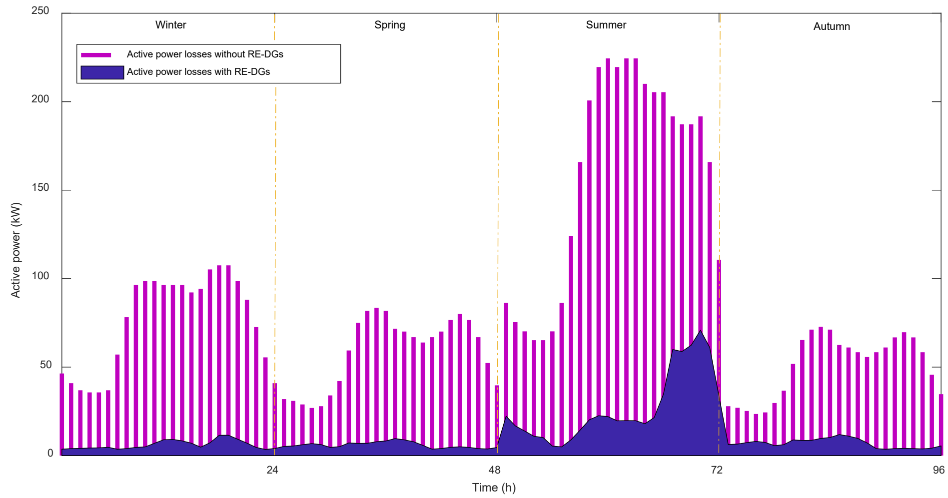

Fig 8. Total active power loss with and without RE-DGs

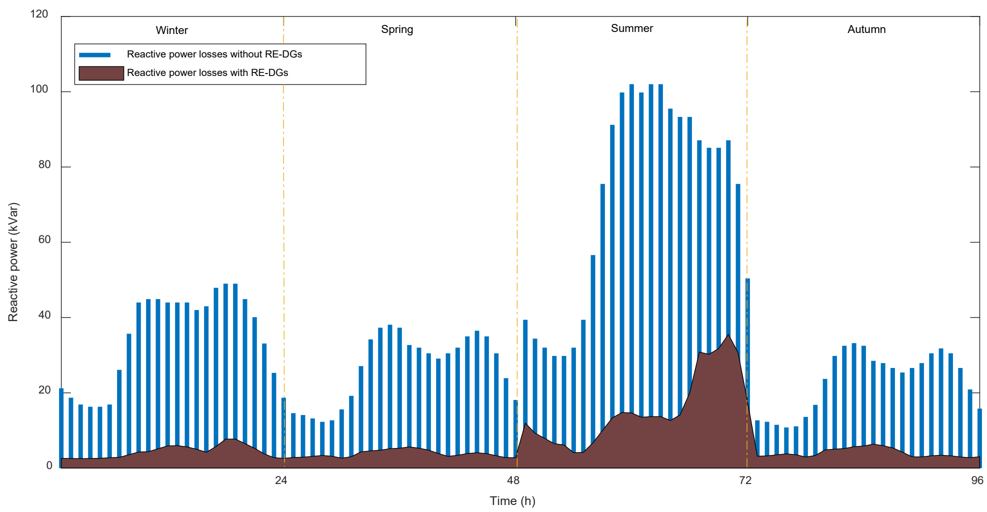

Fig 9. Total reactive power loss with and without RE-DGs

As calculated in 96 hours of 4 seasons, the total generation of SFs and WFs is 156.23 MW/ 75.29 MVar and they account for 67.91%/ 46.78% of the total demand, 230.05 MW/ 160.93 MVar, respectively. Hence, electricity shortage of 73.82 MW/ 85.64 MVar will be imported from the main power grid to ensure the balance between generating power and consuming power. Thanks to the penetration of RE-DGs into the distribution grid, the imported energy from the main grid is minimized and has resulted in a reduction in the total cost of purchasing energy for operation. Besides, with integrating RE-DGs, the total loss in PDN has decreased strongly from 8.2224 MW to 1.1064 MW and from 3.7460 MVar to 0.6665 MVar with corresponding to 86.54% and 82.21% in loss reduction for active and active power losses as presented Figure 8 and Figure 9, respectively. This proves the huge benefit of determining the appropriate connection of RE-DGs for reducing both total active and total reactive power losses in PDN. It also contributes to mitigating operational cost for the system in the long term. Furthermore, an added benefit from suitable integrating RE-DGs is the enhanced node voltage profile. As shown in Figures 10 and 11, the voltage profiles of four representative days for the four seasons of the year are presented. Obviously, before integration of RE-DGs, there were many node voltages outside the acceptance range (0.95, 1.05) p.u with the lowest voltage being 0.9090 p.u at the peak load periods as Figure 10. However, the operating voltage range of the nodes has been significantly increased to (0.9508, 1.0181) p.u thanks to the connection of RE-DGs as demonstrated by Figure 11. This also confirms that proper integration of RE-DGs can positively enhance the voltage profile and that is considered as a great benefit from the penetration of RE-DGs in PDN.

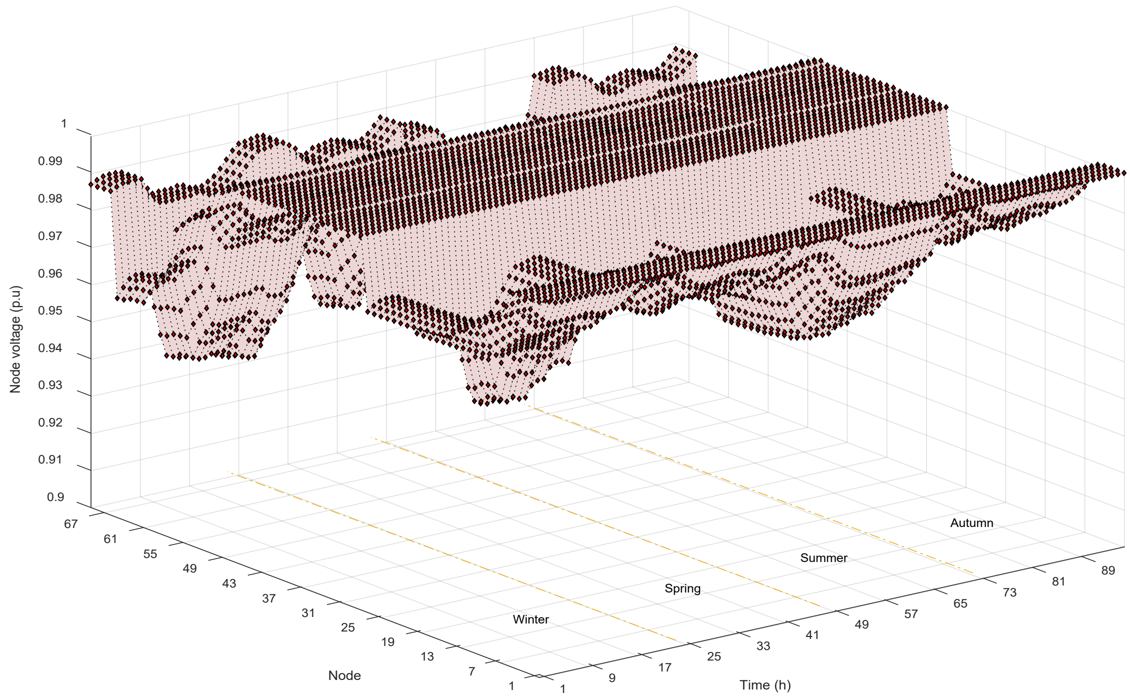

Fig 10. Voltage profile in the considering periods before connecting RE-DGs

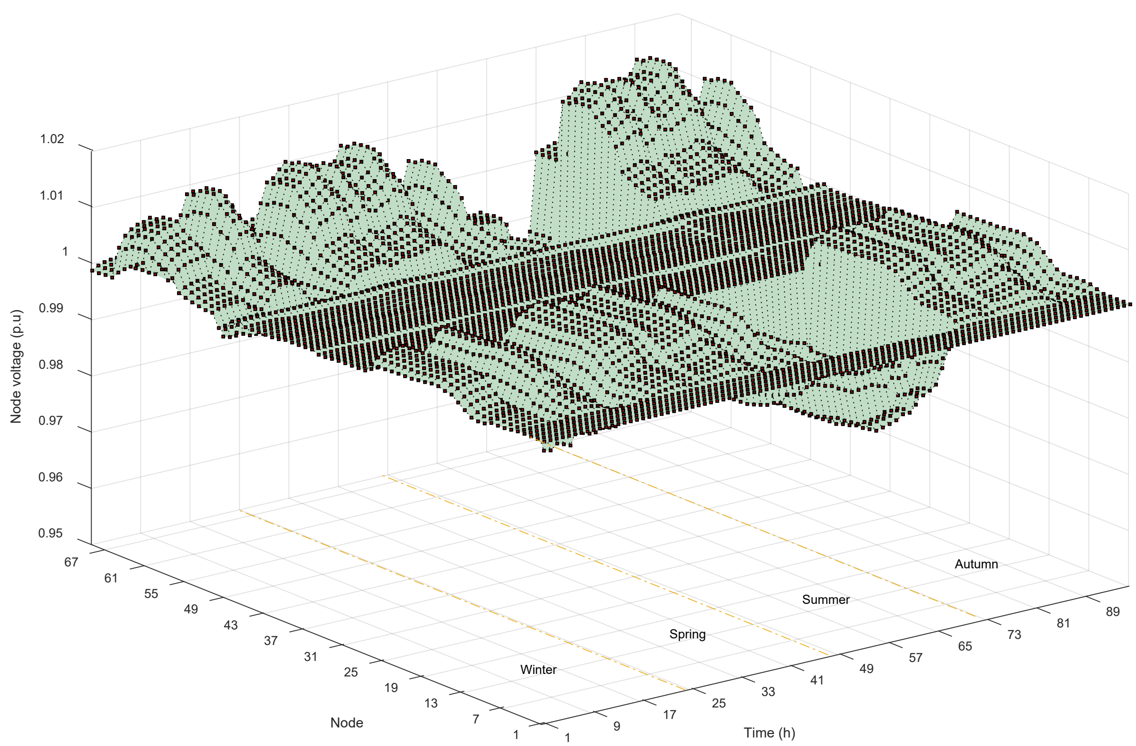

Fig 11. Voltage profile in the considering periods after connecting RE-DGs

Conclusions

In this study, an intelligent and adaptive meta-heuristic algorithm that called BO was introduced for determining the optimal integration of SFs and WFs considering M-OF. The objectives of the study are to minimize total active power loss, total reactive power loss, voltage deviation and the amount of imported energy by the main power grid. This paper also used the weighted sum method for deciding the output of M-OF in the most compromise way considering demand and generation changes according to the seasons of the year. The results from the suggested method (BO) are compared with previously published methods and implemented methods in two cases, and BO has demonstrated its effectiveness compared to others in solving various optimization problems. For the first case of the S-OF, the optimal solution from BO can cut the total loss from 0.2245 MW to 69.204 kW, corresponding to 69.18% in loss reduction compared to the original system. For the second case of M-OF, the best quality solution from BO can achieve 86.54% and 82.21% in active and reactive power losses reduction, respectively. Not only that, voltage profile is also significantly increased from (0.9090, 1.00) p.u to (0.9508, 1.0181) p.u through appropriate connection of RE-DGs in PDN. All of the above has contributed to demonstrate the diverse benefits from integrating RE-DGs in PDN.

In future work, to enhance the benefits from high penetration of renewable distributed generation while maintaining system stability, smart inverters (SI) and battery energy storage systems (BESS) will be considered for integration into the distribution system.

References

[1] T. Ahmad, S. Manzoor, D. Zhang, "Forecasting high penetration of solar and wind power in the smart grid environment using robust ensemble learning approach for large-dimensional data," *Sustainable Cities and Society,* vol. 75, p. 103269, 2021. DOI: 10.1016/j.scs.2021.103269

[2] D. Gielen, F. Boshell, D. Saygin, M. D. Bazilian, N. Wagner, R. Gorini, "The role of renewable energy in the global energy transformation," *Energy strategy reviews,* vol. 24, pp. 38-50, 2019. DOI: 10.1016/j.esr.2019.01.006

[3] D. Gielen, R. Gorini, N. Wagner, R. Leme, L. Gutierrez, G. Prakash, M. Renner, "Global energy transformation: a roadmap to 2050," *International Renewable Energy Agency*, 2019.

[4] D. Q. Hung, N. Mithulananthan, K. Y. Lee, "Optimal placement of dispatchable and nondispatchable renewable DG units in distribution networks for minimizing energy loss", *International Journal of Electrical Power & Energy Systems,* vol. 55, pp. 179-186, 2014. DOI: 10.1016/j.ijepes.2013.09.007

[5] M. D. Hraiz, J. A. M. García, R. J. Castañeda, H. Muhsen, "Optimal PV size and location to reduce active power losses while achieving very high penetration level with improvement in voltage profile using modified Jaya algorithm", *IEEE Journal of Photovoltaics,* vol. 10, no. 4, pp. 1166-1174, 2020. DOI: 10.1109/JPHOTOV.2020.2995580

[6] M. Resener, S. Haffner, L. A. Pereira, P. M. Pardalos, M. J. Ramos, "A comprehensive MILP model for the expansion planning of power distribution systems–Part I: Problem formulation", *Electric Power Systems Research*, vol. 170, pp. 378-384, 2019. DOI: 10.1016/j.epsr.2019.01.040

[7] A. Kumar, W. Gao, "Optimal distributed generation location using mixed integer non-linear programming in hybrid electricity markets", *IET generation, transmission & distribution,* vol. 4, no. 2, pp. 281-298, 2010. DOI: 10.1049/iet-gtd.2009.0026

[8] S. Kaur, G. Kumbhar, J. Sharma, J, "A MINLP technique for optimal placement of multiple DG units in distribution systems", *International Journal of Electrical Power & Energy Systems,* vol. 63, pp. 609-617, 2014. DOI: 10.1016/j.ijepes.2014.06.023

[9] A. S. Siddiqui, "Optimal location and sizing of conglomerate DG-FACTS using an artificial neural network and heuristic probability distribution methodology for modern power system operations", *Protection and Control of Modern Power Systems,* vol. 7, no. 1, pp. 1-25, 2022. DOI: 10.1186/s41601-022-00230-5

[10] E.C. Ashigwuike, S.A. Benson, "Optimal location and sizing of distributed generation in distribution network using adaptive neuro-fuzzy logic technique", *European Journal of Engineering and Technology Research*, vol. 4, no. 4, pp. 83-89, 2019. DOI: 10.24018/ejeng.2019.4.4.1237

[11] M. Addisu, A. O. Salau, H. Takele, "Fuzzy logic based optimal placement of voltage regulators and capacitors for distribution systems efficiency improvement", *Heliyon,* vol. 7, no. 8, pp. 1-9, 2021. DOI: 10.1016/j.heliyon.2021.e07848

[12] R. B. Magadum, D. B. Kulkarni, "Optimal placement and sizing of multiple distributed generators using fuzzy logic", *In 2019 Fifth International Conference on Electrical Energy Systems (ICEES), IEEE*, pp. 1-6, Feb. 2019. DOI: 10.1109/ICEES.2019.8719240

[13] H. Demolli, A. S. Dokuz, A. Ecemis, M. Gokcek, "Location-based optimal sizing of hybrid renewable energy systems using deterministic and heuristic algorithms", *International Journal of Energy Research,* vol. 45, no. 11, pp. 16155-16175, 2021. DOI: https://doi.org/10.1002/er.6849

[14] E. E. Elattar, S. K. Elsayed, "Optimal location and sizing of distributed generators based on renewable energy sources using modified moth flame optimization technique", *IEEE Access,* vol. 8, pp. 109625-109638, 2020. DOI: 10.1109/ACCESS.2020.3001758

[15] G. W. Chang, N. C. Chinh, "Coyote optimization algorithm-based approach for strategic planning of photovoltaic distributed generation", *IEEE Access,* vol. 8, pp. 36180-36190, 2020. DOI: 10.1109/ACCESS.2020.2975107

[16] A. Musa, T.T. Hashim, "Optimal sizing and location of multiple distributed generation for power loss minimization using genetic algorithm", *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 16, no. 2, pp. 956-963, 2019. DOI: 10.11591/ijeecs.v16.i2.pp956-963

[17] W.U.H. Paul, A.S. Siddiqui, S. Kirmani, "Optimal positioning of distributed energy using intelligent hybrid optimization", In *Journal of Physics: Conference Series*, IOP Publishing, vol. 2570, no. 1, p. 012022, 2023. DOI: 10.1088/1742-6596/2570/1/012022

[18] T. R. Ayodele, A. S. O. Ogunjuyigbe, O. O. Akinola, "Optimal location, sizing, and appropriate technology selection of distributed generators for minimizing power loss using genetic algorithm", *Journal of Renewable Energy*, 2015. DOI: 10.1155/2015/832917

[19] E. A. Al-Ammar, K. Farzana, A. Waqar, M. Aamir, A. U. Haq, M. Zahid, 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. DOI: 10.1016/j.asej.2020.05.002

[20] A. A. Ogunsina, M. O. Petinrin, O. O. Petinrin, E. N. Offornedo, J. O. Petinrin, G. O. Asaolu, "Optimal distributed generation location and sizing for loss minimization and voltage profile optimization using ant colony algorithm", *SN Applied Sciences,* vol. 3, pp. 1-10, 2021. DOI: 10.1007/s42452-021-04226-y

[21] E. S. Ali, S. M. Abd Elazim, A. Y. Abdelaziz, "Ant Lion Optimization Algorithm for optimal location and sizing of renewable distributed generations", *Renewable Energy,* vol. 101, pp. 1311-1324, 2017. DOI: 10.1016/j.renene.2016.09.023

[22] H. HassanzadehFard, A. Jalilian, "Optimal sizing and location of renewable energy based DG units in distribution systems considering load growth", *International Journal of Electrical Power & Energy Systems,* vol. 101, pp. 356-370, 2018. DOI: 10.1016/j.ijepes.2018.03.038

[23] T.D. Pham, T.T. Nguyen, "Minimize renewable distributed generator costs while achieving high levels of system uniformity and voltage regulation", *Ain Shams Engineering Journal*, vol. 15, no. 6, 102720, 2024. DOI: 10.1016/j.asej.2024.102720

[24] L. Peng, A. Zabihi, M. Azimian, H. Shirvani, F. Shahnia, "Developing a robust expansion planning approach for transmission networks and privately-owned renewable sources", *IEEE access*, vol. *11*, pp. 76046-76058, 2022. DOI: 10.1109/ACCESS.2022.3226695

[25] A. Zabihi, M. Parhamfarb, "Empowering the grid: toward the integration of electric vehicles and renewable energy in power systems", *International Journal of Energy Security and Sustainable Energy*, vol. *2*, no. 1, pp. 1-14, 2024. DOI: 10.5281/zenodo.12751722

[26] J. Pierezan, L. D. S. Coelho, "Coyote optimization algorithm: a new metaheuristic for global optimization problems", In *2018 IEEE congress on evolutionary computation (CEC) IEEE*, pp. 1-8, 2018. DOI: 10.1109/CEC.2018.8477769

[27] M. Kowsalya, "Optimal size and siting of multiple distributed generators in distribution system using bacterial foraging optimization", *Swarm and Evolutionary computation,* vol. 15, pp. 58-65, 2014. DOI: 10.1016/j.swevo.2013.12.001

[28] R. Fathi, B. Tousi, S. Galvani, "Allocation of renewable resources with radial distribution network reconfiguration using improved salp swarm algorithm", *Applied Soft Computing,* vol. 132, 109828, 2023. DOI: 10.1016/j.asoc.2022.109828

[29] M.C.V. Suresh, E. J. Belwin, "Optimal DG placement for benefit maximization in distribution networks by using Dragonfly algorithm", *Renewables: Wind, Water, and Solar,* vol. 5, pp. 1-8, 2018. DOI: 10.1186/s40807-018-0050-7

[30] M. Dehghani, E. Trojovská, T. Zuščák, "A new human-inspired metaheuristic algorithm for solving optimization problems based on mimicking sewing training", *Scientific Reports,* vol. 12, no. 1, 17387, 2022. DOI: 10.1038/s41598-022-22458-9

[31] P. Trojovský, M. Dehghani, "A new bio-inspired metaheuristic algorithm for solving optimization problems based on walruses behavior", *Scientific Reports*, vol. 13, no. 1, 8775, 2023. DOI: 10.1038/s41598-023-35863-5

[32] M. Dehghani, P. Trojovský, "Osprey optimization algorithm: A new bio-inspired metaheuristic algorithm for solving engineering optimization problems", *Frontiers in Mechanical Engineering,* vol. 8, p. 1126450, 2023. DOI: 10.3389/fmech.2022.1126450

[33] A. K. Das, D. K. Pratihar, "A new bonobo optimizer (BO) for real-parameter optimization", *In 2019 IEEE region 10 symposium (TENSYMP), IEEE*, pp. 108-113, Jun. 2019. DOI: 10.1109/TENSYMP46218.2019.8971108

[34] M. Purlu, B. E. Turkay, "Optimal allocation of renewable distributed generations using heuristic methods to minimize annual energy losses and voltage deviation index", *IEEE Access,* vol. 10, pp. 21455-21474, 2020. DOI: 10.1109/ACCESS.2022.3153042

[35] T. D. Pham, H. D. Nguyen, 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. DOI: 10.52549/ijeei.v11i1.4103

[36] T. D. Pham, "Integration of Photovoltaic Units, Wind Turbine Units, Battery Energy Storage System, and Capacitor Bank in the Distribution System for Minimizing Total Costs Considering Harmonic Distortions", *Iranian Journal of Science and Technology, Transactions of Electrical Engineering,* vol. 47, no. 4, pp. 1265-1282, 2023. DOI: 10.1007/s40998-023-00613-w

[37] T. P. Nguyen, D. V. Vo, "A novel stochastic fractal search algorithm for optimal allocation of distributed generators in radial distribution systems", *Applied Soft Computing,* vol. 70, pp. 773-796, 2018. DOI: 10.1016/j.asoc.2018.06.020

[38] T. H. B. Huy, D. N. Vo, K. H. Truong, T. V. Van, "Optimal Distributed Generation Placement in Radial Distribution Networks Using Enhanced Search Group Algorithm", *IEEE Access,* vol. 11, 2023. DOI: 10.1109/ACCESS.2023.3316725

[39] S. Sharma, S. Bhattacharjee, A. Bhattacharya, "Quasi-Oppositional Swine Influenza Model Based Optimization with Quarantine for optimal allocation of DG in radial distribution network", *International Journal of Electrical Power & Energy Systems,* vol. 74, pp. 348-373, 2016. DOI: 10.1016/j.ijepes.2015.07.034

[40] S. Sultana, P. K. Roy, "Krill herd algorithm for optimal location of distributed generator in radial distribution system", *Applied Soft Computing,* vol. 40, pp. 391-404, 2016. DOI: 10.1016/j.asoc.2015.11.036

[41] S. Sultana, P. K. Roy, "Multi-objective quasi-oppositional teaching learning based optimization for optimal location of distributed generator in radial distribution systems", *International Journal of Electrical Power & Energy Systems,* vol. 63, pp. 534-545, 2014. DOI: 10.1016/j.ijepes.2014.06.031

Biography

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The nomenclatures

PL^{RE_DG}	Total active power loss with connecting RE-DGs
PL^{NoRE_DG}	Total active power loss without connecting RE-DGs
QL^{RE_DG}	Total reactive power loss with connecting RE-DGs
QL^{NoRE_DG}	Total reactive power loss without connecting RE-DGs
VD^{RE_DG}	Voltage deviation with connecting RE-DGs
VD^{NoRE_DG}	Voltage deviation without connecting RE-DGs
IE^{RE_DG}	Imported energy with connecting RE-DGs
IE^{NoRE_DG}	Imported energy without connecting RE-DGs
N^T, N^H, N^S	Number of considering hours, branches of system, nodes of system
$I_{h,t,RE-DG}, I_{h,t}$	The h^{th} branch current at the t^{th} hour after and before connecting RE-DGs
$V_{s,t,RE-DG}, V_{s,t}$	The s^{th} node voltage at the t^{th} hour after and before connecting RE-DGs
R_h, X_h, V_{Nom}	The h^{th} branch resistance and reactance, and nominal voltage (V_{Nom}=1)
$P_{t,RE\_DG}^{Sub}, P_t^{Sub}$	Active power from main power gird that injected at the t^{th} hour
N^D, N^G	Number of loads and distributed generators
N^K, N^N	Number control variables and bonobos (solutions)
$P_{h,loss}, P_{d,load}$	The h^{th} branch active power loss and the d^{th} active power load
P_{g,RE_DG}, P^{Sub}	Active power of the g^{th} generator and injected active power by main grid
$Q_{h,loss}, Q_{d,load}$	The h^{th} branch reactive power loss and reactive power of the d^{th} load
Q_{g,RE_DG}, Q^{Sub}	Reactive power of the g^{th} generator and injected reactive power by main grid
I_h, I_h^{Max}	Branch current and maximum acceptable branch current of the h^{th} branch
V_s, V_s^{Max}	Node voltage and maximum acceptable node voltage of the s^{th} node
PF^{Max}, PF^{Min}, PF_g	Maximum and minimum power factors, and the g^{th} generator's power factor
$P_{RE\_DG}^{Max}, P_{RE\_DG}^{Min}, P_g^{Rated}, P_{g,RE-DGs}$	Maximum and minimum active power of each generator, rated active power for the g^{th} generator and generated active power for the g^{th} generator
bo_k^{new}, bo_k^n	The k^{th} control variables of new bonobo and the n^{th} bonobo
${ctrl_{var}}_k^{max}, {ctrl_{var}}_k^{min}$	The k^{th} maximum and minimum control variables which are predetermined
a_k^{bo}	The k^{th} control variable of alpha-bonobo
Fit^n	The fitness value of the n^{th} solution
$Iter^{max}, Iter_L$	Maximum iteration and the L^{th} iteration