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Improved stochastic fractal search algorithm with chaos for optimal determination of location, size, and quantity of distributed generators in distribution systems

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Abstract

In the power system operation, the reduction of the power loss in distribution systems has significance in the reduction of operating cost. In this paper, a novel chaotic stochastic fractal search (CSFS) method is implemented for determining the optimal siting, sizing, and number of distributed generation (DG) units in distribution systems. The objective of the optimal DG placement problem is to minimize the power loss in distribution systems subject to the constraints such as power balance, bus voltage limits, DG capacity limits, current limits, and DG penetration limit. The proposed CSFS method improves the performance of the original SFS by integrating chaotic maps into it. On the other hand, ten chaotic maps are utilized to replace the random scheme of the original SFS to enhance its performance in terms of accuracy of solution and convergence speed, corresponding to ten chaotic variants of the SFS where variant being chosen is the best chaotic variant regarding search performance. For solving the problem, the CSFS is implemented to simultaneously find the optimal siting and sizing of DG units and the optimal number of DG units will be obtained via comparing optimal results from different numbers of DG in the problem. The proposed method is tested on the IEEE 33-bus, 69-bus, and 118-bus radial distribution systems. The obtained results from the CSFS are verified by comparing to those from the original SFS and other methods in the literature. The result comparisons indicate that the proposed CSFS method can obtain higher quality solutions than the original SFS version and many other methods in the literature for the considered cases of the test systems. Moreover, the incorporation of chaos theory allows performing the search process at higher speeds. Therefore, the proposed CSFS method can be a very promising method for solving the problem of optimal placement of DG units in distribution systems.

Keywords Distribution systems · Optimal placement of distributed generators · Power loss reduction · Chaotic stochastic fractal search algorithm

1 Introduction

The power demand in the world is always increasing together with the development of economy and society. However, the expansion of the power supply and transmission system is limited; thus, the existing system cannot keep pace with the growth. The reason for the limitation is that the hydropower has been very thoroughly exploited and the fossil energy sources are being exhausted and

increasingly environmental pollution while the nuclear energy is a controversial issue. Therefore, the solution is to find alternative energy sources to replace traditional energy sources. As a result, renewable energy sources have emerged as one of the priority options for dealing with the exhaustion of fossil energy sources. These renewable energy sources are often used as small power sources with the size ranging from a few kW to some MW and directly connected to the distribution systems or to the customer side of the meter. The International Council on Large Electricity Systems (CIGRE) considers these small power sources as distributed generation (DG) units [1]. DG units may be internal combustion engines, combustion turbines, micro-turbines, wind turbines, photovoltaic, biomass, fuel cells, geothermal, small hydro, etc. [2]. Thanks to the

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benefits of DG units on electrical systems, the installation of them in distribution systems has become more popular. Some major advantages of DG units integrated into distribution systems are power loss decrease, voltage profile enhancement, power quality improvement, and environmental pollution reduction [3]. However, the inappropriate placement of DG units may cause an increase of system losses and relevant costs [3]. Based on the mentioned benefits, many problems in the DG placement and operation have been also considered. The common optimal DG placement (ODGP) problem refers to the examination of the optimal location and size of DG units to be installed into the existing distribution systems depending on the power system operation and DG operation constraints as well as investment constraints. In general, the ODGP problem is a complex mixed-integer nonlinear optimization problem [3]. In addition to the optimal site and size of DG units, the optimal number of DG units needs to be also investigated since a large number of DG units in a distribution system might negatively result in the system such as overvoltage, line overloading, and losses increment. Therefore, the problem of optimal number, location, and sizing of DG units has attracted the attention of many researchers.

Several conventional methods have been proposed for solving the ODGP problem such as gradient-based method (GM) [4], linear programming (LP) [5], nonlinear programming (NLP) [6], sequential quadratic programming (SQP) [7], and dynamic programming (DP) [8]. In general, these conventional methods are especially effective for dealing with small-scale optimization problems in terms of saving time. However, the key challenge is that they cause time-wasting or no-found solution because of large search space of large-scale and complex optimization problems. In addition, many researchers have also implemented analytical approaches for solving the ODGP problem. In [9], an analytical approach was proposed to optimally integrate a single DG unit generating only active power into both radial and looped systems to reduce power losses. However, the optimum DG size is ignored in this research. Hung et al. [10] used analytical expressions for choosing the optimal placement, size, and power factor of four types of DG units to minimize the losses in distribution systems. However, there is only one DG unit investigated in this study. In [11], the authors presented three analytical methods for placing different renewable DG types such as biomass, wind, and photovoltaic for minimizing of power and energy losses considering the uncertainties of demand and DG generation. An improved analytical method was proposed in [12] for allocating four types of multiple DG units for loss reduction in distribution systems. The analytical methods are initially applied only to solve the problem with single DG, and they are then developed to

deal with the optimal placement of multiple DG units. However, there are only a predetermined number of DG units considered in this research and there is no standard available for determining the optimal number of DG units. Moreover, the main drawback of the analytical approach is that the more the number of DG units installed, the more the complication of the problem suffered.

Recently, meta-heuristic search methods have become popular for solving the ODGP problem due to their advantages of simple implementation and ability to find the near-optimal solution for complex optimization problems. Various meta-heuristic methods have been applied for solving the problem such as augmented Lagrangian genetic algorithm (ALGA) [13], particle swarm optimization (PSO) [14], constriction factor particle swarm optimization (CFPSO) [15], krill herd algorithm (KHA) [16], tabu search (TS) [17], ant colony optimization (ACO) [18], cuckoo search (CS) [19], harmony search algorithm (HSA) [20], bacterial foraging optimization algorithm (BFOA) [21], gravitational search algorithm (GSA) [22], grey wolf optimizer (GWO) [23], ant lion optimization algorithm (ALOA) [24], improved honey bee mating optimization algorithm (IHBMO) [25], improved multi-objective harmony search (IMOHS) [26], Taguchi method and the technique for order of preference by similarity to ideal solution (TM-TOPSIS) [27], and symbiotic organism search (SOS) [28]. In [13], the authors utilized a methodology based on ALGA for the optimal determination of location and size of renewable DG units so as to reduce the total active power loss in radial distribution systems. In [14], a PSO-based method was proposed to determine the optimal size and site of DG units and the reactive power compensation to minimize power losses in unbalanced distribution systems. In [15], a CFPSO-based method was suggested for DG planning considering the loss minimization and viability analysis in electricity market scenarios. A novel krill herd algorithm (KHA) method was presented in [16] to find out the optimal location and size of multiple DG units in distribution systems with the aims of minimizing the active power loss and energy loss. Nara et al. [17] employed a TS method for seeking the optimal location and size of DG units to minimize the network loss. In [18], the authors used an ACO algorithm for solving the DG sizing and placement in order to minimize the investment cost of DG units and operating cost of the network. A CS-based approach for optimal DG allocation to improve voltage profile and reduce the power loss of distribution systems was reported in [19]. In [20], a group of researchers applied a HSA-based approach for selecting the siting and sizing of multiple DG units with the purposes of the active power loss minimization and voltage profile improvement in distribution systems. The study in [21] presented a newly fast combined method of loss sensitivity

factor and BFOA to identify the optimum site and size of multiple DG units to minimize the total power loss and operational cost and improve the voltage stability in RDSs considering various types of loads. GSA was adopted by [22] for finding out the optimal siting and sizing of DG units in distribution systems to minimize active power loss and improve voltage profile. Sultana et al. [23] presented a multi-objective approach to optimally identify the position and size of multiple DG units in distribution systems using GWO with the objective functions of reactive power losses and voltage deviation. Ali et al. [24] employed ALOA for optimal siting and sizing of solar and wind-based DG units to reduce the total power losses and improve the voltage profiles and voltage stability index of distribution systems. A Pareto-based multi-objective IHBMO approach was developed by Niknam et al. [25] for optimizing the site and size of renewable energy sources in distribution systems with the objectives of generation costs, emission, and power losses minimization and voltage profile improvement. In [26], IMOHS was proposed for finding the optimal location and size of DG units based on the Pareto-optimal front. In [27], the authors introduced a new approach for solving the multi-objective ODGP problem based on a combination of the Taguchi method and the technique for the order of preference by similarity to ideal solution (TM-TOPSIS). In [28], the researchers proposed a SOS algorithm for determination of the optimal size and location of DG units in radial distribution systems for the reduction of system power loss.

In addition to the single methods, hybrid methods have been also widely implemented for solving the ODGP problem such as a hybrid genetic algorithm (GA) and PSO [29], a hybrid GA and intelligent water drop (IWD) [30], a hybrid PSO and shuffled frog leaping (SFL) [31], and a hybrid analytical method (AM) and PSO [32] to improve the performance of the single methods. For further analysis, Moradi and Abedini [29] proposed a hybrid GA-PSO algorithm to evaluate the DG site and size for the 33-bus and 69-bus RDSs in simultaneously minimizing the active power loss and voltage deviation together and improving the voltage stability. Moreover, a newly integrated approach based on GA and IWD was proposed for optimally installing DG units into microgrids for the power loss and voltage deviation minimization and the voltage stability improvement of 33-bus and 69-bus RDSs as in [30]. Gitizadeh et al. [31] implemented a hybrid PSO-SFL algorithm for the multi-objective distribution system expansion planning problem considering DG. In [32], a combination of AM-PSO was presented to optimally place different types of multiple DG units in distribution systems in order to minimize power losses and improve voltage profile while considering different loading levels. Normally, the solutions obtained by the hybrid methods are

better than those obtained by the single ones but their main disadvantages are time-consuming and difficulty in implementing.

From the literature survey, it can be observed that the ODGP problem is approached in different ways according to research objectives. Various techniques are used to solve single- or multi-objective problems. From the mentioned studies, the factors are mainly considered in the ODGP problem including the location and size of DG units and used technology. Among the factors mentioned above, the two most vital ones in the DG planning are the optimal location and size of DG units. However, most of the studies in this problem have not considered the optimal number of DG units for minimizing power losses. On the other hand, only the location, size, and used technology have been concerned, whereas the optimal number of DG units which also plays an important role in reducing power losses has been taken no notice. Therefore, the present work is to develop a novel and powerful computation technique to find the optimal number of DG units for the active power loss minimization in distribution systems. Recently, Salimi [33] has developed a promising meta-heuristic algorithm, called stochastic fractal search (SFS) algorithm. This method based on the growing process of nature is powerful and straightforward to apply to various optimization problems due to the use of fewer control parameters than other meta-heuristic search methods. The SFS method was successfully applied to solve some optimization problems in various fields such as optimal relay coordination [34], optimal design of planar steel frames [35], and monitoring of an aerospace structure [36]. However, the original SFS still suffers from local minima stagnation and slow speed of convergence when dealing with complex and large-scale problems. Therefore, a newly modified SFS was proposed by Rahman [37] to avoid being trapped in local minima as well as speed up its convergence to the optimal solution.

The modification is the integration of the SFS algorithm and chaos theory in order to increase both exploration and exploitation capabilities of the SFS algorithm named as chaotic stochastic fractal search (CSFS) algorithm. On the other hand, the formation of the proposed CSFS method involves replacing some random sequences with chaotic maps. The reason for this replacement is that chaos possesses better statistical and dynamical properties, and thus the searching process for a near-optimal solution can be performed at higher speeds.

In terms of improving search performance through CSFS, the number of iterations is reduced and the best solution is found with suitable computational time once the proper chaotic maps are employed. The CSFS algorithm is proposed for finding the optimal location and capacity of DG units in the test systems. The main contributions of this paper can be briefly described as follows:

1. Improved SFS algorithm with chaos is proposed to improve the search performance of original SFS algorithm when tackling the ODGP problem. Specifically, ten chaotic maps, namely Chebyshev, Circle, Gauss/Mouse, Iterative, Logistic, Piecewise, Sine, Singer, Sinusoidal, and Tent, are employed to be integrated into SFS. As a result, ten different variants of the CSFS are proposed for search performance evaluation and the best one is chosen.
2. A new specific process for evaluating the optimal number of DG units with the help of the proposed CSFS is introduced. On the other hand, the solution provided by this process is the inclusion of the optimal number, location, and size of DG units compared to only optimal location and size of DG units from the previous studies.
3. Two different mechanisms of optimizing the decision variables of the problem are considered. The first mechanism, as suggested in this study, is the simultaneous optimization of decision variables. Meanwhile, the second mechanism which serves as a comparable mechanism is the separate treatment of these variables.
4. In addition, the CSFS-based version has not ever been applied for solving the ODGP problem in previous studies. Therefore, this is a great implementation for finding the optimal location and size of DG units in distribution systems to reduce total system loss by employing the CSFS for the first time.

For the implementation of the proposed method, the two location and size variables are simultaneously found by CSFS to ensure the obtained near-optimal solutions for the problem. In order to prove the superiority of this mechanism in evaluating the optimal DG siting and sizing, a mechanism based on the clear separation between siting and sizing is also applied for result comparison. As a further analysis of this separation mechanism, the loss sensitivity factor is first used to find a priority list of the potential locations where DG units can be installed and then meta-heuristic algorithm is applied to find the optimal size of DG units with a predetermined number of DG units. For obtaining the optimal number of DG units, the proposed method is implemented for the problem with different numbers of DG units and the case with a feasible solution corresponding to the lowest power loss among the investigated cases is considered as the best solution with the optimal number of DG units. The proposed method is tested on the IEEE 33-bus, 69-bus and 118-bus systems, and the results obtained by the proposed method are verified by comparing to those from the original SFS as well as other well-known methods in the literature.

The remaining of the paper is organized as follows. Section 2 provides the mathematical formulation of the ODGP problem. Section 3 describes the original SFS algorithm in detail. The introduction of chaotic maps and the method of integrating them into SFS are provided in Sect. 4. The implementation of CSFS algorithm to the ODGP problem is expressed in Sect. 5. The numerical results and discussion follow Sect. 6, and finally, the conclusion is given.

2 Problem formulation

In this research, the objective of the ODGP problem is to minimize the total real power losses in distribution systems satisfying all constraints of the system and DG units. Mathematically, the ODGP problem is formulated as follows:

The objective function for minimization of the total active power loss in a distribution system is expressed by:

$$F = \min(P_{loss}), \tag{1}$$

where P_{loss} is the total active power loss of the system expressed as:

$$P_{loss} = \frac{r_{ij}}{V_i V_j} \left(\sum_{i=1}^{N} \sum_{j=1}^{N} \cos(\delta_i - \delta_j)(P_i P_j + Q_i Q_j) + \sin(\delta_i - \delta_j)(Q_i P_j - P_i Q_j) \right), \tag{2}$$

where V_i and δ_i are the voltage magnitude and angle at bus i, respectively; V_j and δ_j are the voltage magnitude and angle at bus j, respectively; r_{ij} is the resistance of the distribution line connecting buses i and j; P_i and P_j are the net active power at buses i and j, respectively; Q_i and Q_j are the net reactive power at buses i and j, respectively; and N is the number of buses in the system.

The optimal location and sizing of DG need to satisfy all of the operational constraints such as the power balance constraints, limitation of bus voltages, limitation of DG capacity, limitation of branch currents, and limitation of DG penetration as follows.

- *Power balance constraints* The power flow equations are defined as equality constraints in the ODGP problem. The mathematical representation is given by:

$$P_{G,i} - P_{L,i} = |V_i| \sum_{j=1}^{N} |Y_{ij}||V_j| \cos(\delta_i - \delta_j - \theta_{ij}), \tag{3}$$

$$Q_{G,i} - Q_{L,i} = |V_i| \sum_{j=1}^{N} |Y_{ij}||V_j| \sin(\delta_i - \delta_j - \theta_{ij}), \tag{4}$$

where $P_{G,i}$ is the active power output of the generator at bus i; $P_{L,i}$ is the active power of load at bus i; $Q_{G,i}$ is the reactive power output of the generator at bus i; $Q_{L,i}$ is the reactive power of load at bus i; and Y_{ij} and θ_{ij} are the modulus and angle of ith element in the admittance matrix of the system related to bus i and bus j, respectively.

- *Bus voltage limits* The voltage magnitude at each bus must be maintained in their lower and upper limits:

$$V_{i,\min} \leq V_i \leq V_{i,\max}; \quad i = 1, \ldots, N \tag{5}$$

where $V_{i,\min}$ and $V_{i,\max}$ are the minimum and maximum voltage levels at bus i, respectively.

- *Branch current limits* The current flow in branches should not exceed their limits.

$$\left| I_{br,k} \right| \leq \left| I_{br,k}^{\max} \right|; \quad k = 1, \ldots, N_{br} \tag{6}$$

where $I_{br,k}$ represents the branch current of kth branch of the system; $I_{br,k}^{\max}$ is the maximum permissible current flows through kth branch; and N_{br} is the number of branches of the system.

- *DG capacity limits* The used DG units must have the allowable size in their following range:

$$P_{DG,i}^{\min} \leq P_{DG,i} \leq P_{DG,i}^{\max}; \quad i = 2, \ldots, N \tag{7}$$

where $P_{DG,i}^{\min}$ and $P_{DG,i}^{\max}$ are, respectively, the minimum and maximum power output limits of the DG at bus i and $P_{DG,i}$ is the power output of the DG at bus i.

- *DG penetration limits* This constraint is to limit the total amount of DG power output to be installed in the distribution system expressed by:

$$\sum_{i=1}^{ND} P_{DG,i} \leq \sum_{j=1}^{N} P_{D,j} + \sum_{k=1}^{N_{br}} P_{loss,k} \tag{8}$$

where $P_{DG,i}$ is the power output of the ith DG; $P_{D,j}$ is the demand of active power at bus j; $P_{loss,k}$ is the active power loss in kth branch, and ND is the number of DG units.

- *DG candidate location constraint* Allocating some DG units in the same bus is impractical, hence a constraint for site of used DG units is given as:

$$Lo_{DG,i} \neq Lo_{DG,j}; \quad i, j \in N \tag{9}$$

where Lo_{DG} refers to candidate locations for DG units.

3 Stochastic fractal search algorithm

The stochastic fractal search (SFS) algorithm developed by Salimi [33] is a relatively new meta-heuristic algorithm which is inspired by the growing process of nature. This algorithm uses a mathematical idea named the fractal to simulate the growth. SFS consists of two main processes, namely the diffusing process and the updating process. The operation of these two processes is described in the next subsections.

3.1 Diffusion process

In the diffusion process, each individual diffuses around its current position to ensure the capability to exploit the search space. The purposes of the diffusion are to increase the probability of finding the global minimum and avoid being trapped in local minima. The new individuals are created by using the Gaussian distribution. The application of the Gaussian walks in this process can be described by the two mathematical equations as follows:

$$\begin{cases} X_{inew,1}^d = Gaussian(\mu_{X_{best}}, \sigma) + (\varepsilon \cdot X_{best} - \varepsilon' \cdot X_i) & \text{if } rand < W \\ X_{inew,2}^d = Gaussian(\mu_X, \sigma) & \text{otherwise} \end{cases} \tag{10}$$

in which, W is an optional parameter that helps in selecting Gaussian walks to solve the problem; ε and ε' are the random numbers limited to [0, 1]; X_{inew}^d is the new modified position of point X_i at the dth diffusion; X_{best} and X_i are the position of the best point and the ith point in the group, respectively; $\mu_{X_{best}}$, μ_X and σ are Gaussian parameters where $\mu_{X_{best}}$ is equal to X_{best}, μ_X is equal to X_i, and the standard deviation σ is calculated by:

$$\sigma = \left| \frac{\log(g)}{g} \cdot (X_i - X_{best}) \right|, \tag{11}$$

where g is the iteration number. The function $\frac{\log(g)}{g}$ is utilized to adjust the size of the Gaussian jumps over the course of iterations. This means that when g increases, the value of the function $\frac{\log(g)}{g}$ decreases, resulting in a corresponding reduction in the size of the Gaussian jumps. Based on this particular mechanism, the particles are oriented to a more localized search and a closer approach to the optimal solution.

3.2 Updating process

There are two statistical procedures in the updating process. The impact of the first statistical procedure is on each individual vector index while the second is on all points.

3.2.1 The first statistical procedure

In the first statistical procedure, all points are ranked based on the following equation:

$$Pa_i = \frac{rank(X_i)}{NP}, \tag{12}$$

where $rank(X_i)$ is referred as the rank of point X_i in the group and NP is the number of points in the group.

For each point X_i in the group, if the condition $Pa_i < \varepsilon$ is satisfied where ε is a random number between 0 and 1, the jth component of X_i is updated according to Eq. (13). Otherwise, no update process occurs.

$$X_i'(j) = X_r(j) - \varepsilon \cdot (X_t(j) - X_i(j)), \tag{13}$$

where X_i' is the new modified position of X_i; X_r and X_t are the randomly selected points in the group; and ε is a random number between 0 and 1.

3.2.2 The second statistical procedure

Firstly, all points obtained by the first procedure are ranked based on Eq. (12). Then, the condition $Pa_i < \varepsilon$ is checked. If the condition is satisfied, the current position of X_i' is modified according to Eq. (14). Otherwise, there will be no change in the current position.

$$\begin{cases} X_i'' = X_i' - \varepsilon'' \cdot \left(X_t' - X_{best}\right) & \text{if } \varepsilon' \leq 0.5 \\ X_i'' = X_i' + \varepsilon'' \cdot \left(X_t' - X_r'\right) & \text{otherwise} \end{cases}, \tag{14}$$

where X_i'' is the new modified position of X_i'; X_r' and X_t' are the randomly selected points obtained from the first procedure; and ε' and ε'' are random numbers between 0 and 1. If X_i'' gives a better fitness value than X_i', X_i' will be replaced by X_i''. Otherwise, the value of X_i' is kept.

3.3 Chaotic maps for SFS

In this section, at first, the chaotic maps utilized are described in detail in mathematical form. The visualization of these maps is also shown. Then, the method of integrating them into SFS is introduced.

3.4 Chaotic maps

The chaotic maps chosen are presented as follows:

- Chebyshev map [38]:

$$x_{k+1} = \cos\left(k\cos^{-1}(x_k)\right) \tag{15}$$

- Circle map [39]:

$$x_{k+1} = \mathrm{mod}\left(x_k + b - \left(\frac{a}{2\pi}\right)\sin(2\pi x_k), 1\right), \\ a = 0.5 \text{ and } b = 0.2 \tag{16}$$

- Gauss/mouse map [40]:

$$x_{k+1} = \begin{cases} 1 & x_k = 0 \\ \dfrac{1}{\mathrm{mod}(x_k, 1)} & \text{otherwise} \end{cases} \tag{17}$$

- Iterative map [41]:

$$x_{k+1} = \sin\left(\frac{a\pi}{x_k}\right), \quad a = 0.7 \tag{18}$$

- Logistic map [41]:

$$x_{k+1} = ax_k(1 - x_k), \quad a = 4 \tag{19}$$

- Piecewise map [42]:

$$x_{k+1} = \begin{cases} \dfrac{x_k}{P} & 0 \leq x_k < P \\ \dfrac{x_k - P}{0.5 - P} & P \leq x_k < 0.5 \\ \dfrac{1 - P - x_k}{0.5 - P} & 0.5 \leq x_k < 1 - P \\ \dfrac{1 - x_k}{P} & 1 - P \leq x_k < 1 \end{cases}, \quad P = 0.4 \tag{20}$$

- Sine map [43]:

$$x_{k+1} = \frac{a}{4}\sin(\pi x_k), \quad a = 4 \tag{21}$$

- Singer map [44]:

$$x_{k+1} = \mu\left(7.86x_k - 23.31x_k^2 + 28.75x_k^3 - 13.302875x_k^4\right), \\ \mu = 1.07 \tag{22}$$

- Sinusoidal map [45]:

$$x_{k+1} = ax_k^2\sin(\pi x_k), \quad a = 2.3 \tag{23}$$

- Tent map [46]:

$$x_{k+1} = \begin{cases} \dfrac{x_k}{0.7} & x_k < 0.7 \\ \dfrac{10}{3}(1 - x_k) & x_k \geq 0.7 \end{cases} \tag{24}$$

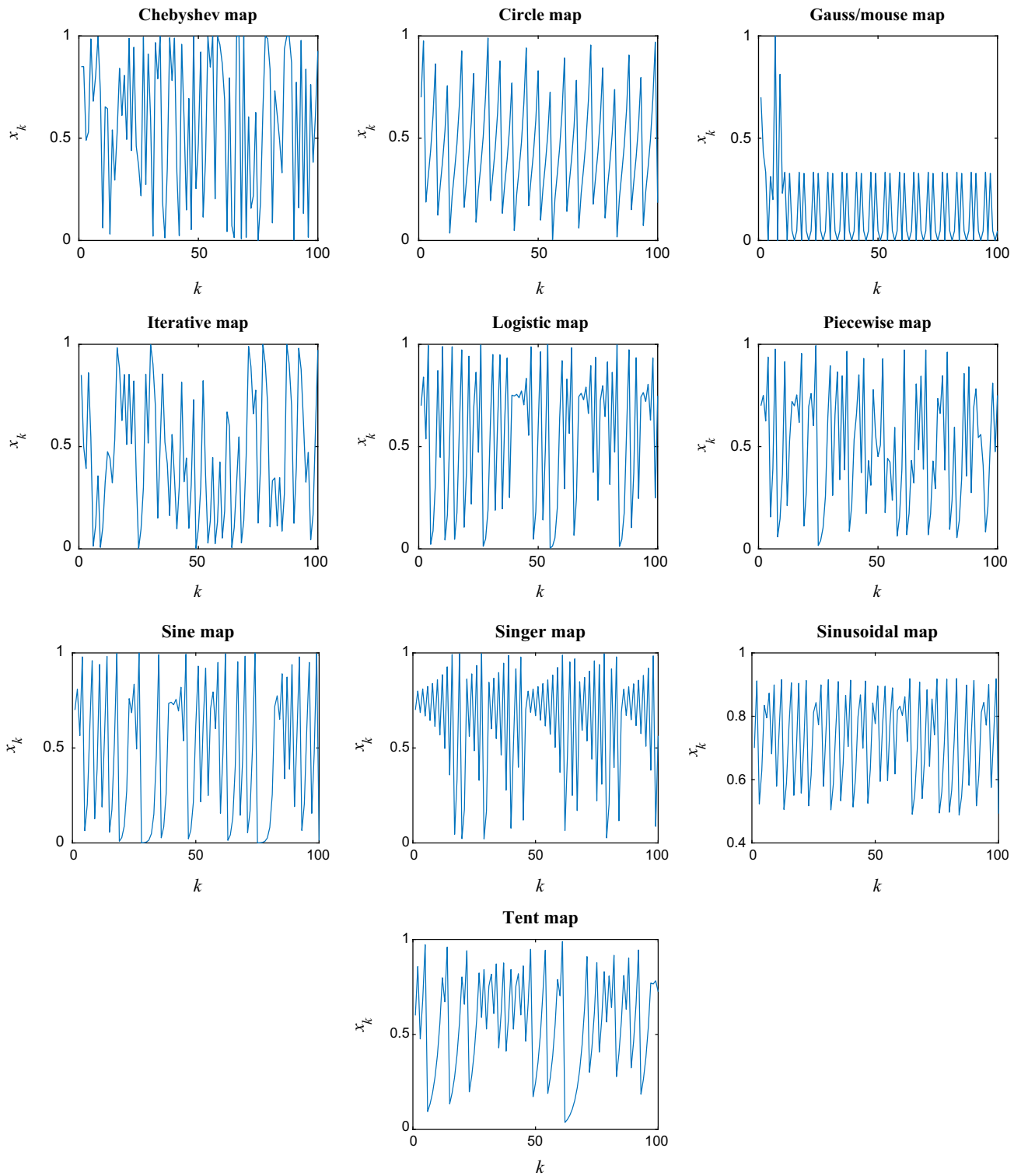These chaotic maps are illustrated in Fig. 1.

Fig. 1 Visualization of chaotic maps

Note that the starting point of all the chaotic maps is 0.7 and the chaotic values are normalized to a range between 0 and 1.

3.5 Method of integrating chaotic maps into SFS

The calculation of Gaussian walk has a significant impact on the performance of SFS. The fundamental of this meta-heuristic technique is usually to use uniform distribution to generate random particles. Nevertheless, when facing complex nonlinear and multimodal problems, this choice exposes its main drawback. To overcome this challenge, the uniform distribution parameter is replaced, ε with several chaotic maps, to improve the convergence rate and fitness accuracy. Two main equations of the original SFS algorithm modified with the introduction of the chaotic variable named cv are shown as follows:

Parameter ε' of the first Gaussian equation is replaced with the chaotic variable cv, and part of Eq. (10) is modified by:

$$X_{inew,1}^d = Gaussian(\mu_{X_{best}}, \sigma) + (\varepsilon \cdot X_{best} - cv \cdot X_i) \quad (25)$$

In the original SFS, ε' is a random number between 0 and 1 but in the CSFS it is a chaotic number between 0 and 1. Parameter ε of the equation in the first updating process is modified using the selected chaotic maps, and the equation is modified by:

$$X_i'(j) = X_r(j) - cv \cdot (X_t(j) - X_i(j)) \quad (26)$$

In the original version of SFS, ε and ε' are uniformly distributed random numbers between 0 and 1, and in the CSFS, they are chaotic numbers between 0 and 1.

Based on these new chaotic equations, the particles are oriented toward the position of the current best point in a chaotic way. In addition, ten different chaotic maps are employed to investigate the effects of them on improving the performance of SFS in terms of local minima avoidance and convergence rate.

4 Implementation of CSFS to ODGP problem

This section describes the application of the CSFS for solving the ODGP problem to minimize the total active power loss in distribution systems. The overall procedure of CSFS for the ODGP problem is presented in the following steps:

Step 1: Select the parameters of CSFS including number of points (NP), maximum diffusion number (MDN), and the maximum number of iterations (max_iter).

Step 2: Tuning of parameters by using chaotic maps [ε' in Eq. (10) and ε in Eq. (13)].

Step 3: The initial population is represented as $\mathbf{X} = [X_1, X_2, \ldots, X_{NP}]^T$, where each point in the population represented by $X_i = \left[Lo_{DG,1}^i, Lo_{DG,2}^i, \ldots, Lo_{DG,ND}^i, P_{DG,1}^i, P_{DG,2}^i, \ldots, P_{DG,ND}^i\right]$, $i = 1, 2, \ldots, NP$, in which $Lo_{DG,1}^i, Lo_{DG,2}^i, \ldots, Lo_{DG,ND}^i$ are the buses for installation of DG units; $P_{DG,1}^i, P_{DG,2}^i, \ldots, P_{DG,ND}^i$ are sizes of DG units (MW) to be installed at the corresponding buses. Similar to other population-based methods, the points in the SFS are also randomly generated between their upper and lower bounds. Then, the first ND elements of points which presented the installed locations of DG units are rounded to the nearest integers.

$$X_i = LB + rand(0, 1) \cdot (UB - LB) \quad (27)$$

$$X_i(1 : ND) = round(X_i(1 : ND)) \quad (28)$$

where UB and LB are the upper and lower bound vectors, respectively.

Step 4: The initialized population is evaluated by using a fitness function defined by:

$$FF = F + \lambda_v \sum_{i=1}^{N} \left(V_i - V_i^{\lim} \right)^2 \\ + \lambda_i \sum_{k=1}^{Nbr} \left(I_{br,k} - I_{br,k}^{\lim} \right)^2, \tag{29}$$

where λ_v and λ_i are penalty factors. The penalty factors used in this study are set to 100,000. The constraint violations belonging to the dependent variables are expressed as the following equations:

$$V_i^{\lim} = \begin{cases} V_{i,max} & \text{if } V_i > V_{i,max} \\ V_{i,min} & \text{if } V_i < V_{i,min} \\ V_i & \text{if } V_{i,min} < V_i < V_{i,max} \end{cases}, \tag{30}$$

$$I_{br,k}^{\lim} = \begin{cases} I_{br,k} & \text{if } I_{br,k} \leq I_{br,k}^{max} \\ I_{br,k}^{max} & \text{if } I_{br,k} > I_{br,k}^{max} \end{cases}, \tag{31}$$

where $V_i^{\lim}$ and $I_{br,k}^{\lim}$ are represented for the limits of V_i and $I_{br,k}$, respectively.

The fitness value of each point is determined by performing the power flow to find the total active power loss of the distribution system. In this paper, a Matpower toolbox [47] based on Newton–Raphson algorithm is applied for solving the power flow problem. The bus voltage and branch current limits are also considered in this step. The evaluation of points is done via choosing the best fitness value having minimum value among the fitness values of all points, and the corresponding point is chosen as the best point X_{best}. Set the iteration counter $k = 1$.

Step 5: Generation of new solution via diffusion process. The new point X_{inew}^d generated via the Gaussian walk is calculated based on Eq. (25) and part of Eq. (10). Limit violations are checked, and a repairing action is needed as any violations found. Evaluate the fitness function for the new point. Note that the best created point from this process is the only point that is retained referred as X_{inew} and the rest of the points are discarded. The point corresponding to the best fitness value is updated as the best point X_{best} obtained by this process.

Step 6: The first updating process.
Firstly, all points are ranked based on Eq. (12). Next, the new point X_i' is created based on Eq. (26). For the new point, limit violations are checked and a repairing action is needed as any violations found. Then, the fitness value is calculated using (29). Each new point X_i' is accepted if it gives a better fitness value than the original X_{inew}. Finally, the minimum fitness value is found and the corresponding point is set to the best point X_{best}.

Step 7: The second updating process.
Once all points obtained by the first process are ranked based on Eq. (12), the position of the points not rated well will be modified based on Eq. (14). For the newly obtained point X_i'', limit violations are checked and a repairing action is needed as any violations found. The value of the fitness function is calculated using (29). Each new point X_i'' is accepted if it gives a better fitness value than the original X_i'.

Step 8: If $k < max\_iter$, $k = k + 1$ and return Step 5. Otherwise, stop.

The optimal number of DG units can be found by investigating the effect of the different numbers of DG units on the active power loss. To illustrate the effectiveness of the proposed algorithm, two different ways of finding the optimal location and size of DG units are investigated. The first one is that both the optimal location and size of DG units are simultaneously found using the proposed CSFS method. The second one is that the loss sensitivity factor [48] is used to find a priority list of the potential locations where DG units can be installed and the top ND buses from the priority list are selected for installation of DG units and then the optimal size of DG units is found using the PSO. The sizing of the DG units varies in discrete steps at the specified location during the optimization process. The number of DG units which results in the smallest total active power loss among the considered cases is considered as the optimal number of DG units. The process of determining the optimal number of DG units by employing the proposed CSFS can be described as in Fig. 2.

5 Numerical results and discussion

The proposed CSFS method is tested on the IEEE 33-bus, 69-bus, and 118-bus radial distribution systems [49–51]. For the test systems, the control parameters of the proposed CSFS method such as the number of points, the maximum diffusion number, and the maximum number of iterations
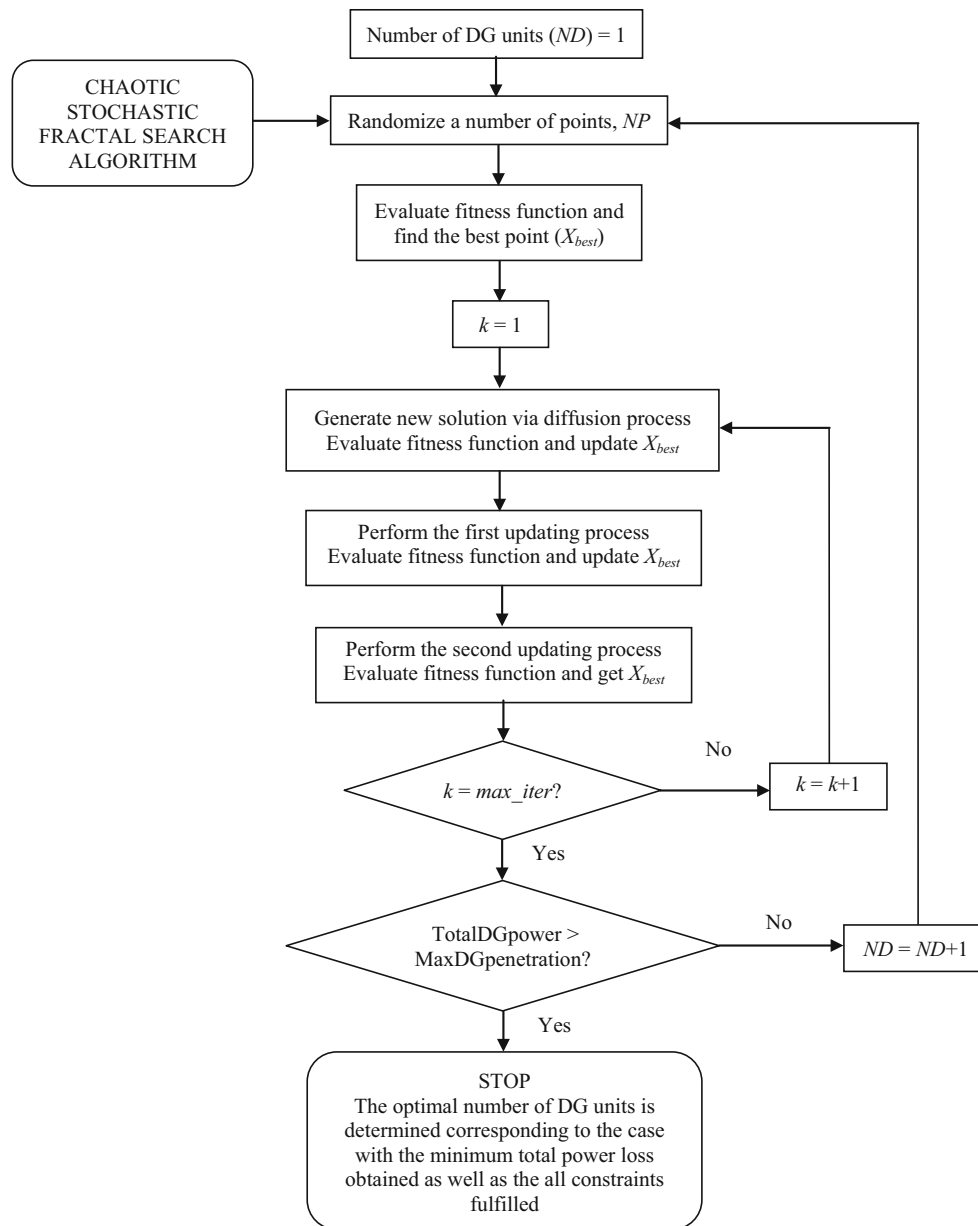
Fig. 2 Flowchart for the process of finding the optimal number of DG units performed by CSFS

are selected by experiments. Likewise, the control parameters of the PSO including the number of particles (NP), the cognitive acceleration coefficient (c_1), the social acceleration coefficient (c_2), the maximum value of the inertia weight (w_{max}), and the minimum value of the inertia weight (w_{min}) are also chosen via experiments. By tuning, these values are selected for each test system as presented in Table 1. The proposed method is run ten independent trials for each system to obtain the best solution. In this research, both the fixed number of DG units and the optimal number of DG units for installation in test systems are considered. For the case with the fixed number of DG units, the results obtained by CSFS for the systems are analyzed

and compared to those from other methods in the literature. For the case with the optimal number of DG units, the PSO and original SFS methods are also implemented to solve the problem for a result comparison. The PSO and original SFS methods are also performed ten independent runs for obtaining the best solution.

5.1 The IEEE 33-bus radial distribution system

This test system consists of 33 buses and 32 branches from [49]. The total active and reactive power loads of the system are 3.715 MW and 2.300 MVAr, respectively. The maximum and minimum power outputs of DG units are

Table 1 Control parameters of CSFS, SFS, and PSO methods for three test systems

Control Parameters	33-bus system	69-bus system	118-bus system
CSFS	$NP = 50$, $MDN = 5$, $max\_iter = 100$	$NP = 50$, $MDN = 5$, $max\_iter = 300$	$NP = 50$, $MDN = 5$, $max\_iter = 1000$
SFS	$NP = 50$, $MDN = 5$, $max\_iter = 100$	$NP = 50$, $MDN = 5$, $max\_iter = 300$	$NP = 50$, $MDN = 5$, $max\_iter = 1000$
PSO	$NP = 100$, $c_1 = c_2 = 2$, $w_{max} = 0.9$, $w_{min} = 0.05$, $max\_iter = 100$	$NP = 100$, $c_1 = c_2 = 2$, $w_{max} = 0.9$, $w_{min} = 0.05$, $max\_iter = 300$	$NP = 100$, $c_1 = c_2 = 2$, $w_{max} = 0.9$, $w_{min} = 0.05$, $max\_iter = 1000$

2.786 and 0.2 MW, respectively. The DG penetration limit is set to 3.926 MW. The base voltage of this system is 12.66 kV. The active and reactive power losses in the system calculated from the power flow are 210.99 kW and 143.13 kVAr, respectively.

5.1.1 Fixed number of DG units

For the cases with a fixed number of DG units, the proposed method is implemented for solving the problem with a predetermined number of DG units of 1, 2, and 3. For each DG unit, two decision variables need to be determined in the optimization problem including siting and sizing and these variables will be optimized simultaneously by utilizing the proposed method. Regarding the siting decision variables, a set of candidate buses for the installation of DG units is mentioned as a possible combination in the search space. Specifically, with the considered 33-bus test system, the number of possible combinations is 32, 496, and 4960 corresponding to the test cases of 1, 2, and 3 DG units. The corresponding sizing variables are also included in the same vector of siting variables and randomly initialized within their upper and lower limits. It can be perceived that the more the number of DG units considered, the more the complication of the problem suffered due to many potential combinations of DG sitings. Furthermore, the presence of many local minima in the search space of the problem is also a major challenge for optimization methods. In terms of the solution method chosen, note that CSFS algorithm with Gauss/mouse map named as CSFS3 is considered as a solution method for this case due to the remarked improvement of optimal solution and convergence speed as compared with other variants.

In order to illustrate the effectiveness of the proposed method, the results obtained from the proposed CSFS3 method are compared to those from other well-known methods such as Method 1 [52], Method 2 [52], Method 3 [52], efficient analytical (EA) [52], EA with optimal power flow (EA-OPF) [52], exhaustive OPF (EOPF) [52], AM-PSO [32], exhaustive load flow (ELF) [12], improved analytical (IA) [12], loss sensitivity factor (LSF) [12], backtracking search optimization algorithm (BSOA) [53],

rank evolutionary PSO (REPSO) [54], KHA [16], GA [29], GA-PSO [29], IWD [30], GA-IWD [30], simulated annealing (SA) [55], BFOA [21], invasive weed optimization (IWO) [56], TLBO [57], quasi-oppositional teaching–learning-based optimization (QOTLBO) [57], harmony search algorithm with PSO embedded artificial bee colony (HSA-PABC) [58], and original SFS as in Tables 2, 3 and 4. It can be observed from the table that for the case with one DG unit, the power loss by the proposed method is reduced from 210.99 kW in the base case to 111.02 kW in the case with the optimal allocation of the DG unit. In this case, the total power loss obtained by the proposed CSFS3 is lower than that from Method 1 [52], Method 3 [52], EA [52], AM-PSO [32], ELF [12], IA [12], LSF [12], and BSOA [53] and identical to that from Method 2 [52], EA-OPF [52], EOPF [52], and original SFS methods. The lower power loss value reveals that the CSFS3 successfully outperforms these methods in searching the best optimum solution. Also, the CSFS3 is capable of providing highly competitive solutions to the remaining methods such as Method 2 [52], EA-OPF [52], EOPF [52], and original SFS methods because the obtained loss values are the same. Moreover, the minimum active power loss for the case with two DG units obtained by the CSFS3 is found to be 87.17 kW, which is less than a total power loss of 91.63 kW from Method 2 [52], 107.95 kW from Method 3 [52], 87.172 kW from EA [52], 87.28 kW from AM-PSO [32], 116.71 kW from REPSO [54], 87.63 kW from ELF [12], 91.63 kW from IA [12], 100.69 kW from LSF [12], and 89.34 kW from BSOA [53] and identical to 87.17 kW from EA-OPF [52], EOPF [52], and original SFS. For the case with three DG units, the total power loss is reduced to 72.79 kW with the help of CSFS3, which is the lowest one compared to that from the cases with one and two DG units. Likewise, the reduction percentage of power loss is up to 65.50%, which is the highest one among the considered cases. This means that the increase in the number of DG units installed into the system leads to more reduced system loss. So, it is necessary to evaluate the performance of the system with larger DG numbers as well as to suggest the optimum DG number for integrating into the system. In addition, via comparing the best power loss in the case with

Table 2 Result comparison for the IEEE 33-bus system with one DG unit

Method	DG size in MW (location)	Total DG size (MW)	Power loss (kW)	Loss reduction (%)
Method 1 [52]	2.49 (6)	2.49	111.24	47.28
Method 2 [52]	2.6 (6)	2.6	111.02	47.38
Method 3 [52]	1.5 (30)	1.5	125.21	40.66
EA [52]	2.53 (6)	2.53	111.07	47.36
EA-OPF [52]	2.59 (6)	2.59	111.02	47.38
EOPF [52]	2.59 (6)	2.59	111.02	47.38
AM-PSO [32]	2.49 (6)	2.49	111.17	47.31
ELF [12]	2.601 (6)	2.601	111.10	47.34
IA [12]	2.601 (6)	2.601	111.10	47.34
LSF [12]	0.743 (18)	0.743	146.82	30.41
BSOA [53]	1.8575 (8)	1.8575	118.12	44.02
SFS	2.590 (6)	2.590	111.02	47.38
CSFS3	2.590 (6)	2.590	111.02	47.38

Table 3 Result comparison for the IEEE 33-bus system with two DG units

Method	DG size in MW (location)	Total DG size (MW)	Power loss (kW)	Loss reduction (%)
Method 2 [52]	0.72 (6) 1.8 (14)	2.52	91.63	56.57
Method 3 [52]	1.5 (30) 1.0 (25)	2.50	107.95	48.84
EA [52]	0.844 (13) 1.149 (30)	1.993	87.172	58.68
EA-OPF [52]	0.852 (13) 1.158 (30)	2.01	87.17	58.69
EOPF [52]	0.852 (13) 1.158 (30)	2.01	87.17	58.69
AM-PSO [32]	0.83 (13) 1.11 (30)	1.94	87.28	58.64
REPSO [54]	1.4830 (30) 0.3836 (32)	1.8666	116.71	44.68
ELF [12]	1.020 (12) 1.020 (30)	2.040	87.63	58.51
IA [12]	1.800 (6) 0.720 (14)	2.520	91.63	56.61
LSF [12]	0.720 (18) 0.900 (33)	1.620	100.69	52.28
BSOA [53]	0.880 (13) 0.924 (31)	1.804	89.34	57.66
SFS	0.852 (13) 1.158 (30)	2.010	87.17	58.69
CSFS3	0.852 (13) 1.158 (30)	2.010	87.17	58.69

Table 4 Result comparison for the IEEE 33-bus system with three DG units

Method	DG size in MW (location)	Total DG size (MW)	Power loss (kW)	Loss reduction (%)
Method 2 [52]	0.9 (6) 0.9 (14) 0.72 (31)	2.52	81.05	61.59
Method 3 [52]	1.5 (30) 1.0 (25) 0.22 (24)	2.72	107.35	49.12
EA [52]	0.798 (13) 1.099 (24) 1.050 (30)	2.947	72.787	65.50
EA-OPF [52]	0.802 (13) 1.091 (24) 1.054 (30)	2.947	72.79	65.50
EOPF [52]	0.802 (13) 1.091 (24) 1.054 (30)	2.947	72.79	65.50
AM-PSO [32]	0.79 (13) 1.07 (24) 1.01 (30)	2.87	72.89	65.45
REPSO [54]	1.2274 (6) 0.6068 (14) 0.6870 (31)	2.5212	76.91	63.55
GA [29]	1.5 (11) 0.4228 (29) 1.0714 (30)	2.9942	106.3	49.61
GA-PSO [29]	1.2000 (32) 0.8630 (16) 0.9250 (11)	2.9880	103.40	50.99
IWD [30]	0.7294 (18) 0.9118 (14) 1.3365 (30)	2.9777	121.4	42.46
GA-IWD [30]	1.2214 (11) 0.6833 (16) 1.2135 (32)	3.1182	110.51	47.62
SA [55]	1.1124 (6) 0.4874 (18) 0.8679 (30)	2.4677	82.03	61.12
KHA [16]	0.8107 (13) 0.8368 (25) 0.8410 (30)	2.4885	75.412	64.26
BFOA [21]	0.6521 (14) 0.1984 (18) 1.0672 (32)	1.9176	89.90	57.38

Table 4 (continued)

Method	DG size in MW (location)	Total DG size (MW)	Power loss (kW)	Loss reduction (%)
IWO [56]	0.6247 (14) 0.1049 (18) 1.0560 (32)	1.7856	85.86	57.47
ELF [12]	0.9 (13) 0.9 (24) 0.9 (30)	2.7	74.27	64.83
IA [12]	0.9 (6) 0.9 (12) 0.72 (31)	2.52	81.05	61.62
LSF [12]	0.720 (18) 0.810 (33) 0.900 (25)	2.430	85.07	59.68
BSOA [53]	0.632 (13) 0.487 (28) 0.550 (31)	1.669	89.05	57.79
TLBO [57]	0.8246 (10) 1.0311 (24) 0.8862 (31)	2.7419	75.540	64.20
QOTLBO [57]	0.8808 (12) 1.0592 (24) 1.0714 (29)	3.0114	74.101	64.88
HSA-PABC [58]	1.068 (30) 1.073 (24) 0.755 (14)	2.896	72.81	65.49
SFS	0.802 (13) 1.091 (24) 1.054 (30)	2.947	72.79	65.50
CSFS3	0.802 (13) 1.091 (24) 1.054 (30)	2.947	72.79	65.50

three DG units, the proposed CSFS3 has the same power loss value as the other solution methods such as EA [52], EA-OPF [52], EOPF [52], and original SFS, but the

proposed CSFS3 has much lower power loss value than Method 2 [52], Method 3 [52], AM-PSO [32], REPSO [54], GA-PSO [29], IWD [30], GA-IWD [30], SA [55], KHA [16], BFOA [21], IWO [56], ELF [12], IA [12], LSF [12], BSOA [53], TLBO [57], QOTLBO [57], and HSA-PABC [58] methods available in the literature. Based on the result comparisons, it can be seen that the best solutions obtained by the proposed CSFS3 do not dominate {Method 2 [52], EA-OPF [52], EOPF [52]} for one DG unit case, {EA-OPF [52], EOPF [52]} for two DG units case, and {EA [52], EA-OPF [52], EOPF [52]} for three DG units case. For further analysis, Method 2 [52], EA [52], EA-OPF [52], and EOPF [52] methods are referred to as an improved form of analytical methods, but they have some

limitations as follows: The larger the number of DG units, the more complex the problem; possibility of inaccurate solutions in complex problems; and lack of robustness. Consequently, these methods may be difficult to cope with large-scale and complex optimization problems considering the integration of a large number of DG units.

Therefore, it can be concluded that the proposed CSFS3 method has equal or better performance than the recently reported state-of-the-art methods as well as the original SFS method for dealing with the fixed number of DG units study case for the tested 33-bus system. It is noteworthy that the proposed CSFS3 method reveals a better global search capability than all of the well-recognized members of the family of meta-heuristic methods.

The superiority of the SFS algorithm over other well-known algorithms can be explained as follows: The SFS possesses two powerful processes for exploring the problem search space, which includes the diffusion process and the update process. In the first process of the SFS, random walk based on Gaussian distribution is employed to generate fractal shapes so that intensification (exploitation) property is satisfied. The purposes of this process are to increase the probability of finding the global minima and also avoid being trapped in local minima. In addition, the size of Gaussian jumps is adjusted to a downward trend as the number of iterations increases, meaning that the search radius of the points would be narrowed over the course of iterations. Such a decreasing trend assists the SFS to achieve a proper balance between exploration and exploitation. In the latter update process, two statistical procedures are utilized to increase the exploration capability of the problem space, which satisfies the diversification (exploration) property. It is worth noting that the integration of chaos theory into the original SFS aims to improve the performance of SFS in terms of avoiding local minima and boosting convergence rate. On the other hand, chaotic maps promote the original SFS to achieve a better trade-off between exploration and exploitation, especially when dealing with complex optimization problems with a large number of local optimum solutions.

5.1.2 Optimal number of DG units

In this case, the optimal number of DG units is obtained via the investigation on different numbers of DG units for installation in the system. Therefore, the problem will be solved many times with each corresponding to a fixed number of DG units. The effect of the different numbers of DG units on the active power loss is investigated by testing the different numbers of DG units as long as the total amount of DG power outputs does not exceed the total permissible DG penetration and the number of DG units leading to the minimum power loss among the different

numbers of DG units is considered as the optimal number of DG units for the system.

Among the values of the active power loss by the different numbers of DG units, a minimum active power loss of 63.668 kW is obtained corresponding to the number of DG units which is 8. Therefore, the optimal number of DG units for the 33-bus system is 8 yielding the smallest total active power loss.

Table 5 exhibits the optimal result obtained by the applied CSFS1-10 and the original SFS from the optimal number of DG units. It is worth mentioning here that CSFS1 to CSFS10 employ Chebyshev, Circle, Gauss/Mouse, Iterative, Logistic, Piecewise, Sine, Singer, Sinusoidal, and Tent, respectively. As observed from Table 5, the proposed CSFS3 can yield the best results for total loss with the corresponding optimal number of DG units compared to the remaining variants. Clearly, the proposed CSFS3 method outperforms all of the examined CSFS variants when dealing with the problem of determining the optimal number of DG units. Moreover, CSFS3 also shows a significant improvement in terms of solution quality compared to its original version. Intuitively, CSFS3 with the incorporation of chaotic behaviors results in a better trade-off between the exploration and exploitation properties of search points, which is evidenced by a prominent search performance.

Table 6 shows the results in detail on optimal location and size of DG units corresponding to the optimal number of DG units. For further analysis, the optimal number of DG units found by both CSFS3 and SFS is 8 while that found by the PSO method is 12 and the total power loss obtained by the CSFS3 is less than that from both PSO and original SFS methods. With the optimal number of DG units, the active power losses obtained by the proposed CSFS3, original SFS, and PSO methods are, respectively, 63.668, 64.596, and 77.034 kW as shown in Table 7. Thus,

Table 5 Result comparison for the IEEE 33-bus system with the optimal number of DG units by the SFS with different chaotic maps

Method	Power loss (kW)	Total DG power output (MW)
SFS	64.596	3.795
CSFS1	64.873	3.641
CSFS2	64.498	3.735
CSFS3	63.668	3.530
CSFS4	64.361	3.621
CSFS5	64.225	3.698
CSFS6	64.075	3.681
CSFS7	63.923	3.565
CSFS8	64.991	3.739
CSFS9	66.154	3.718
CSFS10	65.080	3.729

Table 6 Results of the optimal number of DG units for the IEEE 33-bus system by PSO, SFS, and CSFS3

PSO (The optimal number of DG units: 12)											
Locations	6	28	29	8	30	9	13	10	27	31	26	14
Sizes (MW)	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.309	0.2	0.2

SFS (The optimal number of DG units: 08)							
Locations	9	20	6	24	25	32	29	16
Sizes (MW)	0.430	0.531	0.567	0.419	0.584	0.455	0.425	0.384

CSFS3 (The optimal number of DG units: 08)							
Locations	25	9	32	15	6	20	30	24
Sizes (MW)	0.405	0.376	0.404	0.466	0.628	0.375	0.390	0.486

Table 7 Result comparison for the IEEE 33-bus system with the optimal number of DG units by PSO, SFS, and CSFS3

Power loss (kW)			Total DG power output (MW)		
PSO	SFS	CSFS3	PSO	SFS	CSFS3
77.034	64.596	63.668	2.509	3.795	3.530

it is clear that CSFS3 achieves the lowest power loss value compared with original SFS and PSO methods thanks to integrating the optimum DG number into the system. This reveals that the CSFS3 is computationally more efficient than the original SFS and PSO in terms of solution quality. Furthermore, these results also indicate that a simultaneous optimum solution for siting and sizing of DG units obtained by the proposed CSFS3 and original SFS is better than a solution obtained by the PSO with the separate treatment of siting and sizing variables. The reason is that the separation of the siting and sizing of DG units in the same optimization process may be trapped in the wrong siting and the sub-optimal sizing.

Figure 3 displays the convergence characteristics of the CSFS1-10 and SFS methods for the 33-bus system with the optimal number of DG units. It can be clearly observed that CSFS3 has the fastest convergence speed among other variants. Moreover, CSFS3 also provides a stable and quick convergence with a global searching capability in finding the optimal location, size, and number of DG units in distribution systems. In order to further analyze the convergence process of the proposed CSFS3 method, the CSFS3 outperforms nearly all other methods due to obtaining the lowest loss objective after just 58 iterations and then converges rapidly to the optimal solution, which is obtained at the 99th iteration. Meanwhile, the searching process of the remaining variants, as well as the original SFS method, may be trapped in local minima because these methods do not show much improvement in their objective function values from the 80th iteration to the last iteration. In addition, it can also be seen that the convergence speed of the original SFS algorithm is very slow, meaning that the SFS undergoes slow exploitation. Clearly, the SFS may fail to obtain an optimal solution in this case.

The voltage profiles of the system after installation of the optimal number of DG units by the CSFS1-10, SFS, and PSO methods are shown in Fig. 4. From the figure, it can be seen that the voltage magnitude at all buses of the system is significantly improved after installing the optimal DG number. It is to be noted from the figure that the voltage magnitudes in a large number of load buses obtained by CSFS3 and SFS are better improved than those obtained by PSO. This shows that the mechanism of optimizing the decision variables simultaneously, i.e., the siting and sizing of DG units, is more effective than those separately in terms of bus voltage profile improvement.

In general, the proposed CSFS3 outperforms the original SFS in terms of quality of solution and convergence mobility when solving the problem of determining the optimal number of DG units in the 33-bus test system. On the other hand, the chaotic behaviors, when embedded into SFS, show the ability not only to avoid local optima (exploration) but also to boost convergence speed (exploitation). In addition, the simultaneous optimization of decision variables is known as an efficient mechanism for handling complex problems with multiple local minima.

5.2 The IEEE 69-bus radial distribution system

The second test system is the 69-bus radial distribution system from [50] with a total load demand of 3.80 MW and 2.69 MVAr. The active and reactive power losses of this test system are 225.001 kW and 102.165 kVAr, respectively. The minimum and maximum power outputs of DG units are 0.2 and 2.852 MW, respectively. The DG penetration limit is 4.027 MW, and the base voltage of this system is 12.66 kV.

Fig. 3 Convergence curves for the IEEE 33-bus system with the optimal number of DG units obtained by applying the CSFS1-10 and SFS methods
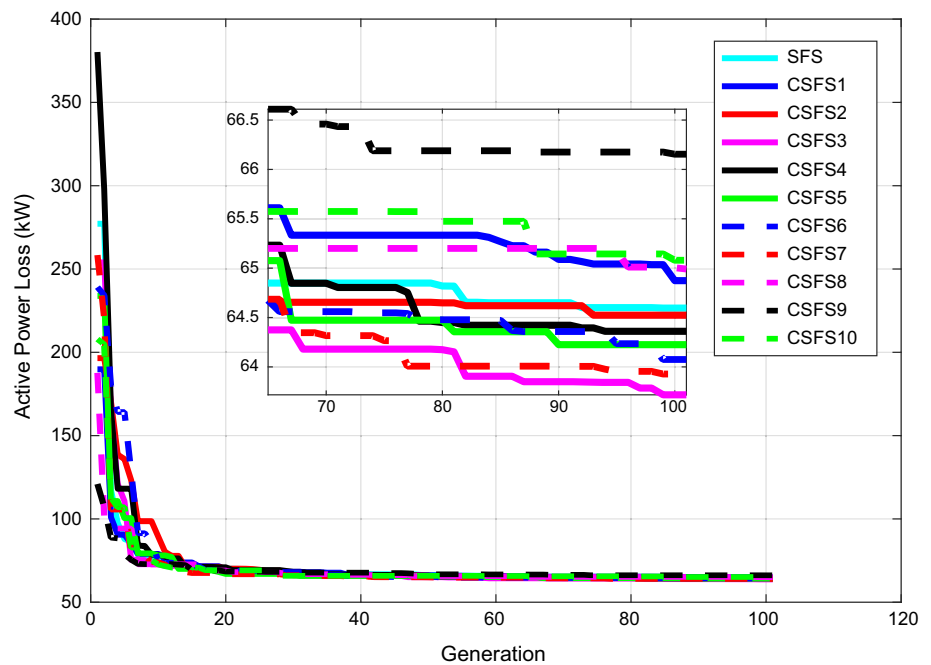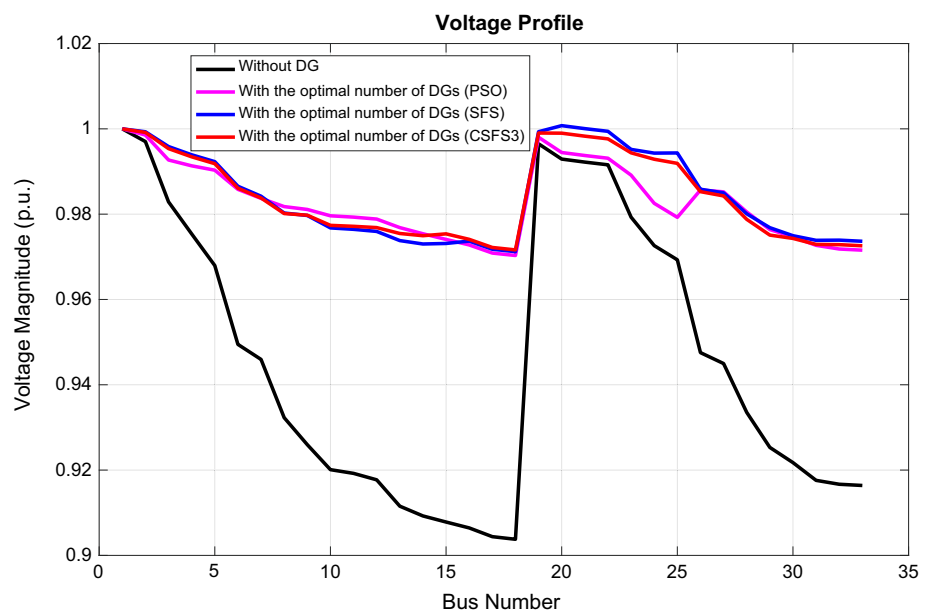

Fig. 4 Voltage profile at buses of the IEEE 33-bus system with the optimal number of DG units

5.2.1 Fixed number of DG units

For the case of the number of DG units fixed in advance, the proposed method is implemented for solving the problem with the number of DG units of 1, 2, and 3. For the siting decision variables, when considered with the 69-bus distribution system, the number of possible combinations is 68, 2278, and 50,116 corresponding to the test cases of one, two, and three DG units. Moreover, the problem becomes very complicated because there are many local minima in the search space. Note that among the different variants of

CSFS, CSFS with Gauss/mouse map known as CSFS3 has the highest performance in terms of quality of solution and convergence speed, so it is selected as a solution approach to tackle the problem in this case. The simulation results of the power loss minimization objective by the proposed CSFS3 method for the three different cases are given in Tables 8, 9, and 10. Obviously, it may be noted that the total power loss in the system for the case with installed DG units is reduced to 83.224, 71.677, and 69.428 kW corresponding to the cases with one, two, and three DG units compared to 225.001 kW for the base case without

Table 8 Result comparison for the IEEE 69-bus system with one DG unit

Method	DG size in MW (location)	Total DG size (MW)	Power loss (kW)	Loss reduction (%)
Method 1 [52]	1.81 (61)	1.81	83.4	62.93
Method 2 [52]	1.9 (61)	1.9	83.25	63.00
Method 3 [52]	1.9 (61)	1.9	83.25	63.00
EA [52]	1.878 (61)	1.878	83.23	63.01
EA-OPF [52]	1.87 (61)	1.87	83.23	63.01
EOPF [52]	1.87 (61)	1.87	83.23	63.01
AM-PSO [32]	1.81 (61)	1.81	83.37	62.95
LSM [20]	1.4363 (65)	1.4363	112.10	50.17
GA [59]	2.085 (61)	2.085	84.776	62.32
AGA [59]	1.872 (61)	1.872	83.225	63.01
SFS	1.873 (61)	1.873	83.22	63.01
CSFS3	1.873 (61)	1.873	83.22	63.01

DG units. The percentage of power loss reduction for the cases with one, two, and three DG units is 63.01, 68.14, and 69.14%, respectively. Among three cases, the power loss reduction in the case with three DG units is the highest one, which demonstrates that the increase in the number of DG units installed into the system results in the better reduction in power loss. This motivates us to propose a specific standard for determining the optimum DG number for the system to achieve the desired objective.

To verify the effectiveness of the proposed CSFS3, the results obtained by CSFS3 are compared to those from other well-established methods such as Method 1 [52], Method 2 [52], Method 3 [52], efficient analytical (EA) [52], EA with optimal power flow (EA-OPF) [52], exhaustive OPF (EOPF) [52], AM-PSO [32], loss sensitivity factor-based method (LSM) [20], GA-PSO [29], IWD [30], GA-IWD [30], GA [59], adaptive genetic algorithm (AGA) [59], SA [55], KHA [16], BFOA [21], IWO [56], TLBO [57], QOTLBO [57], and original SFS as shown in Tables 8, 9, and 10. It is obvious that the proposed CSFS3 can obtain lower total power loss than the previously reported methods, namely Method 1 [52], Method 2 [52], Method 3 [52], AM-PSO [32], LSM [20], GA-PSO [29], IWD [30], GA-IWD [30], GA [59], AGA [59], SA [55], KHA [16], BFOA [21], IWO [56], TLBO [57], and QOTLBO [57] for all the test cases of the system. Also from the table, it is clear that the CSFS3 shows a similar performance to EA [52], EA-OPF [52], and EOPF [52] for the three cases because its best solutions are slightly better or identical to those of EA [52], EA-OPF [52], and EOPF [52]. However, EA [52], EA-OPF [52], and EOPF [52] methods have some major limitations as mentioned above, which is a rather serious challenge when applied to large-scale and complex optimization problems,

especially in the case with the consideration of a large number of DG units. In addition, the minimum loss values yielded by the CSFS3 are identical to those from the original SFS method for all the simulated cases. In summary, the proposed CSFS3 can be a very effective method

Table 9 Result comparison for the IEEE 69-bus system with two DG units

Method	DG size in MW (location)	Total DG size (MW)	Power loss (kW)	Loss reduction (%)
Method 2 [52]	1.7 (61) 0.51 (17)	2.21	71.95	68.02
Method 3 [52]	1.9 (61) 0.02 (64)	1.92	83.23	63.01
EA [52]	1.795 (61) 0.534 (17)	2.329	71.68	68.14
EA-OPF [52]	1.781 (61) 0.531 (17)	2.312	71.68	68.14
EOPF [52]	1.781 (61) 0.531 (17)	2.312	71.68	68.14
AM-PSO [32]	0.52 (17) 1.72 (61)	2.24	71.80	68.09
LSM [20]	1.3791 (65) 0.4461 (27)	1.8252	100.39	55.38
GA [59]	2.176 (61) 0.715 (15)	2.892	78.917	64.92
AGA [59]	1.848 (61) 0.389 (18)	2.217	72.763	67.66
SFS	0.531 (17) 1.781 (61)	2.312	71.68	68.14
CSFS3	0.531 (17) 1.781 (61)	2.312	71.68	68.14

Table 10 Result comparison for the IEEE 69-bus system with three DG units

Method	DG size in MW (location)	Total DG size (MW)	Power loss (kW)	Loss reduction (%)
Method 2 [52]	1.7 (61)	2.55	69.97	68.90
	0.51 (17)			
	0.34 (11)			
Method 3 [52]	1.9 (61)	2.39	72.65	67.71
	0.02 (64)			
	0.47 (21)			
EA [52]	1.795 (61)	2.642	69.62	69.06
	0.38 (18)			
	0.467 (11)			
EA-OPF [52]	1.719 (61)	2.626	69.43	69.14
	0.38 (18)			
	0.527 (11)			
EOPF [52]	1.719 (61)	2.626	69.43	69.14
	0.38 (18)			
	0.527 (11)			
AM-PSO [32]	0.51 (11)	2.56	69.54	69.09
	0.38 (17)			
	1.67 (61)			
LSM [20]	0.1966 (65)	2.2417	73.60	67.28
	0.4168 (27)			
	1.6026 (61)			
GA-PSO [29]	0.8849 (63)	2.9880	81.1	63.95
	1.1926 (61)			
	0.9105 (21)			
IWD [30]	0.8226 (63)	3.0851	83.47	62.90
	1.4513 (61)			
	0.8112 (18)			
GA-IWD [30]	0.8059 (64)	3.11	80.91	64.04
	1.3926 (61)			
	0.9115 (20)			
SA [55]	0.4204 (18)	2.1813	77.1	65.73
	1.3311 (60)			
	0.4298 (65)			
KHA [16]	0.4962 (12)	2.5429	69.563	69.08
	0.3113 (22)			
	1.7354 (61)			
BFOA [21]	0.2954 (27)	2.0881	75.23	66.56
	0.4476 (65)			
	1.3451 (61)			
IWO [56]	0.2381 (27)	1.9981	74.59	66.78
	0.4334 (65)			
	1.3266 (61)			
TLBO [57]	1.1601 (62)	3.1636	82.172	63.47
	0.9901 (61)			
	1.0134 (13)			

Table 10 (continued)

Method	DG size in MW (location)	Total DG size (MW)	Power loss (kW)	Loss reduction (%)
QOTLBO [57]	1.002 (63)	2.9606	80.585	64.18
	1.1470 (61)			
	0.8114 (15)			
GA [59]	2.071 (61)	3.543	77.542	65.54
	0.512 (17)			
	0.960 (9)			
AGA [59]	1.861 (61)	2.443	70.669	68.59
	0.310 (21)			
	0.272 (12)			
SFS	0.527 (11)	2.626	69.43	69.14
	0.380 (18)			
	1.719 (61)			
CSFS3	0.527 (11)	2.626	69.43	69.14
	0.380 (18)			
	1.719 (61)			

for dealing with the fixed number of DG units case for the test 69-bus system.

5.2.2 Optimal number of DG units

For the case of finding the optimal number of DG units, the proposed CSFS3 method is investigated on the effect of the different numbers of DG units on the active power loss. Among the obtained total power losses corresponding to the investigated numbers of DG units, the minimum active power loss of 67.157 kW is obtained when the number of DG units is 7 which is considered as the optimal number of DG units.

Table 11 illustrates the comparison of the obtained results corresponding to the optimal number of DG units from the proposed CSFS3 with the ones of the original SFS and other variants. It can be seen that the CSFS3 achieves a high-quality solution among the rest of the variants. Table 12 shows the results in detail on optimal location and size of DG units corresponding to the optimal number of DG units. Specifically, the number of DG units of 7 considered as the optimal number of DG units is obtained by the proposed CSFS3 method, whereas the optimal numbers of DG units found by the SFS and PSO methods are 5 and 8, respectively. Last but not least, the CSFS3 method can find a better total power loss than the SFS and PSO methods for the system with the optimal number of DG units in which the active power losses obtained by CSFS3, SFS, and PSO methods are, respectively, 67.157, 67.588, and 71.436 kW as referred to Table 13. This reveals that

Table 11 Result comparison for the IEEE 69-bus system with the optimal number of DG units by the SFS with different chaotic maps

Method	Power loss (kW)	Total DG power output (MW)
SFS	67.588	3.526
CSFS1	67.646	3.985
CSFS2	67.284	3.554
CSFS3	67.157	3.920
CSFS4	67.917	3.765
CSFS5	67.428	3.343
CSFS6	67.629	3.916
CSFS7	67.377	3.565
CSFS8	67.709	3.998
CSFS9	67.724	3.988
CSFS10	67.461	4.025

Table 12 Results of the optimal number of DG units for the IEEE 69-bus system by PSO, SFS, and CSFS3

PSO (The optimal number of DG units: 8)

Locations	15	17	57	58	59	60	61	64
Sizes (MW)	0.2	0.324	0.2	0.2	0.2	0.2	0.956	0.2

SFS (The optimal number of DG units: 5)

Locations	11	20	49	61	64
Sizes (MW)	0.531	0.403	0.844	1.357	0.391

CSFS3 (The optimal number of DG units: 7)

Locations	8	11	18	28	50	61	64
Sizes (MW)	0.380	0.380	0.380	0.380	0.717	1.302	0.380

Table 13 Result comparison for the IEEE 69-bus system with the optimal number of DG units by PSO, SFS, and CSFS3

Power loss (kW)			Total DG power (MW)		
PSO	SFS	CSFS3	PSO	SFS	CSFS3
71.436	67.588	67.157	2.480	3.526	3.920

the CSFS3 is computationally more efficient than the original SFS and PSO in terms of solution quality. Moreover, these results also provide a strong evidence that the attained optimal solution is much better when applying the mechanism of simultaneous optimization of DG siting and sizing variables than when applying the separation optimization mechanism of these two variables.

Regarding the convergence characteristic, the proposed CSFS3 method has the fastest convergence speed in the process of detecting the optimal number of DG units among the tested methods as presented in Fig. 5. According to Fig. 5, the CSFS3 outperforms all other methods due to obtaining the lowest loss objective after just 91 iterations and then converges rapidly to the optimal solution, which is obtained at the 175th iteration. Meanwhile, the searching process of the remaining variants, as well as the original SFS method, may be trapped in local minima because these methods do not show much improvement in their objective function values from the 150th iteration to the last iteration. Furthermore, it can be observed that the convergence speed of the original SFS method is very slow, meaning that the SFS undergoes slow exploitation.

Figure 6 shows the voltage profile curves after installation of the optimal number of DG units obtained by the CSFS3, SFS, and PSO methods. A significant improvement of voltage profile at all buses induced by the investigated methods can be observed from the figure. Additionally, simultaneously optimizing the decision variables via the mechanism implemented by CSFS10 and SFS shows a better improvement in the voltage magnitudes in a large number of load buses of the test system compared to separately optimizing these variables through the mechanism performed by PSO.

Generally speaking, the proposed CSFS3 provides better solution quality as well as convergence profile than the original SFS when dealing with the problem of determining the optimal number of DG units in the 69-bus system. On the other hand, the chaotic behaviors, when embedded into SFS, show the ability not only to avoid local optima (exploration) but also to boost convergence speed (exploitation). In addition, the simultaneous optimization of decision variables is known as an efficient mechanism for handling complex problems with multiple local minima.

5.3 The IEEE 118-bus radial distribution system

To illustrate the applicability of the proposed method in large-scale distribution systems, a 118-bus radial distribution system is used to test the proposed method. This is the large-scale distribution system without tie lines, and the base values used are 100 MVA and 11 kV. The total active and reactive power loads of the system are 22.710 MW and 17.041 MVAr, respectively. The initial active and reactive power losses are 1298.091 kW and 978.736 kVAr, respectively. The test system data such as line and load data are taken from [51]. The minimum and maximum power outputs of DG units are 0.2 and 17.032 MW, respectively. The maximum penetration of DG units is limited at 24.008 MW.

Fig. 5 Convergence curves for the IEEE 69-bus system with the optimal number of DG units obtained by applying the CSFS1-10 and SFS methods
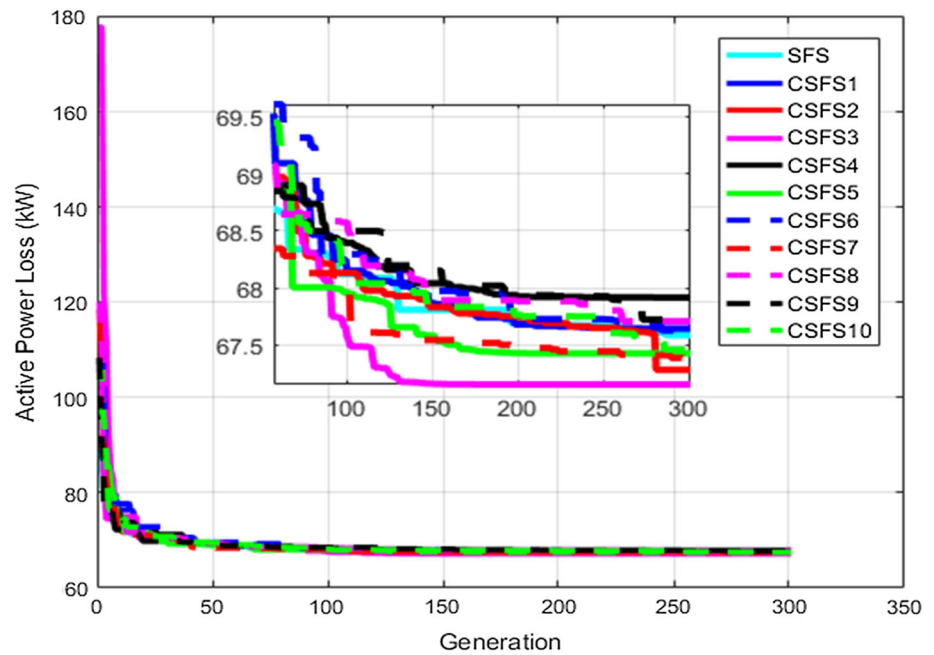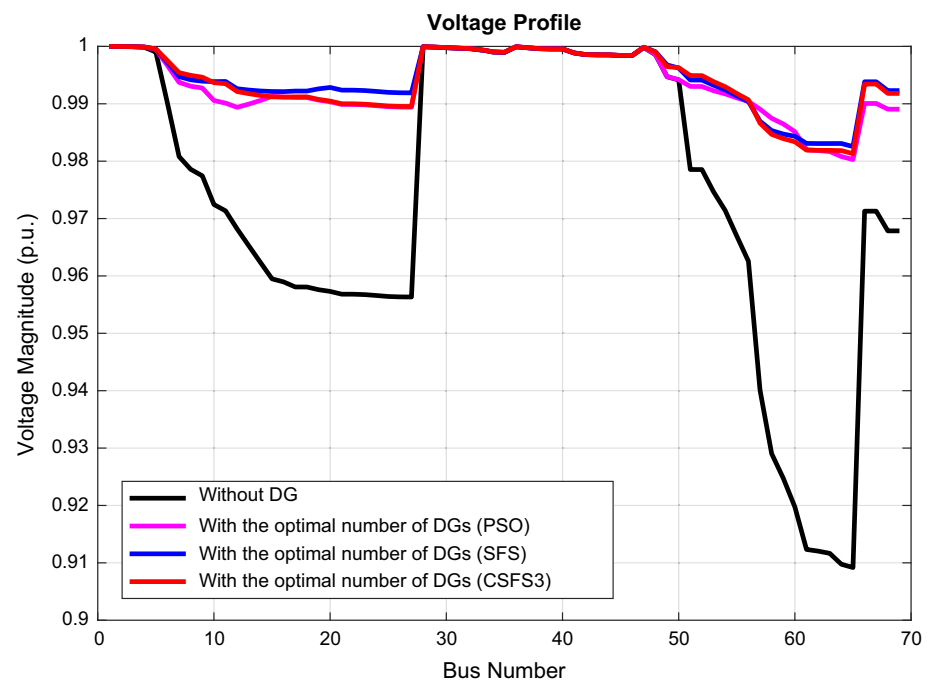

Fig. 6 Voltage profile at buses of the IEEE 69-bus system with the optimal number of DG units

5.3.1 Fixed number of DG units

For the cases with a fixed number of DG units, the proposed method is implemented for solving the problem with a predetermined number of DG units of 1, 3, 5, and 7. In order to effectively investigate this case, the optimal sitings of DG units, together with their sizings, are achieved simultaneously through the consideration of a huge number of possible combinations. When considering with the 118-bus distribution system, the number of possible

combinations is 117, 260,130, 167,549,733, and 49,594,720,968 corresponding to the test cases of one, three, five, and seven DG units. Moreover, the problem becomes very complicated because there are many local minima in the search space. Based on the aim of improving optimal solution and convergence speed, CSFS algorithm with Tent map (CSFS10) can be considered as a solution method. For investigation of the effectiveness of the proposed CSFS10 method, the results obtained by CSFS10 are compared to those from other methods such as loss

sensitivity factors (LSF) [58], HSA-PABC [58], SA [55], TLBO [57], QOTLBO [57], KHA [16], MOTA [27], and original SFS as in Table 14. From this table, it is observed that the performance of the CSFS10 is better compared to LSF [58], HSA-PABC [58], SA [55], TLBO [57], QOTLBO [57], KHA [16], and MOTA [27] in terms of the quality of solutions. For the case with one DG unit, the proposed method obtains a total power loss of 1016.76 kW which is less than that of 1021.09 kW from LSF [58] and 1016.77 kW from HSA-PABC [58] and identical to 1016.76 kW from original SFS. It is clear that the proposed CSFS10 has the lowest minimum loss compared to previously reported methods. For the case with three DG units, the CSFS10 presents a minimum active power loss value equal to 667.29 kW, which is the same yielded by the original SFS, and 237.09 and 10.45 kW lower than LSF [58] and HSA-PABC [58], respectively. Similarly, for the case with five DG units, the total power loss obtained by CSFS10 is 581.58 kW, which is slightly higher than QOTLBO [57], being 0.18 kW higher, but considerably lower than the others, such as 277.23 kW compared to SA [55] and 13.29 kW compared to TLBO [57]. Also, the minimum power losses obtained by the proposed CSFS10 and the original SFS are the same in this case. For the case with seven DG units, the CSFS10 provides the best solution, with a loss value of 524.69 kW, i.e., 375.50, 66.01, 51.49, 50.02, 93.51, and 0.06 kW lower than SA [55], TLBO [57], QOTLBO [57], KHA [16], MOTA [27], and original SFS, respectively. Thus, it is clear that the proposed CSFS10 yields better solutions than almost all previously reported methods in terms of minimizing the active power loss objective except for the QOTLBO [57] method for the case of five DG units. However, when considering with a larger number of DG units, namely seven DG units, the proposed CSFS10 achieves better solution quality than the QOTLBO [57] due to obtaining lower power loss value. This advantage implies that the proposed CSFS10 has more highlighted global search capability than the QOTLBO [57] when applied to the large-scale optimization problem. In general, the proposed CSFS10 can be an effective method for dealing with the fixed number of DG units case for the 118-bus test system.

5.3.2 Optimal number of DG units

For finding the optimal number of DG units, the problem is solved with different numbers of DG units and the optimal number of DG units is determined corresponding to the case with the minimum total power loss obtained. The effect of the different numbers of DG units on the active

Table 14 Result comparison for the IEEE 118-bus system with fixed number of DG units

Method	Number of DG units	Optimal result	
		DG size in MW (location)	Loss (kW)
LSF [58]	1	3.050 (70)	1021.09
	3	2.8 (70), 6.8 (30), 4.7 (64)	904.38
HSA-PABC [58]	1	3.000 (71)	1016.77
	3	2.950 (71), 3.250 (47), 3.200 (108)	677.74
SA [55]	5	2.1318 (75), 0.7501 (116), 1.1329 (56), 4.5353 (36), 4.9452 (103)	858.8133
	7	2.8246 (75), 0.4606 (116), 3.6739 (56), 7.4673 (36), 5.0803 (103), 2.2979 (88), 0.7109 (48)	900.1885
TLBO [57]	5	2.7759 (49), 2.4219 (72), 1.6929 (82), 1.8672 (91), 2.3296 (109)	594.8680
	7	1.7553 (8), 0.5910 (10), 1.5368 (36), 2.6865 (49), 2.5014 (71), 2.4941 (79), 2.6628 (110)	590.6974
QOTLBO [57]	5	3.0135 (49), 2.5435 (72), 1.6655 (82), 1.7662 (91), 3.1376 (109)	581.4016
	7	1.2463 (24), 0.7322 (42), 3.5392 (47), 2.6792 (74), 1.2483 (78), 1.0865 (94), 3.2432 (108)	576.1823
KHA [16]	7	1.7242 (48), 1.3356 (53), 1.8623 (74), 1.8653 (80), 1.6631 (96), 1.9473 (109), 1.1848 (112)	574.7097
MOTA [27]	7	1.380 (72), 3.600 (110), 1.920 (42), 2.880 (78), 2.280 (70), 4.380 (48), 1.920 (96)	618.2
SFS	1	2.979 (71)	1016.76
	3	2.883 (50), 3.120 (109), 2.979 (71)	667.29
	5	3.120 (109), 2.519 (79), 2.497 (50), 2.858 (71), 6.473 (29)	581.58
	7	2.700 (50), 2.271 (40), 2.271 (20), 2.271 (80), 2.350 (73), 2.271 (91), 3.120 (109)	524.75
CSFS10	1	2.979 (71)	1016.76
	3	2.883 (50), 2.979 (71), 3.119 (109)	667.29
	5	2.519 (79), 2.497 (50), 6.473 (29), 3.120 (109), 2.858 (71)	581.58
	7	2.700 (50), 3.120 (109), 2.271 (91), 2.271 (40), 2.281 (74), 2.271 (80), 2.271 (20)	524.69

power loss is investigated. Among the values of the active power loss, a minimum active power loss of 499.004 kW is obtained corresponding to the number of DG units which is 10, resulting in the global optimum. Therefore, the optimal number of DG units for the 118-bus system is 10 yielding a total active power loss of 499.004 kW.

Table 15 demonstrates the best results with the corresponding optimal number of DG units from the proposed CSFS10, original SFS, and CSFS1-9 methods. It can be easily realized that the CSFS10 yields the highest quality solution among others due to the gain of the minimum power loss value. The detailed results on optimal siting and sizing of DG units corresponding to the optimal number of DG units are illustrated in Table 16. It can be seen that

both CSFS10 and SFS methods find the same optimal number of DG units of 10, whereas that found by PSO is 34, which is much higher than the quantity proposed by both CSFS10 and SFS. Compared with the active power loss found by the original SFS after installation of the optimal number of DG units, the one found by the proposed CSFS10 is slightly reduced. However, when compared with the performance of PSO, the CSFS10 apparently outperforms the PSO in terms of power loss minimization. With the optimal number of DG units, the active power losses obtained by CSFS10, SFS, and PSO methods are 499.004, 499.005, and 527.573 kW, respectively, as referred to Table 17. The convergence curves of the CSFS1-10 and SFS methods for the case with the optimal number of DG units are illustrated in Fig. 7. As observed, CSFS10 has the fastest convergence speed among different variants as well as original SFS. Moreover, it can also be observed from the figure that the CSFS10 illustrates a smooth convergence to the optimal solution without any sudden oscillation affecting the convergence process. This confirms the convergence reliability of the proposed CSFS10 method when dealing with a large-scale distribution system. Besides, it is worth noting that the original SFS suffers from slow convergence speed when applied in this case due to lacking of fast exploitation. In fact, the original SFS takes up to 981 iterations to reach the best solution.

Another noteworthy point is that although some variants including CSFS6 and CSFS8 can approximately achieve the optimal solution, in this case, their convergence rates are still rather slow. Specifically, the proposed CSFS10

Table 15 Result comparison for the IEEE 118-bus system with the optimal number of DG units by the SFS with different chaotic maps

Method	Power loss (kW)	Total DG power output (MW)
SFS	499.005	22.821
CSFS1	499.404	23.088
CSFS2	500.802	21.385
CSFS3	503.638	22.211
CSFS4	500.802	21.385
CSFS5	500.465	21.185
CSFS6	499.075	22.895
CSFS7	500.713	23.446
CSFS8	499.007	22.820
CSFS9	500.548	21.269
CSFS10	499.004	22.819

Table 16 Results of the optimal number of DG units for the IEEE 118-bus system by PSO, SFS, and CSFS10

	DG1	DG2	DG3	DG4	DG5	DG6	DG7	DG8	DG9	DG10	DG11	DG12
PSO (The optimal number of DG units: 34)												
Locations	70	104	68	106	108	69	67	89	110	42	47	105
Sizes (MW)	0.2	0.2	0.2	0.953	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2

	DG13	DG14	DG15	DG16	DG17	DG18	DG19	DG20	DG21	DG22	DG23	DG24
Locations	33	34	107	72	32	35	109	73	49	50	90	91
Sizes (MW)	0.2	0.2	0.2	0.2	0.2	1.676	0.2	0.2	0.2	0.2	0.2	0.245

	DG25	DG26	DG27	DG28	DG29	DG30	DG31	DG32	DG33	DG34
Locations	111	48	71	74	80	53	81	51	96	54
Sizes (MW)	1.432	0.2	1.573	0.2	0.2	0.2	1.602	0.2	1.101	0.2
SFS (The optimal number of DG units: 10)										
Locations	40	20	50	31	91	4	110	80	103	74
Sizes (MW)	2.271	2.271	2.271	2.271	2.271	2.271	2.372	2.271	2.271	2.281
CSFS10 (The optimal number of DG units: 10)										
Locations	110	103	80	50	20	40	91	74	31	4
Sizes (MW)	2.370	2.271	2.271	2.271	2.271	2.271	2.271	2.281	2.271	2.271

settles at the best solution after just 613 iterations, while the required iteration numbers when applying the CSFS6 and CSFS8 variants are 1000 and 995 iterations,

respectively. Note that only those which meet the highest standards of accuracy of solution and convergence speed will be considered as an elite method for solving the problem.

The voltage profile curves after installation of the optimal number of DG units by the CSFS1-10, SFS, and PSO methods are shown in Fig. 8. As observed from the figure, the investigated methods result in a significant improvement of the voltage at buses. In addition, simultaneously optimizing the decision variables via the mechanism implemented by CSFS10 and SFS shows a better improvement in the voltage magnitudes in most load buses

Table 17 Result comparison for the IEEE 118-bus system with the optimal number of DG units by PSO, SFS, and CSFS10

Power loss (kW)			Total DG power output (MW)		
PSO	SFS	CSFS10	PSO	SFS	CSFS10
527.573	499.005	499.004	13.983	22.821	22.819

Fig. 7 Convergence curves for the IEEE 118-bus system with the optimal number of DG units obtained by applying the CSFS1-10 and SFS methods
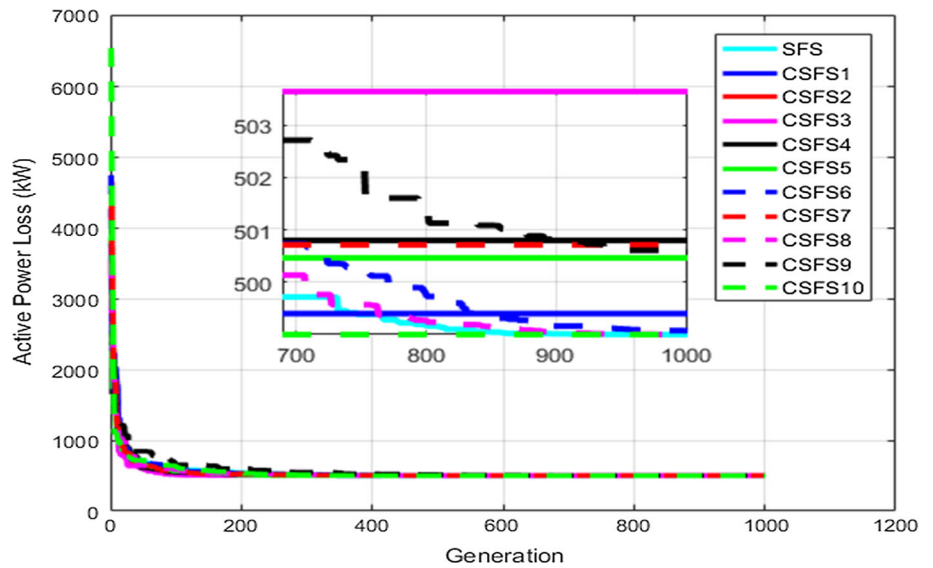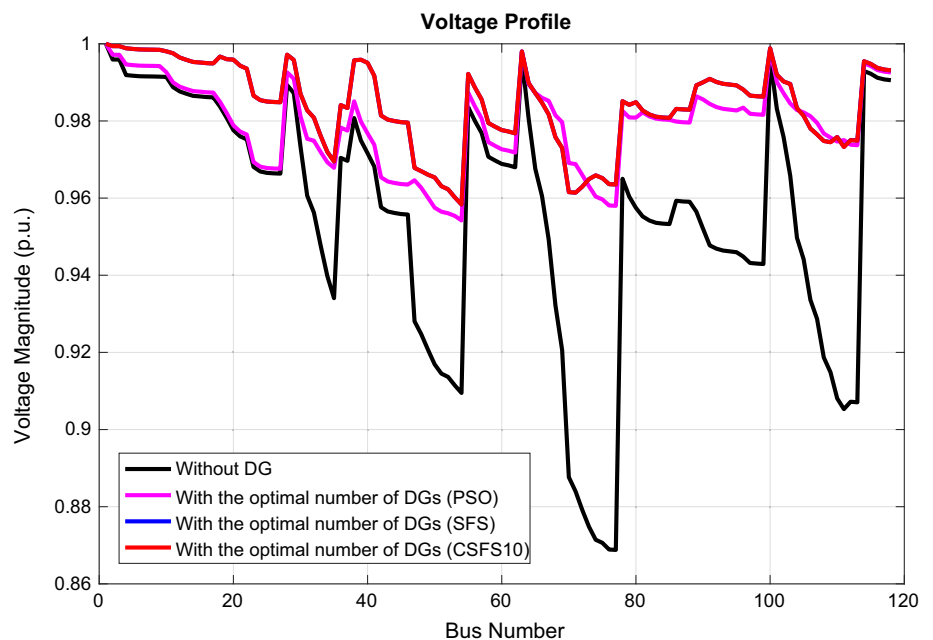

Fig. 8 Voltage profile at buses of the IEEE 118-bus system with the optimal number of DG units

of the test system compared to separately optimizing these variables through the mechanism performed by PSO.

All in all, it has proved that the proposed CSFS10 is able to outperform the original SFS on improving optimal solution and speeding up convergence for the case of the problem of finding the optimal number of DG units in a large-scale RDS with 118 buses. In other words, the chaotic behaviors are capable of enhancing both exploration and exploitation phases of SFS. In addition, the efficiency of the simultaneous optimization mechanism of control variables is again verified based on superior results when applied to the complex study case of a large-scale distribution system.

6 Conclusion

In this paper, the modified CSFS method has been successfully implemented for solving the optimal placement of distributed generators problem in distribution systems. The proposed modification is by introducing chaos into the original SFS algorithm. Ten chaotic maps are employed to be integrated into SFS, resulting in ten chaotic variants of the SFS for search performance evaluation. The considered problem in this research includes the determination of the optimal location, size, and number of DG units in a radial distribution system for minimizing the total active power loss satisfying the system and DG constraints. For the implementation of the CSFS-based method to solve the problem, each individual considered as a candidate solution consists of two variables of location and size. Consequently, both the optimal location and size of DG units are simultaneously found. As revealed from the simulated results above, this mechanism ensures the ability to find the better near-optimal solution than the DG siting and sizing separation mechanism. Furthermore, the study proposes a new specific process for evaluating the optimum DG number with the help of the proposed CSFS. The feasibility and effectiveness of the proposed method for solving the ODGP problem are demonstrated on the IEEE 33-bus, 69-bus, and 118-bus systems, and the obtained results are verified via comparing to those from the original SFS and other methods in the literature. The simulation results confirm that the proposed CSFS easily outperforms its basic version as well as other well-known methods in terms of quality of solution and convergence mobility. The reason for such a superior search performance is due to the integration of chaos theory into the original SFS, which leads to a better balance between the exploration and exploitation properties of search points. Additionally, the proposed method provides a significant reduction of the power loss and improvement in the voltage profile for the case of the installed optimal number of DG units as compared to the case of installing the number of DG units fixed in advance from the previous studies. Therefore, the proposed CSFS can be a very promising method for solving the complex and large-scale problem of optimal placement of distributed generators in distribution systems.

With the successful application on a large-scale distribution system, the proposed method can serve as a useful simulation tool to assist the planners in proposing the optimal location, size, and number of DG units for practical distribution system planning problems. In future work, besides considering the problem in a technical perspective, we will propose an effective cost model for dealing with the problem in an economic perspective. This cost model is a simultaneous consideration of the involved costs, including cost of energy losses as well as investment and operation costs of DG units. In addition, technical and economic risks corresponding to load and electricity market price uncertainties may also be an interesting aspect of research.

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