Maximum Penetration of Distributed Generations and Improvement of Technical Indicators in Distribution Systems

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Received 29 August 2020; Revised 6 December 2020; Accepted 17 December 2020; Published 30 December 2020

1. Introduction

DG is small power sources that are connected directly to the DS [1, 2]. The definition of DG based on its size is a little different among different countries as well as organizations [2, 3], but in general, it can be classified into categories as micro DGs with rating less than 5 kW, small DGs with rating from 5 kW to smaller than 5 MW, medium DGs with rating from 5 MW to smaller than 50 MW, and large DGs with rating from 50 to 300 MW [2, 4]. The benefits related to economic, technical, and environmental obtained by installing of DGs in the distribution systems are remarkable [5]. Thus, the DG placement problem has attracted the attention of the researchers.

One of the biggest technical benefits of DG installation on the DS is to decrease power loss. In addition, because of operating at low voltage level, power loss of the DS always takes a higher portion compared to other parts of the power system. Thus, as installation of DGs on the distribution system, power loss reduction is one of the most concerned objectives. In [6], location and size of DGs are optimized for loss reduction based on genetic algorithm (GA). In [7], binary particle swarm optimization is presented to find the optimal location and size of photovoltaic for loss reduction in the DS. In [8], stud krill herd algorithm is employed for optimizing DG installation in the DS for minimizing the losses. Similar to the above studies, the DG installation in the DS for loss reduction is also addressed in [9–15].

However, installing of DG on the DS affects not only power loss but also other technical factors. Therefore, some studies have focused on solving the DG placement problem to satisfy the multigoal function. In [16], the multigoal function for DG placement consisting of power loss, operational cost, and voltage deviation reduction is considered.
based on the invasive weed algorithm. In [17], backtracking search algorithm is presented for the DG installation problem for losses reduction and voltage profile enhancing. In [18], the multigoal function for DG placement consisting of power losses, voltage stability, and voltage profile indexes is solved based on the quasioppositional teaching learning algorithm. The location and size of DGs are determined to enhance the transient stability factor and voltage and decrease losses in [19]. In [20], power loss, voltage profile, load balancing, and voltage stability indexes are the membership functions considered for optimizing location and size of DGs in the DS.

In terms of solving technique for the DG placement problems, there are two major method groups consisting of the classical optimization methods, such as linear programming [21], mixed integer [22, 23], and dynamic programming [24], and the metaheuristic methods comprising of GA [6], particle swarm optimization [7], honey bee mating optimization [25], cuckoo search [26], runner root algorithm [27], Salp swarm algorithm [28], etc., in which, the first method group proved to be more disadvantaged when compared to the latter group in aspects of quality of obtained solution and handling constraints for the problem.

Cuckoo search algorithm (CSA) belongs to the second group method aforementioned. The CSA was inspired by the generative strategy of cuckoo birds [29]. Since being proposed, CSA has been being used for many optimal problems in different fields [30] and in the power system field [26, 31–33]. In addition, to improve the efficiency of the CSA, a lot of improved versions of CSA have been proposed [34–37], in which, the improved cuckoo search algorithm (ICSA) in [37] is a recent improved version of CSA that has been successfully proposed for a problem related to operation of the distribution system. Moreover, ICSA has demonstrated a better performance compared to CSA. In ICSA, the new local search strategy is used for exploiting the better solution nearby the so-far best solution beside the searching strategies of the original CSA.

Vietnam is located on the equatorial line and has a long coastline, which results in a lot of sunshine and wind resources. In recent years, with many positive policies for the development of renewable energy sources, many electricity sources related to renewable energy such as photovoltaic and wind generations have been built and connected to the electricity system. However, most of them are built with large-capacity, centralized power generation and linked to the transmission system. The small-capacity sources connected to the DS are still very limited. One of the reasons for this situation is that the investment cost per unit of capacity for small DGs connected to distribution system is higher than that of large DGs connected to the transmission system. Therefore, increasing the possible capacity of DGs pumped into the distribution system is one of the solutions to attract investment of small DGs installation in the distribution systems. Increasing DG capacity pumped to the DS will undoubtedly affect the technical factors of the system such as load balancing, power loss, nodes’ voltage, and branches’ current. Thus, it is essential to address the problem of DG placement under multiobjective perspective.

This paper presents the DG placement problem for maximizing the size of DGs pumped to the DS and improving the technical indicators related to operating the distribution system comprising of power loss reduction, increase of balance among feeders, and balance among branches and voltage deviation reduction. The fuzzy technique based on the max-min method is proposed to combine the membership objective functions. In order to search the optimal size and location of DGs, ICSA is adapted to solve the problem. The calculated results for the 84-node practical distribution system show that the proposed multiobjective DG placement problem not only helps to increase the DGs’ capacity but it also improves the technical factors of the system. In terms of solving method, ICSA is one of the efficient methods for searching location and size of DGs to satisfy the multiobjective as well as other goals. The main highlights of this work can be recapitulated as follows:

(i) The problem of optimizing location and size of DGs is addressed in terms of maximizing DGs’ capacity pumped to distribution system and improving the technical indicators of the system
(ii) The max-min technique is proposed for choosing the final solution for the membership objective functions
(iii) The ICSA is adapted to optimize the location and size of DGs in the DS
(iv) The proposed problem and ICSA method are evaluated on the 84-node practical distribution system
(v) The multiobjective problem helps to gain more DGs’ capacity and improvement of technical indicators compared to the case of no DGs placement and the single-objective problems
(vi) The comparisons of ICSA with other methods in the literature present the reliability of ICSA for the DG placement problem

2. Problem Formulation of DG Placement

In this work, the DG placement problem in the DS is considered to satisfy five objective functions consisting of power loss reduction, increasing balance among feeders as well as among branches, increasing the sum of capacity of DGs connected to the DS, and deviation voltage reduction. The details of the membership functions are demonstrated as follows.

2.1. Reduce Power Loss (PL). Because of low voltage level and high current of the DS, its power loss usually takes a high portion in the power system’s losses. DG installation is one of the efficient methods for power loss reduction. The first goal function considered is to reduce the power loss of the DS that is presented as follows:

$$\min f_1 = \sum P_{\text{loss}},$$

where \(\sum P_{\text{loss}}\) is the power loss of the DS.
2.2. Increase the Balance among the Feeders (BF). Increasing the balance among the feeders in the DS helps to reduce the load of the heavy feeders and increase the load for the light feeders. It contributes to enhancing the available power capacity of the feeders as well as the distribution system. The suitable DG installation will improve the balance of the system. Thus, the second objective function considered is to enhance the balance among the feeders, which is determined by the following mathematical formulation:

\[
\min f_2 = \text{var}\left[ S_{f,i} \right], \quad i = 1, \ldots, N_{Fe},
\]

where \( S_{f,i} \) is the power energy of the \( i \)th feeder, \( N_{Fe} \) is the number of feeders in the DS, and \( \text{var} \) is the variance function.

2.3. Increase the Balance among the Branches (BB). Enhancing the balance among the branches in the distribution system helps to transfer the loads from the heavy branches to other branches. It will help to increase the transferring capacity of the DS. The DG installation in the DS not only provides power for on-site demand but also contributes to reducing the overload and ensuring load balancing among branches. Therefore, the third objective function is to increase the balance among the branches, which is determined by the following mathematical formulation:

\[
\min f_3 = \text{var}\left[ LCI_i \right], \quad i = 1, \ldots, N_{br},
\]

where \( LCI_i \) is the load carrying index of the \( i \)th branch that is determined by the quotient of the load current flowing in the \( i \)th branch and its rated current and \( N_{br} \) is the number of lines of the DS.

2.4. Increase the Capacity of DGs Embedded in the DS (CDG). Compared with the small capacity of DGs, the larger the capacity of DG is, the smaller the investment cost per unit of capacity is. However, the large DGs are usually installed in the transmission system. Thus, maximizing the DGs’ capacity which can be pumped to the DS is one of the most effective solutions to entice investors paying for DG installation on the DS. Thus, the fourth goal function considered is to enhance the capacity of DGs connected to the distribution system, which is determined by the following mathematical formulation:

\[
\min f_4 = \left( 1 - \frac{\sum_{i=1}^{N_G} P_{DG,i}}{P_{DG,\text{max}}} \right),
\]

where \( P_{DG,i} \) is the capacity of the \( i \)th DG, \( N_G \) is the number of DGs in the DS, and \( \sum P_{DG,\text{max}} \) is the total permitted capacity of DGs pumped to the distribution system.

2.5. Decrease the Deviation Voltage of the DS (DV). The DG placement is one of the most effective techniques to enhance the nodes’ voltage of the DS and contribute to decreasing the voltage deviation. Thus, the deviation voltage reduction is the final objective function of the DG placement for multiobjective function. It is formulated as follows:

\[
\min f_5 = V_s - V_{\text{min}},
\]

where \( V_s \) is the amplitude of voltage at the slack bus and \( V_{\text{min}} \) is the minimum amplitude of voltage in the distribution system.

2.6. Constraints of the DGs Placement on the DS. Integration of DG into the DS has not caused additional overload and over/underpermitted voltage. Thus, the following constraints must be ensured:

(i) Voltage and current limits:

\[
\begin{align*}
V_{\text{min}} & \leq V_i \leq V_{\text{max}}, & i = 1, 2, \ldots, N_{bu}, \\
L_{CI_i} & \leq L_{CI_i}^{\text{max}}, & i = 1, 2, \ldots, N_{br}.
\end{align*}
\]

(ii) Capacity limits of DGs: the total capacity of DGs has not been greater than the total loads and losses of distribution the system

\[
\sum_{i=1}^{N_G} P_{DG,i} \leq \sum_{j=1}^{N_{bu}} \text{Load}_j + \sum P_{\text{loss}},
\]

(i) where \( \text{Load}_j \) is the \( j \)th load of the DS.

3. Improved Cuckoo Search Algorithm for the DG Placement on the DS

In this section, the overview of ICSA is presented. In addition, the solution vector and the adaptive function for the DG placement with the multiobjective function are described. Finally, the application of ICSA for finding location and size of DGs is demonstrated. Details of the aforementioned sections are presented as follows.

3.1. Improved Cuckoo Search Algorithm. The ICSA is proposed based on the original CSA. Compared to CSA, ICSA is supplemented with a local search technique for exploiting around the so-far best solution. Thus, ICSA has the capability of finding results of the optimization problem with better quality than CSA. In [37], the effectiveness of ICSA has been also demonstrated to outperform many other improved versions of CSA. The details of ICSA for typical problem are depicted as follows:

Step 1 Initialization of the current population of solutions:

At the beginning of the ICSA, the current population of solutions is generated randomly as follows:
\[ s_i = s_{0,i} + \rho_1 \cdot (s_{hi,i} - s_{lo,i}), \quad i = 1, \ldots, N_s; j = 1, \ldots, N_v, \] (8)

where \( s_i \) is the \( i \)th solution in the population with size of \( N_s \). \( s_{lo,i} \) and \( s_{hi,i} \) are the permitted lower and upper limits of the \( j \)th variable. \( N_v \) is the number of variables of the candidate solution vector, \( \rho_1 \) is a random number in \([0, 1]\).

After the initial solutions are generated, their quality is validated by the adaptive function and the solution with the best adaptive function value (\( Q_{\text{best}} \)) is considered as the so-far best solution (\( s_{\text{best}} \)).

Step 2 Production of new solutions based on the Leiby flight mechanism:
The Leiby flight mechanism helps to produce new solutions that distribute far from the current ones in the search space. It is formulated as follows:

\[ s_{\text{new},j} = s_j + \theta \cdot (s_j - s_{\text{best}}) \odot \text{Leiby} (\theta), \] (9)

where \( \theta \) is the step size that is often chosen to be 1. \( \theta \) is distribution coefficient in \([0, 2]\). \( \text{Leiby}(\theta) \) is the Leiby distribution with the distribution coefficient \( \theta \). \( s_{\text{best}} \) is the so-far best solution. The symbol of \( \odot \) stands for the entry-wise multiplications.

After the new solutions are generated, their quality is validated. Then, the current population is updated based on the comparison between the adaptive function value of the new solutions and that of the corresponding ones in the old population. The updated population is performed by

\[ s_i = \begin{cases} s_{\text{new},i} & \text{if } Q_{\text{new},i} < Q_i, \\ s_i & \text{otherwise}. \end{cases} \] (10)

From the current population updated, the so-far best solution is updated again.

Step 3 Production of new solutions based on the selective random walk mechanism:
The selective mechanism helps to produce new solutions that distribute near the current solutions. New solutions are created by adjusting a part of control variables of the current solutions. It is formulated as follows:

\[ s_{\text{new},j} = \begin{cases} s_j + \rho_2 \cdot (s_k - s_h) & \text{if } \rho_3 < \mu, \\ s_j & \text{otherwise}, \end{cases} \] (11)

where \( \rho_2 \) and \( \rho_3 \) are a random number in \([0, 1]\). \( \mu \) is the mutation index that is chosen to be 0.2. \( s_k \) and \( s_h \) are two candidate solutions taken randomly from the current population.

Then, equation (10) is used to renew the current population and the so-far best solution is updated one more time.

Step 4 Production of new solutions nearby the so-far best solution:
This mechanism helps to generate some new solutions in the vicinity of the so-far best solution by modifying a part of variables of the so-far best solution. However, this mechanism is not executed for each iteration, it is performed based on a comparison between the adaptive function value of the so-far best solution in two consecutive iterations. If the so-far best solution is not enhanced in two consecutive iterations, the mechanism is triggered as follows:

Firstly, there are \( 2 \cdot N_v \) new solutions generated by changing only one control variable of the so-far best solution as follows:

\[ s_{\text{new},l} = M_{(k,:)} \cdot \tau_1 \cdot \rho_4 + s_{\text{best}}, \quad k = 1, \ldots, N_v; l = k, \] (12)

\[ s_{\text{new},l} = M_{(k,:)} \cdot \tau_2 \cdot \rho_5 + s_{\text{best}}, \quad k = 1, \ldots, N_v; l = l + k, \] (13)

where \( M \) is the identity matrix of size \( N_v \). \( \tau_1 \) and \( \tau_2 \) are the space between the current variables and the new variables with \( \tau_1 > \tau_2 \). \( \rho_4 \) and \( \rho_5 \) are a random number between \(-1 \) and \( 1 \).

Secondly, \( 2 \cdot N_v \) new solutions are also produced by adjusting some control variables of the so-far best solution as follows:

\[ s_{\text{new},l} = M_{r(1,:)} \cdot \tau_1 \cdot \rho_6 + s_{\text{best}}, \quad k = 1, \ldots, N_v; l = l + k, \] (14)

\[ s_{\text{new},l} = M_{r(1,:)} \cdot \tau_2 \cdot \rho_7 + s_{\text{best}}, \quad k = 1, \ldots, N_v; l = l + k, \] (15)

where \( \rho_6 \) and \( \rho_7 \) are random numbers between \(-1 \) and \( 1 \).

In the above equations, \( M_r \) is a matrix of size \( N_v \) by \( N_v \) that its element is defined by the following equation:

\[ M_r (t,h) = \begin{cases} 1, & \text{if } \rho_7 > \sigma, \\ 0, & \text{otherwise}, \end{cases} \quad t = 1, \ldots, N_v; h = 1, \ldots, N_v, \] (16)

where \( \sigma \) is the scale factor that is usually set to 0.8. \( \rho_7 \) is a random number between 0 and 1.

From \( 4 \cdot N_v \) new solutions generated, their quality is evaluated, and the so-far best solution is updated as follows:

\[ s_{\text{best}} = \begin{cases} s_{\text{new},l} & \text{if } Q_{\text{new},l} < Q_{\text{best}}, \\ s_{\text{best}}, & \text{otherwise}. \end{cases} \] (17)

Steps 2 to 4 are implemented until the stopping condition is reached.
3.2. Solution Vector. To apply ICSA for the DG placement problem, the unknown variables are location and size of DGs, in which, location of DG is one of the nodes of the DS except for the slack bus. Thus, the solution vector is expressed as follows:

$$s_i = [L_{ij}, S_{ij}], \quad i = 1, \ldots, N_s; \, j = 1, \ldots, N_G, \quad (18)$$

where $L_{ij}$ represents location; meanwhile, $S_{ij}$ represents size of the $j$th DG in the $i$th solution.

3.3. The Adaptive Function. To combine the five membership functions, the max-min approach is proposed for selecting the solution as follows [38–43]:

$$F_S = \max\{\min\{F_j\}\}, \quad (19)$$

where $F_S$ is the final quality of each candidate solution. $F_j$ is the normalized vector of the $j$th objective function and expressed as follows:

$$F_j = \begin{cases} 
1, & f_j \leq f_j^{\text{min}}, \\
\frac{f_j^{\text{max}} - f_j}{f_j^{\text{max}} - f_j^{\text{min}}}, & f_j^{\text{min}} < f_j < f_j^{\text{max}}, \\
0, & f_j \geq f_j^{\text{max}},
\end{cases} \quad (20)$$

where $f_j^{\text{min}}$ and $f_j^{\text{max}}$ are, respectively, the minimum and maximum value of the $j$th membership goal function. $f_j$ is the $j$th objective function value.

From the fact that the value of each $F_j$ is not greater than one, the maximization problem described in (19) is altered to the minimization problem as follows [43]:

$$F_S = 1 - \min\{F_j\}. \quad (21)$$

In addition, each candidate solution has to satisfy the constraints of the DG placement problem consisting of current and voltage limits and capacity limit of DGs. Therefore, the adaptive function for multiobjective function is formulated as follows:

$$\min f = K_f \cdot F_S + K_p \cdot \left[ (\max(V_{\text{max}} - V_{\text{min}}), 0) + (\max(LCI_{\text{max}} - LCI_{\text{min}}), 0) \right], \quad (22)$$

where $K_f$ and $K_p$ are the scale factor and penalty coefficient, respectively, $V_{\text{max}}$ and $V_{\text{min}}$ are the maximum and minimum voltages and $LCI_{\text{max}}$ is the maximum load carrying index of the distribution system.

3.4. Steps of ICSA for the DGs Placement on the Distribution System. The location and the capacity of DGs are considered as control variables of the problem. These variables are selected by ICSA to satisfy the member goals and ensure the considered constraints, in which, the member goals consist of reducing power loss, improving the balance of feeders, improving the balance of branches, increasing the capacity of DGs, and decreasing voltage deviation meanwhile the constraints are limits of current, voltage, and DG capacity. For each candidate solution vector including the position and capacity of DGs, the bus data parameters of the distribution system are updated and the power flow problem is solved to calculate the value of the component target functions and the constraint conditions. Then, the solution vector’s quality is determined by calculating the fitness function presented in (22). The process of creating and updating solution vector to find the best solution for the problem is done based on ICSA. The proposed ICSA application for the DG placement problem is described in detail as follows:

**Step 1** Set control parameters of ICSA:
To apply ICSA for the DG placement, the control parameters of ICSA are required to be set before executing, consisting of population size $N_p$, dimension of the problem $N_s$, the space between the current variable and the new variable $r_1$ and $r_2$, and the maximum number of the adaptive function evaluations $AFE_{\text{max}}$.

**Step 2** Generate the current population of solutions:
Generate randomly the current population by using (8) and adjust them according to (18) to be suitable for the DG placement problem.

**Step 3** Generate new solutions based on the Lévy flight mechanism:
Generate the new solutions by (9) and adjust them according to (18).

**Step 4** Generate new solutions based on the selective random walk mechanism:
Validate the quality of each new solution by using the adaptive function in (22).

**Step 5** Check the condition for triggering the mechanism of generating new solutions nearby the so-far best solution:
In this paper, the condition for activating the mechanism is based on the number of successive iterations that the so-far best adaptive function value is not improved ($it_{\text{im}}$). After $it_{\text{im}}$ iterations, the so-far best
solution is not enhanced; the mechanism of creating new solutions nearby the current best one is activated by performing step 6. Otherwise, the searching process will move to step 7.

**Step 6:** Generate new solutions nearby the so-far best solution:

In case of the mechanism activated, the following procedures are performed:

- Generate $4 \cdot N_v$ new solutions by using (12) to (15) in turn and adjust them according to (18).
- Validate the quality of each new solution by using the adaptive function in (22).
- Update the so-far best solution $s_{best}$ with the best adaptive function value ($Q_{best}$) by using (17).

**Step 7:** Check the stopping condition:

In general, ICSA will stop finding better solutions as the number of the adaptive function evaluations (AFE) reaches the maximum value $AFE_{\text{max}}$. However, in order to avoid wasting simulation time, an additional stopping condition is the maximum number of consecutive generations that the best solution function is not improved ($it_{\text{NIP}}$). After $it_{\text{NIP}}$ consecutive iterations, the so-far best solution is still not better than before, ICSA will stop searching, and the so-far best solution is examined as the optimal result of the DG placement problem with the multiobjective function. The steps of ICSA for the multiobjective DG placement are demonstrated in Figure 1.

### 4. Numerical Results

In this section, the efficiency of the problem and the proposed method are evaluated on a practical distribution system [44]. It has the 11.4 kV level, 11 feeders, and 13 open switches. The total active and reactive loads are 28.35 MW and 20.70 MVAR, respectively. The diagram of the system is presented in Figure 2. The data of the system is referenced from [44]. In addition, the impact of uncertainty of DG on the obtained results is also analyzed in this section. The details of them are as follows:

#### 4.1. Finding the Optimal Location and Size of DGs

For optimizing location and capacity of DGs in the system, the rated current of all branches is assumed equal to 200 A. At the initial state, the power loss and the minimum voltage amplitude are 531.9924 kW and 0.9285 pu, respectively. The BF and BB indexes are 1.4418 and 0.1475, respectively. Note that, with the rated current of 200 A for all branches, the maximum LCI of the system is 1.1748. It means that there exists a branch that is overloaded about 17.48%. The number of DGs connected to the system is limited to three.

For applying ICSA to find DGs’ location and size, the population size $N_p$ is selected to be 30. Because the number of DGs is limited to three, the dimension of the problem $N_v$ is set to 6. The maximum number of the adaptive function evaluations $AFE_{\text{max}}$ is set to 18000 corresponding to about 300 iterations. The space between the current variable and the new variables $\tau_1$ and $\tau_2$ is, respectively, set to 4 and 2. The number of consecutive iterations that the so-far best adaptive function value is not improved $it_{lo}$ is set to 3. Finally, the maximum number of consecutive iterations that the best solution function is not improved $it_{\text{NIP}}$ is set to 50. If the scale coefficient of the objective function is much smaller than the penalty coefficient for violation of constraints, the objective function value of the obtained solution will be trivial because the value of constraints takes a high portion in the adaptive function value which consists of the objective function and the constraints. Otherwise, if the scale

![Figure 1: The flowchart of ICSA for the DGs placement problem.](image-url)
have been decreased from 1.4418 and 0.1475 to 0.8329 and 0.1177, respectively. The minimum voltage has been raised from 0.9285 to 0.9488 and the maximum load carrying index has been reduced from 1.1748 to 1.1454 after installation of DGs. For the cases of single-objective optimization, the target index is significantly improved, but the other indicators, which are affected by location and capacity of DGs, are worse than those of the case of no DG installation. For example, for the single-objective function of power loss reduction, the total loss has been decreased from 531.9924 kW to 359.1712 kW corresponding to 32.49% reduction. The BF and BB indexes as well as the minimum voltage amplitude have also been improved after installing 9.2402 MW of DGs in the system. In more details, the BF and BB indexes have been reduced from 1.4418 and 0.1475 to 1.1321 and 0.1028, respectively. The minimum voltage has been raised from 0.9285 pu to 0.9556 pu. However, the LCI_{max} index has not been improved after placing of DGs for power loss reduction. The target index is improved but the other indexes are worse than before for the case with the single-objective functions of BF, BB, CDG, and DV indexes. This situation has been completely overcome when solving the DG placement problem satisfying multiobjective function. The demonstration for this point can be viewed in Table 3. The balance among membership functions shown by their normalized vector value is better than that of the single-objective functions with smaller standard deviation (STD) compared with other cases.

Figures 3 shows the current profiles of the system. From the figure, in the case of multigoal function, the load carrying index of branches reaches better balance than other cases. Except for the case of single-goal function of BB index, the maximum carrying factor index obtained by the multigoal function has been lower than that of other single-objective goals. The voltage profiles of all cases are shown in Figure 4. From the figure, the voltage profile has been enhanced significantly after installation of DGs by the multigoal function. In addition, except for the case of single-goal function of DV index, the voltage profile obtained in the case of multiobjective function is the best one with the better improvement compared to other cases. The capacity of feeders of all cases is presented in Figure 5. Similar to the current and voltage profiles, the capacity of feeders obtained in the case of multiobjective function can reach better balance than those of other cases except for the case of single-objective function of BF index.

The performance of ICSA for the multigoal DG placement as well as the single-objective functions is shown in Table 4. The convergence curve in each trial as well as the maximum, minimum, and average convergence curves in 30 trials for the multiobjective DG placement is presented in Figure 6. The convergence characters of ICSA for five single-
objective functions are shown in Appendix, in which, the PL reduction is presented in Figure 7, the BB reduction is shown Figure 8, the BB reduction is presented in Figure 9; meanwhile, Figure 10 and Figure 11 show the objective of maximum of DGs capacity and deviation voltage reduction, respectively. From Table 4 and Figure 6, for the multi-objective function, ICSA usually converges about 115 iterations. The maximum number of convergence iterations is 201 iterations that has happened for only one trial though the maximum number of iterations is chosen to be 300. This trend also occurs for the single-goal optimization cases. The short number of convergence iterations is due to the stopping condition of the algorithm. When the adaptive function between consecutive iterations is not improved, the number of iterations is not increased and recored as final iteration. Furthermore, the average curve for 30 runs converges very close to the minimum characteristic curve as well as the average adaptive function value is quite close to its minimum value with a small standard deviation. This demonstrates the stability of ICSA for optimizing location and size of DGs. The average run times of each trial for the multiobjective function are about 87.7417 seconds that is suitable for the complex practical system as the 84-node system. The achievement promises positive results for using ICSA to solve DG problem to satisfy other goals.

The multiobjective function in the paper is first proposed. Thus, in order to compare the effectiveness of ICSA with the previous studies, the single-goal optimization problem for power loss reduction is used. This single-goal optimization problem is also the case to find the smallest value of the power loss reduction membership function that ICSA has reached before solving the multiobjective problem. The results compared with some recent studies are demonstrated in Table 5. The results presented that the installation locations of the three DGs obtained are completely similar to those of the stochastic fractal search algorithm (SFSA) [45] and the exact loss formula-based analytical approach (ELF) [46] while the optimum power value of the DGs has a slight difference. Specifically, by using ICSA, the capacity of the DGs installed at the 80th, 72th, and 7th are 3.5835, 2.5263, and 3.304 MW, respectively, while this value is {3.5847(80), 2.883(72)3,139 (7)} and {3.5996(80), 2.5166(72)3,139 (7)} for SFSA and ELF. The power loss obtained by ICSA is 359.1712 kW while this value is 359.7300 and 359.2000 kW for SFSA and ELF, respectively, which are slightly higher than that of ICSA. The value of power loss obtained by using ICSA compared to the above methods shows the efficiency and reliability of the proposed ICSA approach.

4.2. Impact of Uncertainty of DG on the Obtained Results. In order to evaluate the impact of the DG uncertainty, the 2nd DG is assumed to be a wind turbine and the power of the remaining DGs is kept constant. In this case, based on the optimal DG size that has been gained by ICSA and the wind speed at the installation area, the DG capacity at different wind speed values and their effect on the technical indicators of the distribution system are evaluated as follows:

The uncertainty of wind speed can be modeled based on the Weibull PDF as follows [47–52]:

$$f(v) = \frac{h}{c} \left(\frac{v}{c}\right)^{h-1} e^{-\left(\frac{v}{c}\right)^h},$$ (23)

where $h$ is the shape coefficient that is chosen to be 2 [49]. $c$ is the scale coefficient that is chosen based on the mean wind speed at the installation area by $c = 1.128\nu_{ave}$ [49, 53].

The probability of the state $i$th with the wind speed in the range of $v_{i,1}$ and $v_{i,2}$ is determined as follows [49, 53]:

$$\text{Prob}(v_i) = \int_{v_{i,1}}^{v_{i,2}} f(v)dv.$$ (24)

The generated power of the DG based on wind turbine corresponding to the state $i$th is calculated as follows [49]:

### Table 2: Comparisons of the multiobjective function with five single-objective functions.

| Objective function (OF) | Location and size of DGs | PL (kW) | BF | BB | CDG | DV | $\sum$ DG (MW) | $V_{min}$ (pu) | LCI<sub>max</sub> |
|--------------------------|--------------------------|--------|----|----|-----|----|----------------|--------------|--------------|
| No DGs                   | —                        | 531.9924 | 1.4418 | 0.1475 | 1 | 0.0715 | 0 | 0.9285 | 1.1748 |
| Min ($f_1$)              | 3.5835 (80), 2.5263 (72), 3.1304 (7) | 359.1712 | 1.1321 | 0.1028 | 0.6741 | 0.0444 | 9.2402 | 0.9356 | 1.1748 |
| Min ($f_2$)              | 5.2679 (62), 4.8515 (46), 5.2384(74) | 673.5146 | 0.3663 | 0.1796 | 0.4583 | 0.0715 | 15.3577 | 0.9285 | 1.1748 |
| Min ($f_3$)              | 2.2288 (41), 2.7389 (9), 2.4391 (25) | 439.7255 | 0.8396 | 0.0949 | 0.7387 | 0.0521 | 7.4069 | 0.9479 | 1.1688 |
| Min ($f_4$)              | 9.4350 (32), 9.4303 (2), 9.4731 (78) | 654.703 | 3.741 | 0.1874 | 0.0004 | 0.0567 | 28.3384 | 0.9433 | 1.6567 |
| Min ($f_5$)              | 2.8674 (83), 3.7468 (8), 1.7221 (72) | 378.0717 | 1.0110 | 0.0580 | 0.7060 | 0.0399 | 8.3362 | 0.9601 | 1.1748 |
| Multiobj.               | 5.5357 (80), 5.0542 (6), 5.4158 (32) | 416.7929 | 0.8329 | 0.1177 | 0.4354 | 0.0512 | 16.0058 | 0.9488 | 1.1454 |

### Table 3: The balance among the membership functions.

| OF         | $F_1$ | $F_2$ | $F_3$ | $F_4$ | $F_5$ | STD |
|------------|-------|-------|-------|-------|-------|-----|
| Min ($f_1$) | 1     | 0.2880 | 0.8498 | 0.3261 | 0.8576 | 0.3319 |
| Min ($f_2$) | 0     | 1 | 0 | 0.5419 | 0 | 0.4522 |
| Min ($f_3$) | 0.5339 | 0.5599 | 1 | 0.2614 | 0.6139 | 0.2649 |
| Min ($f_4$) | 0     | 0 | 0 | 1 | 0.4684 | 0.4434 |
| Min ($f_5$) | 0.8906 | 0.3169 | 0.7928 | 0.2942 | 1 | 0.3309 |
| Multiobj.  | 0.6666 | 0.5662 | 0.5665 | 0.5648 | 0.64241 | 0.0493 |
where $v_{mi}$ is the mean wind speed of the state $i$th. $v_{ci}$ and $v_{co}$ are the cut-in and cut-off speeds of the DG and $v_r$ is its rated speed.

It is assumed that the wind speed at the DG installation area is divided into states including 0–4, 4–8, 8–12, 12–16, 16–20, and 20–25 m/s and the mean wind speed at this area is 6.07 m/s. The parameters of the DG based on the wind turbine consisting of $v_{ci}$, $v_r$, and $v_{co}$ are, respectively, 4, 14, and 25 m/s. The probabilities of the speed states based on the Weibull PDF model according to (23) and (24) are given in Figure 12.

The obtained parameters of the wind speed state and the output power of DG corresponding to the velocity states are given in Table 6, wherein the 1st column indicates the name of the wind speed states. The 2nd and 3rd columns indicate the speed limits and the mean speed of the states. The 4th column shows the probability values of each state that are determined by (24). The 5th column presents the output power of the DG for each state, which is obtained by (25).
Table 4: The performance of ICSA for the DGs placement in the 84-node system.

| OF       | The adaptive function | Convergence iteration | Run times (sec) |
|----------|-----------------------|-----------------------|-----------------|
|          | Max.                  | Min.                  | Average         | Standard deviation | Max.       | Average | Standard deviation |                  |
| Min \(f_1\) | 3713189               | 3591887               | 3632150         | 32755              | 123        | 86      | 15.8739         | 39.676           |
| Min \(f_2\) | 6656.3658             | 3859.2445             | 4849.6476       | 1232               | 202        | 107     | 39.5122         | 80.9646          |
| Min \(f_3\) | 1144.2555             | 1119.5946             | 1138.7884       | 5.5796             | 108        | 69      | 11.0451         | 49.4073          |
| Min \(f_4\) | 832.5342              | 667.4547              | 735.4465        | 39.6525            | 211        | 96      | 37.4920         | 92.1776          |
| Min \(f_5\) | 574.0958              | 574.0958              | 574.0958        | 0                  | 95         | 19      | 9.3371          | 46.8115          |
| Multiobj. | 5489.4966             | 4498.5513             | 4700.1722       | 205.6555           | 201        | 115     | 41.8766         | 87.7417          |

Figure 5: The capacity of feeders of the 84-node system for the cases of DGs placements.

Figure 6: Convergence curves for the multiobjective function.
The results show that, when the wind speed is lower than the rated speed of the DG, the generated power of the DG decreases. Specifically, when the wind speed is below the cut-off value, the output power of DG is 0 and when the wind speed is in the range of 4–8 m/s in the state no. 2, the DG’s power only reaches 1.01084 MW corresponding to about 20% of its rated power or in the state no. 3, the DG’s power reaches 3.03252 MW corresponding to about 60% of the rated power when the wind speed reaches 8–12 m/s. Thus, it is necessary to validate the impact of the output power of this DG at the states no. 1, no. 2, and no. 3 on the technical factors of the distribution system. It is noted that the states no. 4, no. 5, and no. 6 are identical to the optimal solution in the case of multigoal function DG placement and the state no. 7 is similar to the state no. 1.

The calculation results for the states no. 1 to no. 4 are given in Table 7. For the states no. 1 and no. 2, the component target functions including PL, BF, BB, CDG, and DV are all higher than those of the state no. 4 wherein their value reaches the worst value for the state no. 1. For the state no. 3 when DG output power reaches 60% of the rated capacity, the power loss and load balancing index among the branches are lower than that of the state no. 4, but the feeder balance index and the DG capacity index are higher than those of the state no. 4. Therefore, it can be seen that the technical indicators
have been negatively affected when the wind speed changes.

The balance among the member target functions given in Figure 13 shows that state no. 3 is the best one compared to the states no. 1 and no. 2 when the balance characteristic among member functions is almost similar to the state no. 4. The comparison of capacity among feeders, load carrying coefficient among branches, and node voltage for the wind speed states are shown in Figures 8(b)–8(d), respectively. When the DG output power is much lower than its rated value, it can cause high voltage drop and power loss in the system. Therefore, the process of designing, installing, and operating DG based on renewable energy such as wind turbine should consider the uncertainty of DG to determine suitable operation measures.

Figure 9: Convergence curves for the single-goal function of BB reduction.

Figure 10: Convergence curves for the single-goal function of maximum of DGs capacity.
Figure 11: Convergence curves for the single-goal function of deviation voltage reduction.

Table 5: Comparisons of the single-goal function of power loss reduction with other methods.

| Method      | Location and size of DGs | Δp (kW) | Loss reduction | BF  | BB  | Σ DG (MW) | V_{min} (pu) | LCI_{max} |
|-------------|--------------------------|---------|----------------|-----|-----|-----------|--------------|-----------|
| No DGs      | —                        | 531.9924| —              | 1.1448 | 0.1475 | 0         | 0.9285    | 1.1748    |
| ICSA        | 3.5835 (80), 2.5263 (72), 3.1304 (7) | 359.1712 | 32.49%         | 1.1321 | 0.1028 | 9.2402    | 0.9556    | 1.1748    |
| SFSA [45]   | 3.5847 (80), 2.8350 (72), 3.1389 (7) | 359.7300 | 32.38%         | —    | —    | 9.5586    | 0.9557    | —         |
| ELF [46]    | 3.5996 (80), 2.8166 (72), 3.1045 (7) | 359.2000 | 32.48%         | —    | —    | 9.2207    | 0.9558    | —         |

Table 6: Wind speed probabilities and the corresponding power of the DG.

| State      | v_i (m/s) | v_{ref} | Pro(v_i) | P_i (MW) |
|------------|-----------|---------|----------|----------|
| State no. 1| 0–4       | 4       | 0.2891   | 0        |
| State no. 2| 4–8       | 6       | 0.4555   | 1.01084  |
| State no. 3| 8–12      | 10      | 0.2090   | 3.03252  |
| State no. 4| 12–16     | 14      | 0.0421   | 5.0542   |
| State no. 5| 16–20     | 18      | 0.0041   | 5.0542   |
| State no. 6| 20–25     | 22.5    | 0.0002   | 5.0542   |
| State no. 7| >25       |         | 0        | 0        |
Table 7: Impacts of the DG output power on technical indicators of the distribution system.

| State       | Location and size of DGs | PL (kW) | BF | BB | CDG | DV | ∑ DG (MW) | Vmin (pu) | LCImax |
|-------------|--------------------------|---------|----|----|-----|----|-----------|-----------|--------|
| State no. 1 | 5.5357 (80), 0 (6), 5.4158 (32) | 473.7643 | 1.0347 | 0.1305 | 0.6137 | 0.0715 | 10.9516 | 0.9285 | 1.1454 |
| State no. 2 | 5.5357 (80), 1.01084 (6), 5.4158 (32) | 428.0447 | 0.8689 | 0.1197 | 0.5780 | 0.0625 | 11.9624 | 0.9375 | 1.1454 |
| State no. 3 | 5.5357 (80), 3.03252 (6), 5.4158 (32) | 389.8885 | 0.8458 | 0.1126 | 0.5067 | 0.0512 | 13.9841 | 0.9488 | 1.1454 |
| State no. 4 (multiobj.) | 5.5357 (80), 5.0542 (6), 5.4158 (32) | 416.7929 | 0.8329 | 0.1177 | 0.4354 | 0.0512 | 16.0058 | 0.9488 | 1.1454 |

5. Conclusion

Placement of DGs in the DS not only reduces power loss but also affects many other technical factors of the DS. This paper presents the method of optimizing the location and capacity of DGs in the DS to satisfy the technical criteria including power loss reduction, increase of balance among feeders as well as balance among branches, and voltage deviation reduction. In addition, to attract investment for installing of DGs on the DS, the maximizing DG’s capacity that can be pumped to the DS is also considered as a membership objective function. In terms of the solving method, ICSA is first proposed to apply for the problem of optimizing position and size of DGs. The simulated results on the practical complex distribution system show that the indicators that need to be optimized are improved by using the multiobjective problem and the satisfaction among component objectives is better than the results gained by using the single-objective problems. In addition, the uncertainty of DG is also evaluated to show the negative impacts of the uncertainty of DG on the indicators of the system. Furthermore, the comparisons of ICSA with other studies in the literature have also shown that the effectiveness of ICSA is remarkable and promising to be one of the most reliable methods for DG installation problem.

Data Availability

Data of the 84-node distribution system were taken from [44].

Conflicts of Interest

The authors declare that they have no conflicts of interest regarding the publication of this paper.
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