Swarm and Evolutionary Computation 1 (2011) 129–137

Contents lists available at SciVerse ScienceDirect

Swarm and Evolutionary Computation

journal homepage: www.elsevier.com/locate/swevo

Regular paper

Adapted ant colony optimization for efficient reconfiguration of balanced and unbalanced distribution systems for loss minimization

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ARTICLE INFO

Article history:
Received 19 November 2010
Received in revised form
4 May 2011
Accepted 23 May 2011
Available online 13 June 2011

Keywords:
Ant colony optimization
Distribution network
Graph theory
Real power loss
Reconfiguration

ABSTRACT

This paper presents an efficient method for the reconfiguration of radial distribution systems for minimization of real power loss using adapted ant colony optimization. The conventional ant colony optimization is adapted by the graph theory to always create feasible radial topologies during the whole evolutionary process. This avoids tedious mesh check and hence reduces the computational burden. The initial population is created randomly and a heuristic spark is introduced to enhance the pace of the search process. The effectiveness of the proposed method is demonstrated on balanced and unbalanced test distribution systems. The simulation results show that the proposed method is efficient and promising for reconfiguration problem of radial distribution systems.

1. Introduction

Distribution networks are generally structured in a mesh but operated in the radial configuration for effective co-ordination of their protective schemes and to reduce the fault level. The reconfiguration of a distribution system is a process that alters the feeder topological structure by managing the open/close status of sectionalizing and tie-switches in the system under contingencies or under normal operating conditions. Reconfiguration of the radial distribution system is a very effective and efficient means to reduce distribution network losses, improve voltage profile, manage load congestion and enhance system reliability. The aim of distribution network reconfiguration is to find a radial operating configuration that optimizes certain objectives while satisfying all the operational constraints without islanding of any node(s).

A lot of research work has been carried out to solve distribution network reconfiguration problems. These research efforts can be broadly classified into traditional approaches and artificial intelligence (AI) based approaches. The traditional approaches include heuristic optimization techniques and classical optimization techniques. Merlin and Back [1] were first to report a method for distribution network reconfiguration to minimize feeder loss. They formulated the problem as a mixed integer nonlinear optimization problem and solved it through a discrete branch-and-bound technique. Later, [2–7] also suggested different branch exchange heuristic algorithms. The complexity of reconfiguration problem increases with the exponential growth in the size of modern distribution networks and the heuristic techniques fail to provide a quality solution. Therefore, the researchers diverted toward various stochastic-based search techniques. Nara et al. [8] introduced genetic algorithm (GA) for reconfiguration of distribution networks for loss minimization. Later, several GA based methods [9–14] have been used for the reconfiguration of distribution networks. Mendoza et al. [13] proposed a new methodology for minimal loss reconfiguration using GA with the help of fundamental loops. They restricted the search space of GA by modifying the genetic operators. Enacheanu et al. [14] presented a method based on GA for loss minimization in the distribution networks using matroid theory and graph theory. Some other population-based meta-heuristic techniques, e.g., immune algorithm [15], evolutionary algorithm [16], simulated annealing [17,18], tabu search [19–21], particle swarm optimization [22] also attempted the reconfiguration problem.

The ant colony optimization (ACO) is a population-based meta-heuristic technique, has emerged as a powerful tool for solving combinatorial optimization problems, initially proposed by Marco Dorigo in 1992 in his Ph.D. thesis [23]. The search technique is inspired by the behavior of ants in finding paths from the nest to food and back to the nest. It was implemented to solve the traveling salesman problem (TSP) by Dorigo and Gambardella [24]. Later, Stutzle and Hoos [25] developed the max–min ant system (MMAS) to solve TSP and quadratic assignment problem. Then the basic ACO was further improved and a model-based search (MBS) algorithm was introduced by Blum and Dorigo [26]. Das et al. [27] attempted ant colony

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doi:10.1016/j.swevo.2011.05.004

approach to compute minimum Steiner tree. The original idea of ACO has been diversified to solve a wider class of problems. Recently, the ant algorithm also has been applied to various optimization problems of the power systems, such as short-term generation scheduling problem [28], unit commitment [29], hydroelectric generation scheduling [30], distribution system planning [31,32], joint optimization for capacitor placement and reconfiguration of the distribution systems [33]. Su et al. [34] proposed state transition rule, local and global updating rules to make the ACO computationally efficient to minimize real power loss in the distribution networks. Ahuja et al. [35] introduced the inherent feature of hyper-mutation of Artificial Immune System (AIS) into the ACO algorithm for multi-objective optimization reconfiguration problem to avoid local minima. Carpaneto and Chicco [36] employed restricted branch exchange to improve the computation efficiency of the conventional ACO.

The reconfiguration of the distribution system for loss minimization is a complex, combinatorial optimization problem. The application of these population-based search techniques to solve the reconfiguration problem of the distribution networks faces an additional difficulty of maintaining the radiality constraint throughout the evolutionary process. The methods available in the literature provide different ways of maintaining radiality constraint, but, they are incomplete in the sense that they may generate infeasible individuals during initialization as well as during the evolutionary process. These infeasible individuals are either rejected or corrected using some mechanism and the process is repeated till feasible individuals are obtained, which may be time consuming.

The main contribution of this paper is to propose a new codification to generate only feasible radial topologies of distribution system while solving the reconfiguration problem using the ACO. For this purpose, some rules are framed with the help of the graph theory and the conventional ACO is adapted by these rules, hence named Adaptive Ant Colony Optimization (AACO). The other contributions of this work are: initial feasible population is created randomly to maintain the diversity, a heuristic spark (HS) is introduced to make AACO computationally efficient, and the desirability is defined on the basis of node voltages to guide the ant search.

In this paper, the reconfiguration problem of the balanced and unbalanced distribution networks to minimize real power loss is solved using AACO. The organization of the paper is as follows. The formulation of the loss minimization problem is discussed in Section 2. The conventional ACO is explained in Section 3. The modifications proposed in the conventional ACO are discussed in Section 4, in Section 5 the proposed codification for AACO is illustrated with the help of an example. In Section 6, the application results of the proposed method on balanced and unbalanced distribution systems are presented and finally concluded in Section 7.

2. Problem formulation for minimal power loss

The distribution networks are reconfigured frequently to optimize operational efficiency and maintain power quality. The principal objective of distribution network reconfiguration is to find the radial operating structure having minimum real power loss while satisfying various operating constraints. All the loads are assumed of the nature of constant power. The reconfiguration problem of distribution networks for loss minimization is formulated as below:

$$\text{Minimize} \quad \sum_{n=1}^{E} R_n \frac{P_n^2 + Q_n^2}{|V_n|^2} \tag{1}$$

$$\text{Subject to} \quad I_n \le I_{\max}^n \tag{2}$$

$$V_{\min} \le V_n \le V_{\max} \tag{3}$$

$$\Phi(i) = 0 \tag{4}$$

where, V_n, P_n and Q_n are voltage, real power and reactive power at the sending end of the nth branch respectively, R_n is the resistance of the nth branch and E is the total number of branches in the system.

Eq. (1) corresponds to the objective function to be optimized and represent total real power loss of the distribution system. Eq. (2) corresponds to limit branch current and substation current capacities within the permissible limits. Eq. (3) considers voltage constraints for each node of the system. Eq. (4), represents the radial topology constraint, it ensures radial structure of the ith candidate topology.

3. Ant colony optimization

The ant communication is accomplished primarily through the chemicals called pheromones. While moving, the ants deposit the pheromone trail on the ground. Other ants perceive the presence of the pheromone and tend to follow paths where the pheromone concentration is higher. The probability with which the kth ant will move from node i to node j can be determined by the random-proportional state transition rule [25] as given below:

$$P_{i,j}^k = \frac{(\tau_{i,j})^{\alpha}(\eta_{i,j})^{\beta}}{\sum(\tau_{i,j})^{\alpha}(\eta_{i,j})^{\beta}} \tag{5}$$

where $\tau_{i,j}$ is the amount of the pheromone on the edge $i - j$, α is the parameter to control the influence of $\tau_{i,j}$, $\eta_{i,j}$ is the desirability of the edge $i - j$ (a priori knowledge, typically $1/d_{i,j}$, where d_{ij} is the distance between node i and node j) and β is the parameter to control the influence of $\eta_{i,j}$

While moving from node i to node j, the kth ant updates the pheromone on the edge $i - j$. To escape local minima, the pheromone evaporation is used. A minimum pheromone concentration of small positive number may be considered to avoid zero or negative value. The evaporation is applied uniformly to all the edges with a simple decay coefficient ρ. The pheromone update is given by

$$\tau_{i,j} = (1-\rho)\tau_{i,j} + \Delta\tau_{i,j}^k \tag{6}$$

where $\tau_{i,j}$ is the amount of pheromone on a given edge $i - j$, ρ is the rate of pheromone evaporation and $\Delta\tau_{i,j}^k$ is the amount of pheromone deposited by the kth ant, typically given by

$$\Delta\tau_{i,j}^k = \begin{cases} 1/C_k, & \text{if and } k \text{ travels on the edge } i-j \\ 0, & \text{otherwise} \end{cases} \tag{7}$$

where C_k is the cost of the kth ant's tour (typically length).

4. Proposed adaptive ant colony optimization (AACO)

When the conventional ACO is employed to solve the reconfiguration problem of distribution networks, the radiality constraint imposes the main hurdle since a large number of infeasible individuals appear during initialization as well as at intermediate stages of the evolutionary process. These infeasible individuals may be transformed into feasible ones using some engineering knowledge base. The proposed methodology creates feasible individuals all times by encoding the individual ant with the help of the graph theory [37] and the terms are redefined in the context of distribution network reconfiguration, as described in the next sub-sections.

4.1. Ant encoding using graph theory

The graph of the given distribution network can be obtained by closing all the tie-switches. The radial configuration in which the distribution networks must operate should not possess any closed path with all nodes energized. These radial configurations

$Z_1 \in L_1$	$Z_2 \in L_2$	...	$Z_m \in L_m$	...	$Z_L \in L_L$

Fig. 1. Ant encoding for the proposed AACO.

are called *trees* of the distribution network graph (DNG). The *co-tree* is the compliment of a *tree*. The elements of the *co-tree* are called *links*. When one *link* is added in its corresponding *tree*, one *fundamental loop* is formed. In distribution network reconfiguration problem, the ants may be encoded by a set of definite number of switches to be opened (*links*). The number of *links* or the *fundamental loops* of a DNG is unique [37] and is given by

$$L = E - N + 1 \tag{8}$$

where E is the total number of elements (sectionalizing and tie-switches) and N is the total number of nodes of the distribution network.

The reconfiguration problem of the distribution network can be defined as to find that particular *tree* (i.e., the corresponding *co-tree*), which optimizes all the objectives and satisfies all the constraints set by the optimization problem. Therefore, while using the ACO, the ants may be encoded to represent a *co-tree*. If the ant population is selected randomly for initialization, as in case of the conventional ACO, a large number of infeasible topologies will generate. Moreover, infeasible topologies appear during the evolutionary process, which increases the computational burden. Therefore, some rules are framed to generate only feasible radial topologies. Before framing these rules, let us define

(i) Principal Node: The junction of three or more elements of the distribution network graph (DNG).
(ii) Exterior Node: The node located at the perimeter of the DNG.
(iii) Interior Node: The node located inside the perimeter of the DNG.
(iv) Loop Vector: It is the set of elements constituting closed path in a DNG. The *loop vector* for the kth loop in the given DNG is L_k, where $k = 1, 2, 3, \ldots, L$.
(v) Common Branch Vector: It is the set of elements which are common between any two *loop vectors* of a DNG. The *common branch vector* C_{ij}, containing the set of elements common between two *loop vectors* L_i and L_j.
(vi) Prohibited Group Vector: It is the set of *common branch vectors* incident to principal interior node(s) of the DNG. The *prohibited group vector* $R_{m1m2m3\ldots}$, isolate principal interior node(s) $m1, m2, m3 \ldots$ of the DNG.

Now, the following rules are framed to create feasible individuals during the whole evolutionary process:

Rule 1: The mth member of the individual must belong to the *loop vector* L_m.
Rule 2: Only one member from a *common branch vector* can be selected to form an individual.
Rule 3: All the *common branch vectors* of any *prohibited group vector* cannot participate simultaneously to form an individual.

The Rules 1 and 2 prevent islanding of exterior and interior nodes respectively, whereas Rule 3 prevents the islanding of principal interior nodes of the DNG. Therefore, while encoding the individual ant, these three rules ensure the radial topology of the network without islanding of any node(s) and thus it avoids tedious mesh checks. In general, the ant encoding in real numbers may be defined as shown in Fig. 1, where each member Z_m represents the open switch of the distribution network in real number. The ant consists of L such members, where the Z_m belongs to the *loop vector* L_m; $m = 1, 2, \ldots, L$.

In this paper, the conventional ACO is adapted using fundamentals of the graph theory to generate only feasible individuals during initialization and the various stages of the evolutionary process. Therefore, the proposed ACO is named as AACO. The *loop vectors*, *common branch vectors* and *prohibited group vectors* can be determined by the inspection of the DNG. However, the determination of the *prohibited group vectors* may be difficult, especially for large-sized distribution systems. Therefore, a simple algorithm is developed to obtain the complete set of the *prohibited group vectors* as given below:

- Identify all the principle interior nodes of the DNG.
- Determine all the *prohibited group vectors* corresponding to the isolation of the single principle interior node by observation.
- Combine all possible pairs of the *prohibited group vectors* so obtained and constitute thereon the new *prohibited group vectors* corresponding to the isolation of two principle interior nodes after discarding their common element(s), if any.
- Similarly, the *prohibited group vectors* corresponding to the isolation of three and more principle interior nodes can be obtained with all possible combinations of the previously obtained *prohibited group vectors*, subjected to the condition that the total number of elements of a *prohibited group vector* cannot be more than the total number of *loop vectors* of the DNG.

4.2. Initialization using heuristic spark

In the proposed algorithm, one individual of better fitness is created using the heuristics of [2], which may be called as HS. However, the remaining individuals are created randomly under the guidance of the rules framed to maintain diversity. The HS ignites the search engine of the proposed AACO as the other individuals are influenced by it. In the due course of time, these individuals will get better descendents and this enhances the pace of the search process.

4.3. Edge selection

In the ant codification shown in Fig. 1, the member Z_m indicates that an ant is standing at the switch Z_m and to implement Rule 1, its search is restricted within the corresponding *loop vector* L_m. An edge is defined as the imaginary path between one switch to another switch in the loop. In the next iteration, the probability of the movement of the ant from the current switch position i to all other switch positions within *loop vector* L_m is evaluated using (5) based on the pheromone concentration and desirability. The desirability in the context of reconfiguration is redefined in the next sub-section. The edge having maximum probability is selected. This process of selecting a switch is used for each loop separately, under the guidance of Rule 2 and Rule 3, such that the resultant ant represents a feasible radial configuration.

The loop shown in Fig. 2 is a part of any meshed network. The encircled numbers represent the nodes and numbers without circle represent the switch position in a *loop vector* L_m. It is also shown that an artificial ant is standing at the switch position 6. If its probability of the selection of edge from the switch position 6 to the switch position 10 is maximum, as shown by solid line in the figure, the edge will be selected as the path for the ant.

4.4. Desirability

In ant colony optimization, the term desirability is normally defined as the reciprocal of the distance between two nodes. For the reconfiguration problem, it is redefined in terms of the sending end node voltage of each line for the best radial network of the current iteration, because the sending end node voltage will keep

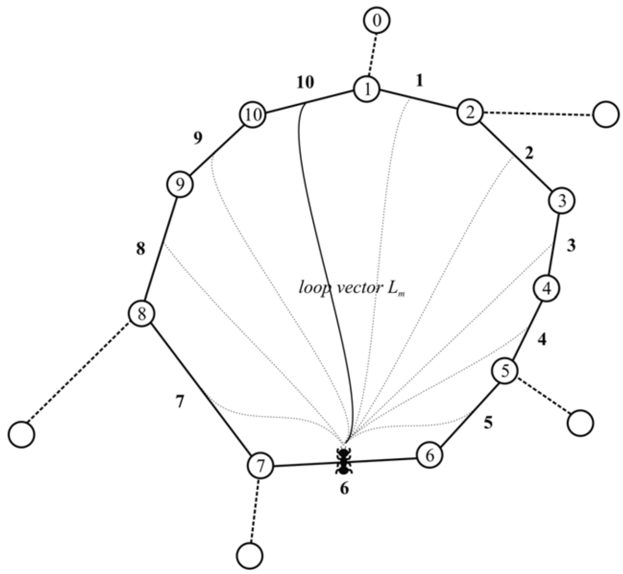

Fig. 2. Edge selection of the ant within *loop vector* L_m.

on decreasing as its distance from the source is increasing. This guides the artificial ants to select the better switches. A desirability matrix is created for each *loop vector*. Let, the *Dm* is the desirability matrix for the *loop vector* L_m and its element Dm_{ij} represents the desirability of selection of a switch *j* from the switch *i*. The value of Dm_{ij} is defined as

$$Dm_{ij} = \begin{cases} V_i - V_j, & i \neq j \\ \lambda V_i, & i = j \end{cases} \tag{9}$$

where λ is a constant multiplier.

4.5. Pheromone update

Whenever an ant moves from a switch position *i* to the switch position *j* in a *loop vector*, the pheromone concentration is updated. Similar to the desirability matrix, a pheromone matrix is created for each *loop vector*. The row number of the pheromone matrix represents the current switch position in the corresponding *loop vector* at which the ant is standing and the column number represents the target switch position in the respective *loop vector*. Initially, the random pheromone concentration is assumed for each probable transition to avoid the biasing of ant movement completely according to the desirability. Once the edge is selected, as discussed in the Section 4.3, the pheromone is updated using (7). The amount of pheromone deposited for the reconfiguration problem is defined as

$$\Delta\tau_{i,j}^{k} = \begin{cases} 1/P_k, & \text{if and } k \text{ travels on edge } i - j \\ 0, & \text{otherwise} \end{cases} \tag{10}$$

where P_k is the real power loss of the radial configuration obtained by the *k*th ant's travel.

4.6. Global update

The ants communicate the best location of food with other ants. To implement this behavior of ants for the reconfiguration problem, some extra pheromone is added for the edge from each switch in a *loop vector* to the switch of the same *loop vector* corresponding to the global best solution. For the *loop vector* L_m

$$\tau_{i,j} = \tau_{i,j} + \sigma\Delta\tau_{i,j} \tag{11}$$

where $i \in L_m$ and *j* is the switch position of the global best solution in the *loop vector* L_m, and σ is a constant multiplier.

Table 1
Loop vectors and the switch positions.

Switch position	Loop vectors				
	L_1	L_2	L_3	L_4	L_5
1	2	8	9	22	25
2	3	9	10	23	26
3	4	10	11	24	27
4	5	11	12	37	28
5	6	35	13	28	29
6	7	21	14	27	30
7	33	33	34	25	31
8	20	–	–	5	32
9	19	–	–	4	36
10	18	–	–	3	17
11	–	–	–	–	16
12	–	–	–	–	15
13	–	–	–	–	34
14	–	–	–	–	8
15	–	–	–	–	7
16	–	–	–	–	6

4.7. Hunting group

In ant colony, the responsibility of a particular group is to explore new possible food location irrespective of the pheromone deposition. This behavior of ants is incorporated for the reconfiguration problem by changing one switch randomly with another switch of the same *loop vector*. The role of the hunting group is same as that of the mutation in GA, i.e., which helps the search algorithm to come out of the local minima by exploring new search space. The mutation is not an appropriate terminology with reference to the ant colonies; hence it is redefined in terms of ant behavior. The size the hunting group ζ is normally selected about 2%–5% of the total ant population.

4.8. Elitism

The stochastic-based algorithms like ACO, the solution with the best fitness in the current iteration may be lost in the next iteration. Therefore, in the proposed algorithm, the ant with the best fitness is preserved for the next iteration.

4.9. Termination

The algorithm is terminated, when all the ants of the current population reach to the solution with same fitness or the iteration number reaches the predefined maximum iteration number to explore the search space rigorously. The flowchart of the proposed AACO is shown in Fig. 3.

5. Illustration of the proposed codification

To understand the application of the graph theory in the proposed codification, let us consider the example of IEEE 33-bus system, shown in Fig. 4. For this system, $E = 37$, $N = 33$ and $L = 37 - 33 + 1 = 5$. Therefore, there are five *loop vectors*. According to their position in the loop, each switch is assigned a position number as shown in Table 1. The network topology suggests seven *common branch vectors* as given in Table 2.

The *loop vectors* and the *common branch vectors* for the system can be pictorially represented by the Venn-diagram shown in Fig. 5. Each circle in the Venn-diagram represents a *loop vector* and the shaded portion represents the *common branch vectors*. The intersection of three or more *loop vectors* denotes the principal interior nodes, i.e., 5, 7 and 8. It can be seen from the figure that if one switch is selected to form an individual from each of the *common branch vectors* C_{14}, C_{15}, and C_{45}, which are incident to

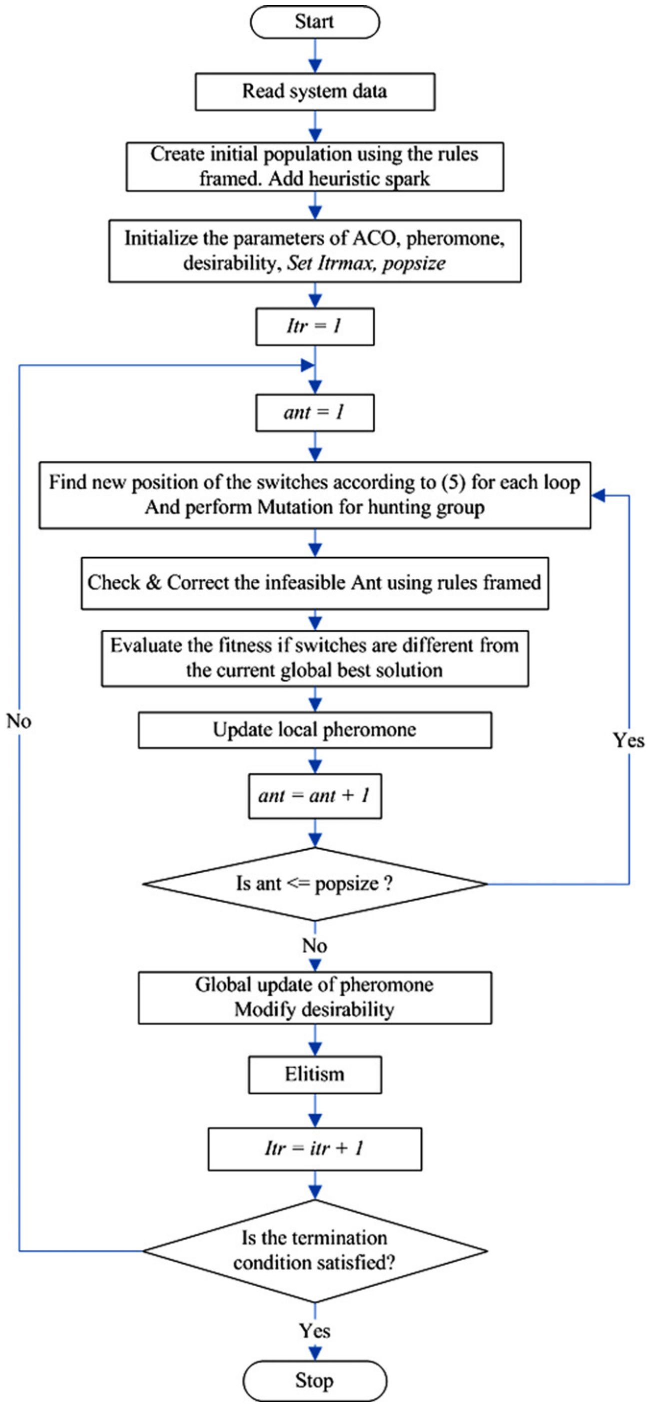

Fig. 3. Flow chart of the proposed AACO.

Table 2
Common branch vectors.

Common branch vectors	
$C_{12} = [33]$	$C_{25} = [8]$
$C_{23} = [9 \quad 10 \quad 11]$	$C_{15} = [6 \quad 7]$
$C_{14} = [3 \quad 4 \quad 5]$	$C_{45} = [25 \quad 26 \quad 27 \quad 28]$
$C_{35} = [34]$	

the principal interior node 5, the principal interior node 5 will be islanded. Therefore, the group of the *common branch vectors* C_{14}, C_{15}, and C_{45} constitute a *prohibited group vector*. Similarly,

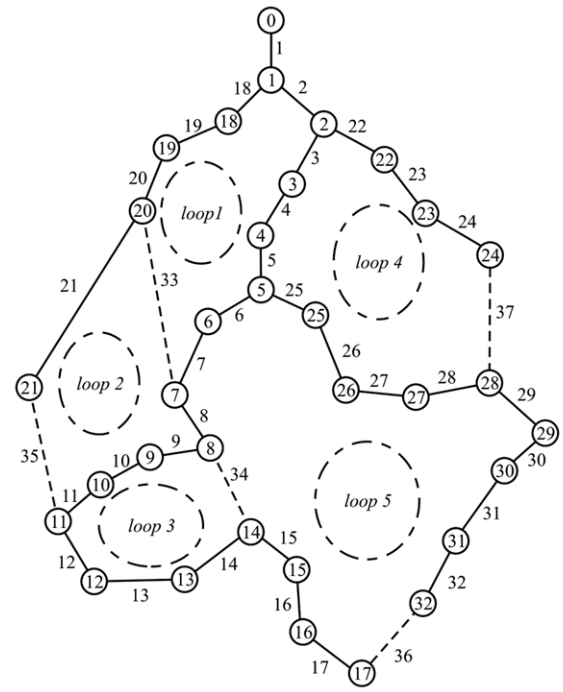

Fig. 4. IEEE 33-bus system.

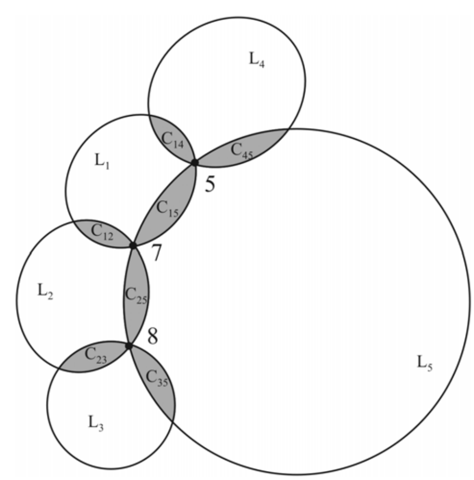

Fig. 5. Venn-diagram of the network.

Table 3
Prohibited group vectors and islanded principal interior nodes.

Prohibited group vectors	Islanded principal interior node(s)
$R_5 = [C_{14} \quad C_{15} \quad C_{45}]$	5
$R_7 = [C_{12} \quad C_{15} \quad C_{25}]$	7
$R_8 = [C_{23} \quad C_{25} \quad C_{35}]$	8
$R_{57} = [C_{12} \quad C_{14} \quad C_{25} \quad C_{45}]$	5, 7
$R_{78} = [C_{12} \quad C_{15} \quad C_{23} \quad C_{35}]$	7, 8
$R_{578} = [C_{12} \quad C_{14} \quad C_{23} \quad C_{35} \quad C_{45}]$	5, 7, 8

other possible *prohibited group vectors* can also be identified from the Venn-diagram. The *prohibited group vectors* and the corresponding islanded principal interior node(s) for the system are given in Table 3.

In all, five switches have to be opened to form an individual to maintain the radial topology, one from each *loop vector* as per Rule 1. Let the individual {6, 21, 14, 22, 7} is selected during the process

Table 4
Initial conditions of test distribution systems.

Test system	Initial configuration with open switches	System voltage (kV)	Nominal real load (MW)	Nominal reactive load (MVAr)	Real power loss (MW)	Minimum node voltage (pu)
33-bus	33–37	12.66	1.715	2.300	0.20268	0.9131
70-bus	69–79	11	4.468	3.869	0.22753	0.9052
83-bus	84–96	11.4	28.350	20.700	0.53199	0.9285
119-bus	118–132	11	22.7097	17.0411	1.2981	0.8688
135-bus	136–156	13.8	18.3138	7.9325	0.3203	0.9307
33-bus (Unbalanced)	33–37	12.66	1.715	2.300	0.20782	0.9225 0.9099 0.9003

Table 5
Simulation results without and with HS.

Topology	Without/with HS	Population size	Best (MW)	Worst (MW)	Mean (MW)	Standard deviation	Average loss reduction (%)	Average computation time (s)
33-bus	A	20	0.139516	0.151755	0.144037	0.003067	28.93	3.45
	B	10	0.139516	0.140243	0.140069	0.000312	30.89	0.30
70-bus	A	40	0.201395	0.217511	0.212723	0.004137	6.51	91.13
	B	25	0.201395	0.206985	0.205745	0.000522	9.57	19.72
83-bus	A	60	0.469311	0.487387	0.477052	0.009615	10.33	343.11
	B	40	0.469311	0.470084	0.470063	0.000038	11.64	95.88
119-bus	A	100	0.865865	0.896624	0.883413	0.00317	31.95	1446.50
	B	70	0.865865	0.889635	0.875542	0.00285	32.55	430.74
135-bus	A	120	0.279155	0.285747	0.283672	0.001075	11.44	2341.11
	B	85	0.279155	0.284042	0.280594	0.000921	11.75	894.20
33-bus (Unbalanced)	A	20	0.14387	0.152336	0.146161	0.00237	29.67	15.39
	B	10	0.14387	0.144501	0.144362	0.00026	30.54	4.59

A: without HS; B: with HS.

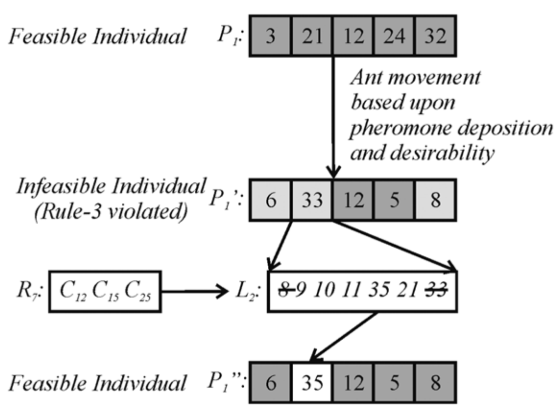

Fig. 6. Correction of an infeasible individual in AACO.

of initialization or during intermediate stages of the evolutionary process. This is not a feasible individual in accordance to Rule 2, since the switches $6, 7 \in C_{15}$. If this individual is selected, then node 6 will be islanded.

Considering another individual {7, 8, 34, 3, 25}, which is also not a feasible individual in accordance to Rule 3, since the switch $7 \in C_{15}, 3 \in C_{14}, 25 \in C_{45}$ and the *prohibited group vector* R_5 is $[C_{14}C_{15}C_{45}]$. If this individual is selected, then the principal interior node 5 will be islanded. There exist many more such infeasible individuals until or unless they are guided by the rules framed. In fact these rules guarantee to generate only feasible radial topologies. The illustrative example to demonstrate the transformation of infeasible individual into the feasible individual during the evolutionary process of the proposed AACO when guided by the rules framed is shown in Fig. 6.

Let after certain iterations, the ant movement transforms the feasible individual $P_1\{3, 21, 12, 24, 32\}$ into a new individual $P_1'\{6, 33, 12, 5, 8\}$, which is infeasible according to Rule 3, since switch $33 \in C_{12}, 6 \in C_{15}, 8 \in C_{25}$ and the *prohibited group vector* R_7 is $[C_{12}C_{15}C_{25}]$. Let, among the switches 33, 6 and 8, switch 33 is selected randomly for correction, which is guided by *common branch vectors* and *prohibited group vector*. Since switch 33 belongs to the *loop vector* L_2, it must be replaced by any other switch from the *loop vector* L_2, except the switches 8 and 33. Let switch 35 is randomly selected from the remaining candidate switches of the *loop vector* L_2 to generate the feasible individual $P_1''\{6, 35, 12, 5, 8\}$.

6. Test and results

In this section, the effectiveness of the proposed algorithm is tested rigorously on balanced IEEE 33-bus test distribution system [5], 70-bus distribution system [38], 83-bus real distribution system [34], 119-bus real distribution system [39] and 135-bus real distribution system [40]. The proposed algorithm is equally applicable, whether the distribution system is balanced or unbalanced. In order to test the proposed algorithm on three-phase unbalanced distribution system, the unbalance is created in the balanced system of [5] by redistributing the given load randomly among three phases of the system in such a way that the total load at each bus remains unaltered. The unbalanced load data used for the simulation is given in Table A.1 of Appendix A. To perform the three-phase load flow, the zero sequence impedances of the feeders are assumed to be three times of their respective positive sequence impedances [41]. The initial configuration, system rated line voltage, nominal real and reactive loadings, real power loss and minimum node voltage of these test distribution systems are summarized in Table 4.

The optimal values of the control parameters $\alpha, \beta, \zeta, \rho$ and σ were determined after numerous trial simulations until it provided the best possible result and the final values used are 1, 0.5, 0.05, 0.1 and 0.25, respectively. The proposed algorithm is run 100 times for each test distribution system with and without HS and the test results for loss minimization are summarized in Table 5. The table clearly shows the effect of HS on the computational efficiency. With HS, the same optimal solution is obtained with less number of individuals and thus the average computation time is reduced

Table 6
Comparison results for test distribution systems.

Test system	Methods	Optimal configuration	Real power loss (MW)	Minimum node voltage (pu)	Average computation time (s)	Average load flows
33-bus	RGA [10]	7, 9, 14, 32, 37	0.13955	0.9378	–	–
	Heuristic [6]	7, 9, 14, 32, 37	0.13955	0.9378	0.41	38
	GA [14]	7, 9, 14, 32, 37	0.13955	0.9378	7.2	450
	HBMO [42][a]	7, 9, 14, 32, 37	0.13955	0.9378	8.0	–
	Proposed AACO	7, 9, 14, 32, 37	0.13955	0.9378	0.30	32
70-bus	Heuristic [38]	14, 28, 39, 46, 51, 67, 70, 71, 73, 76, 79	0.20532	0.9268	3.0	6
	GA [14]	14, 30, 38, 46, 51, 66, 70, 71, 76, 77, 79	0.20317	0.9297	160	2000
	SAPSO–MSFLA/SAPSO/MSFLA [43]	30, 46, 51, 66, 70, 71, 75, 76, 77, 78, 79	0.20218	0.9316	–	1000/4500/4500
	Proposed AACO	13, 30, 45, 51, 66, 70, 75–79	0.201395	0.9312	19.72	382
83-bus	HBMO [42][a]	7, 14, 34, 39, 42, 55, 62, 72, 83, 86, 88, 90, 92	0.48214	0.9529	–	–
	SAPSO–MSFLA/SAPSO/MSFLA [43]	7, 14, 34, 39, 42, 55, 62, 72, 83, 86, 88, 90, 92	0.48094	0.9529	–	1500/3750/4500
	AIS-ACO [35][a]	7, 13, 34, 39, 42, 55, 62, 72, 86, 89, 90, 91, 92	0.471141	0.9479	–	–
	SA/GA/ACSA [34]	7, 13, 34, 39, 41, 55, 62, 72, 83, 86, 89, 90, 92	0.46988	0.9532	247.43/303.66/241.51	4000/5000/2500
	GA [44]	7, 13, 34, 39, 42, 55, 62, 72, 83, 86, 89, 90, 92	0.46987	0.9532	450	1500
	Proposed AACO	7, 13, 34, 39, 42, 55, 62, 72, 83, 86, 89, 90, 92	0.46987	0.9532	95.88	457
119-bus	ITS [39]	24, 27, 35, 40, 43, 52, 59, 72, 75, 96, 98, 110, 123, 130, 131	0.86586	0.9323	600 × unit time	600
	Proposed AACO	24, 27, 35, 40, 43, 52, 59, 72, 75, 96, 98, 110, 123, 130, 131	0.86586	0.9323	430.74	1942
135-bus	Heuristic [40]	53, 106, 136–141, 143–152, 154-156	0.28550	0.9638	–	–
	GA [45][a]	7, 51, 53, 84, 90, 96, 106, 118, 126, 128, 137–139, 141, 144, 145, 147, 148, 150, 151, 156	0.28022	0.9605	3600	43200
	GA [44]	7, 35, 51, 90, 96, 106, 118, 126, 135, 137, 138, 141, 142 144-148, 150, 151, 155	0.28017	0.9581	–	–
	Proposed AACO	7, 35, 51, 90, 95, 106, 118, 126, 135, 137, 138, 141, 142, 144-148, 150, 151, 155	0.27975	0.9602	894.20	3540
33-bus (Unbalanced)	Proposed AACO	7, 9, 14, 28, 32	0.14387	0.9533 0.9300 0.9323	4.59	35

[a] Multi-objective approach.

significantly. Moreover, the standard deviation of the solutions as well as the percentage average loss reduction shows that the inclusion of HS in the initial population generates better quality solutions.

Table 6 presents comparison of the optimal results obtained for these aforementioned test distribution systems using proposed method with other heuristic and meta-heuristic techniques available in the literature. The real power loss and minimum node voltage for the optimal solution are found to be either same or better than those of other methods. The table also depicts that the average computation time using the proposed method is much less as compared to the computation times mentioned in the literature using latest AI techniques. This clearly shows the computation efficiency of the proposed method for small, medium and large-scale distribution systems. Since the computational time may depend on the platform used, programming skills and other criterion, the average load flows performed are also mentioned in the table. In the proposed approach the load flow is performed only if switch combination formed by ant movement is different from the switch combination of the current global best solution, as more and more individuals will approach the current global best solution in the later iterations. If new global best is found during the evolutionary search process, corresponding new switch combination is compared with other individuals formed. This drastically reduces the number of load flow executions. It is to be noted that for the proposed method the quoted average computation time and average number of load flow performed are in accordance with the termination criterion described in the Section 4.9. However, the operator can specify other termination criteria as per his satisfaction to further reduce the computational time or number of load flow executions.

The optimal configuration for IEEE 33-bus system (unbalanced case) is obtained by opening the switches {7, 9, 14, 28, 32}, which causes a power loss of 143.87 kW, as mentioned in Table 6. In case, if this unbalance is ignored, the optimal configuration will be obtained by opening the switches {7, 9, 14, 32, 37}, for which the power loss will be 144.50 kW. This shows the importance of reconfiguration of distribution networks under unbalanced load conditions.

7. Conclusions

The reconfiguration of distribution networks is assuming significant importance in the context of modern distribution systems. In this paper, a new codification for the population-based meta-heuristic techniques to solve reconfiguration problem

Table 7
Importance of rules framed during initialization.

Rule(s) used	33-bus	70-bus	83-bus	119-bus	136-bus
No rule	A: 1056 B: 0.244	A: 50 292 B: 16.07	A: 985 314 B: 452.21	A: 887 182 B: 672.797	A: 35 869 922 B: 19 600
Rule 1	A: 71 B: 0.069	A: 2851 B: 2.6466	A: 2043 B: 4.01	A: 1876 B: 3.2885	A: 17 387 B: 51.87
Rules 1 & 2	A: 9 B: 0.0644	A: 326 B: 0.9555	A: 192 B: 0.92	A: 119 B: 0.999	A: 938 B: 8.92
Rules 1, 2 & 3	A: 0 B: 0.058	A: 0 B: 0.29	A: 0 B: 0.31	A: 0 B: 0.35	A: 0 B: 0.76

A: infeasible individuals appeared during initialization; B: average computation time (s).

of distribution networks is presented. In the proposed method, the topological concepts of the *loop vectors, common branch vectors* and *prohibited group vectors* have been introduced with the help of graph theory and some rules are framed to avoid the generation of infeasible individuals during each stage of the proposed AACO. The importance of each of these rules while randomly creating the initial population of 100 individuals can be observed from Table 7. It can be depicted from the table that the number of infeasible individuals as well as the computation time for the initialization is reduced when these rules are incorporated subsequently. Therefore, these rules not only provide flexibility to initialize the search process by random selection but also generate only feasible individuals. This preserves the diversity for the search process. It can be concluded from the table that the importance of these rules increases with the increase in the size of the distribution systems.

These rules also correct the infeasible individuals, whenever appear during the evolution process. The average computation time required to correct infeasible individuals is shown in Table 8.

Table 8
Average correction time during the evolutionary process.

Topology	Average correction time (s)
33-bus	0.00078
70-bus	0.0029
83-bus	0.0043
119-bus	0.0875
136-bus	0.1573

In fact, the proposed rules guarantee to generate only feasible radial topologies throughout the evolutionary process, irrespective of the size of the distribution system.

The proposed method incorporates the advantages of heuristics to increase the pace of the search technique. The introduction of the HS in the initial population reduces the computation time significantly. Various parameters of the conventional ACO are redefined in the context of the reconfiguration of the distribution networks. The objective function for the loss minimization is optimized using the proposed AACO for balanced and unbalanced

Table A.1
Unbalanced load data of 33-bus distribution system.

Bus no.	Phase A		Phase B		Phase C	
	P Load (kW)	*Q* Load (kVAr)	*P* Load (kW)	*Q* Load (kVAr)	*P* Load (kW)	*Q* Load (kVAr)
1	0	0	0	0	0	0
2	45.383639	27.200906	46.976778	28.156149	7.651557	4.586019
3	40.394259	17.969032	41.400790	18.416735	8.280372	3.683133
4	49.866547	33.221926	24.709155	16.461907	45.470722	30.293691
5	20.161068	10.080801	13.363780	6.681890	26.417693	13.208846
6	26.597202	8.889419	28.533331	9.536398	4.813076	1.608633
7	44.637823	22.318912	92.259978	46.129989	63.126148	31.563074
8	59.197793	29.599164	58.845187	29.422326	81.980969	40.990485
9	15.414239	5.151792	27.331798	9.135175	17.197038	5.747483
10	24.806389	8.291057	18.939233	6.329818	16.196918	5.413576
11	18.159760	12.084780	21.683152	14.429612	5.194532	3.457145
12	13.469561	7.851367	14.877850	8.671978	31.595663	18.416735
13	22.797067	13.287916	26.147361	15.241141	10.998646	6.411024
14	54.155522	36.079640	35.938598	23.943038	29.951770	19.954846
15	12.297947	2.038706	11.594871	1.922239	36.050256	5.976143
16	17.192764	5.746415	26.552859	8.874460	16.196918	5.413576
17	14.278419	4.772473	25.796358	8.621759	19.868298	6.640218
18	34.669215	15.422252	15.797297	7.027551	39.607841	17.619097
19	38.605584	17.172996	42.712379	19.000138	8.756925	3.895766
20	29.794166	13.253724	40.053407	17.817304	20.227315	8.997872
21	18.956329	8.432634	37.825042	16.826267	33.293516	14.810534
22	42.807476	19.042344	40.014406	17.800208	7.252471	3.226348
23	22.800807	12.658033	21.408546	11.884970	45.865534	25.462450
24	143.097261	68.162541	125.606919	59.830881	151.217892	72.030526
25	137.050063	65.281855	209.107836	99.605409	73.764174	35.136686
26	22.068347	9.205162	28.870978	12.042574	9.003749	3.755792
27	19.790297	8.254728	18.741026	7.817175	21.411752	8.931091
28	25.428792	8.498881	24.857677	8.308153	9.656605	3.227416
29	37.731013	22.013854	22.128718	12.910734	60.187228	35.115850
30	39.192727	117.578180	86.542947	259.628307	74.288275	222.865359
31	57.786299	26.979192	26.620174	12.428304	65.612022	30.632941
32	73.981080	35.239796	85.370264	40.665125	50.609692	24.107053
33	12.196439	8.152686	14.319556	9.571659	33.427079	22.344556

distribution systems. The simulation results show that the method provides a promising tool for the reconfiguration problem of distribution network and can be extended to incorporate multi-objective problem without any significant computational burden. The proposed codification can be investigated in other advanced versions of ACOs and other population-based search techniques as a future work.

Acknowledgments

The authors would like to thank the reviewers for their valuable comments and recommendations to improve the quality of the paper.

Appendix

See Table A.1.

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