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A new technique for efficient reconfiguration of distribution networks

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Abstract. This paper presents an effective method to solve the reconfiguration problem of distribution systems for minimizing the real power losses using the new proposed technique and the ant colony optimization. The proposed technique, based on three operations on loop removal, loop update, and loop subscription, is introduced to generate the feasible solutions and correct the infeasible solutions during the whole evolutionary process without applying tedious mesh checks; therefore, the computational burden and optimization time are reduced. The effectiveness of the suggested technique is demonstrated on 33-, 69-, and 118-bus test distribution systems. The simulation results indicate that the proposed method is useful and efficient for the reconfiguration problem of distribution networks.

1. Introduction

In the distribution network, configuration changes under different conditions to optimize the objective function by considering the operational constraints. This change in network structure or reconfiguration is done by altering the close/open status of sectionalizing and tie-switches considering this switching must be done in a way that satisfies the radial structure of the distribution system. Thus, because of the large number of switching states and maintaining the radial structure of the network, reconfiguration of the distribution system is a very complex, combinatorial optimization problem.

In recent years, much research has been done to solve the reconfiguration problem of distribution system. Merlin and Back [1] were the first to present a reconfiguration method to minimize real power losses of distribution network. They formulated the problem as a mixed integer nonlinear optimization problem and solved it by a method called discrete branch-and-bound. Later [2-4] they proposed heuristic algorithms based on the branch exchange. Since the reconfiguration problem has become more complex with increasing the size of real distribution systems, a quality solution cannot be provided by this heuristic techniques. Therefore, researchers were inclined toward using population-based meta-heuristic algorithms so that Nara et al. [5] introduced Genetic Algorithm (GA) to solve reconfiguration problem of the distribution system for power loss reduction. Later, several GA-based methods [6-10] and also some other stochastic-based techniques like tabu search algorithm [11,12], particle swarm optimization [13,14], ant colony optimization [15,16], simulated annealing [17,18], etc. were used for reconfiguration of the distribution systems.

Given that, reconfiguration of the distribution network in order to optimize the objective function must be done in some way that satisfies the radial structure constraint; also, in the stochastic-based search algorithms, a large number of infeasible individuals exist in the initial and produced population during the evolutionary process which violate the radial structure constraint. So this causes more populations to be generated to get the various feasible individuals to achieve

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optimal solution. Consequently, it increases CPU time and computational burden in the optimization process.

To resolve this issue, Morton and Mareels [19] presented a brute-force algorithm to list and evaluate all radial structures of distribution system. For the moderate size distribution network, this method guarantees optimal solution using graph theory including semi-sparse transformations of a current sensitivity matrix; but the method cannot be applied for a large distribution network, because there are a large number of radial configurations. Therefore, to solve this issue, many different codifications have been presented for meta-heuristic algorithms. Hong and Ho [20] proposed the Prufer number codification. In this method, each chromosome is coded as a Prufer number. Therefore, during evolutionary process, after crossover and mutation operation, any chromosome is generated as a Prufer number and is decoded somehow that the radial structure of the network is satisfied. Delbem et al. [21] developed an integral proposal using the graph theory concept. In this approach, only the specialized mutation operator was used and the crossover operator was neglected, because it usually produces infeasible solutions. Romero et al. [22] suggested a method called path-to-node to ensure the generation of feasible individuals. In this method, the paths linking each bus to the substation are obtained; therefore, if there is more than one path to a bus, it means that the loop has been created and a number of buses have been isolated in the network. Therefore, the open/close status of switches is modified in some way that only one path for each bus is created, and consequently, the radial structure of the network is produced. Enacheanu et al. [10] combined the Kruskal algorithm with the Metroid theory to generate a chain of spanning trees during crossover and mutation operation. Carreno et al. [23] proposed a method of genetic algorithm coding to guaranty the production of radial topologies. In this way, the chromosome length is equal to the total number of network branches and each gene only consists of a switch number. So the radial structure is obtained by adding the switches correspond to the first gene to the last gene in succession. But in this method, because of the large length of chromosome, especially for large sized distribution networks, the search space becomes larger and the diversity of solutions is lost, thus obtaining a global optimum will be very time-consuming. On the other hand, this method can only be implemented by genetic algorithm and it is not compatible with other search space-based meta-heuristic algorithms. Abdelaziz et al. [14] proposed an algorithm based on the bus incidence matrix $\hat{A}$ for checking the radiality of network topology. In this algorithm, the determinant value of matrix $\hat{A}$ is calculated so that the values of 1 or -1 and 0, respectively, represent the feasible and infeasible solution. If the solution is infeasible, each switch is replaced by other switches of the network through the correction algorithm. It seems very manually and will be time-consuming, especially for large-sized distribution networks. Swarnkar et al. [24] suggested a new efficient codification based on the concept of graph theory to generate only feasible radial topologies of distribution networks. Thus, the generated infeasible population, in the initial stage and during the evolutionary process, is corrected under the guidance of graph theory rules and is converted to feasible population. Therefore, for small-sized distribution networks, the terms forming the graph rules can be obtained. But for real large-sized distribution networks, the number of these terms is high and, therefore, obtaining them is difficult, and also, correcting the infeasible population according to these terms is very time-consuming. De Macêdo Braz et al. [25] proposed two approaches for network encoding, called subtractive and additive approaches, to generate only feasible radial topologies of distribution networks. In the additive encoding, at first, all branches of the network are opened. Then, the branches are added one after another, sequentially, to produce a radial structure of the distribution network. In the subtractive encoding, all branches are closed first; then by opening a switch in a loop, this loop is removed and if the open switch be common with another loop, then a new loop is formed. Thus, it continues until all the loops are eliminated and the radial structure of the network is formed. However, due to the irregular switching operation, the convergence of solutions will be low and so optimization time will increase.

This paper presents a new efficient technique to generate only feasible radial topologies in initialization and during evolutionary process using three operations of loop removal, loop update, and loop subscription. In this work, the proposed technique is demonstrated using Ant Colony Algorithm (AC) to solve the reconfiguration problem of distribution network. Then, in Section 2, the system power losses formulation will be introduced. In Sections 3 and 4, the proposed new technique and Ant Colony Algorithm (AC) are demonstrated. In Section 5, the simulations are carried out on the IEEE 33-, 69-, and 118-bus networks. The simulation results indicate the effectiveness of the proposed method in comparison with other methods in terms of optimization convergence and time.

2. System power losses formulation

Reconfiguration of the distribution networks is done to achieve various objectives such as reducing power losses, load balancing index, voltage profile improvement, reducing the switching number, etc. In this paper, the network topology is frequently reconfigured to obtain minimum power losses while satisfying various operating constraints. Therefore, the power losses in the distribution network feeders can be formulated as follows:

Minimize:

$$f = \sum_{j=1}^{M} R_j \left|I_j\right|^2 + P. \tag{1}$$

Subject to:

$$V_{\min} \leq V_i \leq V_{\max} \qquad \text{for} \quad i = 1, 2, \cdots, N, \tag{2}$$

$$S_j \leq S_j^{\max} \qquad \text{for} \quad j = 1, 2, \cdots, M, \tag{3}$$

where, N and M are the total numbers of nodes and branches in the system; R_j and $|I_j|$ are the jth branch resistance and current; and P is the penalty function which is equal to a large number when the voltage and apparent power constraints are violated; otherwise, it is zero. Eq. (1) is the objective function which is optimized and represents the sum of power losses of all branches in the distribution system. Eq. (2) considers the minimum and maximum voltage limits for each node of the system. Eq. (3) corresponds to the apparent power and maximum capacity limit of the jth branch.

3. Proposed new technique

In the distribution networks, there are sectionalizing switches and tie switches which are open in the radial mode. In a reconfiguration, a number of these switches are opened or closed and the network topology changes, thus the variable of reconfiguration problem is the number of switches which must be opened to maintain the radial structure of the network. The length of this variable is equal to the number of fundamental loops [26].

$$S = M - N + 1, \tag{4}$$

where S is the number of network fundamental loops or open switches; and N and M are the total numbers of nodes and branches in the network.

According to Eq. (4), the number of switches, equal to the number of fundamental loops, must be open for the radial structure of network to be maintained and so that no load node be isolated so each time testing the network, only one switch be open in each fundamental loop. So the problem variable will be:

$$Z = [Z_1 \in L_1, Z_2 \in L_2, \cdots, Z_S \in L_S]. \tag{5}$$

$L_1, L_2, \cdots, L_S$ are the fundamental loops of distribution network. $Z_1, Z_2, \cdots, Z_S$ are the numbering of opening switches in any fundamental loop.

After the switches are numbered and the fundamental loop is determined, a population of solutions is generated by the search space-based optimization algorithm during initialization as well as at each intermediate evolutionary stage that a large number of these solutions are infeasible, because they violate the radial structure constraint; consequently the convergence of the algorithm will be low. Therefore, to achieve the optimum feasible solution, more populations of solutions must be generated which leads to the enlargement of the search space and, as a result, increases the computational burden and optimization time. To resolve this issue, an algorithm is needed to generate an initial population of feasible solutions as well as correct infeasible solutions during the evolutionary process and convert them to the feasible population. Therefore, in this paper, the proposed technique based on three operations on loop removal, loop update, and loop subscription is introduced. First, to illustrate the proposed technique, there is a need to establish the following two steps for the distribution network.

Step 1. All the fundamental loops of the meshed network are obtained and loop vector L_i including all switches of the ith fundamental loop is created, $i = 1, 2, \cdots, S$.

Step 2. All the initial loop vectors are created as follows:

$$L_{i-\text{initial}} = L_i \qquad \text{for} \quad i = 1, 2, \cdots, S.$$

Definition 1: The loop will be removed by opening a switch inside it. This procedure is called loop removal operation.

Definition 2: By switching in the L_i, if the switch, which has been opened, is common with L_j, then a hybrid loop is formed which includes all members of the L_i and L_j minus a share of them. Since the corresponding switch was selected in the L_i, the L_i is removed and the L_j will be updated which is equal to the hybrid loop:

$$L_j = xor(L_i, L_j). \tag{6}$$

This procedure is called *loop update operation*. For example, as shown in Figure 1, in the 33-bus test network with 33 buses, 37 switches, and 5 fundamental loops, the L_1 is removed by opening switch 4 on the L_1, but since the switch 4 is common with the L_4, a hybrid loop is formed from the combination of L_1 and L_4, therefore the L_4 is updated as follows:

$$L_4 = xor(L_1, L_4)$$

$$= \{2, 18, 19, 20, 33, 7, 6, 25, 26, 27, 28, 37, 24, 23, 22\}.$$

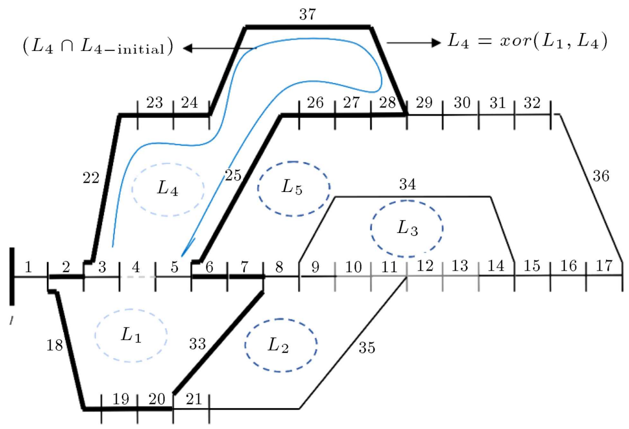

Figure 1. Loop update and loop subscription for the 33-bus system.

Definition 3: To create the radial structure of the network, there is the need to open only one switch within any fundamental loops L_i $(i = 1, 2, \cdots, S)$ which are updated during the switching operation. On the other hand, to have the regular switching operation and thus the better convergence of optimization, a switch that is opened in L_i must belong to the $L_{i-\text{initial}}$. Therefore, to solve this issue, there is a need to share the L_i with the $L_{i-\text{initial}}$, and then select the switch from it. This procedure is called *loop subscription operation*.

For example, as shown in Figure 1, for switching in loop 4, a switch that belongs to:

$$(L_4 \cap L_{4-\text{initial}}) = \{22, 23, 24, 37, 25, 26, 27, 28\},$$

is randomly selected to be opened.

3.1. Implementation of the proposed techniques

In Figure 2, the flowchart of the proposed technique is shown to produce feasible individual. In this technique, the switching operation, respectively, begins from the 1th loop vector L_1 and continues to the Sth loop vector L_S. First, in the L_1, a switch is randomly selected and opened. As a result, this loop is removed; so if the opened switch is not common with another loops, just *loop remove* occurs and other network loops will remain in their previous states. Otherwise, if the open switch is common with another loop, for example L_j, then this loop vector is updating and will be equal to $xor(L_1, L_j)$. After switching operations in L_j, a switch must be selected that belongs to $L_{j-\text{initial}}$ and also removes the L_j; so, to solve this issue, a switch which belongs to $(L_j \cap L_{j-\text{initial}})$ is randomly chosen. This process is performed for all the loop vectors. Finally all fundamental loops are opened and the radial structure of the network is produced. Similarly, as shown in Figure 3, infeasible individuals are corrected during the evolutionary process.

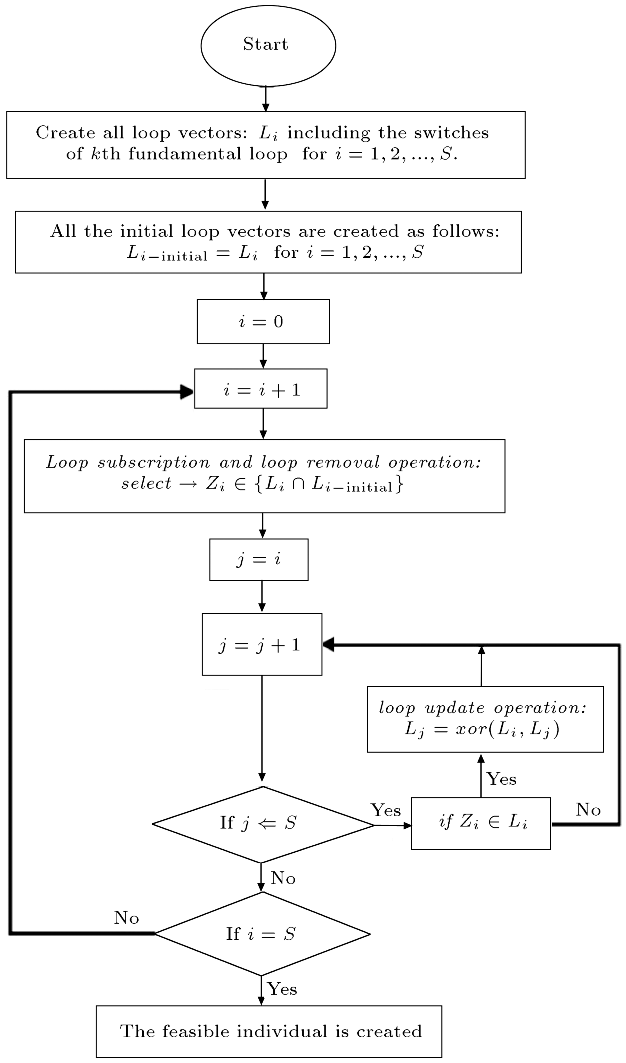

Figure 2. The proposed technique flowchart to create the feasible individual. Z_i is the ith member of problem variable (the switch that is opened in ith fundamental loop).

3.2. Illustration of the proposed technique

To understand more, the above techniques run to generate the radial structure of the network for 33-bus test network. Before switching operation, the mentioned two steps are formed as follows:

$$L_1 = \{2, 3, 4, 5, 6, 7, 33, 20, 19, 18\},$$

$$L_2 = \{8, 9, 10, 11, 35, 21, 33\},$$

$$L_3 = \{9, 10, 11, 12, 13, 14, 34\},$$

$$L_4 = \{22, 23, 24, 37, 28, 27, 26, 25, 5, 4, 3\},$$

$$L_5 = \{26, 27, 28, 29, 30, 31, 32, 36, 17, 16, 15, 34, 8, 7, 6\},$$

$$L_{i-\text{initial}} = L_i \qquad \text{for} \quad i = 1, 2, \cdots, 5,$$

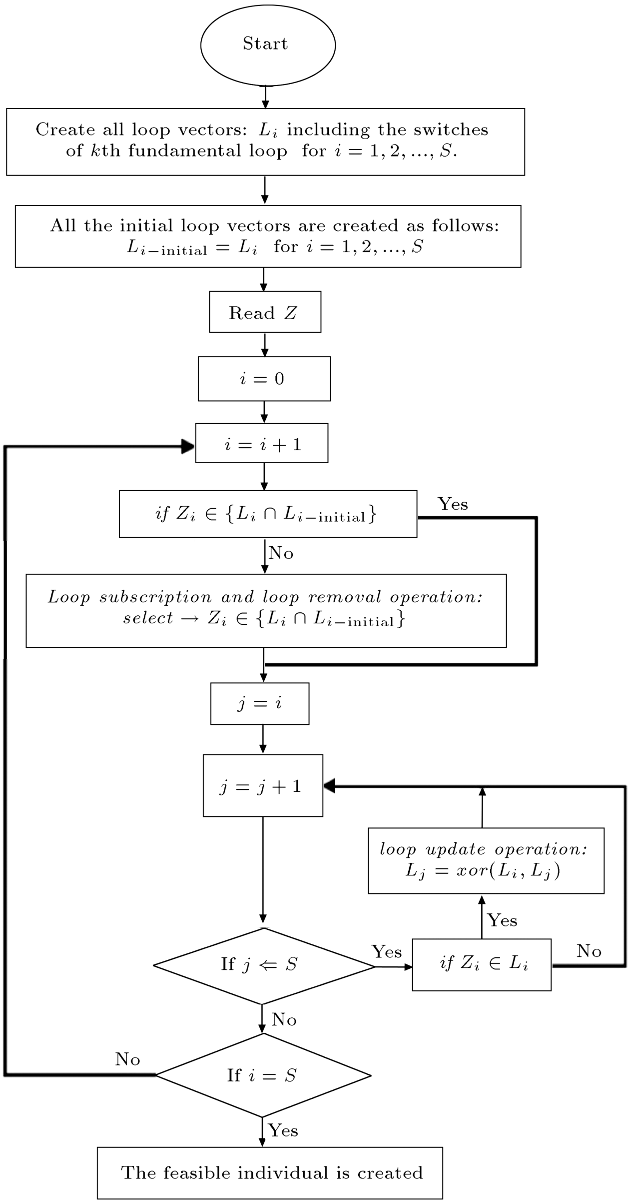

Figure 3. The proposed technique flowchart to correct the infeasible individual. S is the number of fundamental loop; and Z is the problem variable.

since the switching operation sequentially is started from the first loop and is continued to loop 5. So, first, switch 7 is selected randomly in L_1. As a result, according to Figure 4, L_1 is removed and considering that switch 7 is common with L_5, L_5 is updated.

Now, the next switch should be selected in L_2. As shown in Figure 5, L_2 is removed by selecting the switches 9 in it, randomly, and because this switch is common with L_3, L_3 is updated.

In the next stage, for the switching operation in L_3, considering that the L_3 has been updated during the previous stages, a switch must be selected that also belongs to $L_{3-\text{initial}}$ and also removes the updated L_3; therefore, switch 34 which belongs to $(L_3 \cap L_{3-\text{initial}})$ is randomly chosen. As shown in Figure 5, L_3 is removed and considering that switch 34 is common with L_5, this loop is updated again.

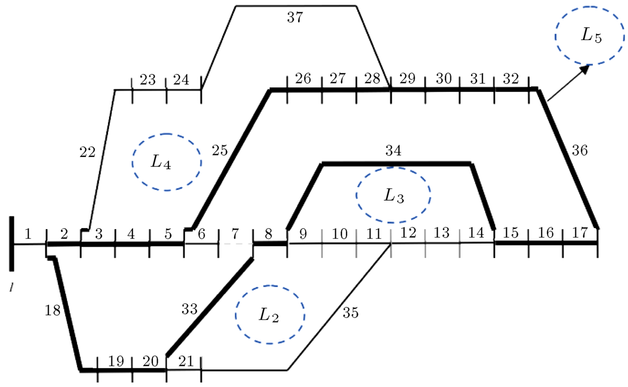

Figure 4. The switching operation in L_1.

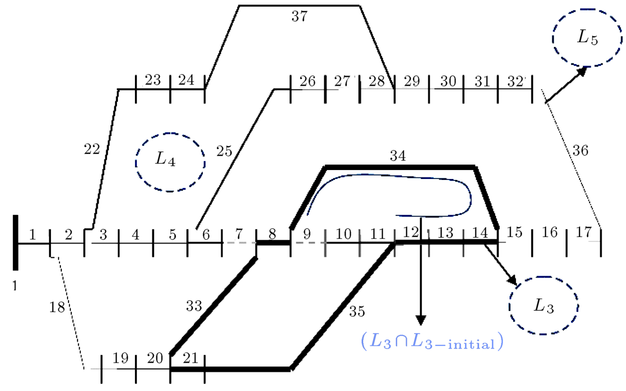

Figure 5. The switching operation in L_2.

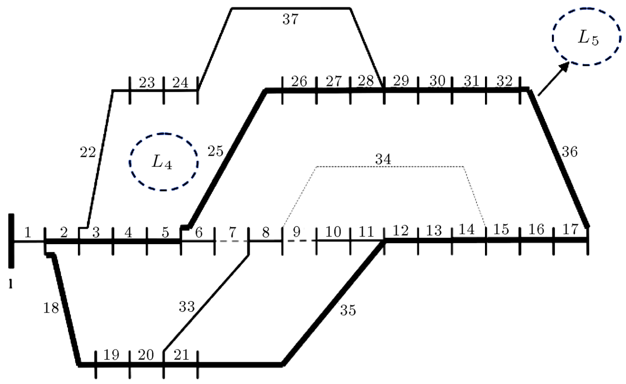

Figure 6. The switching operation in L_3.

According to Figure 6, in this stage, the rings network has been reduced to two loops containing L_4 and updated loop L_5. Continuing switching operation in L_4, considering that this loop has not been updated in the previous steps, it is equal to initial loop vector $L_{4-\text{initial}}$. Therefore, L_4 is removed by selecting the switches 25 in it, randomly, and as this switch is common with L_5, L_5 is updated again.

After switching operation in L_1 to L_4 and removing them, as shown in Figure 7, only updated

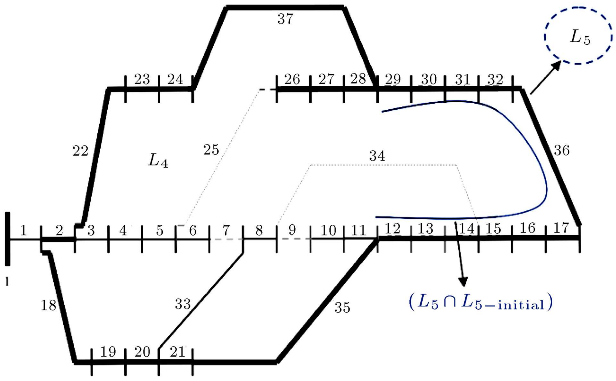

Figure 7. The switching operation in L_4.

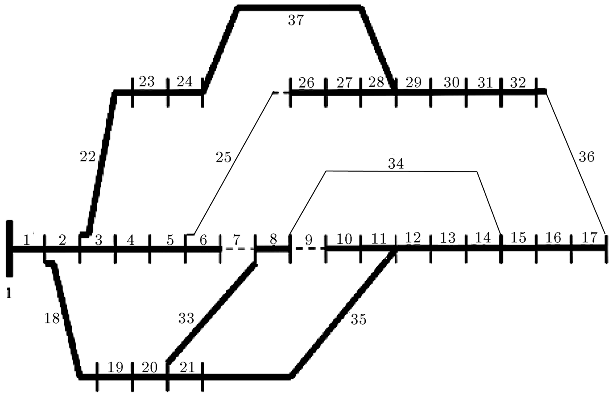

Figure 8. The switching operation in L_5.

L_5 remains which is removed by randomly selecting switch 36 that belongs to $(L_5 \cap L_{5-\text{initial}})$. As shown in Figure 8, the radial topology of network is formed. Finally, the reconfiguration problem variable $Z = [7, 9, 34, 25, 36]$ that satisfies the radial structure of the network is obtained.

4. Ant colony optimization

The ACO is inspired by the behavior of the ants while searching for food. Ants communicate with each other by secret chemicals called pheromone while moving in the paths between the nest and food. This pheromone evaporates with time. So the ants can be directed to cross the shortest path marked with more accumulated pheromone. Therefore, the AC algorithm procedures can be generally summarized as follows [27].

4.1. State transition rule

Each ant is placed on node i. Then, any ant will build a full path from the nod i to the node j, through repetitive application of the state transition rule as follows:

$$P_{i,j}^k = \frac{(\tau_{i,j})^\alpha (\eta_{i,j})^\beta}{\sum\limits_{m \in J_k(i)} (\tau_{i,m})^\alpha (\eta_{i,m})^\beta}, \qquad \forall \quad j \in J_k(i), \quad (7)$$

where $\tau_{i,j}$ is the deposited pheromone on the edge between nodes i and j, $\eta_{i,j}$ is the desirability of the edge between nodes i and j (e.g. $1/d_{i,j}$, where $d_{i,j}$ is the distance between node i and node j), α is the impact factor of deposited pheromone, β is the impact factor of path's desirability, $J_k(i)$ is the set of nodes that remain to be visited by kth ant positioned on node i. Eq. (7) shows that the state transition rule guides ants toward shorter paths with greater amount of deposited pheromone.

4.2. Local updating rule

While constructing its tour, an ant also modifies the amount of pheromone on the visited path by applying the local updating rule.

$$\tau_{i,j} = (1-\rho)\tau_{i,j} + \Delta\tau_{i,j}^k,$$

$$\Delta\tau_{i,j}^k = \begin{cases} \frac{1}{C_k} & \text{if ant } k \text{ travels on the edge } i-j \\ 0 & \text{otherwise} \end{cases} \quad (8)$$

where $\tau_{i,j}$ is the deposited pheromone on the edge between nodes i and j, ρ is the rate of pheromone evaporation, $\Delta\tau_{i,j}^k$ is the amount of pheromone deposited by the kth ant and C_k is the cost of the kth ant's tour (typically length).

The local updating rule provides a wide search space and avoids the convergence of problem toward the local optimum solution.

4.3. Global updating rule

When tours are completed, the global updating rule is applied to edges belonging to the best ant tour. This rule is intended to provide a greater amount of pheromone to shorter tours, which can be expressed below:

$$\tau_{i,j} = \tau_{i,j} + \sigma\Delta\tau_{i,j}, \quad (9)$$

where i, j is the best global path, σ is a constant multiplier, and $\Delta\tau_{i,j}$ is the amount of pheromone of the globally best tour from the beginning of trial. This rule is intended to make the search more directed; therefore, the capability of finding the optimal solution can be enhanced through this rule in the problem solving process.

4.4. Termination

As shown in Figure 9, the algorithm is terminated when the iteration number reaches the predefined maximum or all the ants of the current population reach the solution with the same fitness. The flowchart of the proposed algorithm is shown in Figure 9.

5. Simulation result

In this section, the proposed algorithm is tested on IEEE 33-bus test distribution network [2], 69-bus

Table 1. Test networks information.

System	Open switches before reconfiguration	Rated voltage (kV)	Total active load (kW)	Total reactive load (kVAR)	Power losses (kW)	Minimum node voltage (p.u)
33-bus	33-34-35-36-37	12.66	3715	2300	202.68	0.9133
69-bus	69-70-71-72-73	12.66	3802	2694	224.95	0.9092
118-bus	118-119-120-121-122-123-124-125-126-127-128-129-130- 131-132	11	22709.7	17041.1	1298.09	0.8688

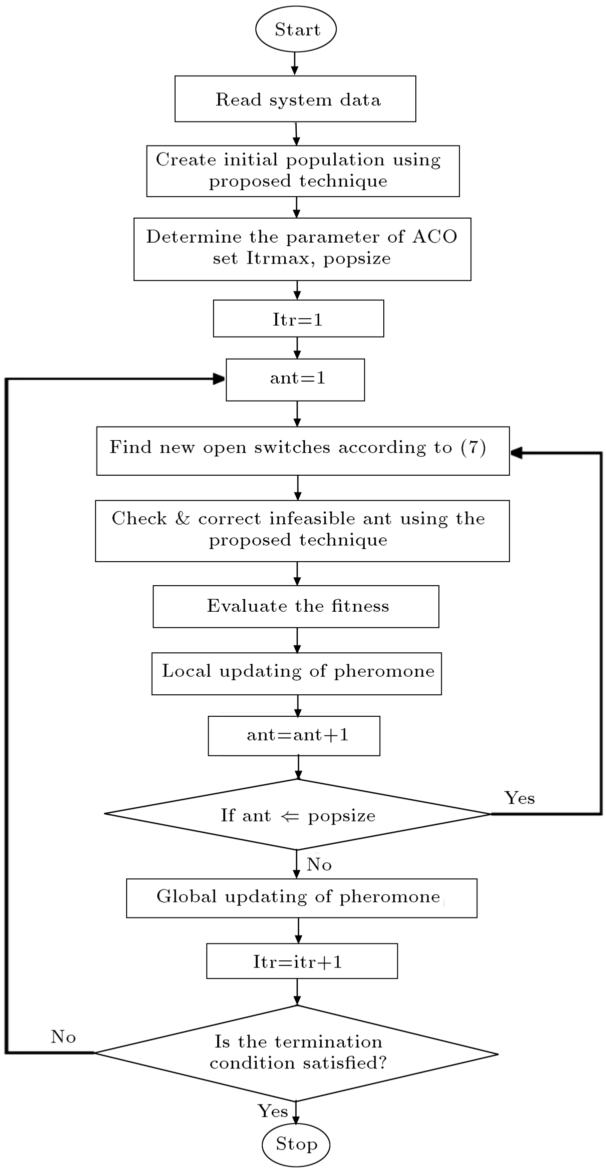

Figure 9. The proposed algorithm flowchart.

distribution network [28], and 118-bus distribution network [29]. Considering that, buses and lines in the 118-bus distribution network are numbered as in Figure 10.

The initial configuration, total real and reactive loads, real power losses, minimum node voltage, and system rated voltage of these test distribution systems are summarized in Table 1.

Table 2. The control parameters of the ACO.

System	ACO parameters
33-bus	Generation=600, $\alpha = 1$, $\beta = 0$, $\rho = 0.1$, $\sigma = 2$, $pc = 0.2^*$
69-bus	Generation=600, $\alpha = 1$, $\beta = 0$, $\rho = 0.1$, $\sigma = 3$, $pc = 0.2^*$
118-bus	Generation=2000, $\alpha = 1$, $\beta = 0$, $\rho = 0.1$, $\sigma = 10$, $pc = 0.2^*$

*: The probability of changing one switch randomly with other switches in the same fundamental loop.

Values of the control parameters of the ACO are frequently changed during numerous trials to provide the best possible result. Finally, the optimal values of the parameters are set as expressed in Table 2.

The proposed algorithm is coded in MATLAB language and run several times for each test distribution system in a PC with CPU: Intel core i7-2630QM and Memory: 6 GB DDR3. The test results for loss minimization are summarized in Table 3. For example, for the 33-bus test network, simulation was run each time with the number of generation 30 over 20 iterations (600 individuals) that during 50 times of running, the best solution with opened switch 7 9 14 37 32, power losses 139.55 kW and the worst result with power losses 142.36 kW are achieved. The simulation runtime is varied, depending on the number of generated infeasible individuals during the evolutionary process and modifying them. Thus, the Average time to run the simulation 50 times is obtained 0.92 second. Therefore, the results show that by using the proposed method and thereby shrinking the search space, the optimal solution is obtained with less number of individuals and thus effectively reduced computation time. Moreover, the negligible difference between the average losses reduction and the optimum one shows the very favorable convergence of the optimization process.

Table 4 presents a comparison of the optimized re-

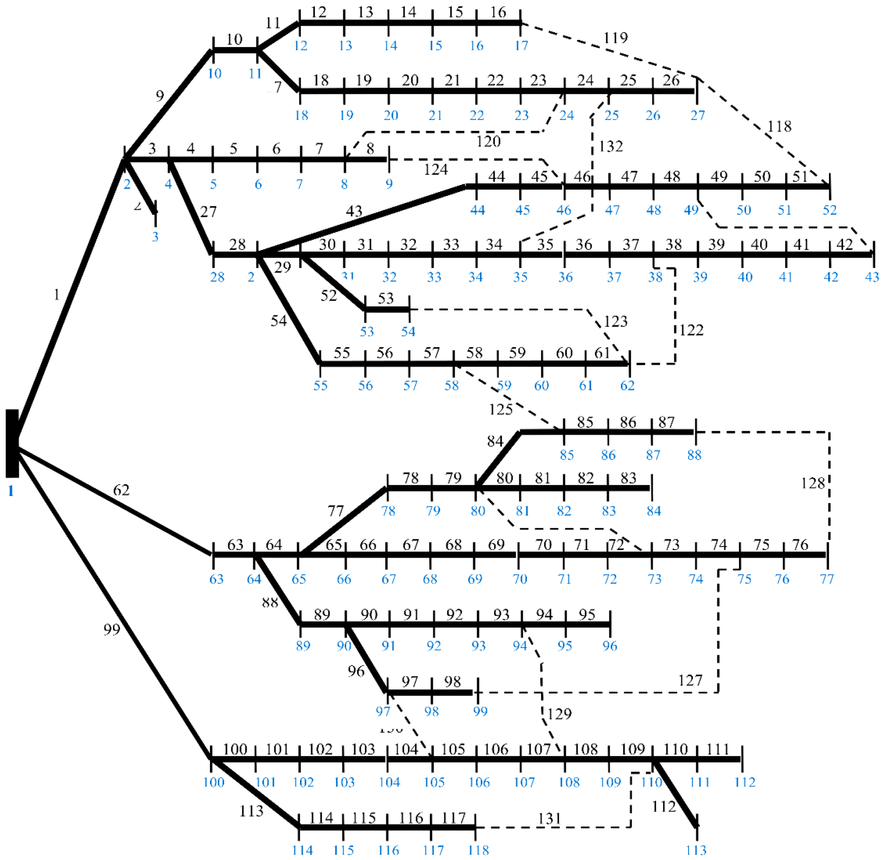

Figure 10. The 118-bus system.

Table 3. Optimization results for minimizing power losses using the proposed method.

System	Open switches after reconfiguration	Best (kW)	Worst (kW)	Mean (kW)	Generation iteration	The number of simulation run	Average computation time (s)
33-bus	7-9-14-37-32	139.55	142.36	140.08	30 20	50	0.92
69-bus	69-14-58-70-61	98.59	104.56	101.57	30 20	50	1.97
118-bus	125-58-44-5-119-26-42-30-122-76-71-130-73-93-109	682.71	869.73	776.22	40 50	30	10.24

sults obtained for these listed test distribution networks using the proposed method with other heuristic and meta-heuristic techniques available in the literature. The minimum node voltage and real power losses for the optimal solution are found to be either the same or better than those of other methods. Considering that the optimization process is terminated when the same global optimal solution is achieved during the predefined iteration number, the average computation time when using the proposed method is much less as compared to the computation times mentioned in the literature using latest AI (Artificial Intelligence) techniques. This clearly shows the computation efficiency of the proposed method for small, medium, and large-scale distribution systems, so that in this work, for 118-bus distribution network, the best solution is obtained which has not been achieved in any of the papers so far. As shown in Table 4, the minimum power losses can be achieved 687.21 kW after reconfiguration of 118-bus distribution network, whereas in the other methods, the minimum power losses obtained are equal to 865.86 kW. To understand more, as shown in Figure 11, node voltages are better improved after reconfiguration using the proposed method compared to the latest AI techniques.

Table 4. Comparison results for test distribution systems

System	Method	Open switches after reconfiguration	Power losses (kW)	Minimum node voltage (p.u)	Average generated solutions	Average computation time (s)
33-bus	**Proposed method**	**7-9-14-37-32**	**139.55**	**0.9378**	**170**	**0.23**
	Heuristic [30]	7-9-14-37-32	139.55	0.9378	38	0.41
	ACO [27]	7-9-14-37-32	139.55	0.9378	32	0.3
	GA [10]	7-9-14-37-32	139.55	0.9378	450	7.2
	PSO & HBMO [31]	7-9-14-37-32	139.55	0.9378	—	8
69-bus	**Proposed method**	**69-14-58-70-61**	**98.581**	**0.9495**	**360**	**1.1**
	GA [24]	69-14-58-70-61	98.581	0.9495	300	3.3
118-bus	**Proposed method**	**125-58-44-5-119-26-42-30-122-76-71-130-73-93-109**	**682.71**	**0.9321**	**1820**	**9.52**
	TS [29]	84-58-45-23-26-48-40-34-86-71-130-74-129-109-122	865.86	0.9323	600	600× unit time*
	ACO [27]	84-58-45-23-26-48-40-34-86-71-130-74-129-109-122	865.86	0.9323	1942	430.74

*: Production time of each generation in [29].

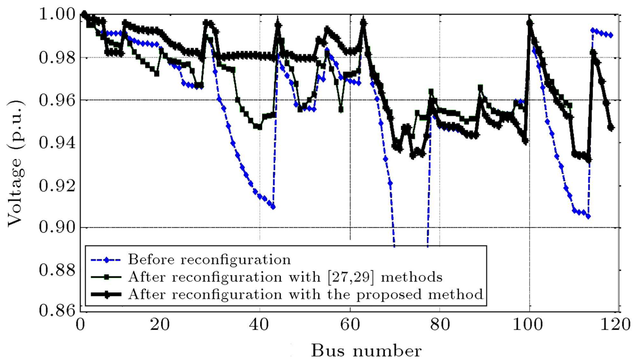

Figure 11. The voltage profile before and after reconfiguration.

Table 5. Computational efficiency of the proposed method.

System	Generated population	Average infeasible population	Average correction time for each infeasible individual (s)
33-bus	600	412	0.00041
69-bus	600	464	0.00084
118-bus	2000	1409	0.0034

6. Conclusions

Network reconfiguration is one of the best ways to optimize distribution network for different purposes. In this paper, a new technique based on three operations on loop removal, loop update, and loop subscription was presented for the population-based meta-heuristic algorithms to solve reconfiguration problem. This proposed technique generates an initial population of feasible solutions and also corrects infeasible solutions during the evolutionary process with the shortest possible time, as shown in Table 5. This preserves the diversity in the search process; thus, the convergence of solutions is increased and optimization time is significantly reduced. The proposed method was performed on the IEEE 33-, 69-, and 118-bus distribution networks. The results showed the effectiveness of the proposed algorithm compared with other methods, especially for large-sized distribution networks.

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