

Research Article

Distribution Network Reconfiguration for Power Loss Reduction and Voltage Profile Improvement Using Chaotic Stochastic Fractal Search Algorithm

Tung Tran The,¹ Dieu Vo Ngoc ¹ and Nguyen Tran Anh²

¹Department of Power Systems, Ho Chi Minh City University of Technology (HCMUT), VNU-HCM, 268 Ly Thuong Kiet Str., Dist. 10, Ho Chi Minh City, Vietnam

²Department of Electrical Engineering, Can Tho University, Campus II, 3/2 Str., Ninh Kieu Dist., Can Tho City, Vietnam

Correspondence should be addressed to Dieu Vo Ngoc; vndieu@gmail.com

Received 26 June 2019; Revised 27 November 2019; Accepted 7 January 2020; Published 21 March 2020

Academic Editor: Dimitri Volchenkov

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This paper proposes a chaotic stochastic fractal search algorithm (CSFSA) method to solve the reconfiguration problem for minimizing the power loss and improving the voltage profile in distribution systems. The proposed method is a metaheuristic method developed for overcoming the weaknesses of the conventional SFSA with two processes of diffuse and update. In the first process, new points will be created from the initial points by the Gaussian walk. For the second one, SFSA will update better positions for the particles obtained in the diffusion process. In addition, this study has also integrated the chaos theory to improve the SFSA diffusion process as well as increase the rate of convergence and the ability to find the optimal solution. The effectiveness of the proposed CSFSA has been verified on the 33-bus, 84-bus, 119-bus, and 136-bus distribution systems. The obtained results from the test cases by CSFSA have been verified to those from other natural methods in the literature. The result comparison has indicated that the proposed method is more effective than many other methods for the test systems in terms of power loss reduction and voltage profile improvement. Therefore, the proposed CSFSA can be a very promising potential method for solving the reconfiguration problem in distribution systems.

1. Introduction

Distribution networks play an important role in providing electricity to loads; however, the power loss in the system is high, and the voltage regulation is poor. There are many ways to decrease the power loss and improve the voltage profile in distribution networks such as compensating reactive power, increasing operating voltage, balancing loads, and increasing wire section. These methods are possible to deploy in terms of technical aspect but need much investment cost. Network reconfiguration is known as an effective method to reduce the power loss and improve the voltage profile significantly in power systems while requiring not much investment cost. The distribution network reconfiguration is performed by opening/closing switches to form a new network structure for reducing power loss while satisfying operation constraints.

Researchers have made tremendous efforts to find the optimal solution for the distribution network reconfiguration (DNR) problem with many approaches from heuristic methods to metaheuristic methods. Merlin and Back [1] first proposed an approach for this problem, in which the discrete branch and bound method was used to find the electrical structure leading to the least power loss. In [2, 3], the branch exchange method was used to solve the problem with the aim of minimizing power loss and balancing the load demand. Zhou et al. [4] proposed heuristic rules and fuzzy logic to solve the reconfiguration problem for the service restoration and load balancing. Some other heuristic methods [5–7] were also used to solve the reconfiguration problem with different objective functions. The advantages of heuristic methods are simple application, few parameters, and fast computation. However, this kind of method is easy

to fall in local minima and is not really effective for solving large-scale problems. Therefore, more effective methods should be developed to efficiently deal with large-scale problems.

The methods inspired from nature have recently developed with the name of metaheuristics. These methods have been widely applied to different optimization problems in many fields. With the advantages of providing good solutions and being applicable to large-scale networks, the metaheuristic methods have been successfully applied to solve the DNR problems in power systems. Olamaei et al. [8] applied an algorithm based on the Artificial Bee Colony (ABC) algorithm to deal with the reconfiguration problem with the purpose of decreasing power loss. Genetic Algorithm (GA) was proposed to solve the problem for enhancing voltage stability as in [9]. In [10, 11], Harmony Search Algorithm (HSA) and Simulated Annealing (SA) algorithm were, respectively, successfully applied to reconfigure the large-scale distribution systems. The Binary Particle Swarm Optimization (BPSO) algorithm was applied to solve the DNR problem for decreasing power loss and balancing load as shown in [12]. The PSO algorithm, Adaptive Cuckoo Search (ACS) algorithm, and GA were used to reconfigure the distribution networks considering impacts of the distributed generators (DGs) with different scenarios as considered in [13–15]. Besides, some other methods [16–18] have successfully solved the problem with a multiobjective function for power loss minimization, voltage quality improvement, load balancing, and switching mitigation. The big bang algorithm combined with big crunch algorithm was applied to solve the reconfiguration and optimal capacitor position problem [19]. In [20], a modified Culture Algorithm (CA) was employed for the reconfiguration problem of distribution network considering power loss. In general, the metaheuristic methods are very appropriate for dealing with the complex and large-scale problems for obtaining near optimum solution. However, the metaheuristic methods have many control parameters to be tuned for each problem which may lead to local optima if they are not properly determined. Moreover, the computational time of some metaheuristic methods is very high when dealing with large-scale optimization problems due to suffering a large number of variables and need several iterations for searching the optimal solution. Therefore, it is very important to find an effective method for dealing with large-scale and complex optimization problems.

Stochastic Fractal Search Algorithm (SFSa) is a powerful metaheuristic method including updating and diffusion processes recently developed by Salimi [21] based on the fractal theory. The SFSa is developed by improving the fractal search algorithm by adding the updating process and manipulating the Gaussian walk in the diffusion process. The diffusion process increases the probability of finding the global maximum, dodging the local solution. In the update process, the best points are kept, and the rest are discarded to increase the efficiency for the finding process. The SFSa has been successfully implemented to solve the complex problem of reconfiguration with distributed generations [22]. Moreover,

the integration of chaos theory into SFSa helps to improve the rate of convergence as well as the accuracy of solutions. The chaos theory is a mathematics researching field which is applied to enhance the random search process. Many studies have integrated chaos theory into different algorithms to improve the effectiveness of metaheuristic algorithms in solving optimization problems such as the PSO algorithm [23], SA [24], Cuckoo Search Algorithm (CSA) [25], Fruit-fly Optimization (FFO) algorithm [26], ABC algorithm [27], and Differential Evolution (DE) [28]. In general, these methods with the integration of chaos theory have offered a higher solution quality than original methods. Therefore, the integration of the chaos theory into metaheuristic methods provides a promising improvement to enhance their search ability so that the solution quality can be improved.

In this paper, a Chaotic Stochastic Fractal Search Algorithm (CSFSa) is implemented for solving the reconfiguration problem in distribution networks to minimize the power loss and improve the voltage quality. In this research, a chaotic map (Gauss/mouse function) is integrated into the conventional SFSa to improve its performance. In fact, the integration of chaotic maps into the SFSa has been recently performed by many researchers. However, the key contribution of this research is the successful adaption of a chaotic map of Gauss/mouse function into the SFSa to solve a complicated problem of reconfiguration with the objectives of power loss reduction and voltage profile improvement in distribution systems. To verify the effectiveness of the proposed method, four distribution networks have been used for testing including the 33-bus, 84-bus, 119-bus, and 136-bus systems. The obtained results from the proposed CSFSa have been compared with those from other methods reported in the literature such as HSA [10], Firework Algorithm (FWA) [29], Runner-root Algorithm (RRA) [30], CSA [31], Hybrid Big Bang-Big Crunch Algorithm (HBB-BCA) [32], Fuzzy Shuffled Frog-Leaping Algorithm (Fuzzy-SFLA) [33], Multiobjective Invasive Weed Optimization (MOIWO) [34], Improved Adaptive Imperialist Competitive Algorithm (IAICA) [35], Improved Mixed-integer hybrid Differential Evolution (IMI-DE) [36], Plant Growth Simulation Algorithm (PGSA) [37], GA [38, 39], hybrid Artificial Immune Systems-Ant Colony Optimization (AIS-ACO) [40], Heuristic method [41], improved Tabu search (ITS) [42], modified Tabu search (MTS) [43], hybrid Ant Colony Optimization-Harmony Search Algorithms (ACO-HAS) [44], adaptive GA (AGA) [45], Uniform Voltage Distribution-based constructive reconfiguration algorithm (UVDA) [46], Mixed-Integer Convex Programming (MICP) [47], Non-revisiting Genetic Algorithm (NRGA) [48], Feasibility-preserving Evolutionary Optimization (FPEO) [49], a hybridization of Grey Wolf Optimizer (GWO) and PSO method (GWO-PSO) [50], and Adaptive Shuffled Frogs Leaping Algorithm (ASFLA) [51] which are available in the literature.

The remaining organization of the paper is represented in the order as follows. The problem formulation is presented in Section 2. The implementation of the CSFSa for the problem is followed in Section 3. The numerical results from test systems are provided in Section 4. Finally, the conclusion is given.

2. Problem Formulation

2.1. Objective Functions. The objective function of the DNR problem is to minimize total power loss and improve voltage deviation subject to the system constraints. Mathematically, the objective function and constraints of the DNR problem can be formulated as follows [29]:

$$\text{Min } F = P_{\text{loss}} + \Delta V_D, \quad (1)$$

where P_{loss} is the total real power loss of the system and ΔV_D is the voltage deviation at load buses.

According to [29], the two objectives are simultaneously considered by combining into one objective as in (1). Therefore, the research in this paper also uses this methodology for dealing with the paper.

2.1.1. Total Real Power Loss. The total real power loss of the network topology is described as follows:

$$P_{\text{loss}} = \sum_{i=1}^{N_{br}} R_i \times \frac{P_i^2 + Q_i^2}{V_i^2}, \quad (2)$$

$$\begin{aligned} P_{Gi} - P_{Di} = P_i &= |V_i| \sum_{j=1}^{N_b} |V_j| [G_{ij} \cos(\delta_i - \delta_j) + B_{ij} \sin(\delta_i - \delta_j)]; \quad i = 1, \dots, N_b, \\ Q_{Gi} - Q_{Di} = Q_i &= |V_i| \sum_{j=1}^{N_b} |V_j| [G_{ij} \sin(\delta_i - \delta_j) - B_{ij} \cos(\delta_i - \delta_j)]; \quad i = 1, \dots, N_b, \end{aligned} \quad (4)$$

where N_b is the number of buses, P_i and Q_i are real and reactive power injection at bus i , respectively, P_{Gi} and Q_{Gi} are real and reactive power generation at bus i , respectively, P_{Di} and Q_{Di} are real and reactive load demand at bus i , respectively, $|V_i|$ and $|V_j|$ are voltage magnitudes at bus i and j , respectively, G_{ij} and B_{ij} are the real and imaginary parts of element Y_{ij} in the admittance matrix Y_{bus} , respectively, and δ_i and δ_j are the voltage angle at buses i and j , respectively.

(ii) Bus voltage limits: the load bus voltages are limited by their minimum and maximum values as

$$V_{i,\min} \leq V_i \leq V_{i,\max}; \quad i = 1, 2, \dots, N_b. \quad (5)$$

(iii) Line current limits: the line currents are bounded by their lower and upper values as

$$0 \leq I_i \leq I_{i,\max}; \quad i = 1, 2, \dots, N_{br}. \quad (6)$$

(iv) Radial network structure must be maintained, and all loads must be served after reconfiguration.

where N_{br} is the number of branches; R_i is the resistance of the i^{th} branch; P_i and Q_i are the real power and reactive power of the i^{th} branch, respectively; and V_i is the voltage magnitude at bus i .

2.1.2. Voltage Deviation at Load Buses. The voltage deviation of the network topology is determined as

$$\Delta V_D = V_{\text{ref}} - V_{\text{min}}, \quad (3)$$

where V_{ref} is a prespecified voltage magnitude at load bus i which is usually set to 1.0 p.u. V_{min} is the minimum bus voltage of the network topology.

2.2. Constraints

(i) Power flow balance: these power flow constraints are to balance the real and reactive power outputs of generators and loads given by

3. Implementation of CSFSA for the Problem

3.1. Checking Radial Constraints. A distribution network is installed with three typical types including radial, loop, and mesh. It is originally constructed in loops; however, the distribution network is operated as a radial network in order to save energy for the protection device and reduce the fault level. Moreover, utilizing a metaheuristic algorithm with a random initialization creates many network configurations which do not satisfy the radial constraints. Therefore, it is important and mandatory to determine the radial network configuration in the reconfiguration problem for distribution networks so as to reduce the searching space and the computational time.

To maintain radial configuration, the number of tie-switches in the reconfiguration process must be fixed and equal to the number of fundamental loops. The number of tie-switches is determined by the following equation [31]:

$$N_{ts} = N_{br} - (N_b - N_s), \quad (7)$$

where N_s is the number of sources.

The steps of the algorithm for radially checking system in the distribution network reconfiguration are as follows:

Step 1: create an incidence matrix $A(b, n)$ with b which is the branch index and n the node index. Matrix A is created as [14]

$$A_{ij} = \begin{cases} 1, & \text{if branch } i \text{ connects from bus } j, \\ -1, & \text{if branch } i \text{ connects toward to bus } j, \\ 0, & \text{if branch } i \text{ has no connection with bus } j. \end{cases} \quad (8)$$

Step 2: eliminate the first column of matrix A (corresponding to the source bus of the network).

Step 3: eliminate rows consisting of tie-switches corresponding to the considerable network configuration.

Step 4 (check conditions): matrix A is a square matrix, and $\det(A) = 1$ or -1 .

Step 5: If both conditions specified above are qualified, the configuration is the radial and vice versa.

3.2. Stochastic Fractal Search Algorithm. SFSA is a new powerful metaheuristic algorithm inspired by the natural phenomenon of growth by simulating the fractal properties for solving the optimization problem developed by Salimi in 2015 [21]. The search process of the SFSA for obtaining an optimal solution has two main processes including diffusion process and update process described as follows.

3.2.1. Diffusion Process. Each point in this process diffuses around its current position to exploit the search space to increase the probability of finding a better solution and avoid local minima. The new points in this process are generated using the Gaussian walk described by the following equations:

$$X_{i,\text{new}} = \begin{cases} \text{Gaussian}(\mu_{X_{\text{best}}}, \sigma) + (\varepsilon \times X_{\text{best}} - \varepsilon' \times X_i) & \text{if } \text{rand} < W, \\ \text{Gaussian}(\mu_X, \sigma), & \text{otherwise,} \end{cases} \quad (9)$$

where W is an additional parameter for choosing Gaussian walks to tackle the problem; ε and ε' are the uniformly distributed random numbers belonging to $[0, 1]$; $X_{i,\text{new}}$ is the newly adjusted location of point X_i ; X_{best} and X_i are the location of the best point and the i^{th} point in the group, respectively; and $\mu_{X_{\text{best}}}$, μ_X , and σ are Gaussian means, where $\mu_{X_{\text{best}}} = |X_{\text{best}}|$, $\mu_X = |X_i|$, and the mathematical equation of standard deviation σ is given as follows:

$$\sigma = \left| \frac{\log(\text{Iter})}{\text{Iter}} \times (X_i - X_{\text{best}}) \right|, \quad (10)$$

in which Iter indicates the iteration number.

The ratio $\log(\text{Iter})/\text{Iter}$ is implemented to reduce the size of the Gaussian jumps over each iteration. This encourages a more localized search ability and reaches closer to the optimal solution of the algorithm.

3.2.2. Updating Process. This process including two statistical procedures is employed to efficiently explore the search

space. In the first statistical procedure, all the points are ranked according to their fitness values, and then a probability value (Pa) is calculated for each point using the following equation:

$$Pa_i = \frac{\text{rank}(X_i)}{N_p}, \quad (11)$$

where N_p is the total number of points in the group and $\text{rank}(X_i)$ is the rank of point X_i in the group.

Equation (11) indicates that a better point has a higher probability. This equation is to improve the chance for the worst points to obtain a better solution in the next generation. For each point X_i in the group, if $Pa_i < \varepsilon$, the j^{th} component of X_i is updated by equation (12). Otherwise, the position of the point remains unchanged.

$$X'_i(j) = X_r(j) - \varepsilon \times (X_i(j) - X_i(j)), \quad (12)$$

where ε is a random number in the range $[0, 1]$; X'_i is the newly adjusted location of X_i ; and X_r and X_t are the points randomly selected in the group.

In the second statistical procedure, all points obtained by the first procedure are again ranked by equation (11). For all points X'_i , if $Pa'_i < \varepsilon'$, the position of X'_i is updated by equation (13). Otherwise, the updating process for X'_i will not occur.

$$\begin{cases} X''_i = X'_i - \varepsilon' \times (X'_i - X_{\text{best}}), & \text{if } \varepsilon' \leq 0.5, \\ X''_i = X'_i + \varepsilon' \times (X'_i - X'_i), & \text{if } \varepsilon' > 0.5. \end{cases} \quad (13)$$

The new point X''_i replaces the position of X'_i if its fitness function value is better than X'_i .

3.3. Chaotic Map Integrated in SFSA. Chaotic maps are known as one of the efficient methods to enhance the convergence rate and local optima avoidance in a metaheuristic algorithm. In this article, the SFSA is improved by changing factor in diffusion and update process of the original SFSA by variable α of chaotic maps. The variable α utilized to integrate into SFSA is Gauss/mouse function in chaotic maps and it is determined as follows [26]:

$$\alpha_i = \begin{cases} 1, & \text{if } x_i = 0, \\ \frac{1}{\text{mod}(x_i, 1)}, & \text{otherwise.} \end{cases} \quad (14)$$

3.4. Implementation of CSFSA for DNR. The steps for applying the CSFSA to solve the distribution network reconfiguration problem are given as follows:

Step 1: determine elements of SFSA

Step 2: initialize a chaotic map

Step 3: initialize initial individuals

By using CSFSA, each radial configuration of the system is described as a point (individual). A population of N points is given as follows:

$$X = [X_1, X_2, \dots, X_{N-1}, X_N]. \quad (15)$$

Every variable X from equation (15) is represented as follows:

$$X_{ts} = [SW_1, SW_2, \dots, SW_{N_{ts}}],$$

$$SW_i^{\min} \leq SW_i \leq SW_i^{\max}, \quad \text{with } i = 1, 2, \dots, N_{ts}. \quad (16)$$

Each individual in assembly is randomly initialized by the following equation

$$X_i = X_i^{\min} + \text{rand} * (X_i^{\max} - X_i^{\min}). \quad (17)$$

Step 4: calculate power flow for initial initialization variables to find the best point (X_{best}) and check radial constraint.

Step 5: conduct the diffusion process as in Section 3.2.1.

Step 6: the points created from diffusion process are checked for the radial structure by the algorithm from Section 3.1, and calculate the power flow to determine the objective function. The points having the best objective function are utilized, and the set of N_p points is improved with new points choosing from points in the diffusion process.

Step 7: conduct the updating process as mentioned in Section 3.2.2.

Step 8: with each point updated, check for the radial constraint and calculate the power flow to determine the objective function.

Step 9: export results including X_{best} , minimum power loss, and voltage deviation.

Step 10: stop criteria for the algorithm.

The new system configuration is created from the diffusion and updating processes until the number of iterations reaches the maximum iteration number (Iter_{max}).

4. Numerical Results

The proposed method has been tested on the 33-bus, 84-bus, 119-bus, and 136-bus test systems. The CSFSA is coded in Matlab platform and run on a 2.5 GHz processor with 4.0 GB of RAM PC. In this paper, the power flow analysis is simulated by using Matpower [52].

4.1. Selection of Parameters. The establishment of initial parameters has an impact on the proposed method of finding the optimal solution for the considered problem. Therefore, the determination of optimal parameters plays an important role in solving the DNR problem. The value of parameters is usually chosen by changing only one parameter while the rest are fixed. Initially, parameters are set at low value and gradually increased to collect different results. The selected parameters are explained as follows. The maximum number of iterations Iter_{max} depends on test systems, and it is set from 50 to 3000 in this paper. The size of

population or number of points N has the selected values from 30 to 70. By experiments, the parameters of CSFSA are chosen as shown in Table 1.

In this table, D_{max} is the maximum diffusion number, and S_{walk} is the Gaussian walk ratio determined by the rule as follows:

+ $S_{\text{walk}} = 1$: SFSA uses the first Gaussian walk

+ $S_{\text{walk}} = 0$: SFSA uses the second Gaussian walk

+ $S_{\text{walk}} = 0.75$: SFSA uses the first Gaussian walk, with the probability of 75% which comes from the uniform, and SFS uses the second Gaussian walk distribution with the probability of 25%

4.2. 33-Bus System. The proposed algorithm is applied to solve the reconfiguration problem for a small-scale 33-bus distribution network. This system consists of 37 branches, 32 sectionalizing switches, and 5 tie-switches. The initial tie-switches are 33, 34, 35, 36, and 37. The system is operated at 12.66 kV and has a total load demand of $3.73 + j2.3$ (MVA) with the lowest voltage 0.91081 p.u at bus 18 [2]. The single-line diagram of the system is demonstrated in Figure 1. The obtained results of the CSFSA are compared with those from other methods including FWA [29], RRA [30], HBB-BCA [32], Fuzzy-SFLA [33], MOIWO [34], IAICA [35], and CSA [31], FPEO [49], GWO-PSO [50], and ASFLA [51] as shown in Table 2.

As demonstrated in Table 2, after the DNR is performed, the proposed algorithm can find an optimal network structure with the tie-switches which are 7-9-14-32-37 corresponding to 138.91 kW of power loss. Therefore, the proposed method has decreased by 31.8% of power loss compared with the initial case. Moreover, the results obtained by the CSFSA are the same as those from the CSA method in Table 2. Obviously, the power loss and voltage deviation from the proposed method are 138.91 kW and 0.0576 p.u, which are 0.64 kW and 0.0046 p.u. lower than those from other methods such as RRA, HBB-BC, and MOIWO. According to the table, the CSFSA also gives better results compared to other methods in terms of power loss and voltage deviation. The comparison has shown that the CSFSA method can obtain a very high-quality solution for the distribution network reconfiguration problem. In terms of the computational time, CSFSA takes 49.59 s to solve the DNR problem, which is longer than FWA, GWO-PSO, and HBB-BCA and faster than RRA. It is noted that the computational time may not be directly compared among the methods due to different computer processors and programming languages used. Therefore, the key factor for the comparative result is mainly the objective function value rather than the computational time.

The convergence characteristics of the proposed method for the power loss and voltage deviation objectives of the 33-bus system are given in Figures 2 and 3, respectively. After 19 iterations, the proposed method has converged to the optimal solution, proving that by integrating the chaos theory has increased the effectiveness of the proposed method with a fast convergence process. From Figures 2 and 3, at the 10th

TABLE 1: The parameters of CSFSA for test systems.

System	N	Iter_{\max}	D_{\max}	S_{walk}
33-bus	30	50	5	1
84-bus	50	200	5	0.75
119-bus	50	1500	5	0.5
136-bus	70	2000	5	0.5

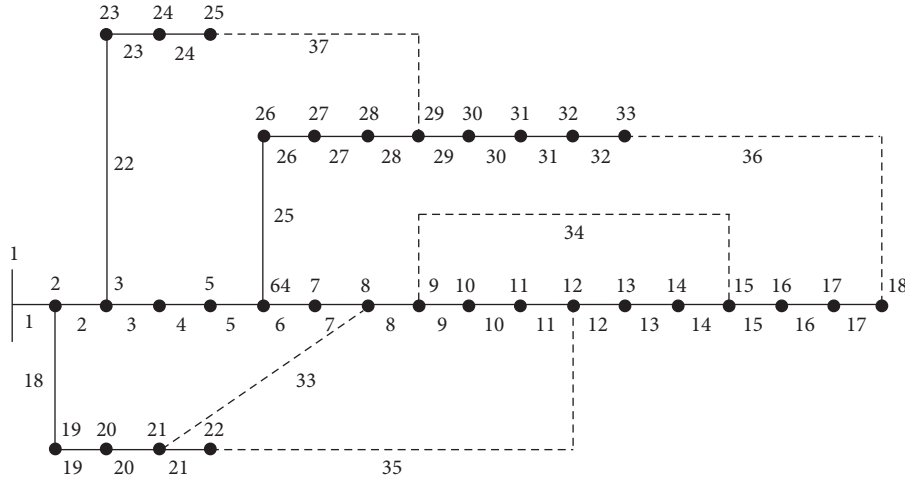


FIGURE 1: Single-line diagram of the 33-bus system.

TABLE 2: Result comparison of CSFSA with other methods for the 33-bus system.

Method	Tie-switches	Power loss (kW)	ΔV_D	V_{\min} (p.u.)	CPU time (s)
Initial	33-34-35-36-37	203.68	0.0891	0.91081	—
FWA [29]	7-9-14-28-32	139.98	0.0587	0.9413	6.4
RRA [30]	7-9-14-32-37	139.55	0.0622	0.9378	74.69
HBB-BCA [32]	7-9-14-32-37	139.55	0.0622	0.9378	3.05
Fuzzy-SFLA [33]	7-9-14-28-32	139.98	0.0588	0.9412	—
MOIWO [34]	7-9-14-32-37	139.55	0.0622	0.9378	—
IAICA [35]	7-9-14-32-37	139.51	0.0622	0.9378	—
CSA [31]	7-9-14-32-37	138.91	0.0576	0.94235	—
FPEO [49]	7-9-14-28-32	140.3350	—	—	—
GWO-PSO [50]	7-9-14-32-37	139.55	—	—	30.61
ASFLA [51]	7-9-14-28-32	139.98	—	0.9413	—
CSFSA	7-9-14-32-37	138.91	0.0576	0.94235	49.59

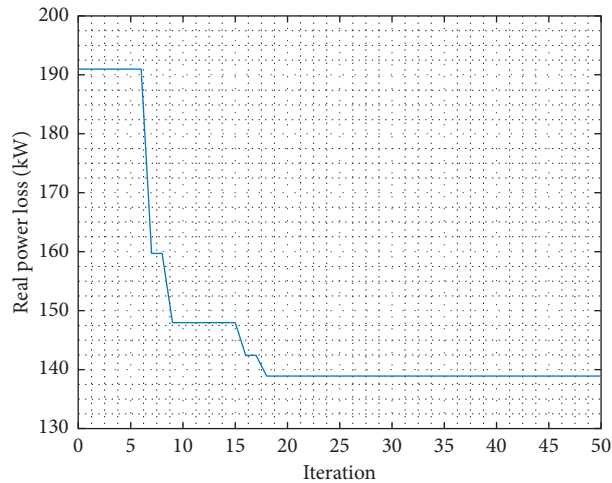


FIGURE 2: The convergence characteristic of power loss for the 33-bus system.

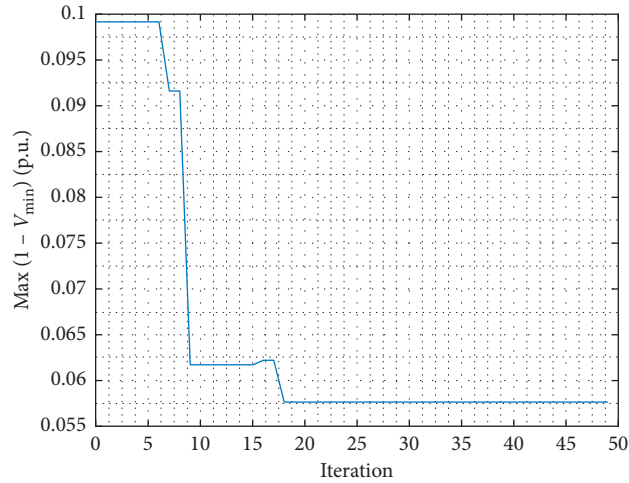


FIGURE 3: The convergence characteristic of voltage deviation for the 33-bus system.

iteration power loss decreased from 159.71 kW to 147.97 kW and the voltage deviation at this iteration also decreased from 0.0916 p.u. to 0.0617 p.u. Besides, the magnitude of the voltage at all buses is significantly improved, and the lowest voltage value increased from 0.91081 p.u. to 0.94235 p.u. as indicated in Figure 4.

4.3. 84-Bus Test System. An 84-bus distribution network is the second case to investigate the efficiency of the CSFSA for the DNR problem. This is the practical network of the Taiwan Power Company with 83 sectionalizing switches and 13 tie-switches with the voltage operated at 11.4 kV. The system is designed with overhead lines and underground cables including 12 feeders. The total load demand of the system is 28.35 MW and 20.70 MVar [36]. The single-line diagram of the system is presented in Figure 5. At the initial case, the tie-switches are 84-85-86-87-88-89-90-91-92-93-94-95-96, and the lowest voltage is 0.9285 p.u. at bus 9.

The collected results from the proposed method are compared to those from IMI-DE [36], PGSA [37], GA, HBB-BCA [32], AIS-ACO [40], and the heuristic method [41] as shown in Table 3. As observed from the table, the power loss obtained by the proposed method is 469.878 kW while the initial case is 531.99 kW, leading to 11.68% of power loss reduction. Moreover, the proposed CSFSA has also found the optimal system structure with the tie-switches of 55-7-86-72-13-89-90-83-92-39-34-42-62. As seen from the table, the proposed method gives a power loss the same as from GA, PGSA, and IMI-DE methods and better than that from BB-BCA, AIS-ACO, and heuristic methods. The proposed CSFSA, PGSA, and GA methods can find the same system structure with the tie-switches of 7-13-34-39-42-55-62-72-83-86-89-90-92. The optimal configuration proposed by the BB-BCA method with the switches of 7-33-38-55-62-72-83-86-88-89-90-92-95 causes a power loss of 471.62 kW, which is 1.742 kW higher than that from the proposed CSFSA while the voltage deviations from the two methods are the same. The optimal result by the AIS-ACO method provides the voltage deviation of 0.0521 p.u., which is 0.00529 p.u. higher

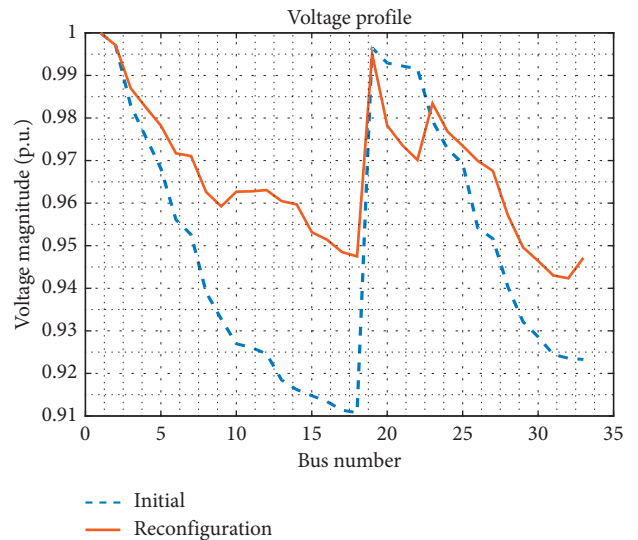


FIGURE 4: The voltage profile for the 33-bus system before and after reconfiguration.

than that from the proposed method. The proposed CSFSA requires longer computational time than other methods reported in Table 3. Table 3 also illustrates that the voltage deviation from the proposed CSFSA is the best among all the compared methods.

For this test system, the DNR problem consists of 13 unknown tie-switches; thus, the number of iterations is increased to reach the best result. The convergence characteristics of the power loss and voltage deviation from the proposed CSFSA for the 84-bus system are, respectively, shown in Figures 6 and 7 where the voltage deviation is 0.04681 p.u. compared with 0.0715 p.u. from the initial case. Therefore, the proposed CSFSA method has shown that the power loss and voltage deviation index have the tendency to converge to the optimal result. Figure 8 denotes the voltage characteristics before and after reconfiguration. The proposed CSFSA has also improved the voltage at buses with the lowest voltage increased from 0.9285 p.u. to 0.95931 p.u.

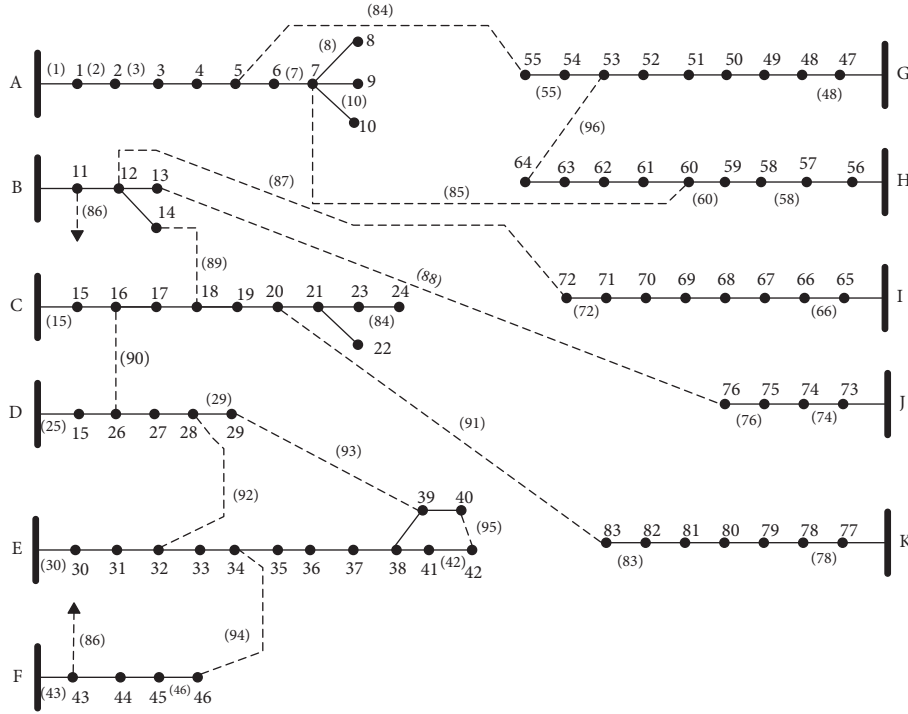


FIGURE 5: Single-line diagram of the 84-bus test system.

TABLE 3: Result comparison of CSFSA with other methods for the 84-bus system.

Method	Tie-switches	Power loss (kW)	ΔV_D	V_{\min} (p.u.)	CPU time (s)
Initial	84-85-86-87-88-89-90-91-92-93-94-95-96	531.99	0.0715	0.9285	
IMI-DE [36]	7-13-34-39-41-55-62-72 - 83-86-89-90-92	469.88	0.0469	0.9531	36.15
PGSA [37]	7-13-34-39-42-55-62-72-83-86-89-90-92	469.88	—	—	113.25
GA [38]	7-13-34-39-42-55-62-72-83-86-89-90-92	469.878	—	—	7.809
BB-BCA [32]	7-33-38-55-62-72-83-86-88-89-90-92-95	471.62	0.04682	0.95318	13.25
AIS-ACO [40]	7-13-34-39-42-55-62-72-86-89-90-91-92	471.14	0.0521	0.9479	—
Heuristic method [41]	7-34-39-42-55-63-72-82-86-88-89-90-92	470.89	—	—	—
CSFSA	55-7-86-72-13-89-90-83-92-39-34-42-62	469.878	0.04681	0.95319	748.95

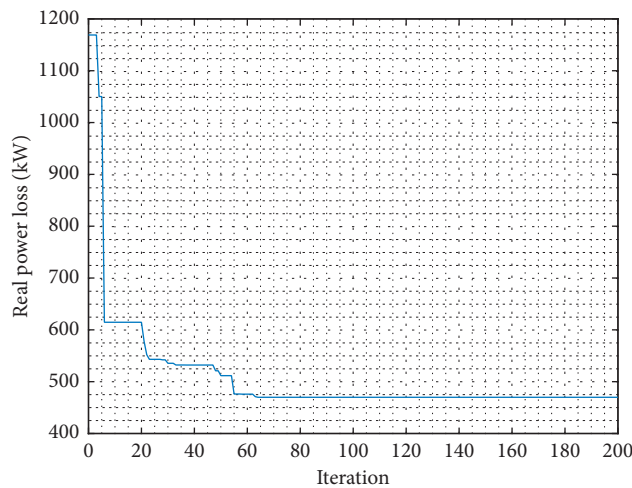


FIGURE 6: The convergence characteristic of power loss for the 84-bus system.

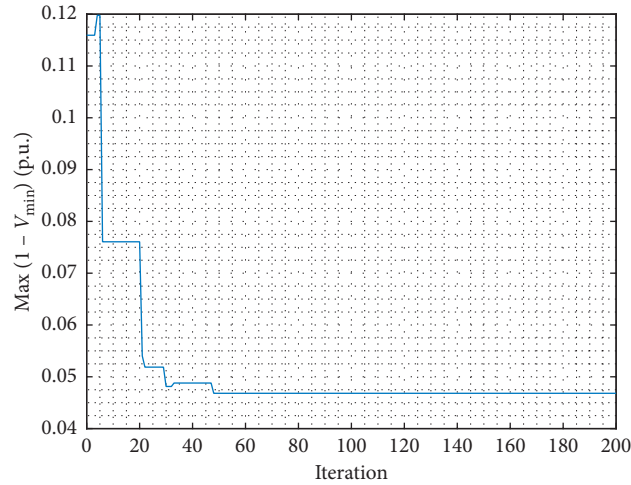


FIGURE 7: The convergence characteristic of voltage deviation for the 84-bus system.

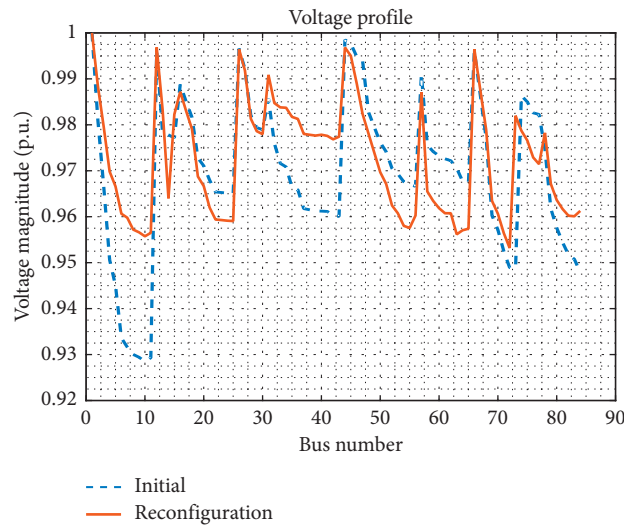


FIGURE 8: The voltage profile for the 84-bus system before and after reconfiguration.

4.4. 119-Bus System. To evaluate the effectiveness of the proposed CSFSA in solving large-scale systems, the 119-bus system is considered in this study. This system consists of 132 branches and 118 sectionalizing switches with the operating voltage of 11 kV. The total load demand of the system is 22.709 MW and 17.041 MVAR. The system bus and branch data are given in [42]. The single-line diagram is demonstrated in Figure 9, and the minimum voltage of the system is 0.8688 p.u. at bus 116. The 119-bus system has 15 tie-switches corresponding to 15 fundamental loops, and the tie-switches are 118-119-120-121-122-123-124-125-126-127-128-129-130-131-132 in the initial case. The results obtained by the proposed CSFSA including power loss, voltage deviation, and minimum voltage for the 119-bus system are compared to those from other methods including ITS [42], MTS [43], HAS [10], ACO-HAS [44], FWA [29], CSA [31], and FPEO [49] as given in Table 4.

After reconfiguration, the power loss provided by the proposed CSFSA is 854.04 kW decreasing by 32.86% compared with the initial case. The proposed CSFSA method finds the optimal structure for this system which is corresponding to the position of tie-switches of 42-25-23-121-50-58-39-95-71-74-97-129-130-109-34. The proposed CSFSA also shows its effectiveness in improving the voltage profile where the lowest voltage increases from 0.8688 p.u. to 0.9298 p.u. As observed from the table, the ITS and MTS method can find the optimal structure with the same tie-switches of 24-27-35-40-43-52-59-72-75-96-98-110-123-130-131 as the proposed CSFSA. The power losses obtained by the ITS and MTS methods are 865.865 kW and 865.86 kW, which are 11.825 and 11.82 kW higher than those from the proposed CSFSA, respectively. Similarly, the FA and CSA methods also give the same tie-switches as the optimal structure obtained by the proposed method, and the power loss obtained from these methods is still higher than the proposed CSFSA. The

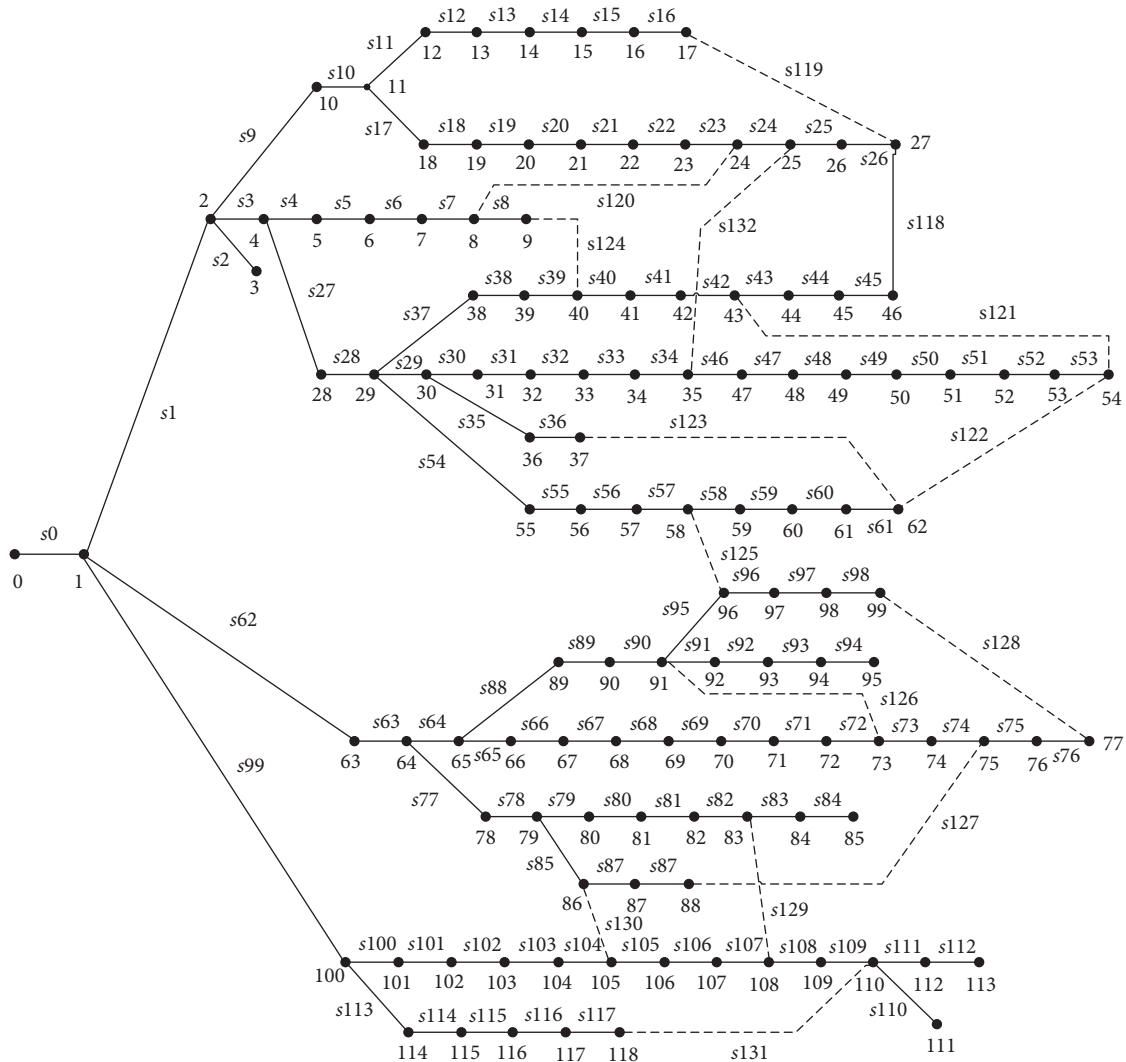


FIGURE 9: Single-line diagram of the 119-bus system.

TABLE 4: Result comparison of CSFSA with other methods for the 119-bus system.

Method	Tie-switches	Power loss (kW)	ΔV_D	V_{\min} (p.u.)	CPU time (s)
Initial	118-119-120-121-122-123-124-125-126-127-128-129-130-131-132	1298.09	0.1312	0.8688	
ITS [42]	24-27-35-40-43-52-59-72-75-96-98-110-123-130-131	865.865	0.0677	0.9323	—
MTS [43]	24-27-35-40-43-52-59-72-75-96-98-110-123-130-131	865.86	0.0679	0.9321	—
HSA [10]	23-27-33-43-53-62-72-75-125-126-129-130-131-132-133	854.205	0.0677	0.9323	8.61
ACO-HSA [44]	23-27-33-40-43-49-52-62-72-74-77-83-110-126-131	865.322	—	—	—
FWA [29]	24-26-35-40-43-51-59-72-75-96-98-110-122-130-131	854.06	0.0677	0.9323	—
CSA [31]	24-26-35-40-43-51-59-72-75-96-98-110-122-130-131	855.0402	0.07025	0.9298	—
FPEO [49]	24-26-35-40-43-51-59-72-75-96-98-110-122-130-131	856.8000	—	—	—
CSFSA	42-25-23-121-50-58-39-95-71-74-97-129-130-109-34	854.04	0.0677	0.9323	4678.4

proposed method also gives the same voltage deviation index with the ITS, HAS, and FA methods. Therefore, the proposed CSFSA method is superior to other methods in terms of power loss and voltage deviation.

In this case, the convergence characteristics of the proposed CSFSA for the power loss and voltage deviation are given in Figures 10 and 11, respectively, where more

iteration than the previous systems is needed to find the optimal solution due to the larger scale system. Accordingly, the proposed method converges after 359 iterations. The computational time of the proposed method is much longer than HSA. There is no report on computational time from other methods. Figure 12 describes the voltage at all buses of the network before and after reconfiguration.

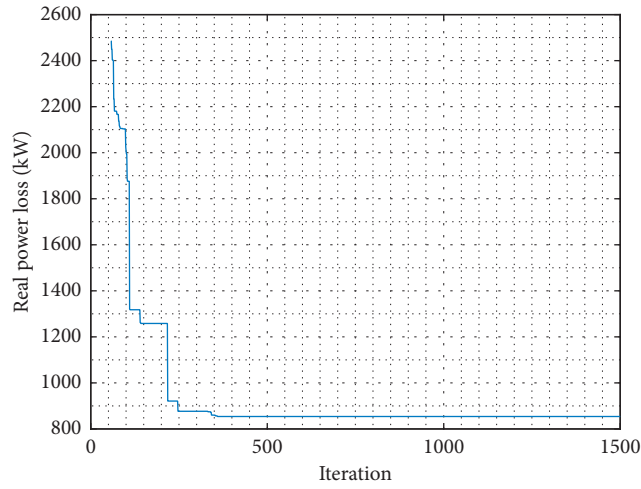


FIGURE 10: Convergence characteristic of the power loss for the 119-bus system.

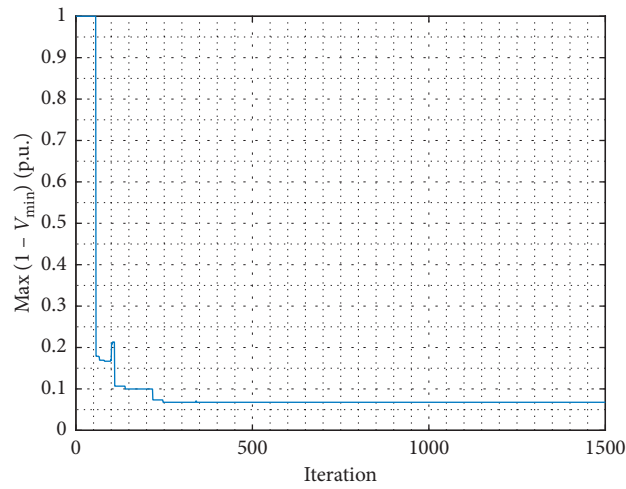


FIGURE 11: Convergence characteristic of the voltage deviation for the 119-bus system.

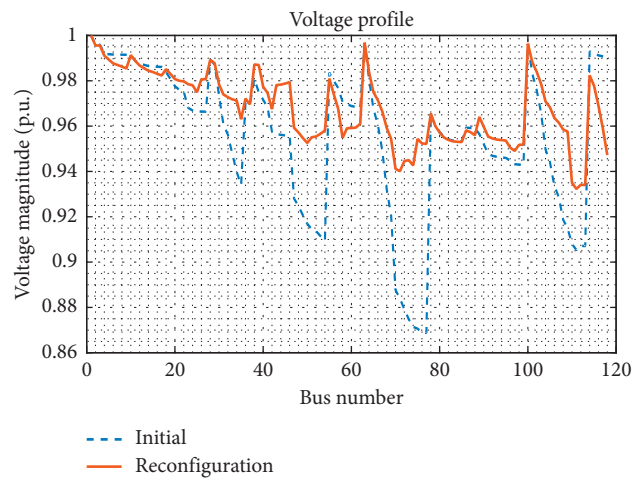


FIGURE 12: Voltage profile for the 119-bus system before and after reconfiguration.

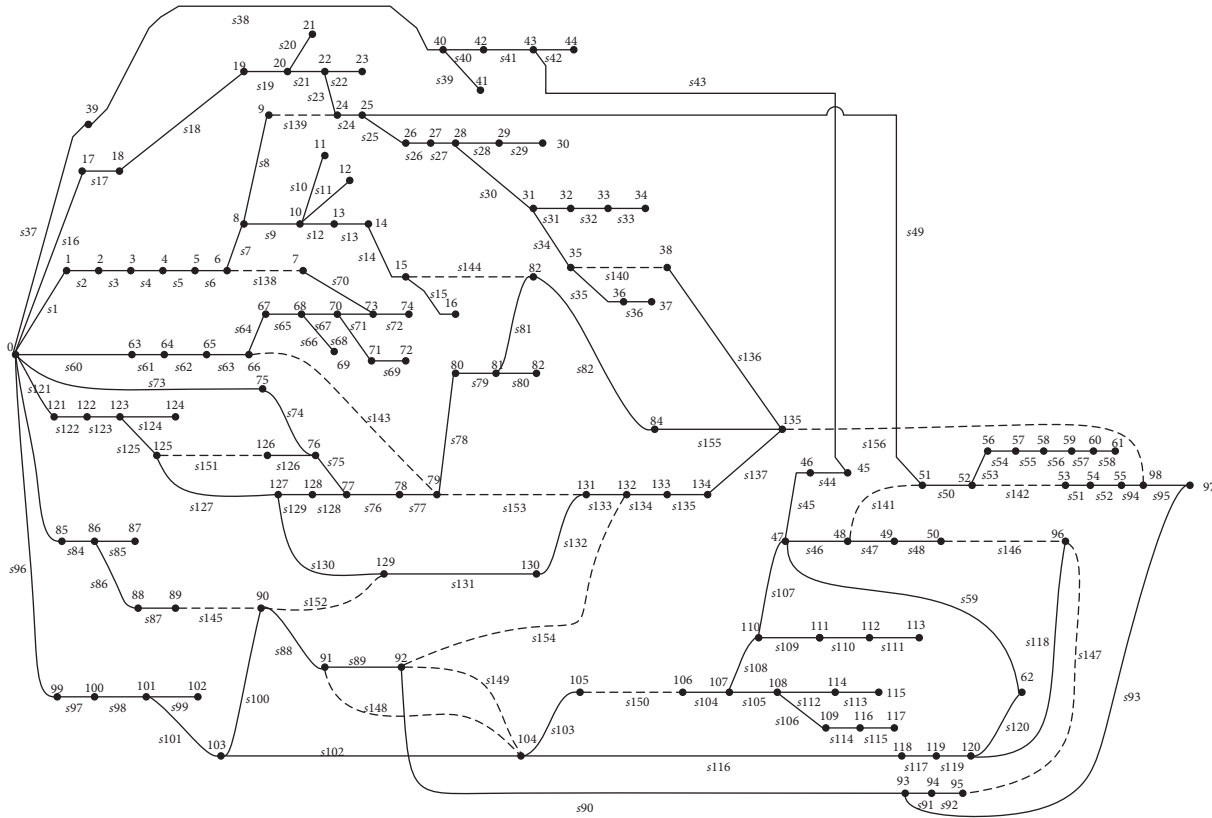


FIGURE 13: Single-line diagram of the 136-bus test system.

TABLE 5: Result comparison of the proposed CSFSA with other methods for the 136-bus system.

Method	Tie-switches	Power loss (kW)	ΔV_D	V_{\min} (p.u.)	CPU time (s)
Initial	136-137-138-139-140-141-142-143-144-145-146-147-148-149-150-151-152-153-154-155-156	320.66	0.0693	0.9307	—
AGA [45]	51-53-90-96-106-118-136-137-138-139-141-144-145-146-147-148-150-151-154-155-156	280.13	—	—	—
UVDA [46]	7-35-51-90-96-106-118-126-135-137-138-141-142-144-145-146-147-148-150-151-155	280.18	0.0411	0.9589	—
GA [39]	7-51-83-84-90-96-106-118-126-128-137-138-139-141-144-145-147-148, 150-151-156	280.22	0.0420	0.9580	—
MICP [47]	7-35-51-90-96-106-118-126-135-137-138-141-142-144-145-146-147-148-150-151-155	280.19	—	—	1800
NRGA [48]	141-146-116-150-34-94-144-138-139-137-154-152-155-149-148-145-153-143-147-151-128	280.19	0.0411	0.9589	—
CSFSA	7-137-138-139-58-141-98-62-144-145-84-147-148-90-150-151-118-106-126-128-135	278.9	0.0384	0.9616	370.91

4.5. 136-Bus Test System. The effectiveness of the proposed method is also verified on a 136-bus practical distribution network with 135 selection switches and 21 tie-switches operated at 13.8 kV. The 136-bus system is one part of the distribution network in the Midwest of Brazil [53]. The initial lowest bus voltage of the system is 0.9307 p.u. at bus 117. The single-line diagram of the system is presented in Figure 13. In the initial case, the tie-switches are 136-137-138-139-140-141-142-143-144-145-146-147-148-149-150-151-152-153-154-155-156. The results obtained from the

proposed CSFSA including the power loss, voltage deviation, and minimum voltage are compared to those from other methods in the literature such as AGA [45], UVDA [46], GA [39], MICP [47], and NRGA [48] as summarized in Table 5.

After reconfiguration, the obtained power loss from the proposed CSFSA is 278.9 kW, which decreases 41.76 kW compared to that from the initial case. The proposed method finds the optimal network configuration with the tie-switches of 7-137-138-139-58-141-98-62-144-145-84-147-148-90-150-151-118-106-126-128-135. The computational time of the

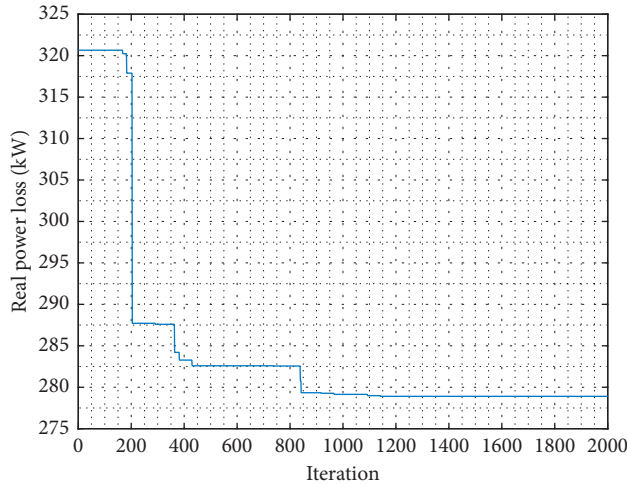


FIGURE 14: Convergence characteristic of power loss for the 136-bus system.

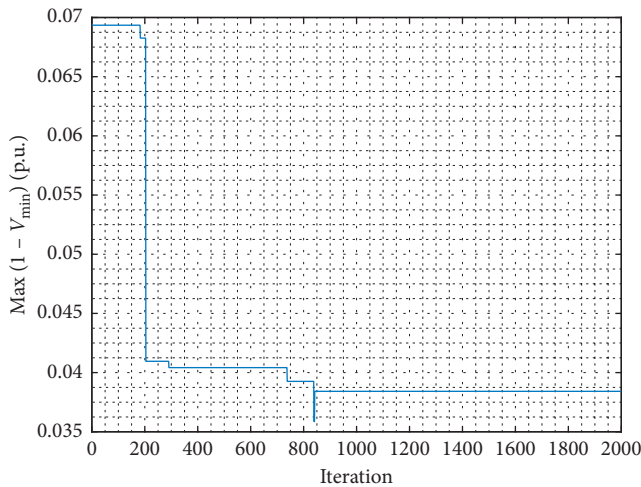


FIGURE 15: Convergence characteristic of voltage deviation for the 136-bus system.

proposed method for finding the solution is 370.91 s, which is faster than MICP. As observed from Table 5, the voltage amplitude is improved from 0.9307 p.u. to 0.9616 p.u. The comparative results provided in Table 5 have proven the effectiveness of CSFSA over other methods in the literature. For this system, the voltage deviation of the proposed CSFSA is less than that from UVDA, GA, and NRGGA. The power loss by the GA method is 280.22 kW, which is 1.32 kW higher than that from the proposed CSFSA. The proposed method can obtain better both power loss and voltage deviation than other methods. Therefore, the proposed CSFA is very effective for dealing with the reconfiguration problem for very large-scale systems.

Figure 14 describes the convergence characteristic of the proposed CSFSA for the power loss and voltage deviation for the 136-bus system, where the proposed CSFSA reaches the best solution after 1,142 iterations. Moreover, the corresponding convergence characteristic of voltage deviation from the proposed method for the system is also given in

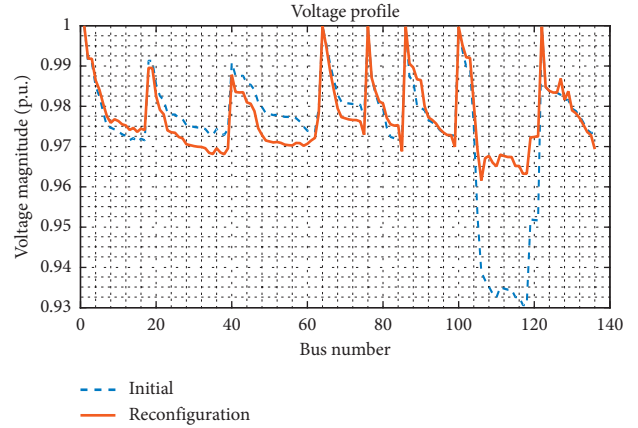


FIGURE 16: Voltage profile for the 136-bus system before and after reconfiguration.

Figure 15. Figure 16 shows that the voltage profile at buses is significantly improved compared with the case before reconfiguration. To solve the distribution network reconfiguration for the real 136-bus system, the number of iterations is higher than that needed for the previous systems for obtaining the optimal result.

5. Conclusion

This study has been successfully applied to the CSFSA method for the DNR problem with the objective function of power loss reduction and voltage profile improvement in distribution systems. The integration of chaos theory in the conventional SFSA has improved the efficiency of diffusing and updating processes so that the search ability of the method has been significantly enhanced. The radial structure of distribution networks has been tested using the graph theory after the new configuration was created. The proposed CSFSA has been tested on the 33-bus, 84-bus, and large-scale systems including 119-bus and 136-bus systems. The obtained results from the CSFSA have confirmed the effectiveness and robustness of the proposed method to solve the reconfiguration problem in distribution networks by providing the better power loss reduction and voltage profile improvement than many other mature methods in the literature. Therefore, the proposed CFSFA can be a favorable method for solving the complex and large-scale reconfiguration problems in distribution systems.

Data Availability

No data were used to support this study.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

This research was funded by Ho Chi Minh City University of Technology (HCMUT), VNU-HCM, under grant number BK-SDH-2020-8141223.

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