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A Novel Metaheuristic Method for Multi-Goal Electric Distribution Network Reconfiguration

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Abstract: This paper demonstrates an artificial ecosystem optimization (AEO) for the multi-goal electric network reconfiguration (ENR) problem (ENRP). The membership goal functions of the ENRP comprise power loss reduction, voltage deviation reduction, reduction of load unbalance index among branches and reduction of number of switch operations. To show the advantages of AEO for the multi-goal ENRP, the multi-goal ENR approaches relied on particle swarm optimization (PSO), genetic algorithm (GA) and cuckoo search algorithm (CSA) are applied to contrast with the AEO method. The result comparisons among methods on the 33-node distribution network show that the AEO method can archive the optimal solution with the higher success rate and the lower average value and standard deviation of the fitness values than GA and PSO. In addition, the result comparisons with other previous approaches also show the reliability of the proposed AEO method for the single and multi-goal function ENRP. Therefore, the AEO can be an effective and useful approach for the ENRP to optimize the single and the multi-goal functions.

Keywords: Artificial ecosystem optimization, PSO, GA, Network reconfiguration.

1. Introduction

Finding and applying effective solutions to improve the efficiency of operating distribution network (DN) always are attracted the attention of researchers. Wherein, the NR is always a preferred solution because it does not have any special requirements related to equipment investment. It is only done by alternating the radial configuration of system relied on changing the switches' status that are installed on the DN.

One of the highest pros of ENR technique is power loss reduction. The process of changing the operating configuration can help transfer load from this branch to other ones and if the selected optimal operating configuration can significantly reduce power loss of the system. Therefore, many studies have considered reducing power loss as a main goal of the ENRP. In [1], power loss reduction is considered as the objective function of the ENRP and mixed PSO (MPSO) has been proposed for searching the optimal network configuration. In [2], the ENRP for power loss reduction problem has been successful solved by the runner root algorithm. In [3], a method based on backtracking search algorithm has been used to search the network configuration that causes minimum power loss. In [4], an analytical approach has been used for searching the optimal network configuration and distributed generation placement (DGP) to reduce power loss. In [5], PSO is applied for the ENRP to reduce power loss. In [6], harmony search algorithm (HSA) is used for the ENRP considering DG placement to reduce power loss. In [7], fireworks algorithm (FWA) is used to solve the ENRP for power loss minimization and voltage improvement. However, changing the operating configuration may affect other indices besides power loss such as voltage of nodes and current of branches. Sometimes a chosen configuration can make a technical factor better but it makes other technical indicators worse than the original configuration. Therefore, for the ENRP to be effectively applied to the practical operation of the distribution network, the ENRP needs to be considered as a multi-goal function.

There are some studies have solved the multi-goal ENRP. In [8], the biogeography based optimization has been applied for the multi-goal ENRP with the considered goals of power loss reduction and voltage enhancement. In [9], the multi-goal ENRP combined with DGP for decreasing power loss and operating costs is considered by the sine–cosine algorithm. In [10], water cycle algorithm is applied to determine the optimal network configuration for reducing power losses and rising voltage stability index. In [11], the hybrid of exchange market and wild goats algorithms is successful used for the multi-goal ENRP with member goals of power loss and reliability indexes. In [12], power loss and voltage enhancement has been considered as the objectives of the multi-goal combination problem of ENRP and DGP, wherein the optimal solution of the problem is determined by equilibrium optimization algorithm. In [13], power losses, voltage deviation and feeder load balancing are optimized by using hybrid big bang–big crunch algorithm (HBB-BC). Similarly, these objectives are optimized by shuffled frog-leaping algorithm (SFLA) [14]. In [15], power loss, voltage deviation, switching operations and load balancing are considered by using invasive weed optimization (IWO). In [16], runner-root algorithm (RRA) is used for the ENRP with objective of power loss, voltage deviation, switching operations, feeder and load balancing. Although there have been studies considering to the multi-goal ENRP, studying of multi-goal ENRP for other objective functions should also be encouraged.

For the ENRP, it is a nonlinear problem with multiple local extremes. Furthermore, a distribution network with n switches can exist up to 2^n different configurations. Therefore, finding new methods to solve the ENRP is necessary to supplement the effective methods for this problem. In recent years, the strong development in the field of optimization has produced many efficient metaheuristic algorithms. However, most of them are proven effective on standard mathematical functions. Therefore, proving their effectiveness on technical problems like the ENRP is also essential.

This paper presents a multi-goal ENR method based on AEO. Where, AEO takes an idea from the production, consumption and decomposition mechanisms of the ecosystem [17]. In order to prove the performance of the proposed AEO method, we have also built the ENR methods based on some well-known algorithms such as CSA, GA and PSO to compare the efficiency with AEO for the multi-goal ENRP. CSA is one of the recent developed algorithm taken idea from the obligate brood parasitism of cuckoo birds. CSA generates new solutions by using Levy flight for exploration and mutation for exploitation [18]. While GA [19] and PSO [20] are the most well-known algorithms. GA generates new solutions by using crossover and mutation, wherein the former helps to explore of the search space and the latter maintains the exploitation. PSO generates new solutions by using the information of the best position of each solution and best position of the whole population. The proposed method is used to search the optimal configuration for the 33-node DN with four optimal cases to be considered including single-goal optimization of power loss reduction, single-goal optimization of voltage deviation reduction, single-goal optimization of reduction of load unbalance index among branches and multi-objective optimization. Some main contributions of this work can be listed as follows:

(i) The multi-goal ENRP based on the max-min approach is considered with four member goals consisting of power loss, voltage deviation, load unbalance index among branches and number of switching operations.
(ii) The AEO algorithm is first adapted for solving the multi-goal ENRP.
(iii) The efficiency of the multi-goal ENRP relied on AEO is validated on the 33-node DN for different cases consisting of the single objective function of power loss, voltage deviation and load balancing as well as the multi objective function.
(iv) CSA, GA and PSO are also executed for comparing with the AEO method.
(v) The multi-goal NR method relied on AEO is very more effective than CSA, GA and PSO for searching the optimal configuration.

2. The multi-goal network reconfiguration problem

The network reconfiguration approach not only reduces power loss but also contributes to improve voltage, load balancing among branches. However, when performing the network reconfiguration, the number of times changing the switches' status of the DN is also a factor that needs to be considered to contribute to reducing the cost of stopping the supply power. Thus, the considered goals of the network reconfiguration include power loss reduction, voltage deviation reduction, load unbalance reduction among branches and reduction of the number of switching operations. Each goal function is calculated as follows:

Power loss (P_{loss}) of the DN is determined by the following equation:

$$P_{loss} = \sum_{i=1}^{N_{br}} k_i . \Delta P_i \quad (1)$$

Where, ΔP_i is the ith branch' power loss. k_i is the status of the ith branch. N_{br} is the number of branches of the DN.

Voltage deviation (VD) of the DN is defined as below:

$$VD = 1 - V_{min} \quad (2)$$

The load unbalance index ($LUBI$) of the DN is defined by the variance of the load carrying level of branches as follows [15] [13]:

$$LUBI = var\left[\frac{I_i}{I_{i,rate}}\right] \; with \; i = 1, \ldots, N_{br} \quad (3)$$

Where, var is the variance function.

The number of switching operations (NSO) is calculated as follows [15]:

$$NSO = \sum_{i=1}^{N_{br}} \left|SW_{0,i} - SW_i\right| \quad (4)$$

The values of the goal functions are normalized as follows [15]:

$$NVF_k = \begin{cases} 1, & fit_k \leq fit_k^{min} \\ \frac{fit_k^{max} - fit_k}{fit_k^{max} - fit_k^{min}}, & fit_k^{min} < fit_k < fit_k^{max} \\ 0, & fit_k \geq fit_k^{max} \end{cases} \quad (5)$$

Where, NVF_k is the normalized value of the kth goal function. fit_k is the value of the kth goal function that is calculated from (1) to (4). fit_k^{min} is the best value of the kth goal function that is determined by solving the single goal function ENRP. fit_k^{max} is the value of the kth goal function that is obtained from the initial network configuration.

Finally, the fitness function of the multi-goal ENRP is determined as follows:

$$fit = 1 - \min(NVF_1, NVF_2, NVF_3, NVF_4) \quad (6)$$

Where, NVF_1, NVF_2, NVF_3 and NVF_4 are the normalized value of the power loss, voltage deviation, load unbalance index and number of switching operations, respectively.

In addition, the obtained network configuration has to maintain the radial topology as follows [21]:

$$|\det(BN)| = \begin{cases} 1, & radial \\ 0, & not\ radial \end{cases} \quad (7)$$

Where, $\det(BN)$ is determinant of matrix BN. Wherein, BN is the matrix that presents for the connection of the DN.

3. AEO for the multi-goal network reconfiguration

In this section, application of AEO for the multi-goal network reconfiguration is presented. Details of steps of AEO are described as follows:

Step 1: Create the initial population

The control variable of the ENRP is switches located on the DN. Thus, each solution of the AEO is presented as follows:

$$SW_i = [s_1, s_2, \ldots, s_D] \quad (8)$$

Where, SW_i is the ith solution, $i = 1,2, \ldots N$.

The initial population is created randomly as follows:

$$SW_i = HB + rand(0,1).(HB - LB) \quad (9)$$

Where, HB and LB are the upper and lower boundary vectors of each solution.

Due to position of switches is expressed by an integer number, each candidate solution modified as follows:

$$SW_i = round[SW_i] \quad (10)$$

Then, each solution is check the radial topology constraint by using (7) and if this constraint is satisfied, it will be calculated the fitness function value by using (6). Finally, the current best solution (SW_{best}) that exists the best fitness value (fit_{best}) is found.

Step 2: Update the current population for the first time relied on production and consumption operators

The solutions in the population are arranged in the order descending of the fitness value. After sorting, the worst solution is located at the top and the best one is placed at the bottom of the population.

Then, the first new solution is created based on the production operator as follows:

$$SW_{1,novel} = \left[1 - \left(1 - {}^{iter}/_{iter_{max}}\right)\right].rand(0,1).SW_{best} + \left(1 - {}^{iter}/_{iter_{max}}\right).SW_{r1} \quad (11)$$

Where, S_{r1} is a solution selected randomly.

The new solutions from the 2nd to the end ones are created relied on the consumption operator by one of three following approaches. Noted that the probability of one approach being selected for creating a new solution is the same.

The 1st approach:

$$SW_{i,novel} = SW_i + \alpha.(SW_i - SW_1) \tag{12}$$

The 2nd approach:

$$SW_{i,novel} = SW_i + \alpha.\left(SW_i - SW_j\right) \tag{13}$$

The 3rd approach:

$$SW_{i,novel} = SW_i + \alpha.\mu_1.(SW_i - SW_1) + (1-\mu_1).\left(SW_i - SW_j\right) \tag{14}$$

Where, SW_j is a random solution with $j \in [2, i-1]$. α is determined as follows:

$$\alpha = \frac{1}{2}.\frac{\vartheta_1}{\vartheta_2} \tag{15}$$

Where, $\vartheta_1 \sim N(0,1)$ and $\vartheta_2 \sim N(0,1)$. $N(0,1)$ is a normally distribution that its mean and standard deviation are 0 and 1, respectively.

Then, each solution is modified by using (10) and checked the radial topology constraint by using (7) and if this constraint is satisfied, it will be evaluated the fitness function value by (6). Then, the new solutions are compared with the corresponding individuals in the current population and if they are better than the old ones, they will substitute for the old ones. Finally, the current best solution (SW_{best}) that exists the best fitness value (fit_{best}) is updated.

Step 3: Update the current population for the second time relied on decomposition operator

The new solutions from the first to the end ones are created relied on the current best solution information as follows:

$$S_{i,novel} = SW_{best} + 3.\vartheta_3.(\tau_1.SW_{best} - \tau_2.SW_i) \tag{16}$$

Where, $\vartheta_3 \sim N(0,1)$. τ_1 and τ_2 are calculated as follows:

$$\begin{cases} \tau_1 = \mu_2.randi([1,2]) - 1 \\ \tau_2 = 2.\mu_2 - 1 \end{cases} \tag{17}$$

Where, $randi([1,2])$ is a random integer number in [1, 2].

Then, each solution is modified by using (10) and checked the radial topology constraint by using (7) and if this constraint is satisfied, it will be evaluated the fitness function value by (6). Then, the new solutions are compared with the corresponding individuals in the current population and if they are better than the old ones, they will substitute for the old ones. Finally, the SW_{best} is updated again. The pseudo code of the AEO for the multi-goal network reconfiguration is presented in Fig. 1.

```
Step 1: Initialization
        Create randomly initial population by (9)
        Modify each solution by (10)
        For each solution do
            Calculate the fitness function value by (6)
        End for
        While iter < iter_max do
Step 2: Update the current population for the first time
        Arrange the population in the order descending of the fitness value
        Generate the first new solution by (11)
        For each solution from the 2nd to the last one do
            If rand < 1/3 then
                    Generate the new solution by (12)
            Else if rand > 1/3 and rand < 2/3 then
                    Generate the new solution by (13)
            Else
                    Generate the new solution by (14)
            End if
        End for
        For each new solution do
            Calculate the fitness function value by (6)
        End for
        Update the current population and the best solution
Step 3: Update the current population for the second time
        Generate the new solutions by (16)
        For each new solution do
            Calculate the fitness function value by (6)
        End for
        Update the current population and the best solution
End While
```

Figure. 1 Pseudo code of the AEO for the multi-goal NR

4. Results and discussion

To show the effectiveness of the proposed AEO method, the 33-node DN shown in Fig. 2 is employed to search the optimal configuration [22]. In which, four cases of network reconfiguration are considered as follows:

Case 1: Finding the optimal configuration for minimizing power loss

Case 2: Finding the optimal configuration for

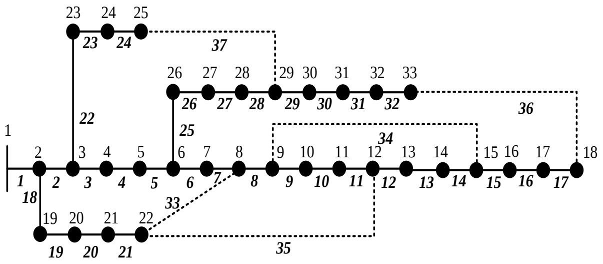

Figure. 2 The 33-node DN

minimizing voltage deviation
Case 3: Finding the optimal configuration for minimizing load balancing index
Case 4: Finding the optimal configuration for the multi-goal function with P_{loss}, VD, $LUBI$ and NSO.

In addition, the multi-goal function NR methods based on other metaheuristic algorithms consisting of CSA [18], GA [19] and PSO [20] are also implemented and run on the same computer to contrast with the AEO. The population size, problem size and the maximum number of iterations of four methods are respectively selected to 20, 5 and 100. The alien eggs discovery rate of CSA is selected to 0.25 [18]. The scale coefficients of PSO is selected to 2 [23], [24], [5].

The optimal network configuration of four cases obtained by AEO are shown in Table 1. The table shows that the configuration obtained in case 1 has the smallest power loss with 139.55 kW while the configuration obtained in case 2 has the best voltage improvement with the lowest voltage amplitude of 0.9412 and the configuration obtained in case 3 has the lowest LUBI of 0.0242. However, it is clear that cases 1 to 3 only optimize component goal functions. For example, in case 1, it takes 8 switch operations to achieve the smallest power loss or in case 2, it takes 10 switch operations to get the smallest voltage deviation while in case 3, in order to achieve the smallest LUBI, the voltage deviation is worse than that of the initial network. These problems have been overcome in case 4, the indicators are improved compared to the original network. Specifically, P_{loss} is reduced by 46.1533 kW corresponding to 22.77 % reduction, VD is reduced by 0.0205 corresponding to 23.59 % reduction and V_{min} has increased by 0.0205 p.u, corresponding to an increase of 2.25 %. In addition, $LUBI$ has decreased by 0.0124, which corresponds to 31.08 % reduction and the maximum current in the DN has been reduced by 2.2065 A corresponding to 1.05 % reduction compared to the original configuration. It is important that all the benefits are gained with only 2 switch operations contrasted to the original network. Fig. 3 shows that the balance among the objective functions in case 4 is the best compared to the remaining cases. The voltage and current of the DN for the considered cases are demonstrated in Figs. 4 and 5. From the figures, the voltage and current profiles obtained by the multi-goal NR method are more improved than those of the initial configuration.

The result comparisons among AEO, CSA, GA and PSO methods for the multi-goal ENRP presented in Table 2 shows that AEO superiors to the other methods. In 50 independent runs, all four methods

Table 1. The optimal results obtained by AEO for all cases

Item	Initial	Case 1	Case 2	Case 3	Case 4
Open switches	33-34-35-36-37	7-9-14-32-37	7-9-14-32-28	7-30-34-35-37	7-33-34-36-37
P_{loss} (kW)	202.6863	139.5543	139.9823	203.0920	156.5330
$1-V_{min}$ (p.u)	0.0869	0.0622	0.0588	0.1305	0.0664
V_{min} (p.u)	0.9131	0.9378	0.9412	0.8695	0.9336
$LUBI$	0.0399	0.0272	0.0290	0.0242	0.0275
I_{max} (A)	210.3656	207.1295	207.2106	211.0853	208.1591
NSO	0	8	10	4	2

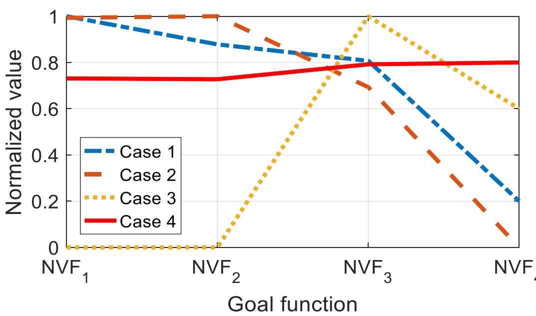

Figure. 3 The balance of the goal functions for four cases

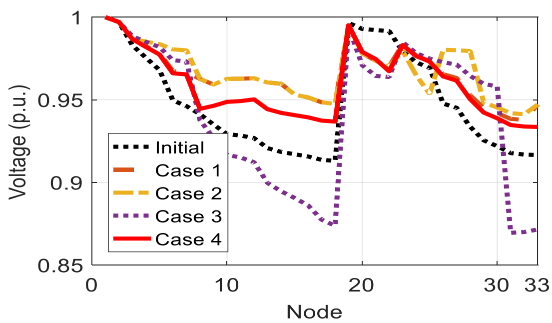

Figure. 4 The voltage profile of all cases

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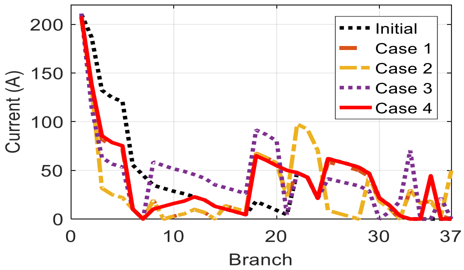

Figure. 5 The current profile of all cases

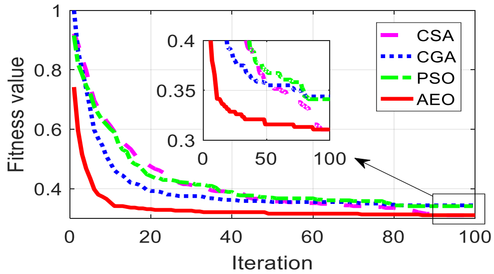

Figure. 6 The comparison of mean convergence line of AEO, CSA, GA and PSO

Table 2. AEO's efficiency compared to CSA, GA and PSO for the multi-goal network reconfiguration

Item	**AEO**	**CSA**	**GA**	**PSO**
$Rate_{succes}$	35/50	35/50	22/50	33/50
fit_{max}	0.4	0.4	0.4	0.4
fit_{min}	0.27257	0.27257	0.27257	0.27257
fit_{mean}	0.3108	0.3108	0.34393	0.34393
STD	0.05898	0.05898	0.06389	0.06389
$iter_{mean}$	13	47	23	23
T_{run} (s)	11.0175	11.4134	6.3659	6.3659

has reached the optimal configuration but the success rate of AEO is higher than that of GA and PSO, the average value and standard deviation (STD) of the fitness values of AEO is also lower than GA and PSO. Moreover, the mean of number of converged iterations gained by AEO is also smaller than the above methods. While compared with CSA, although both AEO and CSA have searched the optimal solution with the same success rate and the mean of the fitness function, it is clear that the AEO has converged more rapidly than CSA. AEO typically converges after about 13 iterations while this number of CSA is about 47 iterations. The mean convergence curve of the methods demonstrated in Fig. 6 presents that the AEO is surpassing than the other methods in term of the convergence.

The result comparisons among AEO with other previous methods is presented in Table 3. For case 1, the optimal configuration obtained by AEO is the same with MPSO [1], RRA [16], HSA [6], PSO [5], HBB-BC [13] and IWO [15]. Compared with FWA [7], ant colony algorithm (ACO) [25] and SFLA [14], the minimum voltage of these methods are higher than that of AEO but their reduction of P_{loss} is lower than that of AEO. For the case 4, the P_{loss} reduction, minimum voltage and LUBI index obtained by AEO are worse than those of RRA [16] and IWO [15] but the number of switch operations of AEO is less than that of RRA and IWO. Compared with HBB-BC [13] and hybrid PSO (HPSO) [26], the P_{loss} reduction and V_{min} of AEO are worse than those of two mentioned method but the LUBI index and the number of switch operations of AEO is better than those of HBB-BC and HPSO. Meanwhile, the minimum voltage and the number of switch operations of AEO are better performance than those of SFLA [14]. This confirms that AEO is an effective approach for the single as well as the multi-goal ENRP.

Table 3. The obtained result comparisons among AEO and other approaches for case 1 and case 4

Item	**Open switches**	P_{loss} **(kW)**	V_{min} **(p.u)**	**LUBI**	**NSO**
Case 1: Power loss reduction single goal function					
AEO	7, 14, 9, 32, 37	139.5543	0.9412	0.0279	8
MPSO [1]	7, 14, 9, 32, 37	139.5543	0.9412	0.0279	8
RRA [16]	7, 14, 9, 32, 37	139.5543	0.9412	0.0279	8
HSA [6]	7, 14, 9, 32, 37	139.5543	0.9412	0.0279	8
HBB-BC [13]	7, 14, 9, 32, 37	139.5543	0.9412	0.0279	8
IWO [15]	7, 14, 9, 32, 37	139.5543	0.9412	0.0279	8
FWA [7]	7, 14, 9, 32, 28	139.98	0.9412	0.0308	10
ACO [25]	7, 9, 14, 28, 32	139.98	0.9412	0.0308	10
SFLA [14]	7, 9, 14, 28, 32	139.98	0.9412	0.0308	10
Case 4: Multi-goal function					
AEO	33, 34, 7, 36, 37	156.5330	0.9336	0.0275	2
RRA [16]	6, 34, 11, 36, 37	145.05	0.9373	0.0271	4
IWO [15]	6, 11, 32, 34, 37	144.41	0.9357	0.0262	6
HBB-BC [13]	7, 9, 14, 28, 32	139.98	0.9412	0.0308	10
SFLA [14]	6, 8, 12, 36, 37	151.51	0.9318	0.0259	6
HPSO [26]	7, 9, 14, 32, 37	139.55	0.9378	0.0279	8

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5. Conclusion

In this work, the NR method for single goal and multi-goal functions based on AEO has been first proposed. The member goals are considered to optimize including power loss, voltage deviation, load unbalance index among branches and number of switch operations. The max-min approach is used to combine the member goal functions. The effectiveness of the AEO method are evaluated on the 33-node DN and compared with CSA, GA and PSO algorithms. The simulated results show that the multi-goal ENRP give the better improvement of power loss, voltage deviation, load unbalance index among branches and number of switch operations than the single ENRP. The result comparisons among methods show that AEO is better performance than CSA in term of number of convergence iterations. The mean number of iterations of AEO is 34 iterations lower than that of CSA. In comparisons with GA and PSO methods, AEO reach the better performance than GA and PSO in indexes of success rate, the mean fitness value and the number of convergence iterations. The success rate of AEO is respectively 13 and 2 higher than that of GA and PSO. The mean fitness value and the number of convergence iterations are 0.03313 and 10 lower than that of GA and PSO. The result comparisons with other previous methods also leads to that AEO is an effective approach method for the ENRP to optimize the single and the multi-goal functions. Future studies may evaluate the AEO's efficiency for the ENRP considering to the presence of distributed sources.

Notation list

V_{min}: Minimum voltage amplitude
I_i: Current of branch i
$I_{i,rate}$: Rate currents of branch i
$SW_{0,i}$: Status of switch i in the initial configuration
SW_i: Status of switch i in the after reconfiguration
N: Number of solutions in the population
D: Number of switches in each solution
$iter$: Current iteration
$iter_{max}$: Maximum iteration
$\mu_1, \mu_2,$: Random number in [0, 1]

Conflicts of interest

The authors declare no conflict of interest.

Author contributions

Conceptualization, methodology, software, T.T.N; validation, H.T.T, H.P.N, T.L.D, T.L.V and T.T.N; writing—original draft preparation, T.T.N; writing—review and editing, H.T.T, H.P.N, T.L.D, T.L.V and T.T.N; supervision, T.T.N.

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