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Research Article

Optimal Network Reconfiguration to Reduce Power Loss Using an Initial Searching Point for Continuous Genetic Algorithm

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In this paper, an effective method to determine an initial searching point (ISP) of the network reconfiguration (NR) problem for power loss reduction is proposed for improving the efficiency of the continuous genetic algorithm (CGA) to the NR problem. The idea of the method is to close each initial open switch in turn and solve power flow for the distribution system with the presence of a closed loop to choose a switch with the smallest current in the closed loop for opening. If the radial topology constraint of the distribution system is satisfied, the switch opened is considered as a control variable of the ISP. Then, ISP is attached to the initial population of CGA. The calculated results from the different distribution systems show that the proposed CGA using ISP could reach the optimal radial topology with better successful rate and obtained solution quality than the method based on CGA using the initial population generated randomly and the method based on CGA using the initial radial configuration attached to the initial population. As a result, CGA using ISP can be a favorable method for finding a more effective radial topology in operating distribution systems.

1. Introduction

Network reconfiguration (NR) is a method of changing the state of the switches on the distribution system in order to obtain the best radial structure to meet the goals such as reducing power loss, improving the load balance between branches or feeders, improving voltage quality, and improving power supply reliability. This is a nonlinear problem with constraints and has been solved by many different methods consisting of mathematical programming techniques such as linear, nonlinear, and dynamic programming [1–8], heuristic methods such as a discrete branch-and-bound and branch exchange techniques [9–12], and meta-heuristic methods such as firework algorithm (FW) [13], genetic algorithm (GA) [14, 15], random-key GA [16], runner root algorithm [17, 18], cuckoo search algorithm (CSA) [19–21], harmony search algorithm (HSA) [22], particle swarm optimization (PSO) [23, 24], backtracking search algorithm (BSA) [25], symbiotic organisms search (SOS) [26], binary PSO [27, 28], ant colony optimization [29], and flower pollination algorithm [30], combination of the wild goats and exchange market algorithms [31], and grey wolf optimizer (GWO) [32].

For using the methods in the first method group, the NR problem is usually described in a rather complicated way. They are generally ineffective for solving the NR problem. The best evidence for this is the limited number of studies that uses this method to solve the NR problem. The second group of methods approaches the NR problem based on technical criteria to find good solutions. The advantage of this method group is the use of knowledge related to the power system, so the NR problem is described relatively simple. However, the obtained solutions are often local extremes, and they are only applied to specific problems. As changing constraint conditions and objective functions, the use of this method group for the NR problem will face many limitations. The third group of methods is based on the general knowledge to solve the NR problem. For example, GA is based on knowledge of evolution, PSO algorithm is inspired from the social behavior of birds during looking for food, CSA has taken idea of cuckoo's parasitic reproductive behavior, and SOS algorithm is based on interaction strategies of organisms in the ecosystem. Compared to the aforementioned two method groups, the third method group does not concern about the type of objective functions and easily handles constraint conditions. In addition, a remarkable feature of the third method group compared to the above two method groups is that it is not only applied to NR problem but also widely applied to other problems in the field of electrical engineering. For example, some metaheuristics have been successful proposed for different problems such as Pachycondyla apicalis algorithm for determining parameters for chaotic electrical system [33], fractal search algorithm for optimal power flow problem [34], differential evolution for optimal active-reactive power dispatch [35], whale optimization algorithm for finding sizing DG hybrid system [36], and coyote optimization algorithm for finding location and size of photovoltaic DG in the power system [37]. However, it is not true to say that an algorithm is strong for one problem, and then, it is also powerful for another one [38]. For example, in [39], the authors have pointed out the limitations of some methods such as PSO and ant colony optimization (ACO) for the problem of determining the control approach for nonlinear system, but in [40], ACO has better performance than simulated annealing. Or in [41], PSO and GA have shown that their performance was worse than ant lion optimizer. Therefore, as using the methods belonging to this group for the NR problem, it is essential to examine the suitability of the algorithm. Furthermore, the number of control parameters and their appropriate values for the NR problem are also an issue to take attention. So far, the methods using metaheuristic algorithms have been the most commonly used for the NR problem. This is evidenced by the huge number of studies using this type of method for the NR problem. Among the reasons justifying the strong development of this method group for the NR problem, it is necessary to mention the advantages that this method group brings when applying to the NR problem as follows. Firstly, describing the NR problem is done in a simple way. In particular, the control variables of the problem are opened switches which are generated by working mechanisms of the metaheuristic algorithms. The constraints and the objective function are expressed by the fitness function. Secondly, the concentration of many researchers in the field of optimization is considered, so more and more powerful algorithms have been developed, leading to the need to apply them in technical problems to prove their effectiveness compared to the other algorithms.

Although the metaheuristic methods are widely used to solve the NR problem, most studies focus on applying the original version of them to the NR problem or improving control parameters as well as enhancing working mechanisms to enhance the efficiency of the algorithms for the NR problem without paying attention to the initial searching point (ISP) for the algorithms. Generally, searching mechanisms of the metaheuristic algorithms usually generate new solutions based on information of the current best solution. Therefore, starting with a good solution in the search space will help metaheuristic algorithms to increase chance for finding an optimal solution of the optimization problem. Recently, some researchers have begun to look for initial solutions for metaheuristic algorithms to solve the NR problems. In [42], the ISP for a mixed-integer programming is propounded to the NR problem for minimizing power loss, in which the NR problem is mapped to a problem of determining a minimum spanning tree in a graph. In [43], ISP is selected relying on the node-node adjacency matrix (called H-matrix) of the initial radial topology of the distribution system. The advantages of this technique is without using power flow and optimization algorithm. The NR results using PSO with H-matrix have demonstrated the effectiveness of using ISP compared with the original PSO.

In this paper, an effective method to determine ISP based on heuristic technology in power systems is proposed to enhance the efficiency of metaheuristic algorithms to NR problem for minimizing power loss. The ISP obtained will be attached to the initialization population of the metaheuristic algorithm for applying to the NR problem. To illustrate the performance of the proposed method, the continuous genetic algorithm (CGA) is adapted to reconfigure the distribution system. The effectiveness of the proposed method is compared with the two cases of NR consisting of NR using CGA with the initial population generated randomly and NR using CGA with the initial radial configuration attached to the initial population generated randomly. Calculation results on different power systems show the effectiveness of the proposed method in terms of successful rate and obtained solution quality and the efficiency of the algorithm compared to other ones.

Based on the obtained results, some of the main contributions of the paper can be summarized as follows:

(i) Propose the new method for finding the ISP for the metaheuristic algorithms to solve the NR problem for power loss reduction

(ii) CGA is adapted to combine with ISP for solving the NR problem

(iii) CGA using ISP is compared with CGA using the initial population generated randomly and CGA using the initial radial topology attached to the initial population

(iv) For all distribution systems, CGA using ISP can find the optimal radial topology of distribution systems with better successful rate and obtained solution quality than other ones

The rest of the study is arranged as follows: the objective function is presented in Section 2. The ISP for the metaheuristic algorithm to apply for the NR problem is mentioned in Section 3. The numerical results are shown in Section 4. The conclusion part is shown in Section 5.

2. The Objective Function

Network reconfiguration has many benefits such as reducing power loss, improving voltage quality, improving load balance, and ensuring reliability. In this study, power loss reduction is considered as the goal of the NR problem. Therefore, the problem's objective function is described mathematically as follows:

$$f = \sum_{i=1}^{N_{\mathrm{br}}} R_i . k_i . \left(\frac{P_i^2 + Q_i^2}{V_i^2} \right), \tag{1}$$

where N_{br} is the number of lines; R_i is the resistance of the ith branch; P_i and Q_i are the active and reactive power on the ith branch; k_i is the status of a switch located in the ith branch, $k_i = 1$ if the ith switch is closed, and $k_i = 0$ if the ith switch is opened; and V_i is the voltage of the end of the ith line.

The NR problem is subject to the below constraints:

Power balance: it must be ensured as follows:

$$\begin{cases} P_{\mathrm{slack}} = \displaystyle\sum_{i=1}^{N_{bu}} P_{\mathrm{load},i} + \sum_{i=1}^{N_{\mathrm{br}}} P_{\mathrm{loss},i}, \\ Q_{\mathrm{slack}} = \displaystyle\sum_{i=1}^{N_{\mathrm{bu}}} Q_{\mathrm{load},i} + \sum_{i=1}^{N_{\mathrm{br}}} Q_{\mathrm{loss},i}, \end{cases} \tag{2}$$

where P_{slack} and Q_{slack} are the active and reactive power of the reference bus, N_{bu} is the number of nodes of the distribution system, and $P_{\mathrm{loss},i}$ and $Q_{\mathrm{loss},i}$ are the active and reactive power losses of the ith branch.

For the NR problem, this constraint is checked based on the results of the load flow problem that is solved by using Newton's method. From a network configuration created by the optimization algorithm, the branches and nodes parameters of the distribution network are updated. Then, the load flow problem is solved. And, if the load flow problem based on Newton's method converges, it means that the power balance constraint is guaranteed; if the problem does not converge after the number of preset iterations, it means that the load flow problem cannot be solved successfully and the power balance constraint is not satisfied.

Node voltage and branch current constraints: voltage amplitude of nodes and current on branches should be in permitted values as follows:

$$\begin{cases} V_{\min}^{\lim} \le V_i \le V_{\max}^{\lim}, & i = 1, 2, \cdots, N_{\mathrm{bu}}, \\ 0 \le I_i \le I_{\max,i}^{\lim}, & i = 1, 2, \cdots, N_{\mathrm{br}}, \end{cases} \tag{3}$$

where $V_{\min}^{\lim}$ and $V_{\max}^{\lim}$ are the allowed minimum and maximum voltage amplitudes, respectively; V_i is the voltage amplitude at the ith node; N_{bu} is the number of nodes of the system; and I_i and $I_{\max,i}^{\lim}$ are the current on the ith branch and the allowed maximum current of the ith branch, respectively.

After successfully resolving the load flow problem, the power losses are not only calculated but also the nodes' voltage and branches' current are determined. Then, these results are compared with the allowed values to determine the level of violation of the above technical constraints. The allowable voltage limit is chosen to be ±5% of the nominal value; meanwhile, the current limit is determined by the rated current value of the branches.

Radial topology: it should be satisfied as follows [44, 45]:

$$|\det(A)| = 1, \tag{4}$$

where A is the $N_{\mathrm{br}} \times N_{\mathrm{bu}}$ matrix representing the connection of the distribution system and A (i, j) is set to 1 or −1 if the ith branch connected from/to the jth node; otherwise, A (i, j) is set to 0.

This is considered a prerequisite constraint of the NR problem. A network structure generated by the optimization algorithm is considered to be valid when this constraint is guaranteed. If the created configuration does not satisfy this constraint, then the load flow problem does not need to be solved and the voltage and current constraints are no longer concerned.

3. The Initial Searching Point for the Metaheuristic Algorithm

3.1. A Method of Determining the Initial Searching Point for the NR Problem. In a simple distribution system as shown in Figure 1, if the switch AB is closed, the system will operate with a closed topology. At that time, the power loss of the closed distribution system (called ΔP_{loop}) will be minimum and determined by

$$\Delta P_{\mathrm{loop}} = \sum_{k=1}^{N_{\mathrm{FA}}} R_k I_k^2 + \sum_{k=1}^{N_{\mathrm{FB}}} R_k I_k^2 + R_{\mathrm{AB}} I_{\mathrm{AB}}^2, \tag{5}$$

where N_{FA} and N_{FB} are the number of branches on the FA side and FB side, respectively. R_k and I_k are the resistance and current of the kth branch, respectively. R_{AB} is the resistance of the branch AB. I_{AB} is the current on the branch AB as the switch AB is closed.

If the switch AB is opened, the system will operate with a radial topology. The current on the FA side will decrease by the amount of I_{AB} and the current on the FB side will increase by amount of I_{AB}. The power loss in the radial system (called ΔP_{open}) is determined by

$$\Delta P_{\mathrm{open}} = \sum_{k=1}^{N_{\mathrm{FA}}} R_k \left(I_k - I_{\mathrm{AB}}\right)^2 + \sum_{k=1}^{N_{\mathrm{FB}}} R_k \left(I_k + I_{\mathrm{AB}}\right)^2. \tag{6}$$

The power loss of the radial distribution system is definitely higher than that of the closed system, and the difference between power loss of the radial and closed system is determined as follows [17]:

$$\Delta P_{\mathrm{open}} - \Delta P_{\mathrm{loop}} = I_{\mathrm{AB}}^2 \left(\sum_{k=1}^{N_{\mathrm{FA}}} R_k + R_{\mathrm{AB}} + \sum_{k=1}^{N_{\mathrm{FB}}} R_k \right). \tag{7}$$

From (7), if the current flowing through the branch AB is the smallest compared to other branches in the closed loop, then opening the branch AB will obtain a radial topology

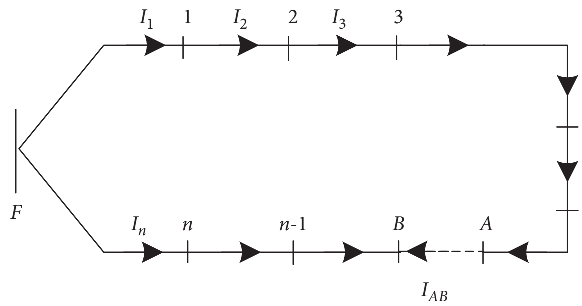

Figure 1: The simple loop distribution system.

with the minimum power loss. Ideally, if there existed a branch with zero current in the closed distribution system, power loss of the radial topology obtained by opening this branch would be equal to power loss of the closed topology.

Thus, for a distribution system existing in D closed loops, we can solve the power flow problem for system once, and then the branch having the smallest current in each closed loop will be opened like the method used in [11] to obtain a radial topology that causes minimum power loss. However, using this method, the influence among closed loops can also affect the obtained results. In addition, the constraint of the radial topology may not be guaranteed for opening a branch with the smallest current. Therefore, in order to overcome the above limitations, in this study, a method of determining the initial search point (ISP) is developed based on an idea of the NR method in [12] as follows:

Step 1: determine the original grid topology with open switches $\{s_1, s_2, \cdots, s_D\}$.

Step 2: close an open switch in the original open switches. At that time, the system has only one closed loop.

Step 3: solve the power flow problem.

Step 4: select the branch with the lowest current value in the closed loop and open this branch.

Step 5: check constraint of radial topology. If the radial topology is obeyed, the open switch is chosen as the initial search point for the first closed loop. Otherwise, if the radial topology is not kept, this branch will be removed from the loop and the algorithm will go back to step 4 to continue selecting the branch for opening.

Step 6: replace the original open switch by the newly defined open switch.

Step 7: repeat steps (2)–(6) to determine the next open switch.

Step 8: the algorithm will be stopped after the last original open switch is replaced by a new open switch.

The flowchart of algorithm for defining ISP for the metaheuristic algorithm to the NR problem for minimizing power loss is shown in Figure 2.

3.2. The Application CGA Using the Initial Searching Point for the NR Problem. To evaluate the effect of ISP to the optimal solution obtained, the genetic algorithm in a continuous form is used to attach ISP for solving the NR problem. Continuous genetic algorithm (CGA) works with continuous variables. This method is inspired from the process of natural selection and evolutionary process. The principal operators of the CGA are selection, crossover, and mutation. The details of CGA using ISP for the NR problem are presented as follows:

Step 1: initialization of the population

In CGA, each chromosome can be considered as a candidate solution that is randomly created in the process of initialization. Therefore, each chromosome of CGA for the NR problem is represented by $[S_d]$with$d = 1, 2, \cdots, D$, in which D is the number of open switches of the distribution system and S_d is a position of open switch in the dth loop vector. Note that the dth loop vector is a set of open switches in the loop that is produced by closing the dth initial open switch of the distribution system. Each candidate solution is randomly generated as follows:

$$X_i = \text{round}\left[1 + r_1 \cdot \left(S_{\max,d} - 1\right)\right], \quad i = 1, \cdots, N, d = 1, \cdots, D, \tag{8}$$

where $S_{\max,d}$ is the length of the dth loop vector, N is the population size, and r_1 is a random number between 0 and 1.

From the initial population created, ISP obtained from Section 3.1 is attached to a random position in the initial population as follows:

$$X_{(r_2,:)} = \text{ISP}, \tag{9}$$

where r_2 is a random integer number between 1 and N.

Based on the initial population, the power flow using the Newton–Raphson load flow method [46] is run, then the fitness function value of each chromosome is evaluated by the fitness function as follows:

$$\text{fit} = f + K \cdot [\Delta V_{\min} + \Delta V_{\max} + \Delta I_{\max}], \tag{10}$$

where $\Delta V_{\min}$ is the positive difference between the allowed lower limit and the minimum voltage in the system. $\Delta V_{\max}$ is the positive difference between the maximum voltage in the system and the allowed upper limit. $\Delta I_{\max}$ is the positive difference between the maximum load carrying factor in the system and the allowed upper limit of load carrying factor. K is the penalty coefficient for violation of constraints.

As mentioned in Section 2, if the radial topology is not guaranteed, the candidate solution is considered invalid. Then, a bad value will be nominated to the fitness function so that the invalid solution is eliminated in the next generation, thanks to the mechanisms of operation

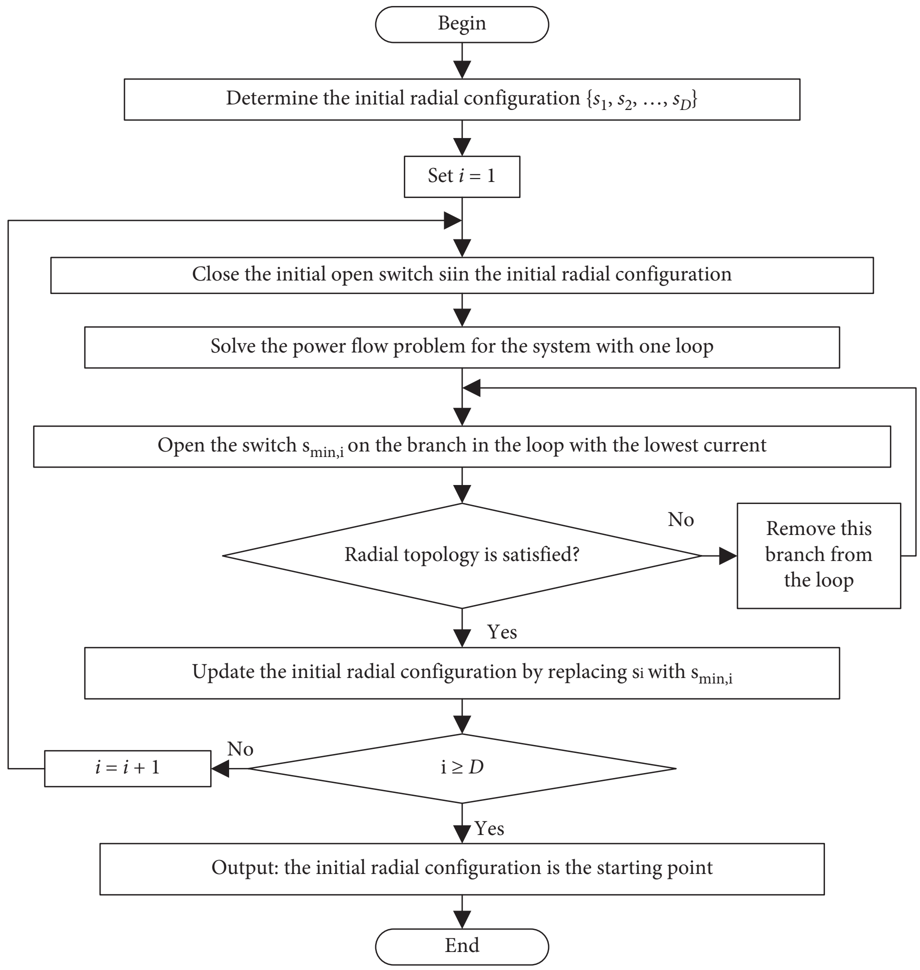

FIGURE 2: The algorithm flowchart of defining ISP.

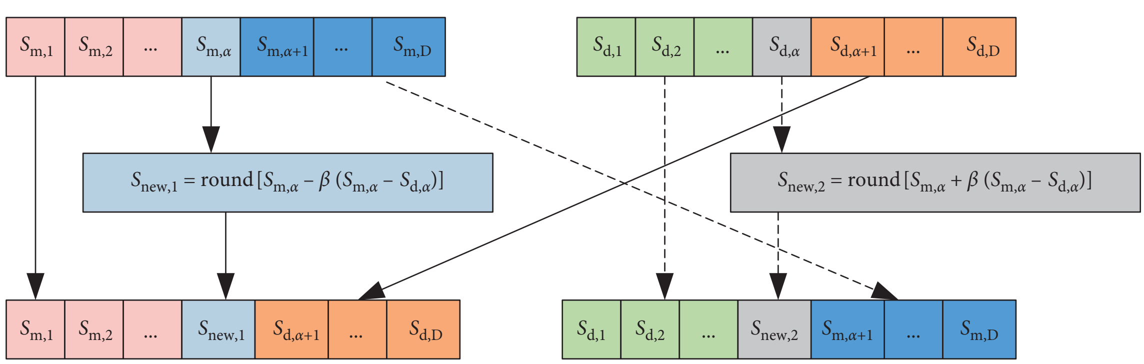

FIGURE 3: CGA crossover operation.

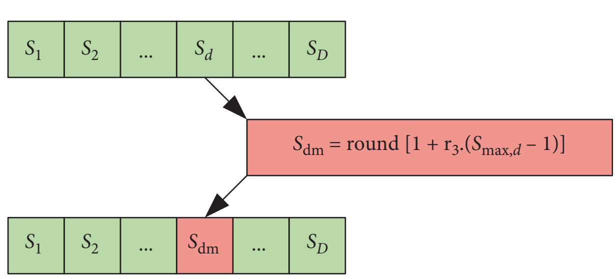

FIGURE 4: CGA mutation representation.

of the algorithm. Noted that, for the minimum problem, the bad value of the fitness function is a very high number. If the radial topology condition is satisfied, the load flow problem is calculated. Then, if the load flow problem succeeds, the fitness value as shown in equation (10) is calculated. Conversely, if the load flow problem fails, the power balance condition is not satisfied, and a bad value is also assigned to the fitness function.

Step 3: selection of the good chromosomes

The purpose of selection helps to enhance chances for the best chromosomes replicated in the population. The selection is executed based on the fitness function value of chromosomes. First, population is ranked from the lowest to highest fitness function value. Then, only the top N_{keep} chromosomes are selected to survive for the next generation, while the rest are deleted to make place for the new offspring. For selecting each parent, the rank weighting method is used to give preference to fitter chromosomes.

Step 4: crossover for new offspring

The crossover helps to exchange of information among different chromosomes. The new chromosomes contribute to increase the diversity of the population. They help CGA to explore new points in the search space. In this paper, the single crossover point is used to generate offspring. However, for the continuous chromosome, the crossover method do not generate new information in the population because each continuous value that was randomly generated in the population is reproduced to the next generation in other combinations. Therefore, the crossover method proposed in [47] is used to generate offspring. The main steps can be described as follows:

(1) To select a random switch in the pair of parents to be the crossover point:

$$\text{Parent}_1 = \left[S_{m,1}, S_{m,2}, \cdots, S_{m,\alpha}, \cdots, S_{m,D}\right], \tag{11}$$

$$\text{Parent}_2 = \left[S_{d,1}, S_{d,2}, \cdots, S_{d,\alpha}, \cdots, S_{d,D}\right], \tag{12}$$

where Parent_1 and Parent_2 are the chromosomes selected to make crossover. m and d subscripts discriminate between the Parent_1 and Parent_2. α is the integer number chosen from [1, D].

(2) To replace $S_{m,\alpha}$ and $S_{d,\alpha}$ by a new switch which is combined by $S_{m,\alpha}$ and $S_{d,\alpha}$:

$$S_{\text{new},1} = \text{round}\left[S_{m,\alpha} - \beta\left(S_{m,\alpha} - S_{d,\alpha}\right)\right], \tag{13}$$

$$S_{\text{new},2} = \text{round}\left[S_{m,\alpha} + \beta\left(S_{m,\alpha} - S_{d,\alpha}\right)\right], \tag{14}$$

where β is a random number in [0, 1].

(3) To generate offspring by a single-point crossover:

$$\text{offspring}_1 = \left[S_{m,1}, S_{m,2}, \cdots, S_{\text{new},1}, \cdots, S_{d,D}\right], \tag{15}$$

$$\text{offspring}_2 = \left[S_{d,1}, S_{d,2}, \cdots, S_{\text{new},2}, \cdots, S_{m,D}\right]. \tag{16}$$

The CGA crossover operation is shown in Figure 3.

Step 5: mutation for generating new chromosomes

To allow CGA to avoid local optimization and to explore new points in the search areas, mutation is used. In this work, the mutation rate (X_{mut}) is selected equal 20% of the total number of open switches in the population. Noted that the first chromosome is not mutated because of elitism. These open switches are replaced by new ones as follows:

$$S(i,d) = \text{round}\left[1 + r_3 \cdot \left(S_{\max,d} - 1\right)\right], \tag{17}$$

where $S(i,d)$ is a position of open switch chosen to mutate. r_3 is a random number between 0 and 1. Figure 4 shows CGA mutation operation.

Step 6: evaluation of the fitness function value.

Based on the new created population, the fitness function value of each chromosome is calculated by using (10). Relying on the fitness function values, the best so far chromosome (X_{gbest}) with the best fitness function value (f_{gbest}) is obtained.

Step 7: checking the stop condition.

The processes of selection, crossover, and mutation are continuously executed until the number of generations arrives to the maximum value ($G_{\max}$). The flowchart of the proposed CGA using the ISP for the NR problem is given in Figure 5.

4. Numerical Results

To evaluate the effectiveness of the proposed method, the method of determining ISP and the method of CGA using ISP is built on Matlab platform and run on personal computers. Three distribution systems including 33 nodes, 69 nodes, and 119 nodes are used to reconfigure for power loss reduction. For each system, the following three cases of network reconfiguration are examined:

Case 1: reconfiguration using CGA with the initial population generated randomly (called the random method)

Case 2: reconfiguration using CGA with the initial radial configuration attached to the initial population generated randomly (called the initial method)

Case 3: reconfiguration using CGA with the ISP attached to the initial population generated randomly (called the heuristic method and the proposed method)

The control parameters for CGA are selected based on many experiments as follows: the selection ratio is set to 0.5, and the mutation ratio is selected to be 0.2. The dimension of

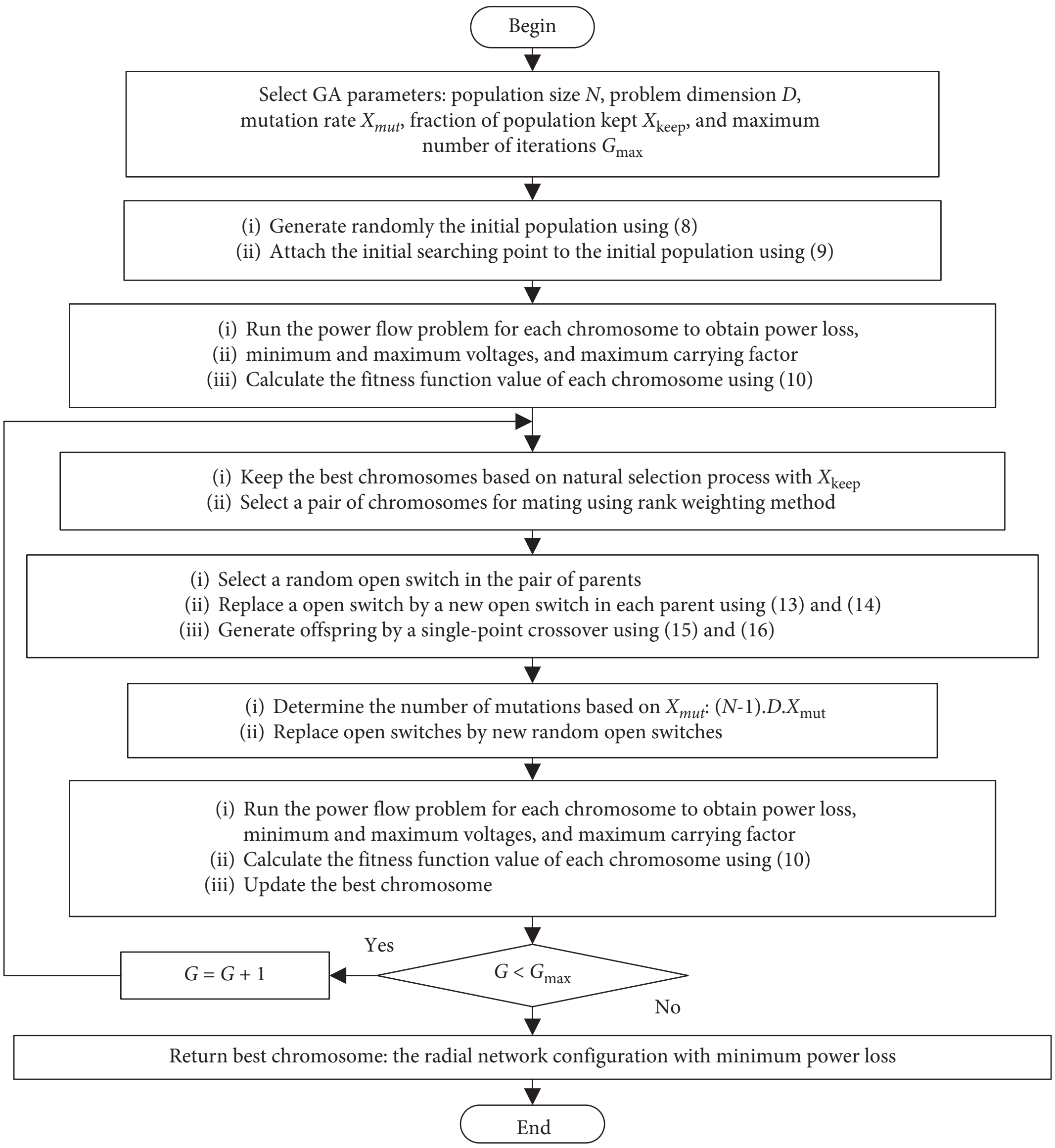

FIGURE 5: The flowchart of the CGA using ISP for the NR problem.

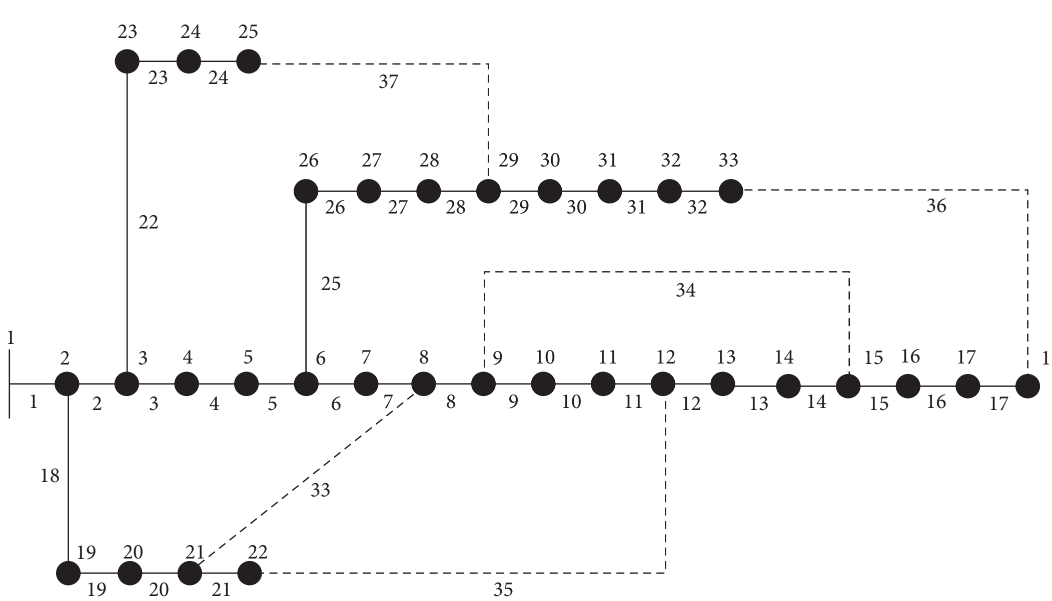

FIGURE 6: The 33-node test system.

Table 1: The initial solution attached to the initial population for the 33-node system.

Methods	Optimal switches	Power loss (kW)	Minimum voltage (p.u)	Maximum load carrying coefficient	Value of fitness function
Random	None	—	—	—	—
Initial	33, 34, 35, 36, 37	202.6863	0.9131	0.8250	239.6095
Heuristic	7, 14, 9, 32, 37	139.5543	0.93782	0.8123	151.7381
H-matrix [43]	7, 11, 14, 28, 32	141.6351	0.9412	0.8130	150.3934

the problem for 33 nodes, 69 nodes, and 119 nodes test systems is selected to 5, 5, and 15, respectively. The penalty coefficient for violating the constraints of the NR problem in the fitness function is chosen by 1000 for all three systems.

4.1. The 33-Node Test System. The 12.66 kV, 33-node test distribution system includes 5 opened switches and 32 closed switches shown in Figure 6. The branch and node parameters of the system are referenced from [48]. The branches' rated current is set to 255 A.

The results of ISP determination using the proposed method are presented in Table 1. The initial radial configuration of the 33-node system is the radial topology with opened switches {33, 34, 35, 36, and 37}. This topology causes the power loss of 202.6863 kW, the minimum voltage amplitude of 0.9131 p.u, and the maximum load carrying factor of 0.8250, corresponding to the fitness function value of 239.6095. Meanwhile, using the proposed method, after solving the power flow problem by five times, the ISP found is {7, 14, 9, 32, and 37}. This radial topology only causes the power loss of 139.5543 kW, the minimum voltage amplitude of 0.93782 p.u, and the maximum load carrying factor of 0.8250, corresponding to the fitness function value of 151.7381. This radial topology is better than the initial radial topology in terms of the fitness function value. It is obvious that CGA starting with ISP will be more effective than starting with the initial radial topology or random initialization. Compared with the ISP obtained by the H-matrix method [43], the ISP obtained by the proposed heuristic method has a power loss of less than 2.0808 kW and the minimum voltage amplitude in the distribution system is lower than 0.00338 p.u. Because of the penalty factors for violating the constraints set to 1000, the value of the ISP's fitness function obtained by the proposed method is slightly higher than that of the *H*-matrix method.

The NR results for the 33-node system in the three cases of population initialization using CGA with the maximum number of generations set to 100 are presented in Table 2. In particular, because ISP is attached to the initialization population, the population size will affect directly to the calculation results. Therefore, population size is set at different values such as 4, 6, 10, and 20 to validate the effectiveness of the suggested method.

For N set to 4, the CGA using ISP obtained from the proposed heuristic method has identified an operating radial topology {7, 9, 14, 28, and 32} with the fitness function value (fit_{min}) of 148.7392. In particular, the successful rate of the proposed method, which is defined by resulting from the division of number of runs finding out the best solution by total of runs, is much higher than that of the random method and the initial method. The successful rate of the proposed method is 54%, while this figure for the remaining two methods is 8%. In addition, the maximum (fit_{max}), mean (fit_{mean}), and standard deviations (STDs) of the fitness function obtained from the proposed method are much lower than the random and the initial methods. Similarly, the average number of converged generations of the proposed method is lower than the two comparison methods. The average number of convergence generations of the proposed method is 13.5 generations, while this value of the random and initial methods is 66.6 and 51.3 generations, respectively.

As N is increased to 6, the successful rate using the proposed heuristic method is also higher than that of the rest two methods. The successful rate of the proposed heuristic method is up to 68%, while for the random and initial methods, the successful rate is also improved compared to the case of N equal to 4 but only reached 20% and 16%, respectively. The inferiority of the random and initial methods compared to the heuristic method continues to be evident when N is increased to 10 and 20. Especially, in the case of N set to 20, the successful rate by using the proposed heuristic method reaches 100%. This means that the CGA has found the optimal radial topology in all 50 runs. Meanwhile, this rate only reaches 72% and 68% for the random and initial methods, respectively. In addition, the quality of the obtained solution shown in terms of the maximum, mean, and STD of the fitness function in 50 runs obtained from the proposed method is also better than the two comparison methods in all cases of different values of N. Meanwhile, the execution times of the methods in each cases of N are similar.

A comparison chart of the three methods with different N values is presented in Figure 7. The figure shows the superiority of the suggested method in terms of indicators fit_{max}, fit_{mean}, successful rate, and G_{mean} compared to the random and initial methods. Figure 7 can give good evidence for the outstanding search ability of the proposed heuristic method over the random and initial methods since approximately all cases of population size of the proposed heuristic method has higher successful rate and lower fit_{max},

Table 2: Comparison of three cases of population initialization of CGA for the 33-node system.

Initialization method	Random	Initial	Heuristic	Random	Initial	Heuristic	Random	Initial	Heuristic	Random	Initial	Heuristic
N	4	4	4	6	6	6	10	10	10	20	20	20
Initial configuration	None	33, 34, 35, 36, 37	7, 14, 9, 32, 37	None	33, 34, 35, 36, 37	7, 14, 9, 32, 37	None	33, 34, 35, 36, 37	7, 14, 9, 32, 37	None	33, 34, 35, 36, 37	7, 14, 9, 32, 37
Best configuration	7, 9, 14, 28, 32	7, 9, 14, 28, 32	7, 9, 14, 28, 32	7, 9, 14, 28, 32	7, 9, 14, 28, 32	7, 9, 14, 28, 32	7, 9, 14, 28, 32	7, 9, 14, 28, 32	7, 9, 14, 28, 32	7, 9, 14, 28, 32	7, 9, 14, 28, 32	7, 9, 14, 28, 32
Successful rate	4/50 (8%)	4/50 (8%)	27/50 (54%)	10/50 (20%)	8/50 (16%)	34/50 (68%)	23/50 (46%)	21/50 (42%)	45/50 (90 %)	36/50 (72%)	34/50 (68%)	50/50 (100 %)
fit_{max}	303.6693	172.961	151.7381	313.7205	164.3427	151.7381	306.7859	161.046	151.7381	161.046	161.046	148.7392
fit_{min}	148.7392	148.7392	148.7392	148.7392	148.7392	148.7392	148.7392	148.7392	148.7392	148.7392	148.7392	148.7392
fit_{mean}	158.395	155.6564	150.1187	156.9228	154.4191	149.6988	154.8182	151.9456	149.0391	150.9891	150.7072	148.7392
STD	21.7029	4.5089	1.5098	23.0539	4.0511	1.4131	22.2315	3.5883	0.9088	4.0911	3.4337	0
G_{mean}	66.6	51.3	13.5	58.06	51.04	15.66	49.9	45.78	17.94	43.52	46.6	14.42
Run time (s)	1.3784	1.5438	1.1712	2.3425	2.3163	1.7703	3.18	3.1456	2.5953	4.9947	5.0228	4.0147

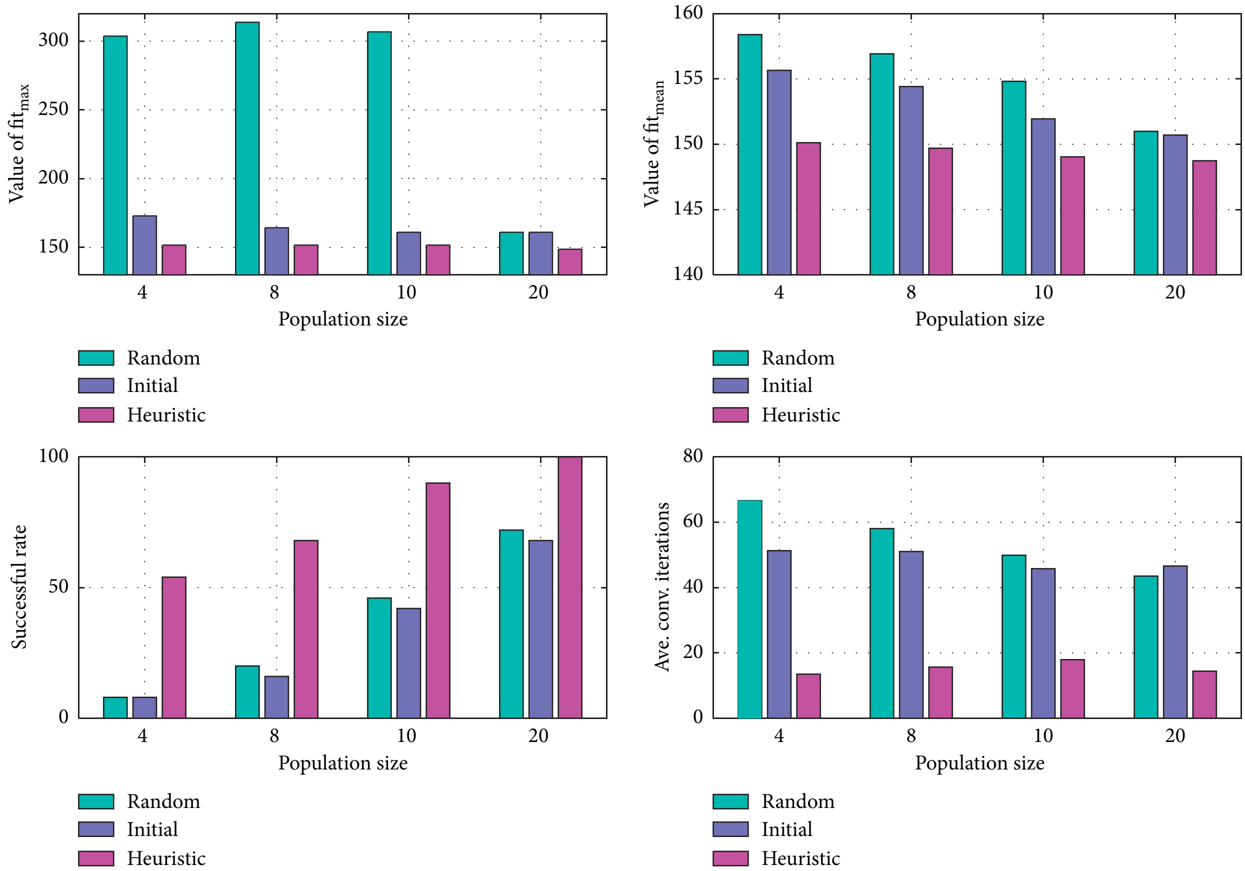

Figure 7: Comparisons among three initialization methods in terms of fit_{max}, fit_{mean}, successful rate, and the number of average convergence iterations (G_{mean}) for the 33-node system.

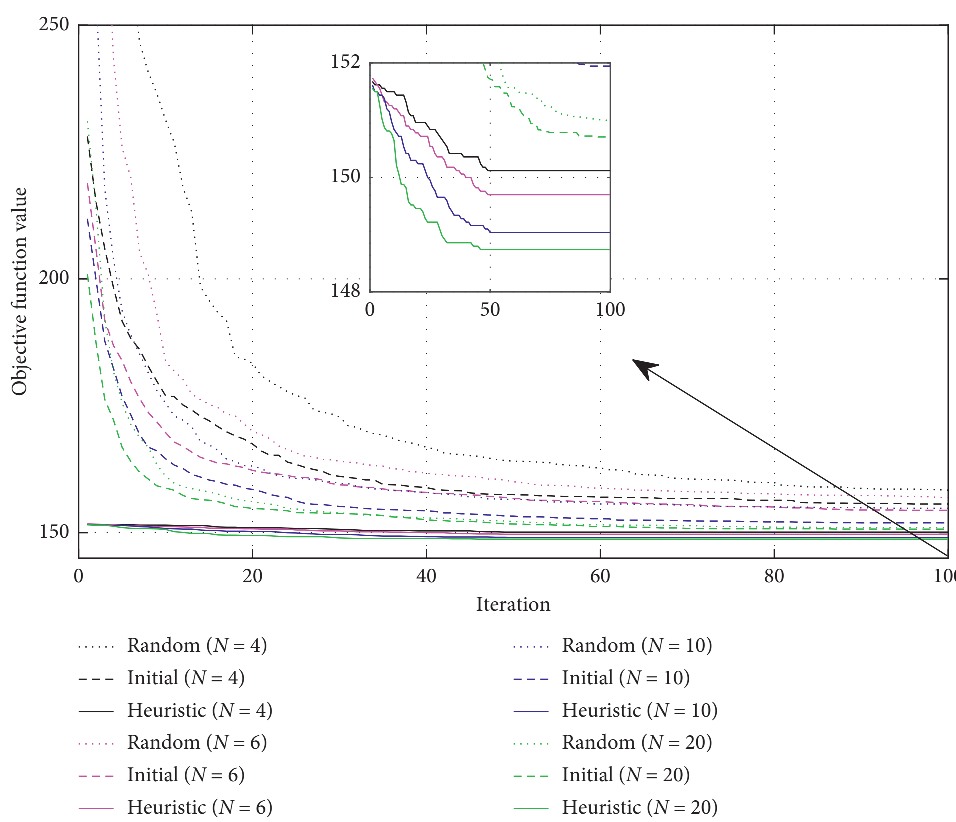

Figure 8: Mean convergence curves of three initialization methods with different population sizes for the 33-node system.

Table 3: Comparison results among proposed method CGA using ISP with different methods for the 33-node system.

Methods	Optimal switches	Power loss (kW)	Minimum voltage (p.u)	Maximum load carrying coefficient
Initial	33, 34, 35, 36, 37	202.6863	0.9131	0.8250
CGA using ISP	7, 9, 14, 28, 32	139.9823	0.9412	0.7878
PSO with *H*-matrix [43]	7, 9, 14, 32, 37	139.55	0.9378	—
ICSA [21]	7, 9, 14, 32, 37	139.55	0.9378	0.8123
RRA [18]	7, 9, 14, 32, 37	139.55	0.9378	0.8123
ACSA [20]	7, 9, 14, 28, 32	139.9823	0.9412	—
CSA [19]	7, 9, 14, 32, 37	139.55	0.9378	—
SFS [49]	7, 9, 14, 32, 37	139.55	0.9378	—
HTELA [50]	7, 9, 14, 32, 37	139.55	0.9378	—
SSA [51]	7, 9, 14, 32, 37	139.55	0.9378	—
GWO-PSO [52]	7, 9, 14, 32, 37	139.55	0.9378	—

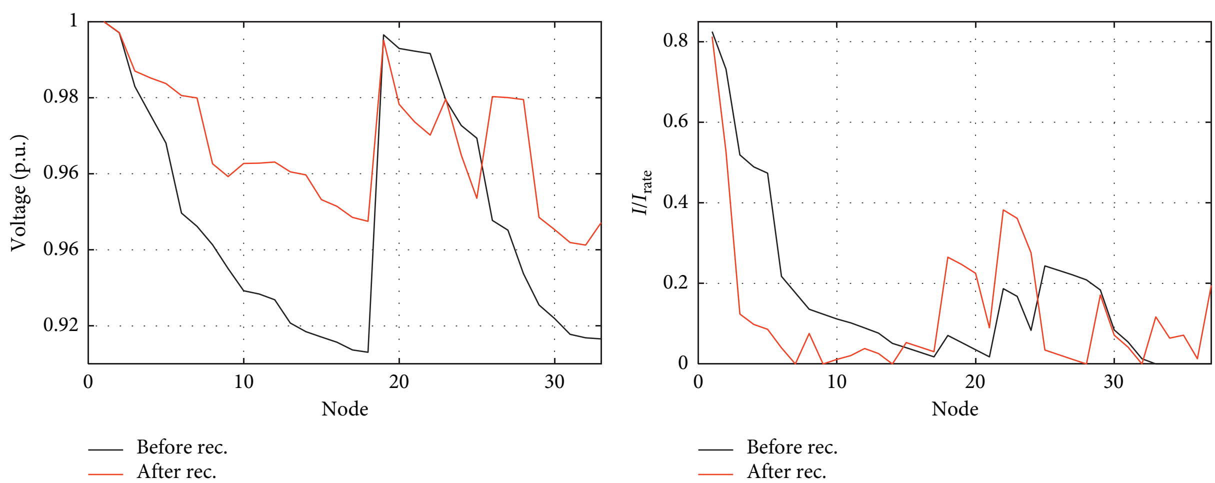

Figure 9: Voltage and current profile obtained for the 33-node system.

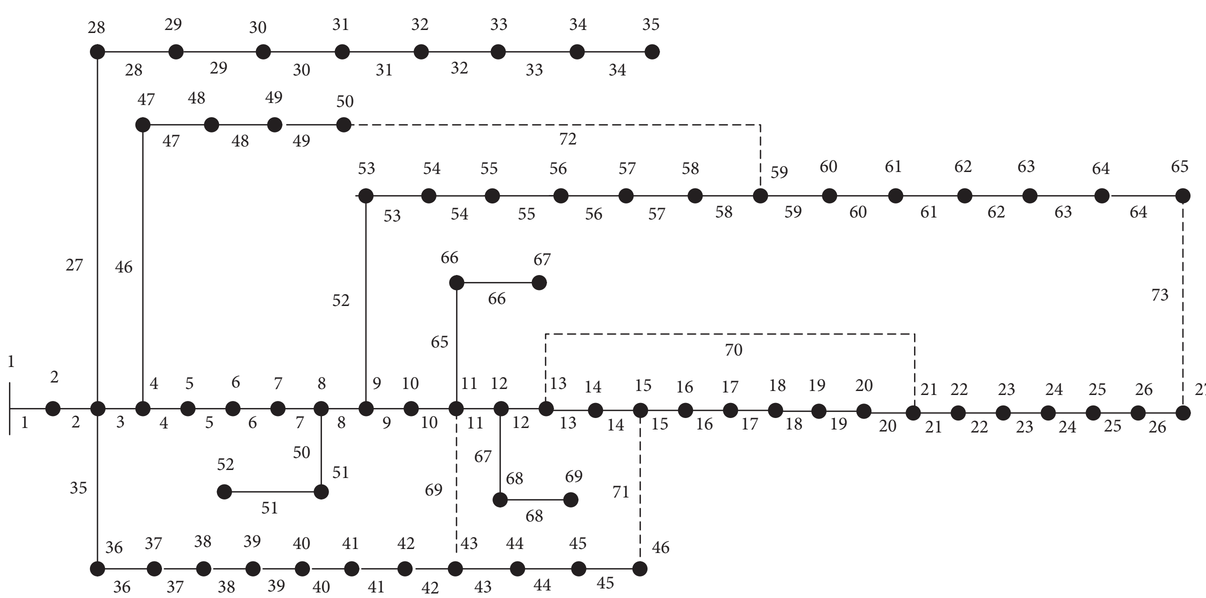

Figure 10: The 69-node test system.

Table 4: The initial solution attached to the initial population for the 69-node system.

Methods	Optimal switches	Power loss (kW)	Minimum voltage (p.u)	Value of fitness function
Random	None	—	—	—
Initial	69, 70, 71, 72, 73	224.8871	0.9092	265.6954
Heuristic	10, 17, 12, 58, 61	108.4602	0.9495	108.9792
H-matrix [43]	20, 42, 45, 58, 64	128.8804	0.9382	140.7283

fit_{mean}, and G_{mean} than the rest two methods. The mean convergence curves of three methods with different population sizes are shown in Figure 8. From the figure, CGA using the heuristic method for finding ISP converges to smaller values compared to the random and initial methods in all of cases of N. In addition, in each generation, the convergence value of the proposed method is lower than that of the rest two methods. Figure 8 sends a message that CGA using the heuristic method for finding ISP outperforms to CGA using the random and initial methods.

Table 3 shows a comparisons among the CGA using ISP and other methods in the literature. The table indicates that CGA using ISP can reach the same power loss, minimum voltage, and maximum load carrying coefficient as the ACSA method. Compared to other methods such as PSO with *H*-matrix, ICSA, RRA, CSA, stochastic fractal search (SFS), heuristic technique relied on the exact loss formula (HTELA), salp swarm algorithm (SSA) and GWO-PSO, and CGA using ISP reaches lower power loss reduction, but the proposed method suffers higher minimum voltage and lower maximum load carrying coefficient than all other methods. The voltage and current profile shown in Figure 9 indicates that the improvement level of voltage and current profile over the initial topology of the 33-node system is significant. The network configuration does not violate the current constraint. For the voltage constraint, although the minimum voltage amplitude is 0.9412 p.u, which is 0.0088 lower than the allowed value, it has been greatly improved compared to its original value of 0.9131 p.u and better than that of almost compared methods.

4.2. The 69-Node Test System. The 12.66 kV, 69-node test distribution system includes 5 opened switches and 68 closed switches. The single line diagram of the system is presented in Figure 10. The branch and node parameters of the system are referenced from [53]. In this system, the current constraint is not considered due to lack of the branches' rated current.

The results of ISP determination using the proposed method are presented in Table 4. The initial radial configuration with opened switches {69, 70, 71, 72, and 73} causes the power loss of 224.8871 kW and the minimum voltage amplitude of 0.9092 p.u corresponding to the fitness function value of 265.6954. Meanwhile, using the proposed ISP method, the ISP obtained is {10, 17, 12, 58 and 61}, which causes a power loss of 108.4602 kW, and the minimum voltage amplitude of 0.9495 p.u corresponding to the fitness function value of 108.9792. This fitness value is much lower than that of the initial radial configuration. Compared with the ISP obtained by the *H*-matrix method [43], the ISP gained by the proposed heuristic method has a power loss of less than 20.4202 kW and the minimum voltage amplitude in the distribution system is higher than 0.0113 p.u. The value of the ISP's fitness function gained by the suggested method is 31.7491 lower than that of the *H*-matrix method. Clearly, the proposed method has identified better ISP than the *H*-matrix method.

The NR results for the 69-node system based on CGA with the different population sizes are presented in Table 5. For N set to 4, 6, 10, and 20, all of three methods have determined the optimal radial topology with open switches {14, 57, 61, 69, and 70}. However, the successful rate obtained by the proposed method is much higher than the random and initial methods. The proposed method's successful rate for N set to 4, 6, 10, and 20 is 14%, 38%, 70%, and 92%, respectively, while this number is 10%, 36%, 46%, and 82% for the initial method and 14%, 32%, 68%, and 82% for the random method. The maximum value of the fitness function in 50 runs of the proposed method in all cases of population size is also the smallest compared to the other two methods. This result is obtained because the ISP based on the heuristic method always ensures the initial radial topology that has a good fitness value in the initial population of CGA. In addition, the mean value and STD of the fitness function are the smallest of the three methods. This shows the stability of CGA using ISP found from the heuristic method. Table 5 also shows that the average number of convergence generations of the proposed method is also much lower than the random and the initial methods. Specifically, for N set to 4, 6, 10, and 20, CGA using ISP obtained by the proposed method has converged after about 29.94, 34.78, 35.52, and 32.52 generations while using the random method; CGA has converged after about 69.76, 53.46, 46.12, and 42.62 generations, and the average number of convergence generations is 58.86, 57.26, 46.06, and 44.44 generations for the initial method.

A comparison chart of the three methods with different N values for the 69-node system is given in Figure 11. From the figure, for all cases of population size, the proposed heuristic method has a higher successful rate and lower fit_{max}, fit_{mean}, and G_{mean} than the random and initial methods. The mean convergence curves of three methods

Table 5: Comparison of three cases of population initialization of CGA for the 69-node system.

Initialization method	Random	Initial	Heuristic	Random	Initial	Heuristic	Random	Initial	Heuristic	Random	Initial	Heuristic
N	4	4	4	6	6	6	10	10	10	20	20	20
Initial configuration	None	69, 70, 71, 72, 73	10, 17, 12, 58, 61	None	69, 70, 71, 72, 73	10, 17, 12, 58, 61	None	69, 70, 71, 72, 73	10, 17, 12, 58, 61	None	69, 70, 71, 72, 73	10, 17, 12, 58, 61
Best configuration	14, 57, 61, 69, 70	14, 57, 61, 69, 70	14, 57, 61, 69, 70	14, 57, 61, 69, 70	14, 57, 61, 69, 70	14, 57, 61, 69, 70	14, 57, 61, 69, 70	14, 57, 61, 69, 70	14, 57, 61, 69, 70	14, 57, 61, 69, 70	14, 57, 61, 69, 70	14, 57, 61, 69, 70
Successful rate	7/50 (14%)	5/50 (10%)	7/50 (14%)	16/50 (32%)	18/50 (36%)	19/50 (38%)	34/50 (68%)	23/50 (46%)	35/50 (70%)	41/50 (82%)	43/50 (86%)	46/50 (92%)
fit_{max}	126.6893	107.2176	101.4554	105.4343	112.1841	101.3691	101.2904	126.6852	99.2094	101.2904	101.2904	99.2094
fit_{min}	99.1169	99.1169	99.1169	99.1169	99.1169	99.1169	99.1169	99.1169	99.1169	99.1169	99.1169	99.1169
fit_{mean}	100.7158	100.4687	99.2793	99.9606	100.0464	99.2075	99.2982	100.0704	99.1262	99.2038	99.2057	99.1188
STD	3.900	1.7396	0.4392	1.3685	2.1427	0.3202	0.5939	3.9317	0.0280	0.4302	0.4300	0.0130
G_{mean}	69.76	58.86	29.94	53.46	57.26	34.78	46.12	46.06	35.52	42.62	44.44	32.52
Run time (s)	4.2816	4.1591	2.8737	6.3675	6.4231	4.6519	8.55	8.9997	6.6284	14.5056	14.0003	11.2716

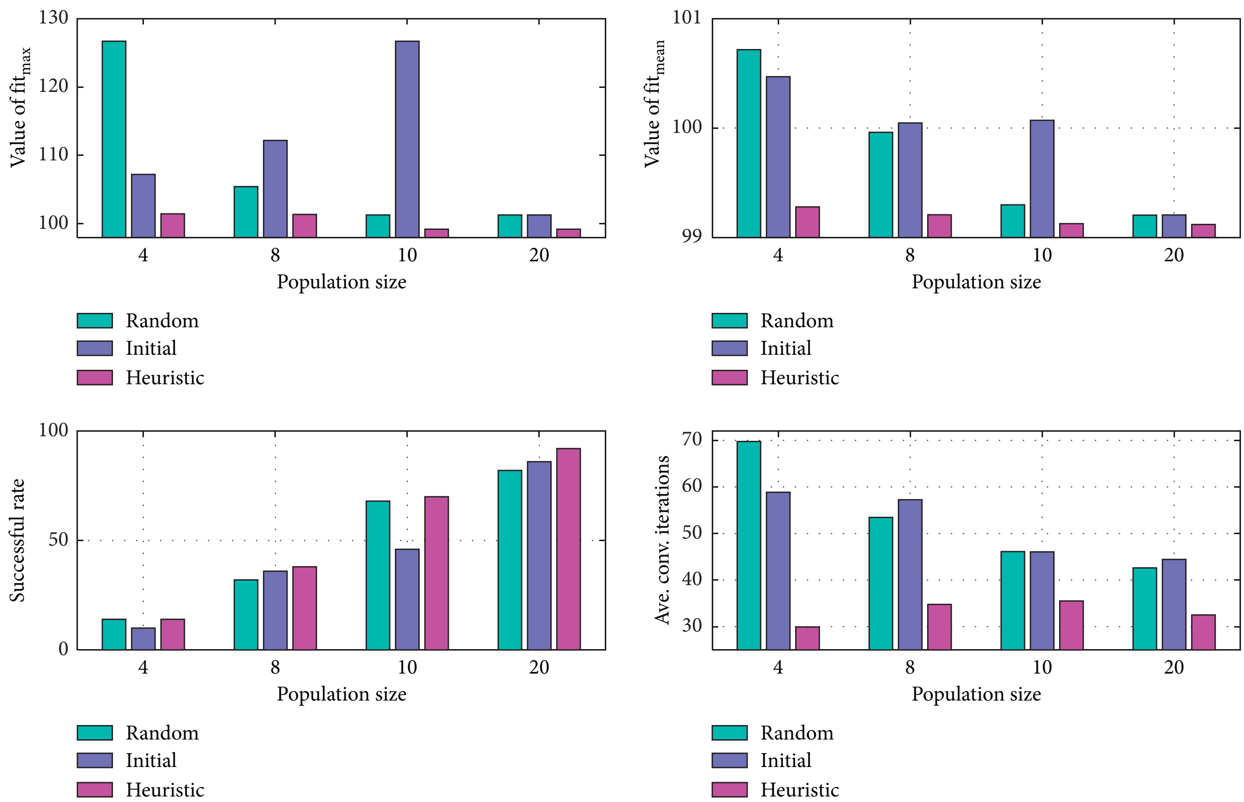

FIGURE 11: Comparisons among three initialization methods in terms of fit_{max}, fit_{mean}, successful rate, and G_{mean} for the 69-node system.

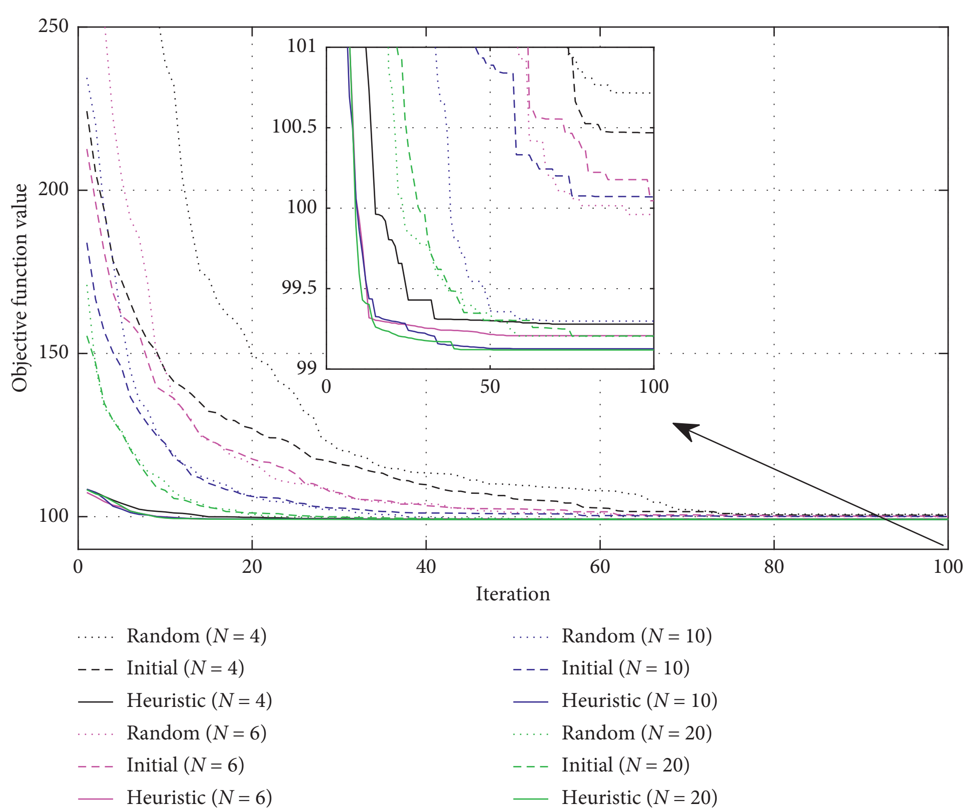

FIGURE 12: Mean convergence curves of three initialization methods with different population sizes for the 69-node system.

Table 6: Comparison results among the proposed method CGA using ISP with other methods for the 69-node system.

Methods	Optimal switches	Power loss (kW)	Minimum voltage (p.u)
Initial	69, 70, 71, 72, 73	224.8871	0.9092
CGA using ISP	14, 57, 61, 69, 70	98.5875	0.9495
PSO with H-matrix [43]	14, 58, 61, 69, 70	98.59	—
BSA [25]	14, 57, 61, 69, 70	98.5875	0.9495
ICSA [21]	69, 70, 14, 57, 61	98.59	0.9495
ACSA [20]	69, 70, 14, 57, 61	98.59	0.9495
CSA [19]	14, 57, 61, 69, 70	98.5875	0.9495
SFS [49]	14, 55, 61, 69, 70	98.62	0.9495
HTELA [50]	13, 55, 61, 69, 70	99.69	0.9428
SSA [51]	69, 14, 71, 61, 58	98.63	0.9492
GWO-PSO [52]	69, 70, 14, 57, 61	98.5875	0.9495

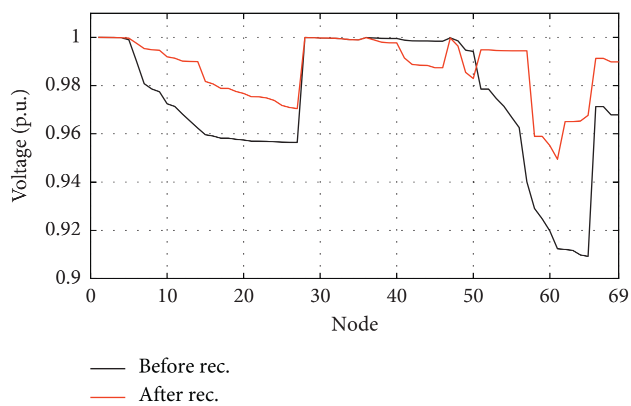

Figure 13: Voltage profile obtained for the 69-node system.

with different population sizes are shown in Figure 12. From the figure, CGA using ISP converges to smaller values compared to the random and initial methods in all cases of N. The figures once again confirms the outstanding advantages of CGA using ISP over CGA using the random and initial methods.

The comparison results with different methods in the literature for the 69-node system are shown in Table 6. This table indicates that CGA using ISP can reach the same power loss and minimum voltage as PSO with H-matrix, BSA, ICSA, ACSA, CSA, and GWO-PSO. The loss and minimum voltage of the above methods are 98.5875 kW and 0.9495 p.u, respectively. Compared to SFS, HTELA, and SSA, CGA using ISP reaches a higher power loss reduction from 0.03 to 1.1 kW. The voltage profile shown in Figure 13 indicates that the improvement level of voltage profile over the initial topology of the 69-node system is significant with the improvement of nodes' voltage amplitude. The minimum voltage amplitude is only 0.0005 lower than the allowed value, but it has been dramatically improved compared to its original value of 0.9092 p.u.

4.3. The 119-Node Test System. The 11 kV, 119-node test system is a complex large-scale system consisting of 15 open switches and 118 closed switches shown in Figure 14 [54]. Similar to the 69-node system, due to lack of rated current parameters, the assumption of reconfiguration does not overload the branches.

The results of ISP determination using the proposed method are presented in Table 7. The initial radial configuration causes the power loss of 1273.4509 kW and the minimum voltage amplitude of 0.8678 p.u corresponding to the fitness function value of 1355.6134. Meanwhile, using the proposed ISP method based on the heuristic technique, the ISP obtained is {43, 23, 120, 51, 122, 61, 39, 95, 71, 74, 97, 129, 130, 109, and 132} which causes the fitness value to be much lower than that of the initial radial configuration. This radial topology only causes power loss of 925.8662 kW and the minimum voltage amplitude of 0.9298 p.u. Compared with the ISP obtained by the H-matrix method [43], the proposed method has identified better ISP than the H-matrix method, in which the ISP obtained by the proposed heuristic method has a power loss of less than 385.134 kW and the minimum voltage amplitude in the distribution system is higher than 0.0552 p.u. The value of the ISP's fitness function gained by the proposed method is 440.286 lower than that of the H-matrix method.

The NR results of CGA using different initialization methods are presented in Table 8. Although on the 119-node

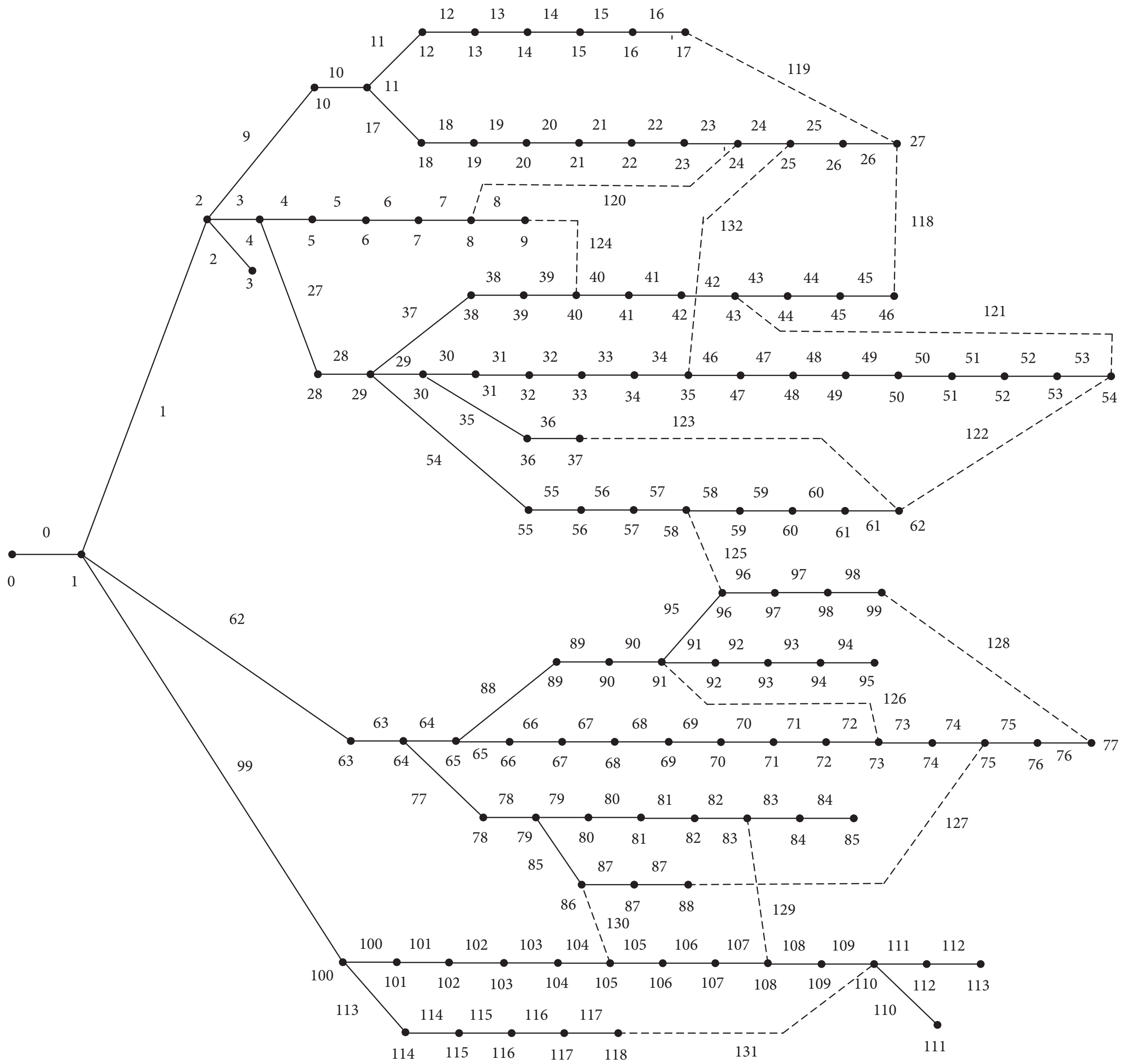

Figure 14: 119-node system.

Table 7: The initial solution attached to the initial population for the 119-node system.

Methods	Optimal switches	Power loss (kW)	Minimum voltage (p.u)	Value of fitness function
Random	None	—	—	—
Initial	118, 119, 120, 121, 122, 123, 124, 125, 126, 127, 128, 129, 130, 131, 132	1273.4509	0.8678	1355.6134
Heuristic	43, 23, 120, 51, 122, 61, 39, 95, 71, 74, 97, 129, 130, 109, 132	925.8662	0.9298	946.1137
H-matrix [43]	23, 26, 34, 39, 42, 48, 61, 74, 76, 82, 90, 95, 117, 118, 130	1311	0.8746	1386.4

system, the number of runs for finding out the optimal radial topology of CGA is quite low, but obviously, the successful rate of the method using ISP is much higher than the random and initial methods. Specifically, with N set to 6, 10, and 20, CGA has determined the optimal radial topology with the successful rate of 2%, 6%, and 6%. Meanwhile, CGA

Table 8: Comparison of three cases of population initialization of CGA for the 119-node system.

Initialization method	Random	Initial	Heuristic	Random	Initial	Heuristic	Random	Initial	Heuristic	Random	Initial	Heuristic
N	4	4	4	6	6	6	10	10	10	20	20	20
Best configuration	21, 26, 34, 39, 43, 50, 58, 71, 74, 95, 97, 109, 121, 129, 130	22, 25, 34, 42, 50, 58, 71, 74, 95, 97, 109, 121, 124, 129, 130	23, 26, 34, 39, 42, 50, 60, 71, 74, 95, 97, 109, 121, 129, 130	23, 26, 34, 39, 42, 50, 58, 71, 74, 95, 97, 109, 121, 129, 130	23, 25, 34, 39, 42, 50, 59, 71, 74, 95, 98, 109, 121, 129, 130	23, 25, 34, 39, 42, 50, 58, 71, 74, 95, 97, 109, 121, 129, 130	23, 26, 34, 39, 42, 50, 58, 72, 74, 95, 97, 109, 121, 129, 130	23, 26, 34, 39, 42, 50, 58, 71, 74, 95, 97, 109, 121, 129, 130	23, 25, 34, 39, 42, 50, 58, 71, 74, 95, 97, 109, 121, 129, 130	23, 25, 34, 39, 42, 50, 59, 71, 74, 95, 97, 109, 121, 129, 130	23, 26, 34, 39, 42, 51, 58, 72, 74, 95, 97, 109, 122, 129, 130	23, 25, 34, 39, 42, 50, 58, 71, 74, 95, 97, 109, 121, 129, 130
Successful rate	1/50 (2%)	1/50 (2%)	1/50 (2%)	1/50 (2%)	1/50 (2%)	1/50 (2%)	1/50 (2%)	1/50 (2%)	3/50 (6%)	1/50 (2%)	1/50 (2%)	3/50 (6%)
fit_{max}	1115.9702	1000.7436	946.1137	1007.8223	1008.2906	938.5475	933.2899	955.3646	941.198	953.1405	938.038	945.9922
fit_{min}	879.9191	883.1292	879.6266	875.5463	876.5684	875.2876	878.2881	875.5464	875.2876	876.108	890.3894	875.2876
fit_{mean}	935.3928	921.0358	918.2238	910.9237	909.9308	905.277	907.9795	905.2039	899.547	912.387	913.1567	906.9527
STD	44.3354	22.5353	19.9554	26.6960	21.7499	18.0110	14.1697	14.9834	20.4825	15.3140	11.9615	19.8936
G_{mean}	646.72	549.44	292.22	475.52	435.06	372.88	434.2	406.64	358.84	420.98	405.96	389
Run time (s)	32.2894	33.6934	34.1316	47.2275	46.6916	39.4119	66.08	62.9562	59.8675	107.2016	112.775	105.2428

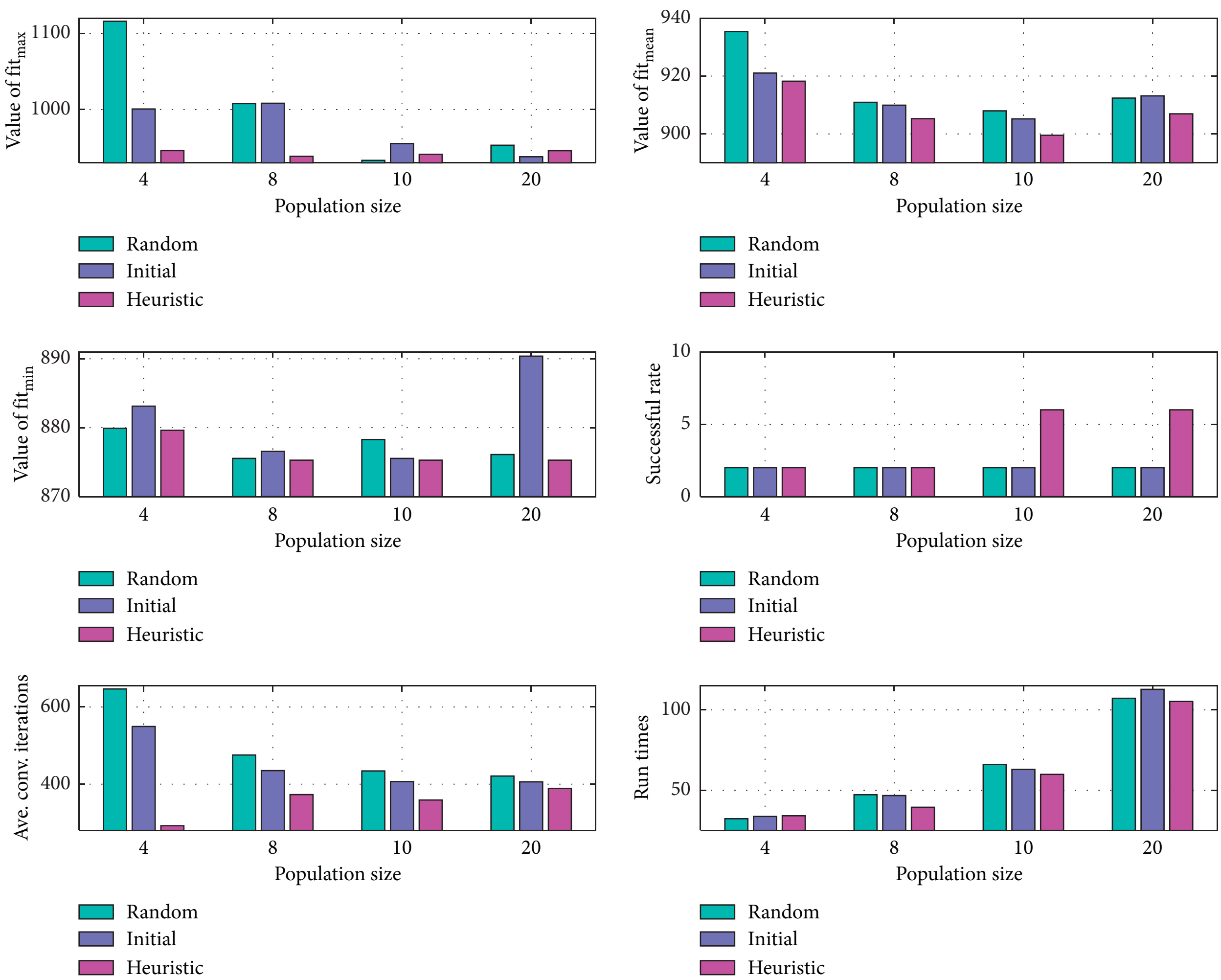

Figure 15: Comparisons among three initialization methods in terms of fit$_{max}$, fit$_{mean}$, successful rate, and G_{mean} for the 119-node system.

using the random and initial methods has not reached the optimal solution in all 50 runs. Similarly, the minimum and mean values of the fitness function and the average number of convergence generations are also lower than those of the other two methods. Figure 15 shows an overview of the effectiveness of CGA using ISP compared to the random and initial methods. The figure shows that the indicators showing the optimal solution quality obtained by CGA using ISP are better than the random and initial methods in all of cases of different values of N. Figure 16 shows that CGA using ISP always converges to a lower value than the two comparison methods.

The comparison results with different methods in the literature for the 119-node system are shown in Table 9. It indicates that CGA using ISP can reach the same power loss and minimum voltage as ICSA, ACSA, SFS, and FWA. The power loss and minimum voltage of the above methods are 855.0402 kW and 0.9298 p.u, respectively. Compared to PSO with H-matrix, improved tabu search (ITS) and modified tabu search (MTS) CGA using ISP reaches a higher power loss reduction of 18.1698 kW, 12.3598 kW, and 12.3598 kW, respectively. The voltage profile shown in Figure 17 indicates that the improvement level of voltage profile over the initial topology of the 119-node system is significant with the improvement of voltage amplitude of nodes. The minimum voltage amplitude is 2.13% lower than the allowed value, but it has been dramatically improved compared to its original value of 0.8678 p.u. that is 8.65% lower than the allowed value.

5. Conclusion

In this paper, the NR problem has been considered for power loss reduction. To enhance the efficiency of the metaheuristic algorithm for the NR problem, an effective method to determine ISP based on heuristic technology of power systems is proposed. The idea of the method is to close each initial open switch in turn and solving the power flow for the distribution system with a closed loop. A switch on a branch with the smallest current in the closed loop is opened, and if the radial topology constraint of the distribution system is satisfied, the switch opened is considered as a control variable of the ISP. The ISP solution is attached to the initial population of the metaheuristic algorithm for applying to the network reconfiguration problem. To validate the effectiveness of the suggested method, CGA is adapted to

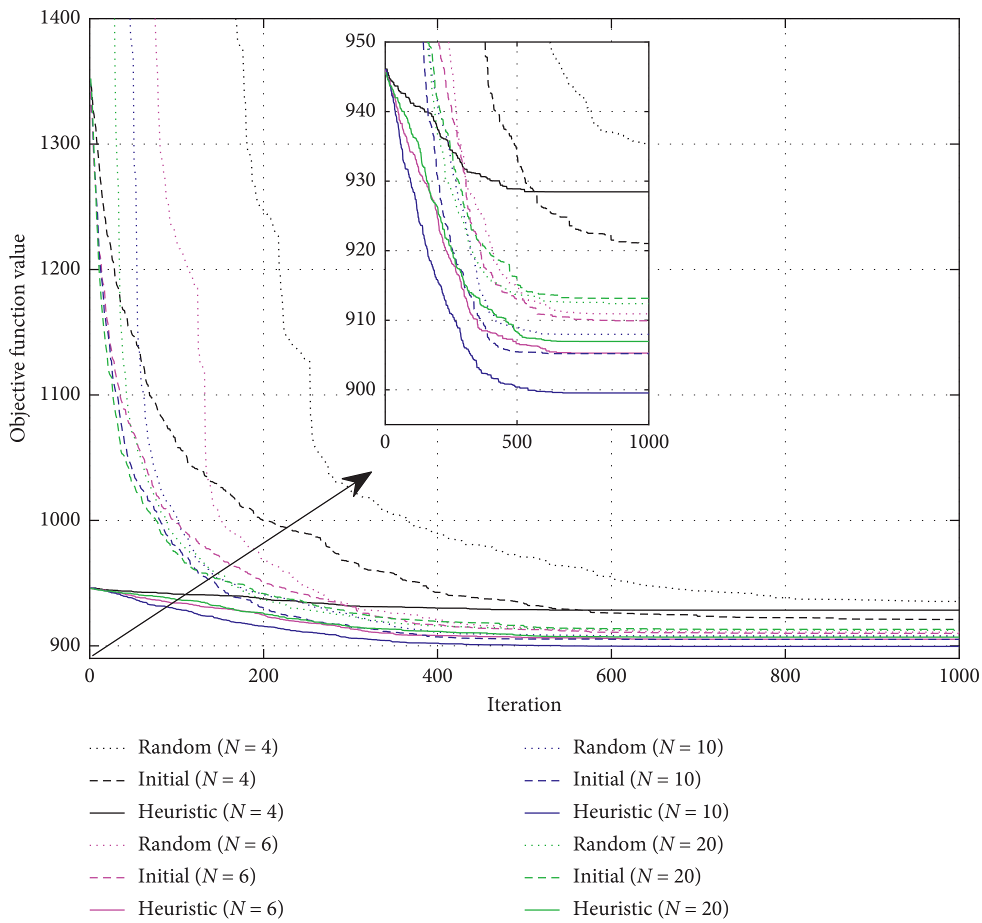

FIGURE 16: Mean convergence curves of three initialization methods with different population sizes for the 119-node system.

TABLE 9: Comparison results among the proposed method CGA using ISP with other methods for the 119-node system.

Methods	Optimal switches	Power loss (kW)	Minimum voltage (p.u)
Initial	118, 119, 120, 121, 122, 123, 124, 125, 126, 127, 128, 129, 130, 131, 132	1273.4509	0.8678
CGA using ISP	23, 25, 34, 39, 42, 50, 58, 71, 74, 95, 97, 109, 121, 129, 130	855.0402	0.9298
PSO with H-matrix [43]	23, 26, 34, 39, 42, 51 58, 71, 74, 95, 97, 109, 122, 129, 130	873.21	—
ICSA [21]	23, 25, 34, 39, 42, 50, 58, 71, 74, 95, 97, 109, 121, 129, 130	855.04	0.9298
ACSA [20]	42, 25, 23, 121, 50, 58, 39, 95, 71, 74, 97, 129, 130, 109, 34	855.04	0.9298
SFS [49]	42, 25, 23, 121, 50, 58, 39, 95, 71, 74, 97, 129, 130, 109, 34	855.04	0.9298
FWA [13]	23, 25, 34, 39, 42, 50, 58, 71, 74, 95, 97, 109, 121, 129, 130	855.04	0.9298
ITS [54]	42, 26, 23, 51, 122, 58, 39, 95, 71, 74, 97, 129, 130, 109, 34	867.4	0.9298
MTS [44]	42, 26, 23, 51, 122, 58, 39, 95, 71, 74, 97, 129, 130, 109, 34	867.4	0.9298

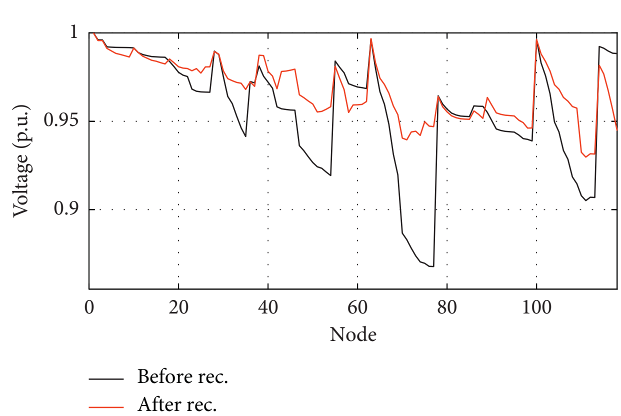

FIGURE 17: Voltage profile obtained for the 119-node system.

reconfigure distribution systems consisting of 33 nodes, 69 nodes, and 119 nodes for reducing power loss. The effectiveness of CGA using ISP has been compared with the network reconfiguration method based on CGA using the initial population generated randomly and the method based on CGA using the initial radial configuration attached to the initial population. The result comparison indicated that the proposed CGA using ISP obtained by the heuristic method could reach a higher successful rate and better obtained solution quality than two comparison methods. Thus, the use of the proposed CGA using ISP is a high contribution to distribution system in supporting for finding more effective radial topology in operating the distribution system.

Data Availability

The data of the three distribution systems consisting of 33 nodes, 69 nodes, and 119 nodes were taken from [48, 53, 54], respectively.

Conflicts of Interest

The authors declare that there have no conflicts of interest.

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