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Reduction of Emission Cost, Loss Cost and Energy Purchase Cost for Distribution Systems with Capacitors, Photovoltaic Distributed Generators, and Harmonics

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ABSTRACT

In this paper, a bonobo optimizer (BO) and two other methods, particle swarm optimization (PSO) and salp swarm algorithm (SSA), are implemented to determine the location and sizing of photovoltaic distributed generators (PDGs) and capacitors (CPs) in IEEE 69-bus radial distribution system with many nonlinear loads. The objective of the study is to minimize the costs for purchasing energy from main grid for load demand and power loss on transmission lines as well as cost for emission fines from fossil fuel generation units of the grid under considering strict constraints on penetration, voltage, current and harmonic distortions. The results have shown that BO is the best and most stable method in solving the considered optimization problem. With the use of the optimal solution from BO, the total cost is significantly reduced up to 80.52%. As compared to base system without CPs and PDGs, the obtained solution can reduce power loss up to 94.48% and increase the voltage profile from the range of [0.9092 1.00] pu to higher range of [0.9907 1.0084] pu. In addition, total harmonic distortion (THD) and individual harmonic distortion (IHD) are also much improved and satisfied under the IEEE Std. 519. Thus, BO is a suitable method for the application of installing CPs and PDGs in distribution systems.

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The list of symbols

$C_{TotalCost}$	Total cost in distribution systems ($)
$C_{emission}$	Emission cost ($)
C_{load}	Energy purchase cost for loads ($)
C_{loss}	Power loss cost ($)
E_{emi}	Emission produced by conventional power plants (kg/MWh)
IHD^{max}	Maximum individual harmonic distortion
IHD_s^h	Individual harmonic distortion at the h^{th} order of the s^{th} bus

I_b^{max}	Maximum thermal current limit of the b^{th} branch
I_b	The thermal current of the b^{th} branch
N_b	Number of branches
N_{cap}	Number of capacitors
N_l	Number of loads
N_{pv}	Number of photovoltaic distributed generators
N_s	Number of buses
$P_{load,l}$	Active power of load demand at the l^{th} load
$P_{loss,b}$	Active power loss at the b^{th} branch
$P_{pv,n}$	Active power produced from the n^{th} photovoltaic distributed generator
P_{sub}	Active power supplied by the main grid
$Price_{emission}$	Price of emissions ($/kg)
$Price_{load}$	Price for purchasing electricity from the substation ($/MWh)
$Price_{loss}$	Price for energy loss on transmission lines ($/MWh)
$Q_{load,l}$	Reactive power of load demand at the l^{th} load
$Q_{loss,b}$	Reactive power loss at the b^{th} branch
$Q_{cap,k}$	Reactive power produced from the k^{th} capacitor bank
Q_{sub}	Reactive power supplied by the main grid
THD^{max}	Maximum total harmonic distortion
THD_s	Total harmonic distortion at the s^{th} bus
V_s	The voltage magnitude at the s^{th} bus
V_s^1	The fundamental voltage magnitude at the s^{th} bus
V_s^h	The voltage magnitude at the h^{th} order harmonic of the s^{th} bus
H	Maximum harmonic order

1. INTRODUCTION

The use of non-renewable fossil fuels as oil, coal and fracked gas causes the release of carbon dioxide and global warming [1-2]. Thus, many countries have policies to encourage the development of renewable energy sources, which rely on the natural processes as wind, solar, hydropower, geothermal, bioenergy, etc. due to many obtained benefits [3-4]. Connection of renewable distributed generators (RDGs) to the distribution systems offers many great advantages in terms of technology, economy and environment [5]. Therefore, RDGs have received a lot of attention of energy researchers around the world. Realistically, the great benefit that the RDGs are integrated in distribution system is to improve the system reliability, reduce the power loss on the transmission line due to using local generation sources, enhance the voltage profile, support the voltage stability and reduce the greenhouse gas emissions [6]. However, obtained benefits mainly depend on the location and capacity of RDGs [7-9]. So, almost studies regarding the installation of RDGs are about the optimization of the two major factors of the RDGs and then evaluations are done by comparing different objective functions such as active power loss, energy loss, investment cost and operation cost for RDGs, etc.

In recent years, many researchers have proposed different algorithms for solving the problem of installing PDGs in distribution systems. Specifically, in [10], the authors have applied the moth flame optimization (MFO) for determining the installation location of RDGs with the aim of minimizing power loss with consideration of operating constraints. This algorithm was developed based on the observation of moth activity in the nature. This moth has a very special nocturnal movement and called directional lateral movement. However, it has many disadvantages that greatly affect its performance such as low accuracy, slow convergence and poor ability to expand the exploration area to find new solutions [11]. With the same objective function, the authors [12] proposed an algorithm, named manta ray foraging optimization (MRFO) to solve this problem. This algorithm is inspired by the food source search behavior of the manta rays. However, researchers have found that it is not very efficient due to slow convergence and easily falls into the local optimal region [13]. In addition to the new algorithms, other popular algorithms were also used to solve the problem to be considered. In [14], the authors have shown that connecting the suitable siting and sizing of RDGs to the distributed systems contribute to a dramatic reduction in losses and voltage drops by using the genetic algorithm (GA). GA is a fairly simple algorithm in implementation, but it is computationally expensive, and the performance is not high due to randomly generated operation of mutation process. In [15], for the multiple objectives of voltage improvement, harmonic mitigation and power loss reduction, the appropriate installation of RDGs is successfully found on two distribution systems 33 and 69 buses by applying biogeography-based optimization (BBO). This algorithm was developed based on the immigration and migration of species between habitats. However, this algorithm is quite complicated, the convergence speed is relatively slow, and its performance is easily affected by the initial parameters. Moreover, there are other positive methods also used in the studies [16-17]. In [16], the optimal sizing of the photovoltaic system has also been proposed by using Lagrange Multipliers (LM). This work minimized the total energy loss during the daily insolation period in various scenarios with test system of 37 buses. Additionally, [17] also appropriately selected the placement for the photovoltaic system and energy store system with the consideration of power loss and voltage stability in the system. These authors proposed the crow search optimization algorithm (CSO) for finding the optimal solution in different radial distributed systems. Besides the traditional distribution systems that only combine with solar generators, some researchers have also focused on solving the problem of optimal installation for hybrid renewable energy systems. Specifically, the study [18] presented an optimal solution for distribution system integrating both photovoltaic and wind turbines by using a combined method of real power loss sensitivity index factor and artificial ecosystem-based optimization algorithm (RPLSI-AEO). The obtained results also proved the effectiveness of the proposed hybrid method with others for the loss reduction in a 33-bus system. Similarly, other researchers have succeeded in determining the size of photovoltaic, wind, battery and diesel generator integrated system [19]. By using grasshopper optimization algorithm (GOA), the cost of energy has been reduced highly, while a high reliability of power supply in the real grid in Nigeria has been still guaranteed. These hybrid systems had a great contribution in keeping stability for the power grid and reaching a big potential in replacing fossil fuel sources. In general, most studies only considered power loss reduction as primary goal and the most optimal capacity range of RDGs was not suggested [20]. However, it is extremely important to consider the reduction of the costs for purchasing electricity for load demand, power loss on transmission lines and generating emissions from fossil fuel generation units. But this has been ignored in most previous studies. Besides, it is necessary to consider the distribution systems with many nonlinear loads to keep the indicators related to harmonic distortions within standard limits. In order to overcome the mentioned disadvantages, this study searches the possible solution for optimal installing PDGs and CPs to minimize the costs of purchasing energy from main grid for load demand and losses as well as cost for emission fines from fossil fuel generation sources of the grid under considering strict constraints on penetration, bus voltage, branch current and harmonic distortions.

In addition, meta-heuristic algorithms have been used widely for different applications of integrating distributed generators, including ant lion optimization algorithm (ALOA) [21], equilibrium optimizer (EO) [22], multi-objective chaotic symbiotic organisms search algorithm (MCSOSA) [23], modified moth flame optimization technique (MMFOT) [24], improved whale optimization approach (IWOA) [25], atom search optimization (ASO) [26], tree growth algorithm (TGA) [27], etc. As a result, the group of meta-heuristic methods has many outstanding advantages in determining global solutions for solving optimization problems. However, these methods are outdated and their main disadvantages are easily fall into the local optimization trap and low stability. This has the effect to the performance of the algorithms in solving various optimization problems [28-29]. The search for a strong optimization algorithm capable of expanding the finding area as well as avoiding the problem of local minima trapping is always welcomed. In recent years, many efficient meta-heuristic algorithms have been introduced and bonobo optimizer (BO) is a good example. BO was first published in 2019 by A.K. Das and D.K. Pratihar [30]. This optimization algorithm was inspired by the social behavior and Bonobos' reproductive strategies. BO is an active method with high stability and quick convergence time, so it is widely applied to solve optimization problems. As in [31], the authors have demonstrated the superiority of BO over other meta-heuristic algorithms in finding the optimal solution for an off-grid hybrid renewable energy system. Besides, a few studies like [32, 33] also tried to combine BO with other techniques to enhance the performance. The authors in [32] proposed the chaotic bonobo optimizer (CBO) to solve the problem for minimizing the operating costs of the system with integrating the renewable energy sources. The effectiveness of the algorithm was improved significantly. This has contributed to CBO's ability in expanding the search area to find the positive optimal solutions and avoid local traps Additionally, the authors in [33] also succeeded in developing a new version of BO, called the improved quasi-oppositional BO (QOBO) algorithm. This improvement includes two techniques. The first is to rely on three leaders instead of the best solution in the original BO. The second is to apply opposition-based learning (OBL) to use candidate solution and its opposite at the same time. The combination between the three leader's section and quasi-opposition-based learning helped to avoid the stuck in the local minimum. On the other hand, authors of the original algorithm also introduced BO with self-adjusting parameters over continuous spaces for various situations in 2022 [34]. In that study, BO was checked on different test functions and it was also compared with many strong methods that have been published recently. The obtained results have demonstrated the superiority of BO in solving optimization problems.

Thus, for this work, BO is applied for determining the optimal location and sizing of PDGs and CPs without negatively affecting for reliable technical indicators of the distribution system. Besides, forward/

backward sweep technique (FW/BWST) was also applied for solving power flow and harmonic flow [35]. Two PDGs and two CPs are proposed for connecting to the test system of IEEE 69 bus radial distribution system. The main objective of this study is to minimize costs of purchasing electricity for load demand, power loss and emissions without any violation for the technical criteria of overvoltage, overcurrent, and harmonic limits in the radial distribution system. The novelties of the paper are as follows:

1) This paper calculates total costs of emissions from fossil fuel generation unit of the main grid, loss on transmission lines and energy purchase for load demand that most previous studies have not fully considered.
2) The study focused on determining the optimal integration of capacitors and photovoltaic distributed generators into a distribution system with nonlinear loads. This is considered a novelty because previous studies were limited in considering harmonic distortions in integrated systems.

After implementing three algorithms for the system and comparing the obtained results, the major contributions of the study can be stated as follows:

1) This research suggests a novel effective and highly stable algorithm, which is called bonobo optimizer (BO). The obtained results from the simulation under considering the same objective function and constraints. The suggested algorithm has superiority over the compared methods in solving optimization problem.
2) This paper shows the most suitable solution for the position and capacity of capacitors and photovoltaic distributed generators in the distribution system. The best obtained solution can strongly cut the emission cost, energy loss cost and energy purchase cost. The reduction is greater than 80% as compared to original scenario. In addition, the power loss on branches is reduced effectively, and the violation of voltage limits and harmonic distortion limits are also eliminated by using distributed generators in the system.

2. RESEARCH METHOD

2.1. Objective function

In this paper, two PDGs and two CPs are installed in the IEEE 69-node system to reduce the sum of emission cost, energy purchase cost and energy loss cost while satisfying all technical criterion, especially THD and IHD at each node. The objective function can be formulated as follows [24, 36]:

$$Minimize\ C_{TotalCost} = C_{load} + C_{loss} + C_{emission}\ (\$) \tag{1}$$

Where,

$$C_{load} = Price_{load} \times \sum_{l=1}^{N_l} P_{load,l}\ (\$) \tag{2}$$

$$C_{loss} = Price_{loss} \times \sum_{b=1}^{N_b} P_{loss,b}\ (\$) \tag{3}$$

$$C_{emission} = Price_{emission} \times E_{emi} \times P_{sub}\ (\$) \tag{4}$$

2.2. Constraints

2.2.1. The power balance constraints

Active power supply and active power demand should be equal as follows [15, 37]:

$$P_{sub} + \sum_{n=1}^{N_{pv}} P_{pv,n} = \sum_{l=1}^{N_l} P_{load,l} + \sum_{b=1}^{N_b} P_{loss,b} \tag{5}$$

Similarly, the equality constraint between reactive power supply and reactive power demand is formulated by [15]:

$$Q_{sub} + \sum_{k=1}^{N_{cap}} Q_{cap,k} = \sum_{l=1}^{N_l} Q_{load,l} + \sum_{b=1}^{N_b} Q_{loss,b} \tag{6}$$

2.2.2. The overvoltage limits

According to the Std. BS EN 50160, the voltage limit must be between 0.9 and to 1.1 pu [38]. However, many studies have shown that the best acceptable limit for voltage profile is from 0.95 pu to 1.05

pu [39-40]. Therefore, it is essential to keep the upper level (V^{max}) and lower level (V^{min}) of the bus voltage at the best limits, and the following inequality is applied for voltage of each node [41]:

$$V^{min} \leq V_s \leq V^{max}, s = 1, \dots, N_s \tag{7}$$

2.2.3. Total harmonic distortion limit

According to the IEEE Std. 519, total voltage harmonic distortion should not exceed the limit of 5% [2]. The distortion is determined and constrained by:

$$THD_s(\%) = \left[\frac{\sqrt{\sum_{h\neq 1}^{H}(V_s^h)^2}}{V_s^1}\right] \times 100 \leq THD^{max}(\%) \tag{8}$$

2.2.4. Individual harmonic distortion limit

Similarly, individual harmonic distortion should be followed the limit of 3% [15]. The distortion is determined and constrained by:

$$IHD_s^h(\%) = \left[\frac{V_s^h}{V_s^1}\right] \times 100 \leq IHD^{max}(\%) \tag{9}$$

2.2.5. The overcurrent limits

There is a line connecting each two nodes and this line is a conductor with a thermal limit. To satisfy the thermal limit, working current should not be higher than the maximum limit as shown in the inequality below [41]:

$$I_b \leq I_b^{max}, b = 1, \dots, N_b \tag{10}$$

2.2.6. The PDG capacity limits

The capacity limits of PDGs must be predetermined and it should be kept within the upper bound (P_{pv}^{max}) and lower bound (P_{pv}^{min}) as follows [42]:

$$P_{pv}^{min} \leq P_{pv,n} \leq P_{pv}^{max}, n=1, \dots, N_{pv} \tag{11}$$

Similarly, the maximum and minimum generating limits of the capacitors (Q_{cap}^{max} and Q_{cap}^{min}) are also predefined as follows:

$$Q_{cap}^{min} \leq Q_{cap,k} \leq Q_{cap}^{max}, k=1, \dots, N_{cap} \tag{12}$$

In addition, the total penetration of all PDGs and CPs in the integrated system must not exceed the load demand during the optimal solution search process. The two following constraints are applied to limit their penetration [43]:

$$\sum_{n=1}^{N_{pv}} P_{pv,n} \leq 80\% \times \sum_{l=1}^{N_l} P_{load,l} \tag{13}$$

$$\sum_{k=1}^{N_{cap}} Q_{cap,k} \leq 80\% \times \sum_{l=1}^{N_l} Q_{load,l} \tag{14}$$

3. THE APPLIED METHOD

In this study, bonobo optimizer (BO) is applied to find the placement and sizing of PDGs and CPs in the distribution system. BO was inspired by the social behavior of bonobos and breeding methods [30]. The community of bonobos adopted a social strategy that could be called a fission-fusion. Basically, it forms many groups with different sizes and different compositions in a community of bonobos. After a short time, it will reunite itself with the community. In BO, each solution is considered like a bonobo and bonobo with the best rank in society is called alpha-bonobo. At the end of each iteration, the verification and evaluation process for all bonobos are implemented. If alpha-bonobo is improved then it is called positive phase, where the most suitable conditions and vice versa is negative phase [30]. The process of applying BO to solve the optimization problem can be briefly summarized in the flowchart of Figure 1 and expressed in detail as follows:

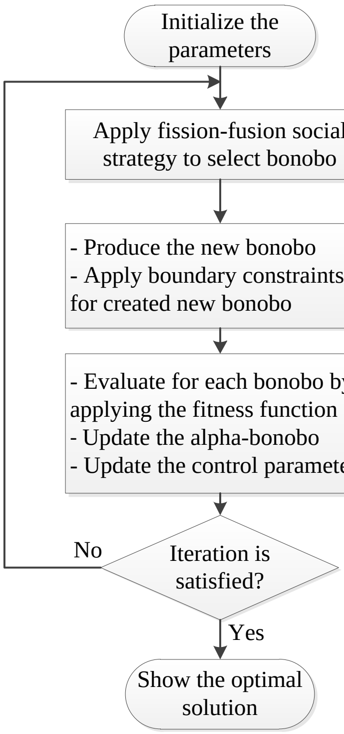

Figure 1. The flowchart of bonobo optimizer

Step 1:
- Initializing the non-user-defined parameters of the algorithm.

Step 2:
- Selecting the bonobo by using fission-fusion social strategy. Before updating, bonobos are determined for the mating based on the fission-fusion social strategy. Here, in a large community, individuals form temporary small groups of varying sizes. This size is unpredictable due to its random nature. The maximum size of a temporary sub-group size factor (tsg^{max}) depends on the population size (N_{pop}) and temporary subgroup size factor (tsg_{factor}). The value of tsg^{max} can be determined by [30]:

$$tsg^{max} = maximum(2, tsg_{factor} \times N_{pop}) \tag{15}$$

In this case, tsg_{factor} can be run from zero to the maximum value of temporary subgroup size factor (tsg^{max}_{factor}) to keep the right balance between exploration and exploitation in the algorithm.

Step 3:
- Producing the new bonobo ($Nbon_j$).

In this algorithm, the phase probability (p_p) is used to decide the mating strategy for generating a bonobo. The initial value of p_p is assigned as 0.5 and is will be updated after each iteration according to the phase count number and the current phase. The value of p_p will be decreased from 0.5 to 0.0 with a predefined rate (*rcpp*) during consecutive negative phases and vice versa, it should be increased from 0.5 to 1.0 for positive phases.

In the promiscuous and restrictive mating strategies, p_p is compared with a random number (rd_1) between zero and one, if p_p is greater than or equal to rd_1 then a new bonobo is produced by applying Eq. (16) as given below [34, 44]:

$$Nbon_j = bon_j^i + rd_1 \times s_1 \times \left(a_j^{bon} - bon_j^i\right) + \left(1 - rd_1\right) \times s_2 \times f \times \left(bon_j^i - bon_j^p\right), j = 1, \dots, N_V \tag{16}$$

Where N_V is the decision variables number; s_1 and s_2 are defined as the sharing cofficient factors for alpha bonobo and selected bonobo; f is a flag (set with -1 or 1) and its value depends on restrictive mating types or promiscuous, respectively; bon_j^i and bon_j^p are the j^{th} variable value of the i^{th} and the p^{th} bonobos. $Nbon_j$ and a_j^{bon} are the j^{th} variable value of the offspring and alpha-bonobo in the current community, respectively.

In the consortship and extra-group mating strategies, the important factor for determing the new bonobo is the probability of extra- group mating strategy (p_{egms}). The value of p_{egms} should be updated at each iteration and it is used to compare with the random number (rd_2) in the range of [0, 1]. If p_{egms} is higher than or equal to rd_2, then Eqs. (19-22) are applying for creating the new bonobo. For this stage, the two interrmediate measured values (B_1 and B_2) for determining the equation of producing offspring ($Nbon_j^i$) can be defined by [30]:

$$B_1 = e^{(rd_4^2+rd_4 -2/rd_4)} \tag{17}$$

$$B_2 = e^{(-rd_4^2+2.rd_4 -2/rd_4)} \tag{18}$$

The equations and accompanying conditions for generating new bonobo at this stage can be listed as follows [34]:

$$Nbon_j = bon_j^i + B_1 \times \left(cv_j^{max} - bon_j^i\right), \text{ if } (a_j^{bon} \geq bon_j^i \,\&\, p_p \geq rd_3) \tag{19}$$

$$Nbon_j = bon_j^i - B_2 \times \left(-cv_j^{min} + bon_j^i\right), \text{ if } (a_j^{bon} \geq bon_j^i \,\&\, p_p < rd_3) \tag{20}$$

$$Nbon_j = bon_j^i - B_1 \times \left(-cv_j^{min} + bon_j^i\right), \text{ if } (a_j^{bon} < bon_j^i \,\&\, p_p \geq rd_3) \tag{21}$$

$$Nbon_j = bon_j^i + B_2 \times \left(cv_j^{max} - bon_j^i\right), \text{ if } (a_j^{bon} < bon_j^i \,\&\, p_p < rd_3) \tag{22}$$

In the Eqs. (17-22), rd_3 and rd_4 are the random numbers in the range of [0, 1] ($rd_4 \neq 0$). cv_j^{max} *and* cv_j^{min} are the upper and lower limits of the j^{th} decision variable, respectively.
In the case of p_{egms} is smaller than rd_2, the new bonobo is generated by using Eq. (23) [34].

$$Nbon_j = \begin{cases} bon_j^i + f \times e^{-rd_5} \times \left(bon_j^i - bon_j^p\right), if\ (f = 1 \,||\, p_p \geq rd_6) \\ bon_j^p, otherwise \end{cases} \tag{23}$$

In the Eq. (23), rd_5 *and* rd_6 are the random numbers from zero to one.
- Appling boundary limiting conditions. If the generated $Nbon_j$ is greater than cv_j^{max}, it is assigned as cv_j^{max}. Similarly, $Nbon_j$ does not change if it is not smaller than cv_j^{min}.

Step 4:
- Evaluating the quality of the i^{th} solution by using the fitness function (F^i) below:

$$F^i = C_{TotalCost}^i + \partial.\Delta PE^i \tag{24}$$

Where $C_{TotalCost}^i$ is the objective function value of the i^{th} solution which obtained by using Eq. (1), ∂ is the penalty factor and ΔPE^i is the sum of penalty elements of the i^{th} solution which clearly descripted in [42].
- Determining the alpha-bonobo and updating the control parameters that process was clearly described in [34]. If the next generation can produce bonobos with a better fitness than the old alpha-bonobo, the created new bonobo is selected to be a new alpha-bonobo. Besides, the problem parameters are also updated in the specific fashion with updating alpha-bonobo.

Step 5:
- Repeating the above steps until the termination condition is satisfied.

4. THE SIMULATION RESULTS AND DISCUSSION

In this paper, two PDGs and two CPs are considered for connection into the IEEE-69 node distribution system. The single line diagram of the system is shown in Figure 2. Bus data and line data of the system were given in [39], and total load demand is respectively, 3.8019 MW and 2.6941 MVar. The locations that we can install the generators and capacitors are from Bus 2 to Bus 69 excluding slack bus 1. Capacity limits are within 0 and 2 MW for PDGs and within 0 to 2 MVar for CPs. This study establishes the limits for the fundamental bus voltage in the range of [0.95 1.05] (pu), and the maximum limits for THD and IHD is respectively 5% and 3% [2]. To generate harmonics, nonlinear loads are placed at Bus 8, Bus 12, Bus 18, Bus 22, Bus 24, Bus 34, Bus 46, Bus 55, and Bus 65. The detail of the nonlinear loads was given in the study [39]. For this paper, $Price_{load}$ and $Price_{loss}$are set to 96 \$/MWh and 60 \$/MWh, respectively [45]. Besides, $Price_{emission}$ is taken as 0.004 (\$/kg) with emissions produced by conventional power plants (E_{emi}) is 724 kg/MWh [46].

To reach the best results for the system, three methods including PSO, SSA and BO are implemented. To compare objectively, the parameters for these algorithms are referenced from previously published studies. For running PSOs, the acceleration factors (c_a and c_b) are taken as 2, the weighting function (W) is set to 0.99 and the ramdom numbers (r_1 and r_2) are between 0 and 1 [15]. To implement SSA, the coefficient (c_1) is the most important and its value is taken from the function of $c_1 = 2e^{-(\frac{4l}{L})^2}$, where l and

L are defined as the current and maximum iteration. While, c_2 and c_3 are the random numbers in the interval of [0, 1] [47]. For operating the BO, s_1 and s_2 are set to 1.55 and 1.4, respectively; $rcpp$ is selected as 0.0039; tsg_{factor}^{max} is set to 0.07 and the value of p_{egms} is updated at each iteration with its initial value is 0.001 for this study [34]. The code of BO which is developed for this study, is referenced from [34]. Finally, the total trial run number (Tr), the maximum number of iterations (It^{max}) and the population number (N_{po}) are selected to be 40, 180 and 30, respectively for all methods. The simulations are performed by coding program on MATLAB ver.2017 on a personal computer with 1.8 GHz and 8.0 GB.

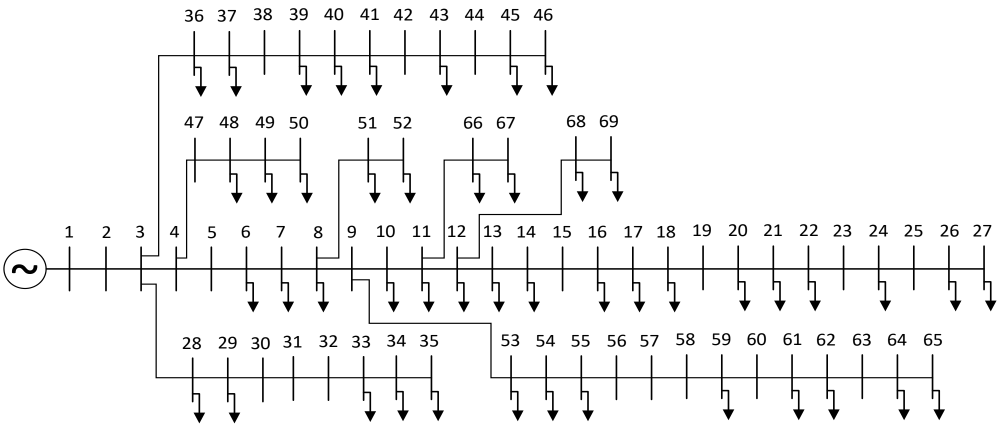

Figure 2. IEEE 69-bus radial distribution system

In addition to the use of proper update mechanisms, these algorithms are also based on randomization factors such as the use of random scaling factors from 0 to 1, and the use of randomly picked solutions from current population. Thus, one computation run is not high enough to reach the most optimal solution and obtained results from the sole run cannot reflect the performance of applied algorithms. But, 40 trial runs are enough and results from the runs are reported in Figure 3. Total costs from 40 runs are sorted from the lowest to the highest for the clear comparison. Red curve of BO is below than blue curve of SSA and green curve of PSO for all 40 runs. Like as counted, there are 33 solutions of the suggested method that are better than PSO, corresponding to 82.5% and there are 17 better solutions than SSA, accounting for 42.5%. This phenomenon indicates that the suggested method (BO) win compared methods (PSO and SSA) in reaching the best cost and the most stable cost.

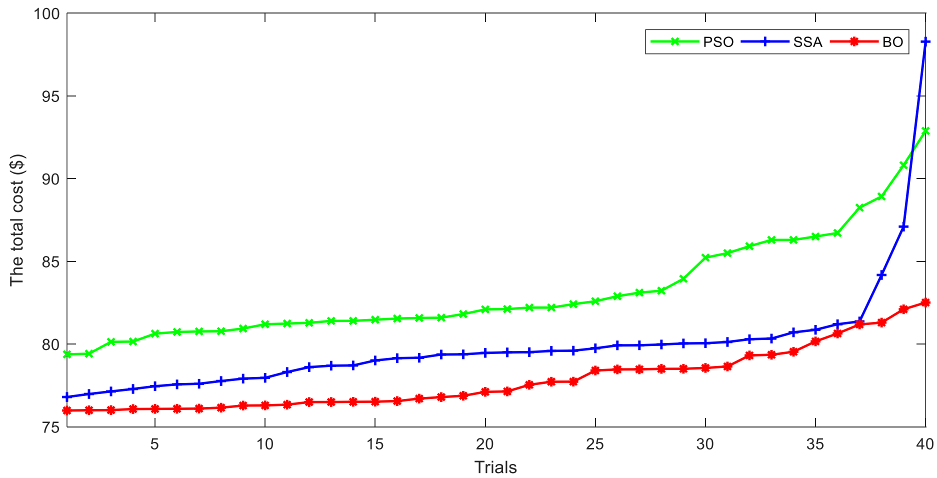

Figure 3. The objective function fitness values in 40 trials

Metaheuristic algorithms which are based on randomization need three comparison criteria to evaluate the performance including 1) Minimum fitness function is used to conclude the effectiveness of obtained solutions; 2) Average fitness function is used to evaluate the possibility of finding good solutions; and 3) Maximum fitness function is used to evaluate the fluctuation of algorithms. Among the three criteria, the minimum fitness function, which is also the total cost, is the most important factor to conclude the performance of algorithms. The comparison of the minimum total cost is to reflect the quality of the best run from a number of trials, and the best solution with the smaller total minimum cost is adopted for the test system. So, the algorithm reaching the best run is the most effective ones among applied algorithms. However, there is a possibility to reach the best run and the possibility can be determined by using the average total cost. Algorithms with smaller average total cost will have a higher possibility to reach the best run. So, the average total cost is the second important factor. Finally, the maximum total cost is to reflect the fluctuation of the applied algorithms. The comparison criterion is not very necessary, but it can confirm the real superiority of algorithms. A method with smaller minimum fitness, smaller average fitness and smaller maximum fitness is the best. For another case, the method with smaller minimum fitness and smaller average fitness but higher maximum fitness is also the best. For the worst case, the method with smaller minimum fitness but higher average fitness and higher maximum fitness is also the best because the obtained solution with the lower minimum fitness is applied for the test system. To determine the best algorithm among PSO, SSA and BO, the best, average and worst total cost calculated from 40 trial runs are reported in Figure 4. BO can reach smaller best, mean and worst total cost than SSA and PSO. The best total costs of PSO, SSA and BO are $79.3833, $76.8041 and $75.9889, while the worst total cost is $92.8906, $98.2851 and $82.5147 for PSO, SSA and BO, respectively. Furthermore, the mean of 40 total cost values that can be relied on to evaluate the stability is calculated and it is $83.1933 for PSO, $79.9198 for SSA and $77.8357 for BO. Clearly, BO can reach better all values than PSO and SSA. So, BO is superior to PSO and SSA.

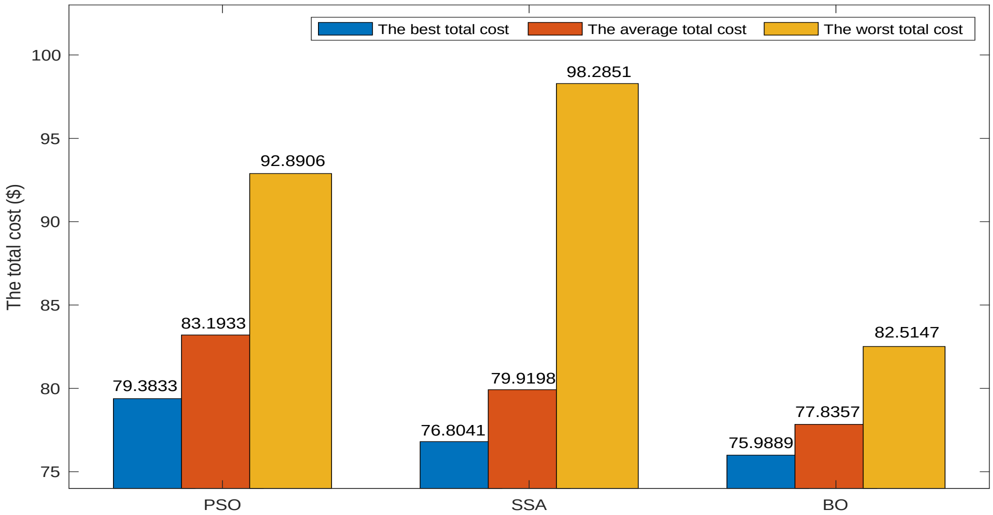

Figure 4. The best, the average and the worst total in 40 trials

The optimal position and capacity of two PDGs and two CPs are clearly reported in Table 1. Besides, the cost of purchasing energy for the load demand from the main grid (C_{load}), the cost to pay for the distribution energy loss (C_{loss}) as well as the cost of emission penalty from fossil fuel generator of the main grid ($C_{emission}$) are also presented in detail.

Table 1. The optimal solution from the implemented methods

Method	Optimal solution		C_{load} ($)	C_{loss} ($)	$C_{emission}$ ($)	$C_{TotalCost}$ ($)
	PDGs	CPs				
Base	–	–	364.9814	13.4700	11.6604	390.1119
PSO	Bus 55 – 1.1290 MW Bus 58 – 1.9007 MW	Bus 63 – 1.5306 MVar Bus 50 – 0.4317 MVar	74.1302	2.8780	2.3752	79.3833
SSA	Bus 60 – 1.9858 MW Bus 11 – 1.0557 MW	Bus 60 – 1.2706 MVar Bus 10 – 0.3823 MVar	72.9974	1.5318	2.2760	76.8041
BO	Bus 61 – 1.8865 MW Bus 11 – 1.1549 MW	Bus 61 – 1.1948 MVar Bus 12 – 0.5386 MVar	73.0070	0.7465	2.2384	75.9889

As shown in Table 1, after connecting the PDGs and CPs, the C_{load} dropped drastically from $364.9814 to $74.1302 by using PSO, $72.9974 by using SSA and $73.0070 by using BO. The significant drops prove that the integration of PDGs and CPs has contributed greatly in reducing the electricity cost to supply energy to the loads. For comparing between implemented methods, this cost reduction for BO and SSA is 80.00% and it is higher than PSO of 79.68%. In terms of the C_{loss}, the three algorithms can reduce the energy loss cost effectively and their costs are smaller than the base system by $12.7235 (BO), $10.5920

(PSO) and \$11.9382 (SSA). Thereby, the solution from BO has the highest cost saving compared to other methods. In other words, BO is a more effective method than others in proposing the feasible solution to solve the problem of power loss cost on the transmission lines. About the $C_{emission}$, the base system suffers from the highest penalty with \$11.6604, but that is much smaller for the solutions from the three algorithms. The emission penalty cost is \$2.3752 for PSO, \$2.2760 for SSA, and \$2.2384 for BO. Clearly, BO's cost is the lowest, so it will be the best among three applied algorithms. As a result, the total cost saving from BO is the highest, \$314.1230, while this value for PSO and SSA is \$310.7286 and \$313.3078, respectively.

As pointed above, the suggested BO method is an effective method in solving the considered optimization problem. By using its optimal solution, the power loss, the voltage profile and the harmonic distortions in the system have been positively changed. As shown in Figure 5, the power loss on the transmission lines was markedly reduced from 0.2245 MW in the original system to 0.0124 MW in the modified system with PDGs and CPs. The loss is reduced by 94.48%. This has demonstrated the great advantage of integrating distributed sources in the distribution system to obtain both technical and economic benefits.

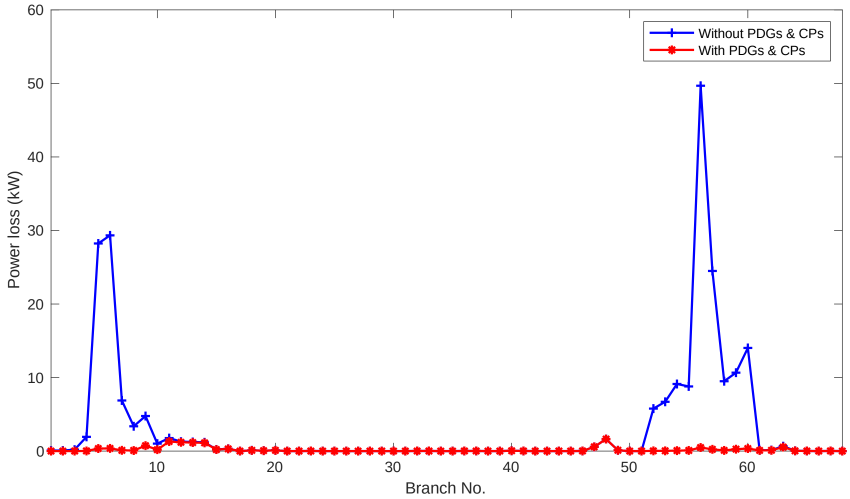

Figure 5. Power loss on distribution lines

Figure 6 is voltage profiles before and after applying the optimal solution from suggested method. For the original system, the lowest bus voltage is 0.9092 pu at Buses 65 and there are 9 buses with voltage beyond the allowable range of [0.95 1.05] pu. However, the voltage profile has been improved significantly in the modified system. The lowest bus voltage is 0.9907 pu at Bus 27 and the voltage of all buses voltages fluctuates in the range of [0.9907 1.0084] pu. Clearly, one more benefit of connecting PDGs and CPs in the distribution system is to enhance the voltage profile.

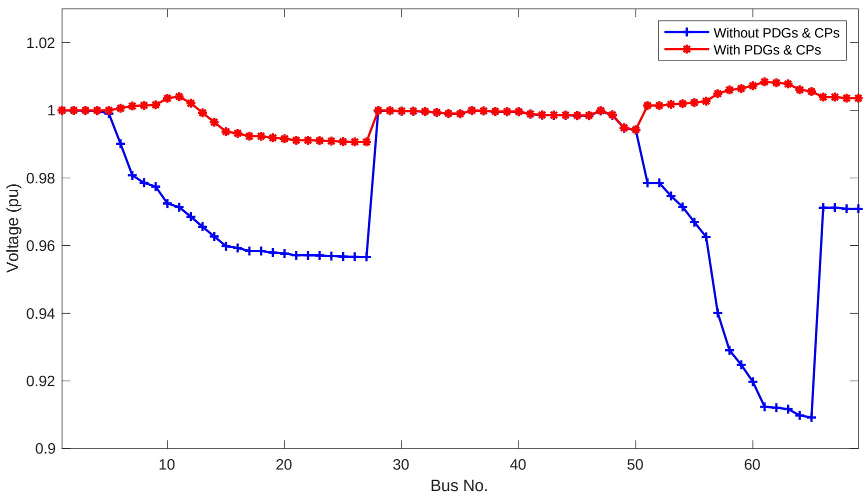

Figure 6. The voltage profile before and after connecting PDGs and CPs

Additionally, THD and IHD values representing for harmonic distortions are also changed positively when adding PDGs and CPs in the system. By implementing the proper connection, the maximum

THD value is drastically reduced from 5.265% to 2.766% as plotted in Figure 7. Similarly, as shown in Figure 8, the maximum IHD value is also mitigated to 1.786%, while that is 3.403% in the base system. As drawing a line of 5% in Figure 7 and another line of 3% in Figure 8, we can see some buses in the base system violating the THD and IHD limits. Clearly, the installation of distributed generators for supplying additional active and reactive power to distribution system, the IEEE Std. 519 about harmonic distortions is satisfied as expected.

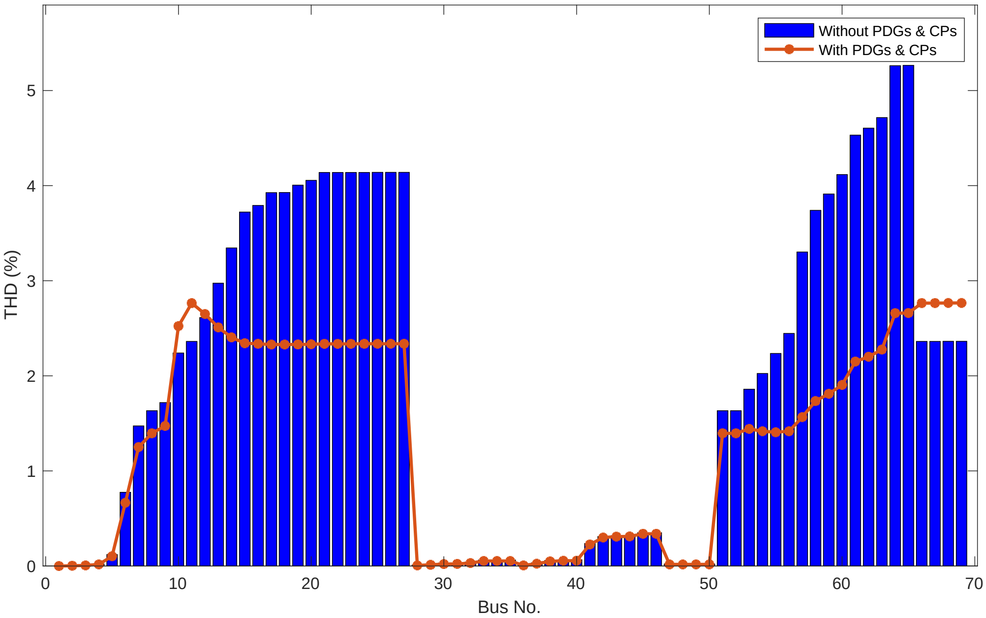

Figure 7. The THD before connecting PDGs and capacitors

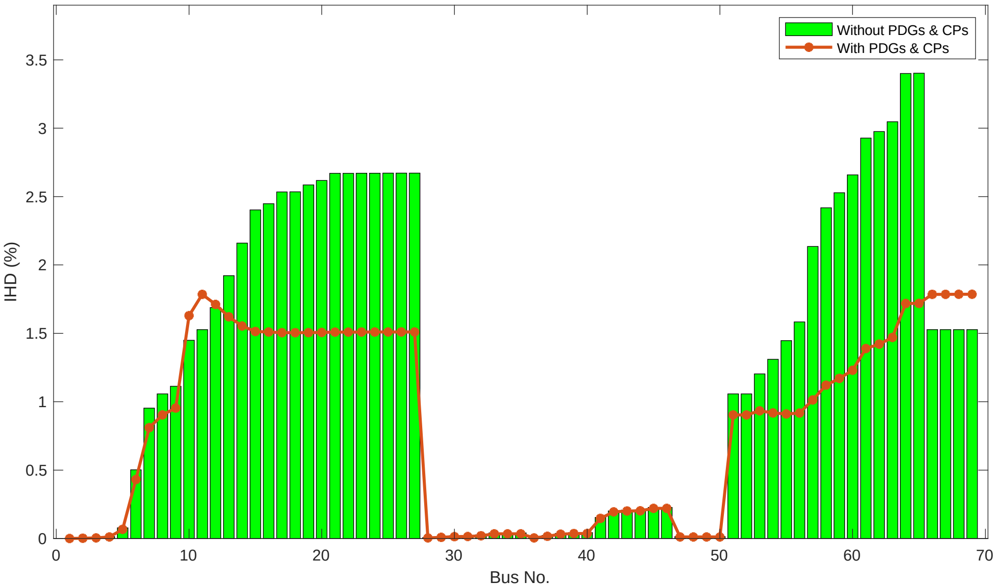

Figure 8. The IHD after connecting PDGs and CPs

5. CONCLUSION

In this study, three metaheuristic methods, including of PSO, SSA and BO, were developed to search the optimal solutions for position and capacity of PDGs and CPs in IEEE 69-bus radial distribution system with many nonlinear loads for maximizing economic and technical benefits. The main objective was to minimize the total cost, including of the cost of purchasing energy to supply the load demand, power loss on the lines and emission fines from the generator of the main power source under consideration of constraints on voltage, current, harmonics, etc. Overall, this study has obtained the following achievements:

- The suggested method (BO) together with PSO and SSA were implemented for the same objective and the conditions. The achieved results have proved that BO is the best and most stable method compared to the compared methods. By integrating BO's optimal solution, the total cost was significantly reduced from $390.1119 to $75.9889, equivalent to 80.52% in total cost reduction.

- In addition, the power loss was also reduced by 94.48%, the voltage variation range was also improved dramatically from the range of [0.9092 1.00] pu to [0.9907 1.0084] pu. This greatly contributes to enhance the power quality of the system.
- Besides, thanks to the optimal integration, harmonic distortions were actively mitigated and met IEEE Std. 519. Specifically, the maximum values of THD and IHD were reduced from 5.265% to 2.766% and from 3.403% to 1.786%, respectively.

In the future, the next work of this study is to consider the time-varying load and power output of renewable energy sources (RER) such as wind turbines and photovoltaic units. On the other hand, the time of charged and discharged energy to achieve the optimal total costs of the battery energy store system (BESS) will also be considered while still satisfying the technical criteria. Finally, a new version of BO modification will be developed for enhancing the performance and stability of the original BO after this work.

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