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Optimal distribution network configuration using improved backtracking search algorithm

Thuan Thanh Nguyen
Faculty of Electrical Engineering Technology, Industrial University of Ho Chi Minh City, Ho Chi Minh City, Vietnam

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ABSTRACT

Optimal network configuration is one of the effective approaches for power loss reduction of the distribution network. This paper shows a network reconfiguration method using improved backtracking search algorithm (IBSA). Wherein, IBSA is improved in the process of generating randomly the initialization population. The network reconfiguration method based on IBSA is used to find the optimal network configuration for the 33-node and 69-node systems. The results are compared to the original backtracking search algorithm (BSA), particle swarm optimization (PSO), firefly algorithm (FA) and previous approaches. From the compared results, IBSA can determine the optimal network configuration with higher success rate than BSA, PSO, FA and lower power loss than other previous approaches. As a result, IBSA is an effective approach for finding the optimal network configuration.

Corresponding Author:

Thuan Thanh Nguyen
Faculty of Electrical Engineering Technology
Industrial University of Ho Chi Minh City
No. 12 Nguyen Van Bao, Ward 4, Go Vap District, Ho Chi Minh City, Vietnam
Email: nguyenthanhthuan@iuh.edu.vn

1. INTRODUCTION

Network reconfiguration is one of the effective techniques for power loss reduction in the distribution system due to without requiring cost. This technique is implemented by changing the status of switches existing in the distribution system. However, network reconfiguration is a nonlinear and discrete problem that needs to have effective solving methods. For finding optimal network configuration, there are a lot of solving methods consisting of methods based on mathematical approaches [1-4] methods based on experience of operating the power system [5-7] and methods developed from metaheuristic algorithms [8-16]. By using the methods based on mathematical approaches, description of network reconfiguration problem and solving process are complicated because the network reconfiguration problem has to be linearized. While using the methods based on experience of operating the power system, the description of network reconfiguration problem and solving technique seem easier to understand but the gained solution is not guaranteed to be a global optimal solution. When using methods based on metaheuristic algorithms for the network reconfiguration problem, these methods have many advantages compared to the mathematical and experience approaches. An illustration for advantages of the method based on metaheuristic algorithms can be shown that the problem formulation is simpler than that of the mathematical approaches meanwhile the obtained solution is better than that of the experience approaches. Moreover, there are many new algorithms promising to bring high efficiency to the network reconfiguration problem. The issue of using these methods for the network reconfiguration problem is to find suitable algorithms or improve existing algorithms to increase their efficiency for the network reconfiguration problem. In addition, the main trend is application of the new algorithms or improvement of the searching process of the original algorithms. Very few studies have sought to improve the initialization process to create good initial populations for algorithms such as [10, 14, 17]. Thus, improving the initialization process for the algorithms when solving the network reconfiguration problems is also a solution that needs to be considered to improve the efficiency of metaheuristic algorithms for finding the optimal network configuration.

Backtracking search algorithm (BSA) is developed based on the idea of natural evolutions consisting of selection, mutation and crossover [18]. In [18], efficiency of BSA compared to other algorithms has been demonstrated over 75 benchmark functions. In [19], the authors have indicated the advantages of BSA compared to other algorithms such as generation of efficiently trial populations, balance between exploration and exploitation, the efficient crossover operator and the simply implement. Moreover in [19, 20], BSA has demonstrated the higher performance than particle swarm optimization, differential evolution algorithm, firefly algorithm and artificial bee colony for 16 benchmark problems. In addition, BSA has also shown its performance for some problems in power system field such as distributed generation placement [21], economic load dispatch [22, 23] and network reconfiguration [24].

In this study, improved BSA (IBSA) is proposed for searching the optimal network configuration of the distribution network to reduce power loss. Wherein, in order to apply IBSA for the network configuration problem, a starting solution is first determined by a heuristic rule in power system. Then, the starting solution is assigned to the initialization population of IBSA. The effectiveness of IBSA for the network configuration problem is compared with BSA, PSO, FA and other techniques in the literature on two distribution networks consisting of the 33-node and 69-node systems. Based on the performance of IBSA for two test systems, the main highlights of this work are follows:

- IBSA is first proposed for the network configuration problem to minimize power loss.
- The starting network configuration is proposed for IBSA to enhance the efficiency of IBSA for the network configuration problem.
- IBSA outperforms BSA, PSO and FA in terms of success rate and obtained solution quality for finding optimal network configuration.
- IBSA can find the better network configuration compared to some previous methods.

2. PROBLEM FORMULATION

The objective function of the network reconfiguration problem in this study is to minimize power loss of the distribution network. It is calculated as follows:

$$\min \text{obj} = \sum_{i=1}^{n_{br}} \Delta \mathrm{P}_i \tag{1}$$

where $\Delta \mathrm{P}_i$ is power loss of the ith branch. n_{br} is number of branches of distribution network. Installing DG in the distribution system should be maintained the following constraints:

- Radial topology: this constraint is satisfied by the below equation [25]:

$$|det\ (MT)| = 1 \tag{2}$$

where, $det\ (MT)$ is determinant of matrix MT. MT is a matrix that simulates the connection of a network configuration.

- Voltage and current limits:

$$\begin{cases} V_{per,lo} \le V_i \le V_{per,up}\ ; i = 1 \div n_{bu} \\ I_i \le I_{rate,i} \qquad\qquad ; i = 1 \div n_{br} \end{cases} \tag{3}$$

where $V_{per,lo}$ and $V_{per,up}$ are the lower and upper permitted ranges voltage. V_i is the voltage amplitude of the ith node. I_i and $I_{rate,i}$ are current and rated current of the ith branch. n_{bu} is number of buses of the distribution network. The adaptive function (f) of the network reconfiguration problem is determined based on the objective function and inequality constraints as follows:

$$f = \text{obj} + P.\left[max\left(V_{per,lo} - V_{min}, 0\right) + max\left(\max\left(I_i/I_{rate,i}\right) - 1{,}0\right)\right] \tag{4}$$

where P is a penalty coefficient.

3. IMPROVED BACKTRACKING SEARCH ALGORITHM FOR ELECTRIC DISTRIBUTION NETWORK RECONFIGURATION

There are many factors that affect the outcome of an optimal algorithm such as search mechanisms, control parameters, initial initialized populations. In this study, the initial initialization population of BSA is improved to enhance efficiency of BSA.

Step 1: Generate randomly the population of solutions.

$$s_{i,j} = s_{min,ij} + rand(0,1).\left(s_{max,ij} - s_{min,ij}\right); i = 1, \dots, n_s; j = 1, \dots, n_v \tag{5}$$

Where, $s_{i,j}$ is the jth variable of the ith solution. $s_{max,ij}$ and $s_{min,ij}$ are upper and lower limits of the jth variable of the ith solution. n_s and n_v are population size and dimension of the optimization problem. Each solution created is adjusted for mapping with the network reconfiguration as follows:

$$s_i = round[s_i] \tag{6}$$

Step 2: Find the starting solution (st).

From the population created randomly as (5), a good solution to the network reconfiguration problem is assigned to the population to improve the quality of the original population. This solution is determined by the heuristic rule of the power system that opening the branch with the smallest current in a closed-loop network, the closed-loop network will become a radial network that has the smallest power loss [10]. To determine the starting solution, the first open switch of the original network configuration is closed and the load flow problem is run for the system with a loop. Then, the switch that exits the smallest current in the loop is opened to substitute for the first open switch. This process is carried out until the final open switch of the original network configuration is replaced by a new switch.

Then st solution is substituted for a random solution of the initial population as follows:

$$s_{r1} = st \tag{7}$$

where, s_{r1} is a random solution selected from the initial population. From the population created, the adaptive function of each solution is validated by (4) and the best so-far solution (s_{gbest}) with the best adaptive function value (f_{gbest}) is determined. Furthermore, BSA is also used another population called historical population to serve for generating new solutions. Thus, each solution of the historical population (hs_i) is generated at the beginning by using (5) and (6).

Step 3: Redefine the historical population.

The each solution in the historical population is redefined as follows:

$$hs_i = \begin{cases} s_i \;\; ; \, if \; r_2 < r_3 \\ hs_i \; ; otherwise \end{cases} ; i = 1, \dots, \, n_s \tag{8}$$

where, r_2 and r_3 are two random numbers in [0, 1]. The solutions in the historical population is permuted as follows:

$$hs_i = hs_{r_4(i)} \; ; \; i = 1, \dots, \, n_s \tag{9}$$

where r_4 is a vector containing a random permutation of 1: n_s.

Step 4: Generate new population.

Firstly, temporary new solutions called (ts) are generated as follows:

$$ts_i = s_i + \mu . r_5 . (hs_i - s_i) \; ; \; i = 1, \dots, \, n_s \tag{10}$$

where, r_4 is a random number in [0,1]. μ is a scale coefficient that is set to 3 [18]. Secondly, the new population (new_s) are generated as follows:

$$new\_s_{i,j} = \begin{cases} s_{i,j} \; ; \;\; if \; m_{i,j} = 1 \\ ts_{i,j} \; ; \; otherwise \end{cases} ; \; i = 1, \dots, \, n_s; \; j = 1, \dots, \, n_v \tag{11}$$

wherein, m is the $n_s . n_v$ binary matrix. All of elements of m is first set to 0. Then some of elements are adjusted to 1 as follows:

$$\begin{cases} m_{i,u_{(1:\alpha . r_6 . \, n_v)}} = 1; \; if \; r_7 < r_8 \\ m_{i,randi(\, n_v)} = 1; \; otherwise \end{cases} ; \; i = 1, \dots, \, n_s \tag{12}$$

where, $u_{(1:\alpha.r_6.\,n_v)}$ is a vector containing a random permutation of $1{:}\,\alpha.r_6.\,n_v$. α is a mix-rate coefficient. r_6, r_7 and r_8 are random numbers in [0,1]. $randi(\,n_v)$ is a integer random number in [1, n_v]. Each new solution in the population is checked and corrected its limit as follows:

$$new\_s_{i,j} = \begin{cases} s_{min,ij}\ ; if\ new\_s_{i,j} < s_{min,ij} \\ s_{max,ij}\ ;\ if\ new\_s_{i,j} > s_{max,ij} \\ new\_s_{i,j}\ ; otherwise \end{cases} ;\ i = 1, \dots, n_s;\ j = 1, \dots, n_v \quad (13)$$

Step 5: update the population for next generation.

The new population is rounded to integer value by using (6) and validated the adaptive function by (4) and the population is updated for the next generation based on the selection technique as follows:

$$s_i = \begin{cases} new\_s_i\ ;\ if\ f(new\_s_i) < f(s_i) \\ s_i\ ;\ otherwise \end{cases} ;\ i = 1, \dots, n_s \quad (14)$$

$$f_i = \begin{cases} f(new\_s_i)\ ;\ if\ f(new\_s_i) < f(s_i) \\ f(s_i)\ ;\ otherwise \end{cases} ;\ i = 1, \dots, n_s \quad (15)$$

Step 6: update the best so-far solution.

Based on the adaptive function value of the population, the best solution (s_{best}) with the best adaptive function value (f_{best}) is determined. Then the best so-far solution is updated as bellow:

$$f_{gbest} = \begin{cases} f_{best}\ ;\ if\ f_{best} < f_{gbest} \\ f_{gbest}\ ;\ otherwise \end{cases} \quad (16)$$

$$s_{gbest} = \begin{cases} s_{best}\ ;\ if\ \min(f_i) < f_{gbest} \\ s_{gbest}\ ;\ otherwise \end{cases} \quad (17)$$

Step 7: stop searching process.

The steps 3 to 6 will be performed until the maximum generation (Gen_{max}) reaches. Then the best so far solution is considered as the optimal solution of the problem. The pseudo-code of IBSA for solving the network reconfiguration problem is shown in Figure 1.

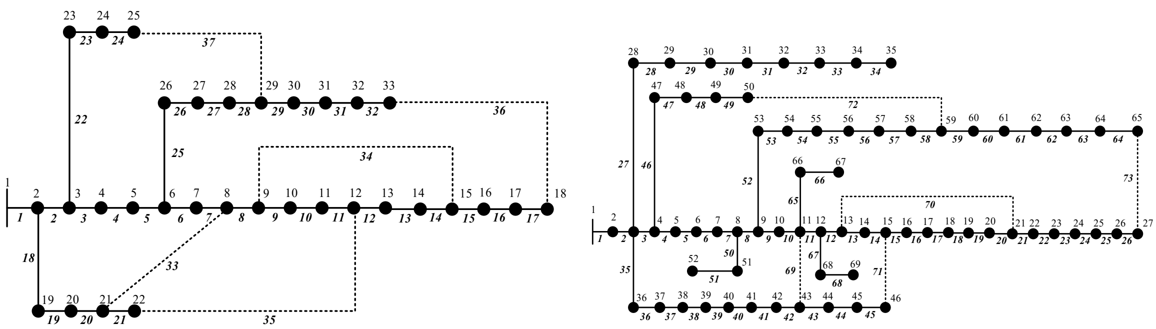
```
// Step 1: Generate randomly the population of solutions
Generate randomly the current population by using (5)
Modify the generated population by using (6)
// Step 2: Find the starting solution
For i = 1 to number of the original open switches of the distribution system do
     Close the ith original open switch to form a loop for the distribution system
     Run power load flow
     Open the switch in the loop with the smallest current
     Save the open switch as the variable ith for the starting solution
End for
     Assign the starting solution to the current population by using (7)
     Validate the adaptive function of each solution is validated by (4)
     Determine the best so-far solution (s_gbest) with the best adaptive function value (f_gbest)
     Generate the historical population by using (5) and (6)
     Set the current generation equal to zero
While the current generation < Gen_max do
     // Step 3: Redefine the historical population
     Redefine the historical population by using (8)
     Permute the historical population by using (9)
     // Step 4: Generate new population
     Generate new population by using (11)
     Check and correct the bound of new population by using (13)
     // Step 5: update the population for next generation
     Modify the generated population by using (6)
     Validate the adaptive function of each solution is validated by (4)
     Update the current population by using (14) and (15)
     // Step 6: update the best so-far solution
     Update the best so-far solution by using (16) and (17)
     Increase the current generation
End while
```

Figure 1. The pseudo-code of IBSA for solving the network reconfiguration problem

4. RESULTS AND DISCUSSION

In order to evaluate the effectiveness of IBSA for the network reconfiguration problem, two test systems are used to reconfigure including the 33-node and 69-node systems as shown in Figure 2. The data of two test systems are referenced from [26, 27], respectively. The rated current of branches for two test systems is set to 250 A and 150 A, respectively. The network reconfiguration program is developed on the Matlab software and executed on a personal computer with 4GB of RAM and CPU core-i5 2.4GH. The power flow based on the Newton-Raphson method is used for calculating power loss, voltage and current profiles of the systems [28]. For the control parameters of IBSA, population size n_s, dimension n_v and number of maximum generations Gen_{max} are chosen to 20, 5 and 150, respectively. The mix-rate coefficient α in (12) is chosen by 0.7 [24]. Moreover, in order to demonstrate effectiveness of improvement of IBSA, the original BSA, PSO and FA have been also implemented for the network reconfiguration problem to compare with IBSA. The parameters of BSA for two test systems are chosen identical to those of IBSA meanwhile for PSO, the C_1, C_2, n_s and Gen_{max} are chosen to 2, 2, 20 and 150, respectively. For FA, the α and β coefficients are set to 1 [29, 30]. The maximum number of evaluation the adaptive function (MNE) is used as the stop condition instead of the number of maximum generations because in each generation, there are $n_s \times n_s$ new individuals created and evaluated the adaptive function that is different from the IBSA, BSA and PSO algorithms (only n_s new individuals are created in each generation). The MNE value of FA is set to 3,000 similar to IBSA, BSA and PSO which is determined by $n_s \times Gen_{max}$. Due to this character, the convergence curves of FA will not be used to compare with the remaining algorithms.

The starting solution of two test systems is determined by IBSA shown in Table 1. Compared to the initial configuration, power loss caused by the starting configuration is much lower than that of the initial configuration. Wherein, for the 33-node system, power loss of the starting configuration is 63.1363 kW lower than that of the initial configuration meanwhile power loss of the starting configuration of the 69-node system is 116.4269 kW lower than that of the initial configuration. Obviously, assigning of these configurations to the initialization population will help IBSA to increase the chances of finding the optimal configuration compared with the process of generating randomly population of BSA.



(a) (b)

Figure 2. 33-node and 69-node distribution systems; (a) the 33-nodes test system and (b) the 69 nodes test sytem

Table 1. Starting solution for two test systems

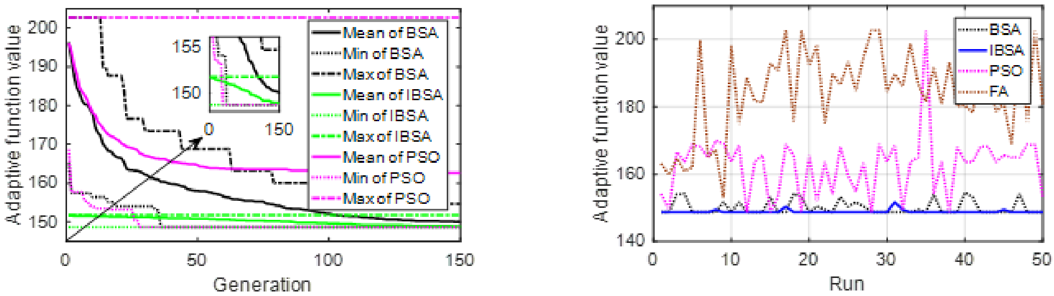
System	33-node system		69-node system	
Configuration	Initial configuration	Starting configuration	Initial configuration	Starting configuration
Open switch	33, 34, 35, 36, 37	7, 14, 9, 32, 37	69, 70, 71, 72, 73	10, 17, 12, 58, 61
$\sum \Delta P$ (kW)	202.6863	139.5543	224.8871	108.4602
V_{min} (p.u.)	0.9131	0.9378	0.9092	0.9495
I_{max} (A)	210.3656	207.1295	124.1330	121.7679

The optimal solutions obtained of IBSA and BSA for two test systems and the indexes obtained in 50 independent runs consisting of maximum (f_{max}), minimum (f_{min}), mean (f_{mean}) values and standard deviation (STD) of the adaptive function and maximum (CG_{max}), minimum (CG_{min}), mean (CG_{mean}) number of convergence generations are shown in Table 2. From the table, although both of IBSA and BSA have determined the optimal configuration, it is clear that IBSA has determined the optimal configuration with a higher success rate than BSA. The success rate of IBSA for the 33-node and 69-node system is 90 % and 92 %, respectively meanwhile it is only 64% and 74 % for BSA. For PSO and FA, the success rate for two systems is only 10 % and 16 %

for PSO and 2% and 2% for FA that is much lower than that of IBSA. The f_{mean} value of IBSA is also lower than that of BSA. Specially, the CG_{mean} value of IBSA is lower than that of BSA. The lower CG_{mean} value of IBSA shows that using starting configuration, IBSA has determined the optimal configuration faster than BSA. Table 2 also shows that improvement of IBSA does not increase significantly the calculation time of IBSA. The convergence curves and the optimal adaptive function values in each run of IBSA and BSA for the 33-node and 69-node systems are shown in Figure 3 and Figure 4, respectively. From Figures 3 (a) and 4 (a), IBSA has converged to the lower values with shorter generations than BSA for both of the systems. From Figures 3 (b) and 4 (b), the optimal adaptive function value in each run of IBSA is usually lower than that of BSA. Also, from the figures, IBSA outperforms PSO and FA in term of the optimal adaptive function value in each run and the mean convergence curve of IBSA is much lower than that of PSO. This confirms the superiority of IBSA compared to PSO and FA.

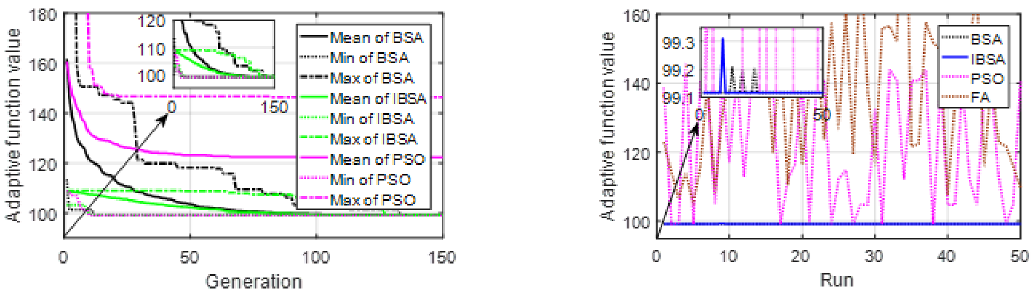
Table 2. The effectiveness of IBSA compared to BSA, PSO and FA for two test systems

Term	The 33-nodes system				The 69-nodes system			
Method	IBSA	BSA	PSO	FA	IBSA	BSA	PSO	FA
Optimal solution	7, 9, 14, 28, 32	7, 9, 14, 28, 32	7, 9, 14, 28, 32	7, 9, 13, 28, 32	14, 57, 61, 69, 70	14, 57, 61, 69, 70	14, 57, 61, 69, 70	10, 12, 57, 61, 70
Success rate	90%	64%	10%	2%	92%	74%	16%	2%
f_{max}	151.7381	154.6217	202.6863	202.6863	99.3091	99.2094	146.3933	224.8871
f_{min}	148.7392	148.7392	148.7392	153.1073	99.1169	99.1169	99.1169	104.9158
f_{mean}	148.8759	150.062	162.6213	184.067	99.1208	99.1225	122.3322	136.2245
STD	0.5027	2.0632	9.1471	12.9972	0.0211	0.0221	18.1440	22.4502
CG_{max}	149	149	116	-	148	149	105	-
CG_{min}	1	36	1	-	19	45	5	-
CG_{mean}	77.2	106.32	38.58	-	110.8	111.14	38.44	-
Run times (second)	6.3634	6.1734	8.7469	8.4475	22.8038	22.8031	27.5072	26.1687



(a) (b)

Figure 3. Convergence curves and optimal value over 50 runs for the 33-node distribution system; (a) convergence curves and (b) optimal adaptive value



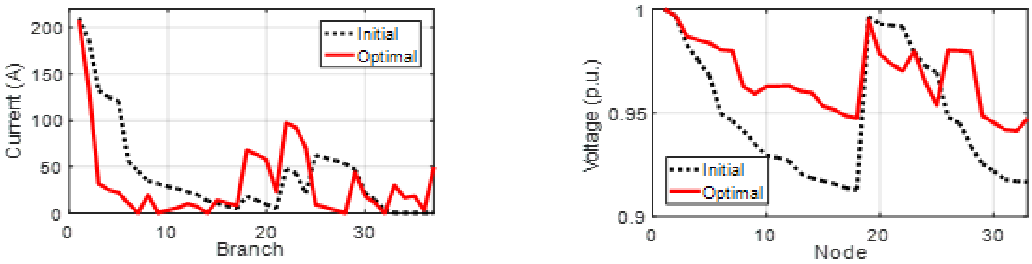
(a) (b)

Figure 4. Convergence curves and optimal value over 50 runs for the 69-node distribution system; (a) convergence curves and (b) optimal adaptive value

The optimal network configuration of the 33-node system after performing IBSA is shown in Table 3. From the table, the optimal open switches are {7, 9, 14, 28, 32} that causes power loss of 139.9823 kW. Power loss caused by the optimal configuration is 62.704 kW lower than that of the initial configuration. The minimum voltage amplitude of the system has been improved from 0.9131 p.u to 0.9412 p.u. The maximum current of the system has been also decreased 3.155A from 210.3656 A to 207.2106 A. The result of IBSA is identical to that of PSO, CGA [10] and better than that of FA. Compared with HTELA [13], GWO-PSO [12], SSA [15] and SFS [11] power loss reduction of IBSA is 0.21% lower but the minimum voltage amplitude is 0.0034 higher than that of the aforementioned methods. The current of branches of the system before and after reconfiguration is shown in Figure 5 (a). From the figure, the current of heavier branches has been transferred to lighter branches. The voltage amplitude of nodes has been improved after reconfiguration as shown in Figure 5 (b).

Table 3. Optimal network configuration for the 33-node system

Method	Open switch	$\sum \Delta P$ (kW)	Power loss reduction (%)	V_{min} (p.u.)	I_{max} (A)
Initial	33, 34, 35, 36, 37	202.6863	-	0.9131	210.3656
IBSA	7, 9, 14, 28, 32	139.9823	30.94%	0.9412	207.2106
BSA	7, 9, 14, 28, 32	139.9823	30.94%	0.9412	207.2106
PSO	7, 9, 14, 28, 32	139.9823	30.94%	0.9412	207.2106
FA	7, 9, 13, 28, 32	143.5234	29.19%	0.9404	207.4225
CGA [10]	7, 9, 14, 28, 32	139.9823	30.94%	0.9412	
HTELA [13]	7, 9, 14, 32, 37	139.55	31.15%	0.9378	
GWO-PSO [12]	7, 9, 14, 32, 37	139.55	31.15%	0.9378	
SSA [15]	7, 9, 14, 32, 37	139.55	31.15%	0.9378	
SFS [11]	7, 9, 14, 32, 37	139.55	31.15%	0.9378	



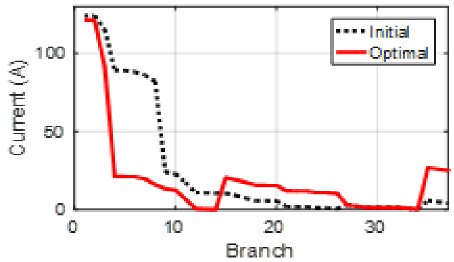
(a) (b)

Figure 5. Current and voltage of the 33-node distribution system; (a) branch current and (b) node voltage

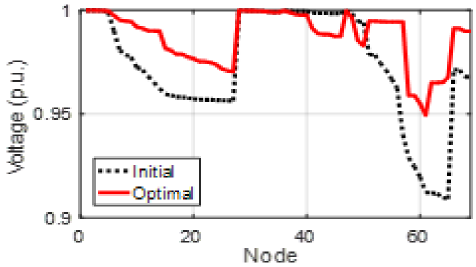
The optimal network configuration of the 69-node system is shown in Table 4. The optimal configuration of {14, 57, 61, 69, 70} causes power loss of 98.5875 kW. Power loss of the optimal configuration is 126.2996 kW lower than that of the initial configuration. The minimum voltage amplitude of the system has been improved from 0.9092 p.u to 0.9495 p.u. The maximum current of the system has been also decreased 2.762A from 124.1330 A to 121.3710 A. The result of IBSA is identical to that of PSO and CGA [10]. Compared to FA, HTELA [13], SFS [11] and SSA [15], power loss reduction of IBSA is respectively 2.58%, 0.49%, 0.01% and 0.02% higher and the minimum voltage amplitude of IBSA is 0.0067 and 0.0003 higher than that of the HTELA [13] and SSA [15] methods. The current of branches of the system before and after reconfiguration is shown in Figure 6 (a). Similar to the 33-node system, the current of heavier branches has been transferred to lighter branches. The voltage amplitude of nodes compared to that of the initial configuration in Figure 6 (b) shows that most of voltage amplitudes has been improved after reconfiguration by IBSA.

Table 4. Optimal network configuration for the 69-node system

Method	Open switch	$\sum \Delta P$ (kW	Power loss reduction (%)	V_{min} (p.u.)	I_{max} (A)
Initial	69, 70, 71, 72, 73	224.8871	-	0.9092	124.1330
IBSA	14, 57, 61, 69, 70	98.5875	56.16%	0.9495	121.3710
BSA	14, 57, 61, 69, 70	98.5875	56.16%	0.9495	121.3710
PSO	14, 57, 61, 69, 70	98.5875	56.16%	0.9495	121.3710
FA	10, 12, 57, 61, 70	104.3969	53.58%	0.9495	121.6465
CGA [10]	14, 57, 61, 69, 70	98.5875	56.16%	0.9495	
HTELA [13]	13, 55, 61, 69, 70	99.69	55.67%	0.9428	
SFS [11]	14, 55, 61, 69, 70	98.62	56.15%	0.9495	
SSA [15]	69, 14, 71, 61, 58	98.63	56.14%	0.9492	



(a)



(b)

Figure 6. Current and voltage of the 69-node distribution system; (a) branch current and (b) node voltage

5. CONCLUSION

In this paper, the optimal method of electric distribution network configuration for power loss reduction using IBSA is presented. Compared with BSA, the initialization population of IBSA is modified by assigning a good solution that found by the heuristic rule in the power system. The efficiency of IBSA on the 33-node and 69-node systems shows that IBSA outperforms BSA in terms of successful rate and obtained solution quality. About the success rate, IBSA can find the optimal configuration with success rate of 90% and 92% for the 33-node and 69-node systems meanwhile this index of BSA for two test systems is only 64% and 74%, respectively. The comparisons of IBSA with PSO, FA and other methods in the literature also show that IBSA is better than some previous methods. Therefore, IBSA is one of effective methods for determining the optimal network configuration. For future work, IBSA can be applied for solving the network reconfiguration problem with varying loads to reduce energy loss or solving the network reconfiguration problem considering the distributed generations to reduce power loss or energy loss.

REFERENCES

[1] A. Abur, “A modified linear programming method for distribution system reconfiguration,” *International Journal of Electrical Power and Energy Systems*, vol. 18, no. 7, pp. 469-474, 1996.
[2] F. Llorens-Iborra, J. Riquelme-Santos, and E. Romero-Ramos, “Mixed-integer linear programming model for solving reconfiguration problems in large-scale distribution systems,” *Electric Power Systems Research*, vol. 88, pp. 137-145, 2012.
[3] A. Augugliaro, L. Dusonchet, and S. Mangione, “Optimal re-configuration of distribution network for loss reduction using non-linear programming,” *European Transactions on Electrical Power*, vol. 1, no. 6, pp. 317-324, 1991.
[4] J. A. Taylor and F. S. Hover, “Convex models of distribution system reconfiguration,” *IEEE Transactions on Power Systems*, vol. 27, no. 3, pp. 1407-1413, 2012.
[5] A. Merlin and H. Back, “Search for a minimal loss operating spanning tree configuration in an urban power distribution system,” *Proceeding in 5th power system computation conf (PSCC),* Cambridge, UK, vol. 1, pp. 1-18, 1975.
[6] S. Civanlar, J. J. Grainger, H. Yin, and S. S. H. Lee, “Distribution feeder reconfiguration for loss reduction,” *IEEE Transactions on Power Delivery*, vol. 3, no. 3, pp. 1217-1223, 1988.
[7] D. Shirmohammadi and H. W. Hong, “Reconfiguration of electric distribution networks for resistive line losses reduction,” *IEEE Transactions on Power Delivery*, vol. 4, no. 2, pp. 1492-1498, 1989.
[8] J. Z. Zhu, “Optimal reconfiguration of electrical distribution network using the refined genetic algorithm,” *Electric Power Systems Research*, vol. 62, no. 1, pp. 37-42, 2002.
[9] A. M. Othman, A. A. El-Fergany, and A. Y. Abdelaziz, “Optimal Reconfiguration Comprising Voltage Stability Aspect Using Enhanced Binary Particle Swarm Optimization Algorithm,” *Electric Power Components and Systems*, vol. 43, no. 14, pp. 1656-1666, 2015.

[10] T. Thanh Nguyen, T. T. Nguyen, and N. A. Nguyen, "Optimal Network Reconfiguration to Reduce Power Loss Using an Initial Searching Point for Continuous Genetic Algorithm," *Complexity*, vol. 2020, 2020.
[11] T. T. Tran, K. H. Truong, and D. N. Vo, "Stochastic fractal search algorithm for reconfiguration of distribution networks with distributed generations," *Ain Shams Engineering Journal*, no. 11, no. 2, pp. 389-407, 2019.
[12] M. F. Abd El-salam, E. Beshr, and M. B. Eteiba, "A new hybrid technique for minimizing power losses in a distribution system by optimal sizing and siting of distributed generators with network reconfiguration," *Energies*, vol. 11, no. 12, 2018.
[13] K. Jasthi and D. Das, "Simultaneous distribution system reconfiguration and DG sizing algorithm without load flow solution," *IET Generation, Transmission and Distribution*, vol. 12, no. 6, pp. 1303-1313, 2018.
[14] H. Karimianfard and H. Haghighat, "An initial-point strategy for optimizing distribution system reconfiguration," *Electric Power Systems Research*, vol. 176, 2019.
[15] K. S. Sambaiah and T. Jayabarathi, "Optimal reconfiguration and renewable distributed generation allocation in electric distribution systems," *International Journal of Ambient Energy*, pp. 1-29, 2019.
[16] T. T. Nguyen, "Electric distribution network reconfiguration for power loss reduction based on runner root algorithm," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 10, no. 5, pp. 5016-5024, 2020.
[17] H. Ahmadi and J. R. Martí, "Minimum-loss network reconfiguration: A minimum spanning tree problem," *Sustainable Energy, Grids and Networks*, vol. 1, pp. 1-9, 2015.
[18] P. Civicioglu, "Backtracking Search Optimization Algorithm for numerical optimization problems," *Applied Mathematics and Computation*, vol. 219, no. 15, pp. 8121-8144, 2013.
[19] B. A. Hassan and T. A. Rashid, "Operational framework for recent advances in backtracking search optimisation algorithm: A systematic review and performance evaluation," *Applied Mathematics and Computation*, vol. 370, 2020.
[20] B. A. Hassan and T. A. Rashid, "Datasets on statistical analysis and performance evaluation of backtracking search optimisation algorithm compared with its counterpart algorithms," *Data in Brief*, vol. 28, 2020.
[21] A. El-Fergany, "Multi-objective Allocation of Multi-type Distributed Generators along Distribution Networks Using Backtracking Search Algorithm and Fuzzy Expert Rules," *Electric Power Components and Systems*, vol. 5008, no. January, pp. 1-16, 2015.
[22] K. Bhattacharjee, A. Bhattacharya, and S. Halder nee Dey, "Backtracking search optimization based economic environmental power dispatch problems," *International Journal of Electrical Power and Energy Systems*, vol. 73, pp. 830-842, 2015.
[23] M. Modiri-Delshad and N. A. Rahim, "Solving non-convex economic dispatch problem via backtracking search algorithm," *Energy*, vol. 77, pp. 372-381, 2014.
[24] N. T. Thuan, P. N. Hiep, T. V. Anh, P. A. Tuan, and N. T. Thang, "A Backtracking Search Algorithm for Distribution Network Reconfiguration Problem," *AETA 2015: Recent Advances in Electrical Engineering and Related Sciences, Lecture Notes in Electrical Engineering 371*, pp. 223-230, 2015.
[25] A. Y. Abdelaziz, F. M. Mohamed, S. F. Mekhamer, and M. A. L. Badr, "Distribution system reconfiguration using a modified Tabu Search algorithm," *Electric Power Systems Research*, vol. 80, no. 8, pp. 943-953, 2010.
[26] M. E. Baran and F. F. Wu, "Network reconfiguration in distribution systems for loss reduction and load balancing," *IEEE Transactions on Power Delivery*, vol. 4, no. 2. pp. 1401-1407, 1989.
[27] H.-D. Chiang and R. Jean-Jumeau, "Optimal network reconfigurations in distribution systems: Part 2: Solution algorithms and numerical results," *IEEE Transactions on Power Delivery*, vol. 5, no. 3, pp. 1568-1574, 1990.
[28] R. D. Zimmerman, C. E. Murillo-Sanchez, and R. J. Thomas, "MATPOWER: Steady-State Operations, Planning, and Analysis Tools for Power Systems Research and Education," *IEEE Transactions on Power Systems*, vol. 26, no. 1, pp. 12–19, 2011.
[29] X. Yang, "Nature-Inspired Metaheuristic Algorithms," Second Edi. *Luniver Press*, 2010.
[30] X. S. Yang, "Firefly algorithm, stochastic test functions and design optimization," *International Journal of Bio-Inspired Computation*, vol. 2, no. 2, pp. 78-84, 2010.