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Real Power Loss Reduction in Distribution Systems Using Ant Colony Optimization Adapted By Graph Theory

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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 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 IEEE 14& 30-bus real distribution system. The simulation results show that the proposed method is efficient and promising for reconfiguration problem of radial distribution systems.*

IndexTerms: *Ant colony optimization, distribution network, graph theory, real power loss, and reconfiguration*

I. INTRODUCTION

DISTRIBUTION networks are generally structured in mesh but operated in 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 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 radial distribution systems is a very effective and efficient means to reduce distribution network losses, improve voltage profile, to manage load congestion and to 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 reasearch efforts can be broadly classified into traditional approaches and AI based approaches. The traditional approaches include heuristic optimization techniques and classical optimization techniques. Merlin *et al*. [1] were first to report a method for distribution network reconfiguration to minimize feeder loss. They formulated the problem as mixed integer non-linear optimization problem and solved it through a discrete branch and- bound technique. Later on [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 fails to provide a quality solution. Therefore, the researchers diverted towards 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 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 the loss minimization in 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] and ant colony optimization [23]-[27] etc. also have been attempted to solve the reconfiguration problem of distribution network.

The reconfiguration of 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 distribution networks faces an additional difficulty of maintaining the radiality constraint throughout the evolutionary process. These methods in the literature provide different ways of maintaining radiality constraint, but, they are incomplete as they may generate infeasible intermediate solutions during the evolutionary process.

These infeasible intermediate solutions have to be rejected and the process is to be repeated until it gets a feasible individual, which may be time consuming. This paper presents a new codification to represent feasible radial topologies of distribution system for the meta-heuristic search techniques. For this purpose some rules are framed with the help of graph theory. As the ant colony optimization (ACO) is one of the latest meta-heuristic techniques based on swarm intelligence and considered to be an efficient method for solving the large-scale.

The formulation of the loss minimization problem is discussed in Section II. The conventional ACO is explained in Section III. The modifications proposed in the conventional ACO are discussed in Section IV, in Section V the proposed codification for AACO is illustrated with the help of an example. In Section VI the application results of the proposed method are presented and finally concluded in Section VII.

II. PROBLEM FORMULATION FOR MINIMAL POWER LOSS

The distribution networks 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:

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

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

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

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

where, *Vn*, *Pn* and *Qn* are voltage, real power and reactive power at the sending end of the *nth* branch respectively, *Rn* is the resistance of the *nth* branch and *E* is the total number of branches in the system. Equation (1) corresponds to the objective function to be optimized and represent total real power loss of the distribution system. Equation (2) corresponds to limit branch current and substation current capacities within permissible limits. Equation (3) considers voltage constraints for each node of the system. Equation (4), deals with the radial topology constraint, it ensures radial structure of the *ith* candidate topology.

III. ANT COLONY OPTIMIZATION

Ant colony optimization (ACO) is a population-based meta-heuristic technique for solving combinatorial optimization problems, initially proposed by Marco Dorigo in 1992 in his PhD thesis [28], inspired by the behavior of ants in finding paths from the nest to food and back to the nest. The original idea has since diversified to solve a wider class of numerical problems, and as a result, several problems have emerged, drawing on various aspects of the behavior of ants. Ant communication is accomplished primarily through chemicals called pheromones. Other ants perceive the presence of pheromone and tend to follow paths where pheromone concentration is higher. An ant will move from node *i* to node *j* with probability

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

where *τi,j* is the amount of pheromone on edge *i-j*, *α* is a parameter to control the influence of *τi,j*, *ηi,j* is the desirability of edge *i-j* (a priori knowledge, typically *1/di,j*; *dij* is the distance between node *i* and *j*) and *β* is a parameter to control the influence of *ηi,j*. While moving from node *i* to *j*, the ant updates the pheromone on the edge *i-j*. To escape local minima, pheromone evaporation is used. Evaporation is applied uniformly to all edges with a simple decay coefficient *ρ*. The pheromone update is given by

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

where *τi,j* is the amount of pheromone on a given edge *i-j*, *ρ* is the rate of pheromone evaporation and *Δτi,j* is the amount of pheromone deposited, typically given by

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

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

IV. PROPOSED ADAPTIVE ANT COLONY OPTIMIZATION

While the conventional ACO is applied to solve the reconfiguration problem of distribution networks, the radiality constraint imposes main hurdle since a large number of infeasible individuals appears during initialization as well as at intermediate stages of the evolutionary process. These infeasible individuals may be transformed into the feasible ones using some engineering knowledge base. The proposed methodology creates feasible individuals all times for ACO by encoding the Individual ant with the help of graph theory [29] and the terms are redefined in the context of distribution network reconfiguration, as described in the next sub-sections.

A. Ant encoding using Graph Theory

The graph of the given distribution network can be obtained by closing all tie-switches. The radial configuration in which the distribution networks must operate should not posses any closed path with all nodes energized. These radial configurations are called *trees* of the distribution network graph (DNG). The *co-tree* is the compliment of a *tree*. The elements of *co-tree* are called *links*. When one *link* is added in its corresponding *tree*, one *fundamental loop* is formed. In the distribution network reconfiguration problem, 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 [29] and is given by $L = E - N + 1$ (8) where, *E* is total number of elements (sectionalizing and tie switches) of the network and *N* is total number of nodes of the network.

The reconfiguration problem of distribution network can be defined as to find that particular *tree*, i.e., *co-tree*, which optimizes all objectives and satisfies all constraints set by the optimization problem. Therefore, while using ACO 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 some infeasible topologies may appears during the evolutionary process, which increases the computational burden. Therefore, in the proposed AACO, 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 total number of loop vectors for a given DNG are *Lk, where k = 1, 2, 3, … 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 Cij* , containing the set of elements common between two *loop vectors Li* and *Lj*.

(vi) Prohibited Group Vector: It is the set of the *common Branch vectors* incident to interior node(s) of the DNG.

The *prohibited group vector Rm1 m2 m3 …..*, isolate principal interior node(s) *m1, m2, m3 ….* of the DNG.

Now, the following rules are framed to create feasible individuals during the whole evolutionary process of AACO: Rule 1: The *mth* member of the individual must belong to *loop vector Lm*. 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 Rule 1 and Rule 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 for AACO, 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 *Zm* represents the open switch of the distribution network in real number. The ant consists of *L* such members, where the *Zm* belongs to the *loop vector Lm*; *m= 1, 2,…, L*.

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

Fig. 1. Ant encoding for the proposed AACO

In this paper, the conventional ACO is adapted using fundamentals of graph theory to generate feasible individuals. Therefore the proposed ACO is named as Adapted Ant Colony Optimization (AACO). The AACO transforms infeasible individual, whenever generated, into feasible ones under the guidance of the rules framed.

B. 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 heuristic spark. However, the remaining individuals are created randomly under the guidance of rules framed to maintain the diversity. The heuristic spark 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 ACO.

C. Edge Selection

In ant codification shown in Fig. 1, the member *Zm* indicates that an ant is standing at switch *Zm* and to implement Rule 1 its search is restricted to corresponding *loop vector Lm*.

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 current switch position *i* to all other switch positions within *loop vector Lm* 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 the maximum probability is selected. This process of selecting switch is used for each loop separately, in the guidance of Rule 2 and Rule 3, such that the resultant ant represents a radial network.
Fig.

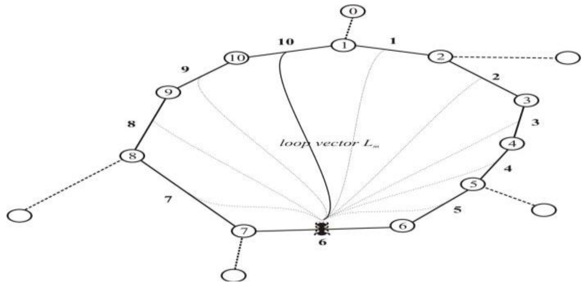


Fig. 2. Edge Selection of the ant within loop vector L_m

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

D. 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 voltage of each line for the best radial network obtained; as sending end voltage will keep on decreasing as its distance from the source increasing. A desirability matrix is created for each *loop vector*. The matrix *Dm* is the desirability matrix for *loop vector Lm* and the element *Dmij* represents the desirability of selection of switch *j* from switch *i*. The value of *Dmij* is defined as

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

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

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

F. Global Update

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

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

G. Hunting Group

In ant colony the responsibility of a particular group is to explore new possible food location irrespective of the pheromone deposition.

H. Elitism

At the end of each iteration, all the tours visited by ants are evaluated and the ant with the best fitness is preserved for the next iteration.

I. Termination

The algorithm is terminated if all the ants of the current population reach to the solution with same fitness or the iteration number reaches the predefined maximum iteration number. The flow chart of the proposed AACO is shown in the Fig. 3.

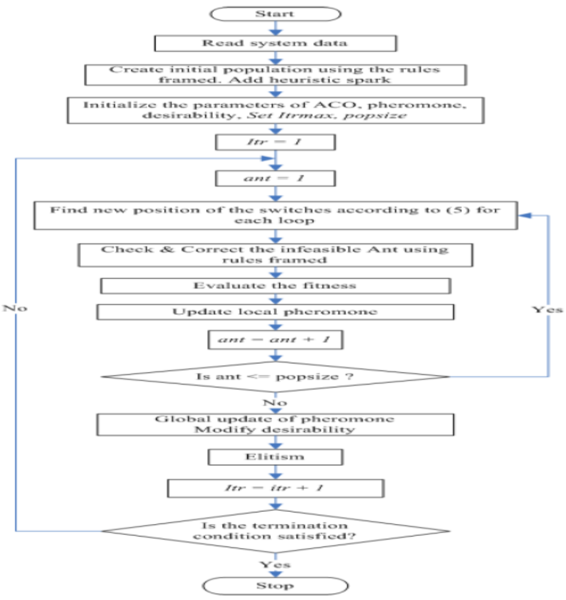


Fig. 3. Flow chart of the proposed AACO

V. ILLUSTRATION OF THE PROPOSED CODIFICATION

To understand the application of graph theory in the proposed codification, let us consider the example of IEEE 14- bus system, shown in the Fig. 4. For this system $E = 17$, $N = 14$ and $L = 16 - 14 + 1 = 3$. Therefore, there are three *loop vectors.* According to their position in the loop, each switch is assigned a position number as shown .For IEEE 30-bus system L=35-31+1=5.Such that there are five loops

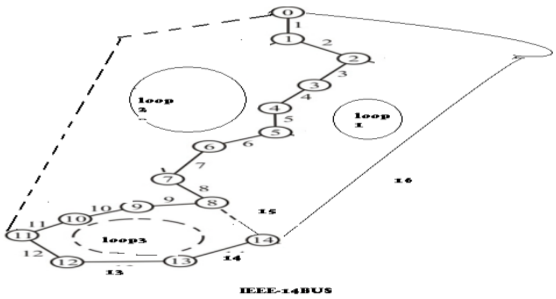
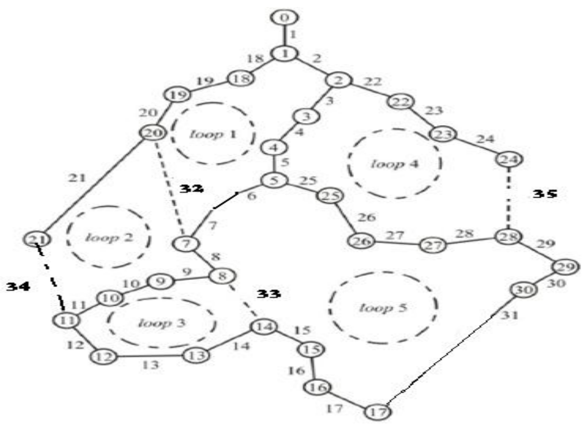


Fig. 4. IEEE 14-bus system



IEEE 30-bus system

In this section, the effectiveness of the proposed algorithm is tested on balanced IEEE 14-bus test distribution system [5], [31]. The initial configuration, system rated line voltage, nominal real and reactive loadings, real power loss and minimum node voltage of these test systems . The proposed AACO is implemented with the ant population size and maximum iterations as shown in Table V. The parameters α, β, ζ, ρ and σ are adjusted for their optimal values by hit and trial and the final values are. The simulation results for these aforementioned test distribution systems and are found to be either identical or better with the results

Test and Results of IEEE 14 & 30 bus

From Bus	to bus	PL(LF)	PL(ACO)	PL(AACO)
1.0000	2.0000	12.9630	5.7350	4.8280
1.0000	5.0000	11.6430	7.1320	6.7740
2.0000	3.0000	9.5990	6.8760	6.6640
2.0000	4.0000	5.0870	3.7500	2.7500
2.0000	5.0000	2.8210	2.1810	1.1810
3.0000	4.0000	0.9630	0.1910	0.1910
4.0000	5.0000	1.4940	1.4470	1.4170
4.0000	7.0000	1.6310	1.6830	1.6520
4.0000	9.0000	1.2870	1.2760	1.2510
5.0000	6.0000	5.1520	6.2470	5.2470
6.0000	11.0000	0.2690	0.2650	0.2650
6.0000	12.0000	0.1680	0.1670	0.1670
6.0000	13.0000	0.4940	0.4860	0.4860
7.0000	8.0000	1.1110	1.1460	1.1460
7.0000	9.0000	1.0500	1.0730	1.0500
9.0000	10.0000	0.0200	0.0280	0.0200
9.0000	14.0000	0.2040	0.2120	0.2020
10.0000	11.0000	0.1390	0.1330	0.1320
12.0000	13.0000	0.0100	0.0100	0.0100
13.0000	14.0000	0.2280	0.2220	0.2220

IEEE30 bus

From-Bus	To-Bus	RPL(without)	RPL(ACO)	RPL(AACO)
1.0000	2.0000	16.3620	6.4790	4.4329
1.0000	3.0000	11.5060	7.0560	5.5006
2.0000	4.0000	3.3718	3.1450	3.2245
2.0000	5.0000	62.0440	58.8760	57.0890
2.0000	6.0000	5.7961	5.7000	5.7890
3.0000	4.0000	0.4810	0.4110	0.6741
4.0000	6.0000	2.1020	1.9870	2.2117
4.0000	12.0000	9.2030	8.9530	9.7453
5.0000	7.0000	0.5630	0.5110	0.5015
6.0000	7.0000	2.2520	2.1560	2.4501
6.0000	8.0000	0.0790	0.0710	0.0820
6.0000	9.0000	0.8090	0.8070	0.8879
6.0000	10.0000	3.8120	3.8040	3.9844
6.0000	28.0000	0.1240	0.1260	0.1264
8.0000	28.0000	0.0006	0.0002	0.0006
9.0000	10.0000	0.6350	0.6330	0.6443
9.0000	11.0000	0.3060	0.3280	0.4328
10.0000	17.0000	0.0220	0.0320	0.0202
10.0000	20.0000	0.1850	0.1850	0.1825
10.0000	21.0000	0.0480	0.0490	0.0494
10.0000	22.0000	0.0860	0.0880	0.0887
12.0000	13.0000	0.0680	0.1100	0.1182
12.0000	14.0000	0.3030	0.3190	0.3129

12.0000	15.0000	0.8260	0.8300	0.8608
12.0000	16.0000	0.1072	0.1080	0.1183
14.0000	15.0000	0.0250	0.0280	0.0281
15.0000	18.0000	0.2360	0.2460	0.2496
15.0000	23.0000	0.0850	0.0925	0.0955
16.0000	17.0000	0.2110	0.2436	0.2446
18.0000	19.0000	0.0060	0.0031	0.0071
19.0000	20.0000	0.0110	0.0080	0.0110
21.0000	22.0000	0.0007	0.0006	0.0001
22.0000	24.0000	0.0385	0.0340	0.0403
23.0000	24.0000	0.0074	0.0090	0.0097
24.0000	25.0000	0.0224	0.0238	0.0276
25.0000	26.0000	0.0923	0.0950	0.0945
25.0000	27.0000	0.0245	0.0232	0.0220
27.0000	28.0000	0.6362	0.6309	0.6390
27.0000	29.0000	0.1485	0.1510	0.1510
27.0000	30.0000	1.0863	1.0670	1.0770
29.0000	30.0000	0.5860	0.5770	0.5670

NOTE:PL=power Loss, RPL=Real power loss, ACO=Ant colony optimization, AACO=Adaptive ant colony optimization

VI. CONCLUSIONS

The reconfiguration of distribution network 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 of distribution networks is presented. In the proposed method, the topological concepts of *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 generation of infeasible individuals during each stage of the proposed AACO. Several parameter of the conventional ACO are redefined in the context of the reconfiguration of the distribution networks. Moreover, the proposed method incorporates the advantages of heuristics to increase the pace of the search techniques without losing diversity. The objective function for loss minimization is optimized using AACO. The proposed method has been extended on three different IEEE-,33,70 and 135 BUS distribution networks. The simulation results show that the method provides a promising tool for reconfiguration problem of distribution network and can be extended to incorporate multi-objective problem without any significant computational burden

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