Research Article

Coot Optimization Algorithm for Optimal Placement of Photovoltaic Generators in Distribution Systems Considering Variation of Load and Solar Radiation

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In this paper, photovoltaic generators (PVGs) are placed in radial distribution networks (RDNs) for reducing active power loss of one operation day by using three recently published metaheuristics algorithms including coot optimization algorithm (COOA), transient search algorithm (TSA), and crystal structure algorithm (CRSA). In one operation day, the variation of loads is considered, and the change of solar radiation over daytime is also taken. The study has two main contributions regarding the effectiveness of COOA: energy loss reduction and voltage improvement. COOA can reach high energy loss reduction, better solutions, and faster search speed than TSA and CRSA. In fact, COOA finds better energy loss than the algorithms by 1% and 1.77% for the IEEE 69-node system and 0.75% and 1.4% for the IEEE 85-node system. Furthermore, COOA is at least three times faster than CRSA and two times faster than TSA. As compared to a base system without PVGs, COOA can find better energy loss up to 60.96% and improve voltage up to 4.5%. Thus, COOA is a highly effective optimization tool with the optimal solution, high stability, and fast computation process for placing PVGs in RDNs.

1. Introduction

1.1. Motivation. Distribution networks are major electric components distributing power to loads via conductors called distribution lines (DLs) [1]. DLs have resistance and reactance, causing active power loss, reactive power loss, and voltage drop [2]. For RDNs with low voltage, the losses and voltage drop are significant and methods for reducing loss and improving voltage drop are meaningful. The losses reduce the benefit of power companies, while the voltage drop causes unstable operation for loads. As a result, power companies must suffer from the damage derived from the unexpected issue of loads. For overcoming the drawback of distribution networks, the placement of distributed generators (DGs) has been selected as one of the leading effective methods [3–5]. In recent years, renewable energies have been developing, and PVGs have been installed increasingly in distribution systems [6, 7]. The differences between DGs and PVGs are power generation and generation time limit. In fact, DGs are regarded as active and reactive power generation sources [8, 9], while PVGs are mainly used as only active power generation sources [10]. So, in the paper, the placement of PVGs is studied over one operation day of RDNs.

1.2. Literature Review. In recent decades, the placement of PVGs has attracted a huge number of researchers, and there have been many optimization tools developed for the problem such as mathematical methods based on the configuration of networks, hybrid methods, and
metaheuristic algorithms. The studies [8, 11–13] have applied mathematical methods based on the configuration of distribution networks and mathematical function of power loss reduction (PLRF) to optimize the placement of PVGs in distribution systems. The four studies had a difference in installed electric components but the same purpose of loss minimization. Only DGs were installed for loss minimization [8, 11], whereas both DGs and shunt capacitors (SCs) were installed in [12, 13]. The four studies used the same solution methods based on three main steps. Branch current was found in the first step, and obtained value was used to determine the placement location of PVGs in the second step. In the last step, PLRF was solved for the power output of all the installed PVGs. These studies have reported smaller loss and higher voltage than base systems without PVGs; however, these applied methods were not highly successful for large systems with a high number of lines and nodes. It was stated that these methods could cope with the ineffective location due to the analysis on the branch current, but PLRF was highly effective for getting power [14]. So a combined method by using PSO and PLRF was proposed in [14] to tackle the shortcomings of configuration-based mathematical methods. The site of PVGs was found by using PSO, and the power of PVGs was reached by solving PLRF. The combined method could reach optimal solutions, but the implementation of the combined method took high simulation time.

On the contrary to mathematical methods and hybrid methods, metaheuristic algorithms have been widely applied, and they have reached more promising results. Furthermore, the applications of these metaheuristic algorithms were simpler and took a shorter simulation time. Metaheuristic algorithms can simultaneously determine the site and size of all DGs and other electrical components such as capacitors and energy storage systems without the analysis of the configuration of networks. However, not every metaheuristic algorithm can find good results. The study [15] used genetic algorithm (GA) for optimally selecting the rated power of a hybrid PV and wind turbine system. Both wind and solar were taken for one year with 8,760 hours, and the objective of the study was to minimize total capital cost. Energy loss as well as voltage have not been reported, while only the total capital cost of DGs found by only GA was given. There was no indication of the benefit of PVGs installation in the distribution system. The study [16] used whale optimization algorithm (WOA) for solving a multi-objective optimization problem, but WOA was only compared to a few other algorithms for a single objective. The study [17] has installed wind and solar generators in a real distribution network. Nodes are located on the geography map for calculating power generation. Speed of wind together with temperature and solar radiation were taken by using the specific locations but only one hour of a day was considered in the study. This study [18] applied heuristic optimization algorithms based on the configuration of networks for the IEEE 69-node system. The algorithms were stated to be more robust than PSO and gravitational search algorithms; however, the simulation time and the solving process were not discussed. The study [19] has optimized power generation for wind generators, solar generators, and pumped storage systems. The study has used the one operation day with 24 hours considering the change of wind speed and solar radiation where the data of wind and solar were fixed and given. The difference in data collection is the unreasonable issue of the study. This study [20] proposed Chaotic Mutation Immune Evolutionary Programming (CMIEP) for a multiobjective problem of PVGs placement including voltage stability and power loss. Only one system was solved by CMIEP and two other versions of Evolutionary Programming to conclude the advantage of CMIEP. The study [21] has considered the highest power of PVGs in RDNs for optimizing economic objectives and technical objectives. The study proved the highest power of PVGs could reach the best loss and the most stable voltage; however, the consideration of one hour was not the best data for the real results. The study [22] has used wind turbines as renewable generators in RDNs for cutting energy loss and investment costs. It has been considered an operation day with the change of load and power of DGs over 24 hours. However, the wind speed data were given not based on the geography location map. The study [23] has installed a typical DG with pure active power generation in RDNs for cutting power loss and the operation cost of PVGs. The study [24] has placed PVGs in the transmission network for cutting loss of the system. It has placed PVGs at given locations and unknown locations for checking the effectiveness of the loss sensitivity factor. The study also used 1 hour to select the rated power and location of PVGs, while solar radiation was not considered as the input data of PVGs. The study [25] has proposed one-day load data and one-day solar radiation data for PVGs placement problems. This study has proposed a discrete-continuous genetic algorithm (DCGA), but it has not proved DCGA to be more effective than others. This study [26] applied a metaheuristic algorithm called the sparrow search algorithm to get the highest penetration of PVGs. The study has used one-day solar radiation data, but it has a fixed load of a day. The study [27] supposed four different data of solar radiation in four seasons of a year. The IEEE 69 bus has been employed for the assumption, and a multiobjective function with loss, voltage, and cost has been optimized. In [28], a slime mould algorithm (SMA) has been employed to find the size and site of PVGs in a distribution network of North Cameroon. This study proved SMA was more effective than other algorithms. In addition to the consideration of a one-day period, three studies [29–31] also considered load demand response programs in the problem of DGs placement to enable electric customers to find their suitable energy consumption dependent on punitive policy and incentive policy. The study [29] has optimized three objectives including power losses, operation cost, and voltage stability index simultaneously in distribution systems as well as possible by adding PVGs, DGs, SCs, and energy storage systems. The study [30] has placed only DGs and SCs, but it has considered insufficient supplied energy for the case of lack of power from DGs. The study [31] became more practical since it considered electricity market prices, the uncertainty of PVGs, and network configuration change. The three studies had a huge contribution to real
distribution systems when complicated issues have been concerned. However, there were no comparisons of results obtained by algorithms. So the optimal solutions in the studies might not be the most suitable, and the achieved objective function could be better improved.

1.3. Contributions and Organization. In general, these studies above have installed PVGs in RDNs for power loss reduction, voltage improvement, and total capital cost reduction. Almost all the studies have simulated a single period, and only 1 hour was considered. So this study used the one-day solar radiation data to simulate the results of PVGs placement in RDNs for clarifying the importance of PVGs in cutting energy losses in distribution lines and improving the operating voltage of loads for periods with high demand. To determine the reasonable site and size of PVGs, three new metaheuristic algorithms consisting of COOA [32], transient search algorithm (TSA) [33], and crystal structure algorithm (CSA) [34] are applied for solving two systems, IEEE 69-node system and IEEE 85-node system. In the original study of COOA [32], COOA was run on over thirty benchmark functions and eight other real problems for comparison with tens of algorithms. Through the result comparisons, COOA was shown to be superior to others in terms of the best solution and the most stable ability. For the considered problem of PVGs placement in IEEE 69-node system and IEEE 85-node system, COOA can reach better results in terms of smaller energy loss, the higher success rate of finding high-quality solutions, and faster convergence to optimal solutions. The contributions of the paper are summarized as follows:

1. Apply three new metaheuristic algorithms including COOA, TSA, and CSA successfully for finding the site and size of PVGs.
2. Find the best locations and the most effective rated power for PVGs to reach smaller energy loss than the two base systems without PVGs by 60.96% and 46.33%, respectively.
3. Find the highest performance for COOA. COOA can get smaller energy loss than two others by 1% and 1.77% for the first system and 0.75% and 1.4% for the second system. COOA is two and three times faster than TSA and CSA, respectively.
4. Voltage of two applied systems is increased highly up to 3.3% and 4.5% thanks to the use of PVGs.

Other parts of the paper are as follows: objectives and constraints are presented in Section 2. The main algorithm, COOA, is presented in Section 3. The application of COOA for the placement of PVGs in RDNs is expressed in Section 4. The obtained results and discussion are presented in Section 5. Finally, Section 6 summarizes achievements and conclusions.

2. Problem Formulation

Photovoltaic generators (PVGs) can produce both reactive and active power. So the renewable power source can reduce the supply from the conventional power source at the slack node. Current in conductors can be reduced, and loss of the conductor is reduced as a result. However, to reach the highest loss reduction, the location and size of PVGs must be selected optimally. The objective and constraints of the problem are expressed as follows.

2.1. Objective Function. Conductors have two main factors, resistance and reactance. If we consider the h-th hour of the c-th distribution line with the resistance of R and the current of Ic,h, the resistance causes active power loss on the line by \((3.1^2)hR_c\). Over one operation day with 24 hours, the power loss is converted into energy loss, and the objective of the study is to minimize the total energy loss as follows:

\[
\text{Minimize } \Delta A_L = 3 \sum_{h=1}^{H} \sum_{c=1}^{N_c} T_h I_c,h R_c, \tag{1}
\]

where \(R_c\) and \(I_c,h\) are the resistance of the c-th line and the current of the c-th line at the h-th hour. \(H\) is the number of periods for one day, and \(T_h\) is the number of hours for the h-th period. When considering the energy loss of a day, \(H\) is 24, and \(T_h\) is 1 hour.

2.2. Constraints. The problem considers the change of load over one operation day and variation of solar radiation for daytime. So the consideration also has an impact on constraints. However, there are still unchanged constraints as other problems neglect the considerations. The constraints are presented in detail as follows.

2.2.1. Constraints of Power Balance. When installing PVGs into the power system, these installed PVGs and a transformer at a slack node are two supply sources, while loads and the losses on distribution lines consume the electricity from the sources. The total active power supplied by the PVGs and the transformer is equal to the sum of the active power demand of loads and active power losses. This expression is the active power balance constraint and formulated by

\[
\sum_{m=1}^{N_{PVG}} P_{PVG,m,h} + P_{cps,h} - \sum_{c=1}^{N_c} \Delta P_{Lc,h} - \sum_{L=2}^{N_L} P_{Load,L,h} = 0. \tag{2}
\]

Due to the use of PVGs without reactive power generation, only the transformer at the slack node supplies reactive power to loads and losses on conductors. So the reactive power balance constraint is formulated as follows:

\[
Q_{cps,h} - \sum_{c=1}^{N_c} \Delta Q_{Lc,h} - \sum_{L=2}^{N_L} Q_{Load,L,h} = 0, \tag{3}
\]

where \(N_{PVG}\) is the number of installed PVGs; \(P_{PVG,m,h}\) is active power generated by the n-th PVG over the h-th hour in (kW); \(P_{cps}\) and \(Q_{cps}\) are active power and reactive power generated by conventional power source at the slack node over the h-th hour in kW; \(P_{Load,L,h}\) and \(Q_{Load,L,h}\) are the active and reactive power of the load at the L-th node over the h-th
hour in kW; and $\Delta P_{c,h}$ and $\Delta Q_{c,h}$ are the active and reactive power losses on the $c$-th line over the $h$-th hour in kW. $\Delta P_{c,h}$ and $\Delta Q_{c,h}$ are obtained as follows:

$$\Delta P_{c,h} = 3 \sum_{c=1}^{N_c} I_{c,h}^2 R_c,$$

$$\Delta Q_{c,h} = 3 \sum_{c=1}^{N_c} I_{c,h}^2 X_c,$$  \hfill (4)

where $X_c$ is the conductor reactance of the $c$-th line in $\Omega$.

2.2.2. Load Voltage Constraint. The distribution systems have two major node types including a slack node (where the transformer is located and acted as sole power source) and load nodes (where loads are working). The voltage of the transformer is the highest in the system, while the voltage of loads is dependent on the demand of loads and the length of lines. There is no voltage constraint for the transformer, but all the load nodes suffer from the same constraint within the lower bound and the upper bound as the below model as follows:

$$U_{\text{min,Load}} \leq U_{\text{Load,L,h}} \leq U_{\text{max,Load}},$$

where $U_{\text{min,Load}}$ and $U_{\text{max,Load}}$ are the minimum and maximum limits of load voltage, respectively, and $U_{\text{Load,L,h}}$ is the voltage of the load at node $L$ over the $h$-th hour.

2.2.3. Distribution Line Constraint. Each distribution line is a conductor connecting two different nodes, while the conductor is constrained by the maximum current limit. So the limit of the conductor is also the constraint of the line. If operating current flowing through the line is higher than the maximum limit of the conductor, the line is violating constraint, and overload fault is happening. So the operating current through each line must be either smaller than or equal to the maximum limit of the conductor as shown in the following model:

$$I_{c,h} \leq I_{c,max}, \ c = 1, \ldots, N_c,$$  \hfill (6)

where $I_{c,max}$ is the maximum current limit of the conductor connecting two nodes of the $c$-th line.

2.2.4. Generation and Location Limits of PVGs. As installing PVGs in distribution systems, two major factors of these PVGs that should be determined effectively are rated power and placement location. Rated power is selected within a predetermined range including the lowest and highest capacity, while placement location can be one out of available nodes in the system excluding the slack node. The rated power and placement location must satisfy the following expressions [35]:

$$P_{\text{PVG}}^{\text{min}} \leq P_{\text{PVGn}} \leq P_{\text{PVG}}^{\text{max}},$$

$$L_{\text{PVG}}^{\text{min}} \leq L_{\text{PVGn}} \leq L_{\text{PVG}}^{\text{max}},$$

where $P_{\text{PVG}}^{\text{min}}$ and $P_{\text{PVG}}^{\text{max}}$ are the minimum and maximum generation limit of PVGs, respectively; $P_{\text{PVGn}}$ and $L_{\text{PVGn}}$ are the rated power and site of the $n$th PVG, respectively; and $L_{\text{PVG}}^{\text{min}}$ and $L_{\text{PVG}}^{\text{max}}$ are the minimum and maximum nodes for installing PVGs, which are corresponding to 2 and $N_{\text{PVG}}$, respectively.

3. Coot Optimization Algorithm

COOA is a metaheuristic algorithm based on the behavior of coots when they are looking for foods in nature. COOA has separated the population into leaders and members in which leaders are represented by good-quality solutions and members are low quality solutions. The three main steps of COOA are expressed in detail as follows.

3.1. Generation of Initial Solution Set. Each coot $k$ in the population is considered as a solution $A_k$, and $A_k$ is produced as follows:

$$A_k = A_{\text{min}} + r_1 (A_{\text{max}} - A_{\text{min}}); \ 1, \ldots, N_{\text{Po}},$$

where $A_{\text{max}}$ and $A_{\text{min}}$ are upper and lower bound of each existing solution, respectively, and $r_1$ random number in the range of 0 and 1.

In equation (8), $N_{\text{Po}}$ is the size of the population, and it is divided into two groups, good group with $N_L$ leaders and bad group with $N_M$ members. Each individual in the population is evaluated by calculating fitness function, and then each individual is put in a suitable group based on its obtained fitness value. Each solution in the leader group is represented by $L_{drd}$ where $m = 1, \ldots, N_L$, and each solution in the member group is represented by $Mr_j$, where $j = 1, \ldots, N_M$.

3.2. Update of Member Group. Each solution in the member group is updated by using one out of three following methods:

$$Mr_{j,new} = Mr_j + FG \cdot r_2 \cdot (A_{r,d} - Mr_j),$$

$$Mr_{j,new} = 0.5 \cdot ((Mr_{j-1} + Mr_j)), \text{ (9)}$$

$$Mr_{j,new} = L_{drd} + 2 \cdot r_3 \cdot \cos (2 \cdot \pi \cdot r'), (L_{drd} - Mr_j),$$

where $r_2$ and $r_3$ are random numbers within 0 and 1, while $r'$ is random number within $-1$ and 1. $L_{drd}$ is a randomly picked solution in the leader group. $A_{r,d}$ and $FG$ are the random solution and function of iteration obtained by

$$A_{r,d} = A_{\text{min}} + r_4 (A_{\text{max}} - A_{\text{min}}),$$

$$FG_1 = 1 - G \times \left( \frac{1}{G_{\text{max}}} \right),$$

where $r_4$ is a random number within 0 and 1. $G$ and $G_{\text{max}}$ are the current iteration and maximum iteration number, respectively.
3.3. Update for Leader Group. COOA updates solutions in leader group by using local search, that is, searching around the best solution of the population, which is \( L_{d_{\text{best}}} \). Two different methods are used for the group as follows:

\[
\begin{align*}
L_{d_{m}}^{\text{new}} &= L_{d_{\text{best}}} + \left[ FG_{2}.r_{5}. \cos(2.\pi.r_{7}).(L_{d_{\text{best}}}-L_{d_{m}}) \right] \text{ if } r_{5} < 0.5 \\
L_{d_{m}}^{\text{new}} &= -L_{d_{\text{best}}} + \left[ FG_{2}.r_{7}. \cos(2.\pi.r_{7}).(L_{d_{\text{best}}}-L_{d_{m}}) \right] \text{ if } r_{5} \geq 0.5,
\end{align*}
\]  

(11)

where \( r_{5}, r_{6}, \) and \( r_{7} \) are random numbers between 1 and 0. \( FG_{2} \) is a function of iteration expressed as follows:

\[
FG_{2} = 2 - \left( \frac{1}{G_{\text{max}}} \right).G.
\]  

(12)

In summary, the implementation of COOA for a general problem can be expressed in Figure 1.

4. COOA Implementation for PVGs Installation in RDNs

4.1. Decision Control Variables. Over 24 hours a day, the power generation of PVGs can reduce the loss of RDNs. The effectiveness and ineffectiveness of loss reduction are dependent on the installed location and rated power of PVGs. So the duty of applied algorithms is to find the installed location and rated power of PVGs, and these parameters are decision variables included in solutions.

4.2. Fitness Function. The fitness function of a solution is calculated to know the quality of variables in the solution. After having decision variables of the solution, other dependent variables are found by running forward/backward sweep technique (FBST) [36]. Then, the objective function shown in equation (1) is obtained, and other penalty terms are found [37]. As a results, the fitness function of the solution \( k \) is determined by

\[
Fit_{k} = 3 \sum_{h=1}^{N_{h}} \sum_{i=1}^{N_{i}} T_{h,i,c} L_{d,h,c} R_{c} \left( \Delta I_{c,h} \right)^{2} + \left( \Delta U_{\text{load},h} \right)^{2},
\]  

(13)

where \( \Delta I_{c,h} \) and \( \Delta U_{\text{load},h} \) are penalty terms of the current and voltage violation, respectively [37].

4.3. The Whole Process of COOA. The iterative algorithm of using COOA for optimizing the site and size of PVGs in RDNs is presented in Figure 2.

5. Numerical Results and Discussion

In this section, we run three algorithms including TSA, CRSA, and COOA for reaching optimal solutions of PVGs placement in two test systems, IEEE 69-node system and IEEE 85-node system. Each algorithm is executed 50 independent runs in which each run of the first and second systems comprises 100 and 150 computation iterations, respectively. These methods are coded on MATLAB programming language and run on a personal computer with 8 GB of ram and 2.4 GHz of a processor. The numerical results and discussion for each system are presented as follows.

5.1. Results Obtained for the IEEE 69-Node System. In this section, three algorithms including TSA, CRSA, and COOA are applied for reaching optimal solutions of PVGs placement in a distribution system. The considered IEEE 69-node system is plotted in Figure 3. The load demand [38] and energy loss over 24 hour are plotted in Figure 4. The whole data of the system and solar radiation can be reached by using [39, 40]. These methods are coded on MATLAB programming language and run on a personal computer with 8 GB of ram and 2.4 GHz of the processor.

In order to find the best performing algorithm among the three algorithms, we use 50 solutions obtained by them. The whole 50 energy loss values are arranged from the lowest to the highest to compare the performance and the stability of algorithms, while the summary of the 50 energy loss values including minimum, mean, maximum, and standard deviation \((\text{Std})\) is used to calculate the effective and stable level of the superior algorithm. The IEEE 69-node system, Figure 5 presents all energy loss values, and Figure 6 summarizes the values. As observing Figure 5, the red curve of COOA is below the blue and black curves of TSA and CRSA from the first point to the last point. It means COOA has smaller energy losses than TSA and CRSA for 50 runs. Furthermore, COOA has a high number of runs finding the same energy loss or slightly higher energy loss than that of the best run, whereas TSA and CRSA have a small number of runs with the same or slightly higher than the best energy loss of them.

From Figure 6, we can see COOA has better stability and more powerful search ability than TSA and CRSA, since all bars of COOA are shorter than those of TSA and CRSA. Namely, its standard deviation is smaller than that of TSA and CRSA by 25.656 and 9.236, respectively. Also, COOA has fewer minimum, mean, and maximum losses than TSA by 9.98 kWh, 54.57 kWh, and 157.93 kWh and than CRSA by 17.88 kWh, 44.64 kWh, and 26.54 kWh. The loss reduction values are equal to 1%, 5.1%, and 12.6% of losses from TSA and 1.77%, 4.2%, and 2.37% of losses from CRSA. The best energy losses obtained by the three applied methods are the results from the location and size of PVGs given in Table 1. The sites of PVGs are 11, 21, and 61 for COOA, while those are 18, 61, and 66 for TSA, and 7, 26, and 61 for CRSA. Clearly, COOA can find different sites from TSA and CRSA, and this is the reason why COOA can find less energy loss than these two others. Also, the size of PVGs from COOA is
also different from that of TSA and CRSA. Due to the unlimited requirement of total rated power, COOA has higher power than TSA but smaller power than CRSA.

The best runs of the three applied algorithms are plotted in Figure 7. The figure can show the outstanding performance of COOA over CRSA and TSA. From the second to the last iteration, COOA is much faster than CRSA, and it has a much smaller energy loss than CRSA for approximately the whole search process. TSA has fallen into the local optimal zones from the fifth iteration to the last iteration, and it could not reach a better solution than COOA from the 50th iteration to the last iteration.

Figure 8 presents the energy loss of each hour obtained by three applied algorithms and a base system without the installation of PVGs. Generally speaking, the loss of the base system is much higher than that of three applied algorithms from the 7th to the 18th hours, but the loss from base system and other algorithms is the same for other periods. During the 1st–6th hours and the 19th–24th hours, the three algorithms and base system have the same loss because there is
Figure 3: The IEEE 69-node system.

Figure 4: Load demand and energy loss of the IEEE 69-node system without PVGs installation.

Figure 5: One-day energy loss of 50 solutions obtained by algorithms for the IEEE 69-node system.
no solar radiation for the nighttime. For other hours, approximately all red points are below black and blue points. That is the cause that total energy loss of a day from COOA is less than that of TSA and CRSA.

In order to show a high benefit that the placement of PVGs can reach, the energy loss of the base system without PVGs and the energy loss obtained by COOA in Figure 8 are used to calculate the loss reduction. As a result, Figure 9
shows the reduction in kW and % from the 7th to the 18th hours. The lowest energy loss reduction is 11.624 kWh at the 18th hour, and the highest energy loss reduction is 155.391 kWh at the 11th hour. The loss reduction values are converted into percent, and they are corresponding to 25.6% and 69.1%. The total energy loss values before and after placement of PVGs during the time period are, respectively, 1,802.7857 kWh and 703.7348 kWh. The total energy loss reduction is 1,099.0509 kWh corresponding to 60.96%. The value indicates the installation of PVGs in the system can bring a high benefit to power companies. They can reduce not only the energy supplied by conventional power plants with high cost but also energy loss in distribution lines. For each hour, each node has a voltage value. So, to evaluate the operating voltage of the system, the minimum voltage and maximum voltages of each node over 24 hours are selected and plotted. Figure 10 shows the two values of each node. In general, all nodes have a higher voltage than 0.9 pu and smaller than 1.05 pu as constrained by the voltage limits. However, nodes 57–65 have smaller voltages than other nodes. The results are understood easily because the nodes are on branches with high current, and the nodes are far from the conventional power source. Although the three applied algorithms selected node 61 to install one PVG, the PVG cannot produce electricity at nighttime. The lowest voltage of the base system is about 0.91, but that of algorithms is about 0.94. This indicates that the voltage of the

Figure 8: Energy loss of each hour in the IEEE 69-nodes system without and with PVGs.  

Figure 9: Energy loss reduction for the IEEE 69-node system.
system can be improved up to 3.3% because of the use of PVGs. Clearly, the installation of PVGs can improve the voltage of load nodes significantly.

The optimal power output of PVGs and power loss for the system are reported in Supplementary Materials.

5.2. Results Obtained for the IEEE 85-Node System. In this part, the installation of PVGs is implemented in the IEEE 85-node system for the target of energy loss reduction. The system is shown in Figure 11, and its data are taken from [41]. The load demand and energy loss of each hour in the base system are plotted in Figure 12.

All energy loss values for 50 runs obtained by algorithms are plotted in Figure 13 and summarized in Figure 14. By ranking from the lowest to the highest energy loss values, each red point is much below each blue point and each black point at the same run. The minimum, mean, and maximum energy losses of COOA are also much smaller than those of TSA and CRSA. COOA can reach less minimum, mean, and maximum losses than TSA by 13.134 kWh, 57.1 kWh, and 85.03 kWh, which are equivalent to 0.75%, 3.14%, and 4.49% of those values from TSA. Similarly, COOA can find less minimum, mean, and maximum losses than CRSA by 24.65 kWh, 39.14 kWh, and 80.69 kWh, which are corresponding to 1.4%, 2.18, and 4.27% of those from CRSA. On the other hand, COOA is also more stable than TSA and CRSA for the system since its standard deviation is equal to 52.6% and 79.7% of that from the two algorithms. These values confirm that COOA outperforms TSA and CRSA in terms of the most economical solution and the most stable characteristic.

The optimal solutions that reach the smallest energy losses are reported in Table 2. The three algorithms have the same node 67, while the two remaining nodes are totally different. In addition, the size of each PG is also different. The total generation of COOA is higher than that of TSA and CRSA.

The whole search process of the best run that reaches the optimal solutions in Table 2 is plotted in Figure 15. Before the 50th iteration, COOA can reach a better loss than CRSA, but it must suffer from a much higher loss than TSA. After the 65th iteration, COOA finds better optimal solutions than TSA, and it reaches the lower loss until the process terminates. It is emphasized that the solution of COOA at the 70th iteration is much better than the solution of TSA and CRSA at the last iteration (the 150th iteration). This means that COOA can be at least two times faster than TSA and CRSA.

Energy loss of the base system without PVGs and three applied algorithms with PVGs placement are plotted in Figure 16. From the 7th to the 18th hours, the loss of three applied algorithms is much smaller than that of base system. For a clear view of the benefit of PVGs placement, loss reduction of COOA as compared to a base system is plotted in Figure 17. The loss reduction is from 11.666 kWh to 167.158 kWh corresponding to the smallest and highest solar radiation at the 18th and 11th hours. For the period of time, the total energy loss values before and after placement of PVGs during the time period are, respectively, 2,509.9326 kWh and 1,347.1027 kWh. The total energy loss reduction is 1,162.8299 kWh corresponding to 46.33%.

The minimum and maximum voltages of each node over 24 hours are plotted in Figure 18. The figure indicates that nodes in the system with PVGs placement have a range of voltage from 0.92 pu to lower 1.0 pu satisfying the voltage...
constraint, whereas nodes of the base system must suffer from the violation of voltage limit. In fact, approximately all nodes from 26 nodes to 85 nodes have smaller voltages than 0.88 pu. The voltage of the system can be improved up to 4.5% because of the use of PVGs. The phenomenon can reflect the significance of the placement of PVGs in improving load voltage during hours with high load demand.

The optimal power output of PVGs and power loss for the system are reported in Supplementary Materials.

5.3. Computation Speed and Limitations of COOA. The settings of parameters and average simulation time for each run are given in Table 3. The mean time for each method is about 100 seconds for the IEEE 69-node system and 200 seconds for the IEEE 85-node system. The time sees that the three algorithms have approximately the same time. This result is derived from the setting of the population and iteration number. TSA and COOA have one solution updating generation, while CRSA has four generations per iteration. Thus, the setting of the population is the same for TSA and COOA, while this is different from that of CRSA. The same setting of iteration number aims to guarantee a fair comparison for three methods. It is recalled that COOA can reach smaller losses than TSA and CRSA for the two systems. Furthermore, COOA is much faster than these methods as analyzed above. The settings and simulation time indicate that COOA is much more effective than TSA and CRSA for the two systems.
However, the performance of COOA is not really very high for the problem via graphic and table results. Although the settings of 20 for population and 100 and 150 for iteration number are not high for the two systems with 69 and 85 nodes, the average simulation time about 100 seconds for the 69-node system and 200 seconds for the 85-node system is not small for reaching the best solution. In fact, to reach the most optimal solution, we have implemented COOA 50 runs, and the

![Figure 13: One-day energy loss of 50 solutions obtained by algorithms for the IEEE 85-node system.](image1)

![Figure 14: Summary of 50 runs obtained by algorithms for the IEEE 85-node system.](image2)

| Method | TSA | CRSA | COOA |
|--------|-----|------|------|
| Site   | Size (kW) | Site | Size (kW) | Site | Size (kW) |
| PVG₁   | 25 | 1,088.336 | 12 | 547.221 | 9 | 1,285.114 |
| PVG₂   | 35 | 748.874 | 30 | 1,297.141 | 34 | 888.617 |
| PVG₃   | 67 | 822.549 | 67 | 923.072 | 67 | 660.32 |
| Total size (kW) | 2,659.759 | 2,767.434 | 2,834.051 |

However, the performance of COOA is not really very high for the problem via graphic and table results. Although the settings of 20 for population and 100 and 150 for iteration number are not high for the two systems with 69 and 85 nodes, the average simulation time about 100 seconds for the 69-node system and 200 seconds for the 85-node system is not small for reaching the best solution. In fact, to reach the most optimal solution, we have implemented COOA 50 runs, and the
Simulation time is about 5,000 seconds for the first system and 10,000 seconds for the second system. In addition, to get the most suitable parameter settings, we had to try different values, and the most suitable settings were then selected by analyzing results. Another limit of COOA is the stability as shown in Figures 5 and 13. Although 50 runs of COOA are more effective than TSA and CRSA, the red curves in the figures have high increases from the first solution to the last solution. The low stability is the cause of running COOA many times and trying different settings of control parameters for finding the best solution. The energy losses in Figures 5 and 13 indicated that COOA found the best solution only two times for the 69-node system and one time for the 85-node system over 50 runs. The probability of reaching the best solution is 4% and 2% for the two systems, respectively. In order to achieve a higher probability of finding the best solution, we need to set higher values to population and iteration number for COOA, and it will take COOA longer simulation time.
Figure 17: Energy loss reduction for the IEEE 85-node system.

Table 3: Setting of parameters and mean computation time of three applied algorithms.

| Method               | NP | TSA | CRSA | COOA |
|----------------------|----|-----|------|------|
| IEEE 69-node system  |    | 20  | 5    | 20   |
|                      | Gmax | 100 | 100  | 100  |
|                      | Times (s) | 97.33 | 101.98 | 99.96 |
| IEEE 85-node system  |    | 150 | 150  | 150  |
|                      | Gmax | 189.93 | 230.05 | 193.96 |
|                      | Times (s) |  |  |  |
6. Conclusions

In this paper, three recently published metaheuristic algorithms including coot optimization algorithm (COOA), transient search algorithm (TSA), and crystal structure algorithm (CRSA) have been employed to solve the problem of PVGs placement in two RDNs. The loads have been considered to be variable over 24 hours of a day and solar radiations are different from 7 am to 6 pm. The location and size of three PVGs have been determined so that the voltage of loads satisfied operation limits and energy loss was minimum. As a result, COOA could get energy loss reduction more effectively than TSA and CRSRA at the two applied systems. COOA reached energy loss reduction by 1% and 1.77% for the IEEE 69-node system, and 0.75% and 1.4% for the IEEE 85-node system as compared to TSA and CRSRA. In addition, the mean and maximum losses of COOA were also much smaller than those of TSA and CRSRA, which were 5.1% and 12.6% of losses from TSA and 4.2% and 2.37% of losses from CRSRA for the two systems, respectively. In addition, COOA also found more optimal solutions before TSA and CRSRA could do. The solutions of COOA at the 60th iteration and 75th iteration were better than those of TSA and CRSRA at the 100th and 150th iterations for the two systems respectively. Compared to base systems, COOA could reach the load reduction by 60.96% and 46.33%, respectively. So it leads to two conclusions that COOA is a high-performance metaheuristic algorithm, and the solution of PVGs placement from COOA can reduce energy losses for two RDNs effectively.

In this study, authors have considered the certainty of solar radiation and the given load demand in addition to one operation day within 24 hours. The study is more practical and complicated than previous studies considering only 1 hour. We have used three applied algorithms to find the location and size of PVGs for one 69-node distribution system and one 85-node distribution system. The two systems were supplied by a transformer at the first node, and the rated voltages of the two systems were, respectively, 12.66 kV and 11 kV. The capacity of the transformer was limited, and it only supplied a power that was not higher than its capacity. So the shortcoming of the study was to consider the certainty of load and power generation of PVGs. So we will consider the demand uncertainty of loads [42] and the generation uncertainty of PVGs [43]. The uncertainty models of power source and loads will be modeled by using mathematical equations and highly effective algorithms will be found for interesting future problems. In addition, the study had another limit and that will be improved in future work. As taking into account the constraint of voltage in equation (5), the voltage limit was considered to be from 0.9 pu to 1.1 pu where 1.0 pu was rated voltage. Figures 10 and 18 showing the lowest and highest values of voltage in the 69-node and 85-node systems indicated voltage of all nodes falls into the range as expected. However, if we want higher voltage for nodes with smaller voltage than 0.95 pu, the placement of PVGs can be unsuccessful for the purpose. So the on-load tap changer (OLTC) of the transformer at the slack node [44, 45] should be selected, and the consideration of OLTC in distribution systems is the future work.

Data Availability

The data of the employed systems were extracted from [38–41].

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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Supplementary Materials

Figures S1 and S2: the optimal power output of PVGs and power loss for two applied systems. (Supplementary Materials)

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