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# Optimal reconfiguration of electrical distribution network using the refined genetic algorithm

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**Abstract**

This paper proposes an improved method to study distribution network reconfiguration (DNRC) based on a refined genetic algorithm (GA). The DNRC model, in which the objective is to minimize the system power loss, is set up. In order to get the precise branch current and system power loss, a radiation distribution network load flow (RDNLF) method is presented in the study. The refined genetic algorithm is also set up, in which some improvements are made on chromosome coding, fitness function and mutation pattern. As a result, premature convergence is avoided. The proposed approach is tested on 16-bus and 33-bus distribution networks. Study results are given in the paper. 

*Keywords:* Optimization; Artificial intelligence; Genetic algorithms; Distribution systems; Network reconfiguration

## 1. Introduction

It is known that distribution networks are built as interconnected meshed networks, while in the operation they are arranged into a radial tree structure. This means that distribution systems are divided into subsystems of radial feeders, which contain a number of normally-closed switches and a number of normally-open switches. From graph theory, a distribution network can be represented with a graph of $G$ ($N$, $B$) that contains a set of nodes $N$ and a set of branches $B$. Every node represents either a source node (supply transformer) or a sink node (customer load point), while a branch represents a feeder section that can either be loaded (switch closed) or unloaded (switch open). The network is radial, so that feeder sections form a set of trees where each sink node is supplied from exactly one source node. Therefore, the distribution network reconfiguration (DNRC) problem is to find a radial operating structure that minimizes the system power loss while satisfying operating constraints. In fact, this problem can be viewed as a problem of determining an optimal tree of the given graph. However, real distribution systems contain many nodes and branches (and switches), and the total number of trees is extremely large. Ordinary optimization methods have shown to be ineffective and impractical to this problem [1].

Merlin et al. proposed a heuristic approach to the DNRC problem [2]. It begins with all branches closed (a complete graph) and performs a procedure of opening branches which carry the least current. This method is a greedy algorithm that does not necessarily guarantee feasibility of the final solution.

Nahman et al. presented another heuristic approach in [3,4]. The algorithm starts from a completely empty network, with all switches open and all loads disconnected. Load points are connected one by one by switching branches onto the current subtree. The search technique also does not necessarily guarantee global optima.

Recently, the branch exchange approach has been used in research on DNRC [5–7]. In fact, this is a gradient method in the space of a graph structure. In this method, one normally-open switch is closed, which forms a loop and violates the topological constraints. When a closed branch (or switch) in the loop opens, a new topology is produced. However, the existing branch exchange based algorithms are capable of finding only local optima, where the final solution heavily depends on the starting configuration.

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At present, new methods based on artificial intelligence have been used in DNRC [8,9]. Chiang et al. [8] presented a simulated annealing (SA) method to solve the DNRC problem, in which the SA was very time-consuming. It is needed to apply the improved SA with high speed to handle the DNRC problem. For the first time, genetic algorithm (GA) was applied to the global optimal solution of DNRC in [9], which has shown a better performance over the SA approach. In this paper, the GA method is further refined by modifying the string structure and fitness function:

1) In Ref. [9], the string used in GA describes all the switch positions and their 'on/off' states. The string can be very long and it grows in proportion with the number of switches. For large distribution systems, such long strings can not be effectively searched by GA. In this paper, the string will be shortened.
2) To reduce computational burden, approximate fitness functions was used in GA to represent the system power loss [9]. It may affect the accuracy and effectiveness of GA. GA is essentially unconstrained search procedures within the given represented space [10–12]. All information should be fully represented in the fitness function. Over-approximated fitness function would lead directly to unreliable solution.

In this paper, the DNRC model, in which the objective is to minimize the system power loss, is set up. Since the distribution network is a simple radial tree structure, in which the ratio of $R/X$ is relatively big, even bigger than 1.0 for some transmission lines, neither $P$–$Q$ decoupled method nor Newton–Raphson method is suited to compute the distribution network loadflow. Therefore, a radiation distribution network loadflow (RDNLF) method is presented in the study. In order to enhance performance of GA, some improvements are made on chromosome coding, fitness function and mutation pattern. Among these improved features, an adaptive process of mutation is developed not only to prevent premature convergence, but also to produce smooth convergence. The proposed approach is tested with satisfactory results on 16-bus and 33-bus distribution networks.

## 2. Brief description of GA

GAs are effective parameter search techniques. They are considered when conventional techniques have not achieved the desired speed, accuracy or efficiency [10]. GAs are different from conventional optimization and search procedures in the following ways [12].

1) GAs work with coding of parameters rather than the parameters themselves.
2) GAs search from a population of points rather than a single point.
3) GAs use only objective functions rather than additional information such as their derivatives.
4) GAs use probabilistic transition rules, and not deterministic rules.

These properties make GAs more robust, more powerful and less data-independent than many other conventional techniques.

The theoretical foundation for GAs was first described by Holland [11], and was presented tutorially by Goldberg [12]. GAs provide a solution to a problem by working with a population of individuals each representing a possible solution. Each possible solution is termed a 'chromosome'. New points of the search space are generated through GA operations, known as reproduction, crossover and mutation. These operations consistently produce fitter offsprings through successive generations, which rapidly lead the search towards global optima [12].

## 3. Mathematical model of DNRC

The purpose of DNRC is to find a radial operating structure that minimizes the system power loss while satisfying operating constraints. Thus, the following model can represent the DNRC problem.

$$\text{Min } f = \Sigma_b\ |I_b|^2 k_b R_b \quad b \in NL \tag{1}$$

such that

$$k_b |I_b| \le I_{b\max} \quad b \in NL \tag{2}$$

$$V_{i\min} \le V_i \le V_{i\max} \quad i \in N \tag{3}$$

$$g_i(I,\ k) = 0 \tag{4}$$

$$g_v(V,\ k) = 0 \tag{5}$$

$$\varphi(k) = 0 \tag{6}$$

where $I_b$ is the current in branch $b$; $R_b$ is the resistance of branch $b$. $V_i$ is the node voltage at node $i$. $k_b$ represents the topological status of the branches. $k_b = 1$ if the branch $b$ is closed, and $k_b = 0$ if the branch $b$ is open. $N$ is the set of nodes, and $NL$ is the set of branches. Subscripts 'min' and 'max' represent the lower and upper bounds of the constraint.

In the above model, Eq. (2) stands for the branch current thermal stability constraints. Eq. (3) stands for the node voltage constraints. Eqs. (4) and (5) represent Kirchhoff's current and voltage laws. Eq. (6) stands for topological constraints which ensure radial structure of each candidate topology.

In order to get the precise expression of system power loss, the current branch $I_b$, will be computed through a

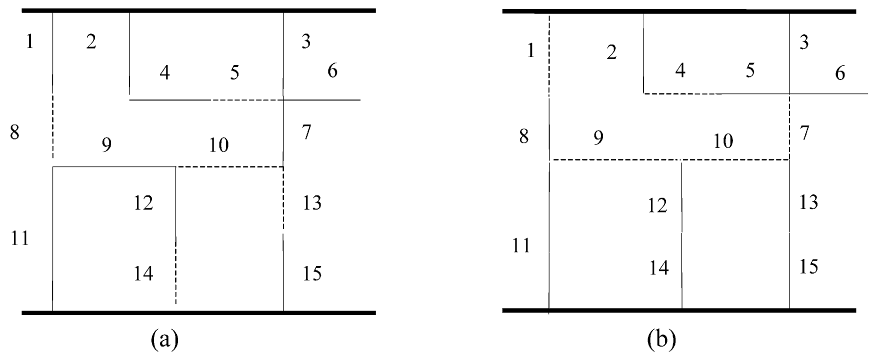


Fig. 1. A simple distribution network. Source transformer busbars —; closed switches –; open switches ---; sink nodes (load nodes) ●.

radiation distribution network loadflow (RDNLF) method in the study. It is well known that in the distribution network, the ratio of $R/X$ (resistance/reactance) is relatively big, even bigger than 1.0 for some transmission lines. In this case, $P-Q$ decoupled loadflow is invalid for distribution network load flow calculation. It will also be complicated and time-consuming to use the Newton–Raphson loadflow because the distribution network is only a simple radial tree structure. Therefore, RDNLF method is presented in the paper. RDNLF calculation consists of two parts. One is calculation of branch current from the 'top of a tree' node to the 'root of a tree' node. Another is the calculation of node voltage from the 'root of a tree' node to the 'top of a tree node. The initial conditions are the given voltage vectors at root nodes as well as real and reactive power at load nodes. In final, the deviation of injection power at all nodes can be computed. The iteration calculation will be ceased if the deviation is less than the given permissive error.

## 4. Refined GA approach to DNRC problem

Model M-1 may be solved by first generating all graph trees and subsequently by performing evaluation. However, real distribution systems contain many nodes and branches, and many trees. Conventional optimization methods have shown to be ineffective and impractical, because of dimensionality [1]. GAs has shown to be an effective and useful approach for the DNRC problem [9]. Some refinements of the approach are described in this paper.

### 4.1. Genetic string

In Ref. [9], the string structure is expressed by 'Arc No.($i$)' and 'SW. No.($i$)' for each switch $i$. 'Arc No.($i$)' identifies the arc (branch) number that contains the $i$-th open switch, and 'SW. No.($i$)' identifies the switch that is normally open on Arc No.($i$). For large distribution networks, it is not efficient to represent every arc in the string, since its length will be very long. In fact, the number of open switch positions is identical to keep the system radial once the topology of the distribution networks is fixed, even if the open switch positions are changed. Therefore, to memorize the radial configuration, it is enough to number only the open switch positions. Fig. 1 shows a simple distribution network with five switches that are normally open.

In Fig. 1(a), positions of five initially-open switches 5, 8, 10, 13 and 14 determine a radial topology. In Fig. 1(b), positions of five initially-open switches 1, 4, 7, 9 and 10 determine another radial topology. Therefore, in order to represent a network topology, only positions of the open switches in the distribution network need to be known. Suppose the number of normally open switches is $N_o$, the length of a genetic string depends on the number of open switches $N_o$. Genetic strings for Fig. 1(a) and (b) are represented as follows, respectively.

| 0 1 0 1 | 1 0 0 0 | 1 0 1 0 | 1 1 0 1 | 1 1 1 0 |
|---|---|---|---|---|
| Switch 5 | Switch 8 | Switch 10 | Switch 13 | Switch 14 |

Genetic string for Fig. 1(a).

| 0 0 0 1 | 0 1 0 0 | 0 1 1 1 | 1 0 0 1 | 1 0 1 0 |
|---|---|---|---|---|
| Switch 1 | Switch 4 | Switch 7 | Switch 9 | Switch 10 |

Genetic string for Fig. 1(b).

### 4.2. Fitness function

GAs are essentially unconstrained search procedures within a given represented space. Therefore, it is very important to construct an accurate fitness function as its value is the only information available to guide the search. In this paper, the fitness function is formed by combining the object function and the penalty function, i.e.

$$\text{Max}\, f = 1/L \tag{7}$$

where

$$\begin{aligned} L = \Sigma_i |I_i|^2 k_i R_i &+ \beta_1 \max\{0,\ (|I_i| - I_{i\max})^2\} \\ &+ \beta_2 \max\{0,\ (V_{i\min} - V_i)^2\} \\ &+ \beta_3 \max\{0,\ (V_i - V_{i\max})^2\} \end{aligned} \tag{8}$$

where $\beta_i$ ($i = 1, 2, 3$) is a large constant.

Suppose $m$ is the population size, the values of the maximum fitness, the minimum fitness, sum of fitness and average fitness of a generation are calculated as follows.

$$f_{\max} = \{f_i | f_i \geq f_j \forall f_j, \quad j = 1, \ldots, m\} \tag{9}$$

$$f_{\min} = \{f_i | f_i \leq f_j \forall f_j, \quad j = 1, \ldots, m\} \tag{10}$$

$$f_{\Sigma} = \Sigma_i f_i, \quad i = 1, \ldots, m \tag{11}$$

$$f_{av} = f_{\Sigma}/m \tag{12}$$

The strings are sorted according to their fitness which are then ranked accordingly.

### 4.3. Selection

In order to obtain and maintain good performance of the fittest individuals, it is important to keep the selection competitive enough. It is no doubt that the fittest individuals have higher chances to be selected. In this paper, the 'roulette wheel selection' scheme is used, in which each string occupies an area of the wheel that is equal to the string's share of the total fitness, i.e. $f_i/f_{\Sigma}$.

### 4.4. Crossover and mutation

Crossover takes random pairs from the mating pool and produces two new strings, each being made of one part of the parent string. Mutation provides a way to introduce new information into the knowledge base. With this operator, individual genetic representations are changed according to some probabilistic rules. In general, the GA mutation probability is fixed throughout the whole search process. However, in practical application of DNRC, a small fixed mutation probability can only result in a premature convergence. In this paper, an adaptive mutation process is used to change the mutation probability, i.e.

$$p(k+1) = \begin{array}{ll} p(k) - p_{\text{step}} & \text{if } f_{\min}(k) \text{ unchanged} \\ p(k) & \text{if } f_{\min}(k) \text{ decreased} \\ p_{\text{final}} & \text{if } p(k) - p_{\text{step}} < p_{\text{final}} \end{array}$$

$$p(0) = p_{\text{init}} = 1.0$$

$$p_{\text{step}} = 0.001$$

$$p_{\text{final}} = 0.05$$

where $k$ is the generation number; and $p$ is the mutation probability.

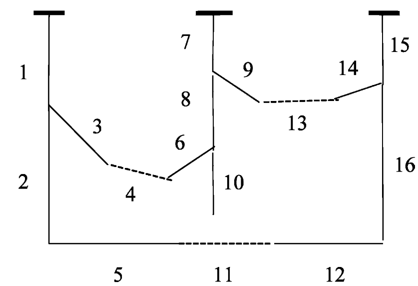


Fig. 2. A 16-bus distribution system.

The mutation scale will decrease as the process continues. The minimum mutation probability in this study is given as 0.05. This adaptive mutation not only prevents premature convergence, but also leads to a smooth convergence.

## 5. Numerical examples

The proposed approach for distribution network reconfiguration is tested on 16-bus and 33-bus distribution systems as shown in Figs. 2 and 3, respectively. System data and parameters are listed on Tables 1 and 2. The 16-bus test system contains 3 source transformers and 13 load nodes. The three initially-open switches are '4', '11' and '13'. The total system load is 23.7 MW, while the initial system power loss is 0.5114 MW. The 33-bus test system consists of one source transformer

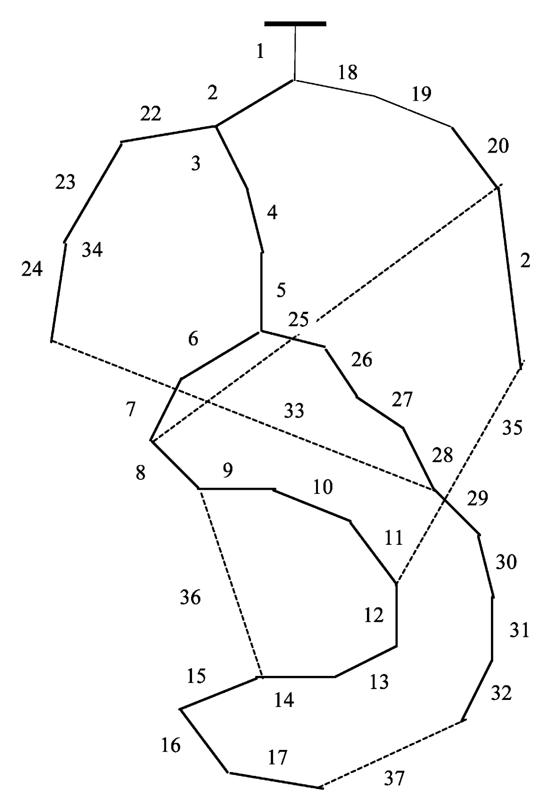


Fig. 3. A 33-bus distribution system.

Table 1
System data and parameters for 16-bus distribution network

| Line no. | Node $i$ | Node $j$ | Resistance $R$ (Ω) | Reactance $X$ (Ω) | Receiving node $j$ $P$ (MW) | $Q$ (MVAr) | Receiving node $j$ Voltage (p.u.) |
|---|---|---|---|---|---|---|---|
| 1 | 1 | 4 | 0.0750 | 0.1000 | 2.0 | 1.6 | 0.9907 ∠ −0.3968 |
| 3 | 4 | 5 | 0.0800 | 0.1100 | 3.0 | 0.4 | 0.9878 ∠ −0.5443 |
| 2 | 4 | 6 | 0.0900 | 0.1800 | 2.0 | −0.4 | 0.9860 ∠ −0.6972 |
| 5 | 6 | 7 | 0.0400 | 0.0400 | 1.5 | 1.2 | 0.9849 ∠ −0.7043 |
| 7 | 2 | 8 | 0.1100 | 0.1100 | 4.0 | 2.7 | 0.9791 ∠ −0.7635 |
| 8 | 8 | 9 | 0.0800 | 0.1100 | 5.0 | 1.8 | 0.9711 ∠ −1.452 |
| 9 | 8 | 10 | 0.1100 | 0.1100 | 1.0 | 0.9 | 0.9769 ∠ −0.7701 |
| 6 | 9 | 11 | 0.1100 | 0.1100 | 0.6 | −0.5 | 0.9710 ∠ −1.526 |
| 10 | 9 | 12 | 0.0800 | 0.1100 | 4.5 | −1.7 | 0.9693 ∠ −1.837 |
| 15 | 3 | 13 | 0.1100 | 0.1100 | 1.0 | 0.9 | 0.9944 ∠ −0.3293 |
| 14 | 13 | 14 | 0.0900 | 0.1200 | 1.0 | −1.1 | 0.9948 ∠ −0.4562 |
| 16 | 13 | 15 | 0.0800 | 0.1100 | 1.0 | 0.9 | 0.9918 ∠ −0.5228 |
| 12 | 15 | 16 | 0.0400 | 0.0400 | 2.1 | −0.8 | 0.9913 ∠ −0.5904 |
| 4 | 5 | 11 | 0.0400 | 0.0400 | | | |
| 13 | 10 | 14 | 0.0400 | 0.0400 | | | |
| 11 | 7 | 16 | 0.0900 | 0.1200 | | | |

Table 2
System data and parameters for 33-bus distribution network

| Line no. | Node $i$ | Node $j$ | Resistance $R$ (Ω) | Reactance $X$ (Ω) | Receiving node $P$ (MW) | $Q$ (MVAr) | Receiving node Voltage (p.u.) |
|---|---|---|---|---|---|---|---|
| 1 | 1 | 2 | 0.0922 | 0.0470 | 100.0 | 60.0 | 0.9970 ∠ 0.0145 |
| 2 | 2 | 3 | 0.4930 | 0.2512 | 90.0 | 40.0 | 0.9829 ∠ 0.0960 |
| 3 | 3 | 4 | 0.3661 | 0.1864 | 120.0 | 80.0 | 0.9755 ∠ 0.1617 |
| 4 | 4 | 5 | 0.3811 | 0.1941 | 60.0 | 30.0 | 0.9681 ∠ 0.2283 |
| 5 | 5 | 6 | 0.8190 | 0.7070 | 60.0 | 20.0 | 0.9497 ∠ 0.1339 |
| 6 | 6 | 7 | 0.1872 | 0.6188 | 200.0 | 100.0 | 0.9462 ∠ −0.0964 |
| 7 | 7 | 8 | 0.7115 | 0.2351 | 200.0 | 100.0 | 0.9413 ∠ −0.0603 |
| 8 | 8 | 9 | 1.0299 | 0.7400 | 60.0 | 20.0 | 0.9351 ∠ −0.1334 |
| 9 | 9 | 10 | 1.0440 | 0.7400 | 60.0 | 20.0 | 0.9292 ∠ −0.1959 |
| 10 | 10 | 11 | 0.1967 | 0.0651 | 45.0 | 30.0 | 0.9284 ∠ −0.1887 |
| 11 | 11 | 12 | 0.3744 | 0.1298 | 60.0 | 35.0 | 0.9269 ∠ −0.1785 |
| 12 | 12 | 13 | 1.4680 | 1.1549 | 60.0 | 35.0 | 0.9208 ∠ −0.2698 |
| 13 | 13 | 14 | 0.5416 | 0.7129 | 120.0 | 80.0 | 0.9185 ∠ −0.3485 |
| 14 | 14 | 15 | 0.5909 | 0.5260 | 60.0 | 10.0 | 0.9171 ∠ −0.3862 |
| 15 | 15 | 16 | 0.7462 | 0.5449 | 60.0 | 20.0 | 0.9157 ∠ −0.4094 |
| 16 | 16 | 17 | 1.2889 | 1.7210 | 60.0 | 20.0 | 0.9137 ∠ −0.4868 |
| 17 | 17 | 18 | 0.7320 | 0.5739 | 90.0 | 40.0 | 0.9131 ∠ −0.4963 |
| 18 | 2 | 19 | 0.1640 | 0.1565 | 90.0 | 40.0 | 0.9965 ∠ −0.0037 |
| 19 | 19 | 20 | 1.5042 | 1.3555 | 90.0 | 40.0 | 0.9929 ∠ −0.0633 |
| 20 | 20 | 21 | 0.4095 | 0.4784 | 90.0 | 40.0 | 0.9922 ∠ −0.0827 |
| 21 | 21 | 22 | 0.7089 | 0.9373 | 90.0 | 40.0 | 0.9916 ∠ −0.1030 |
| 22 | 3 | 23 | 0.4512 | 0.3084 | 90.0 | 50.0 | 0.9794 ∠ −0.0650 |
| 23 | 23 | 24 | 0.8980 | 0.7091 | 420.0 | 200.0 | 0.9727 ∠ −0.0237 |
| 24 | 24 | 25 | 0.8959 | 0.7071 | 420.0 | 200.0 | 0.9694 ∠ −0.0674 |
| 25 | 6 | 26 | 0.2031 | 0.1034 | 60.0 | 25.0 | 0.9477 ∠ 0.1734 |
| 26 | 26 | 27 | 0.2842 | 0.1447 | 60.0 | 25.0 | 0.9452 ∠ 0.2295 |
| 27 | 27 | 28 | 1.0589 | 0.9338 | 60.0 | 20.0 | 0.9337 ∠ 0.3124 |
| 28 | 28 | 29 | 0.8043 | 0.7006 | 120.0 | 70.0 | 0.9255 ∠ 0.3904 |
| 29 | 29 | 30 | 0.5074 | 0.2585 | 200.0 | 100.0 | 0.9219 ∠ 0.4956 |
| 30 | 30 | 31 | 0.9745 | 0.9629 | 150.0 | 70.0 | 0.9178 ∠ 0.4112 |
| 31 | 31 | 32 | 0.3105 | 0.3619 | 210.0 | 100.0 | 0.9169 ∠ 0.3882 |
| 32 | 32 | 33 | 0.3411 | 0.5302 | 60.0 | 40.0 | 0.9166 ∠ 0.3805 |
| 34 | 8 | 21 | 2.0000 | 2.0000 | | | |
| 36 | 9 | 15 | 2.0000 | 2.0000 | | | |
| 35 | 12 | 22 | 2.0000 | 2.0000 | | | |
| 37 | 18 | 33 | 0.5000 | 0.5000 | | | |
| 33 | 25 | 29 | 0.5000 | 0.5000 | | | |

Table 3
DNRC results for 16-bus test system

| Radial network | Initial network | Proposed method |
|---|---|---|
| Open switches | Switch 4 | Switch 6 |
| | Switch 11 | Switch 9 |
| | Switch 13 | Switch 11 |
| Power loss (MW) | 0.5114 | 0.4661 |

Table 4
Comparison of DNRC results for 33-bus test system

| Radial network | Initial network | Method in Ref. [7] | Proposed method |
|---|---|---|---|
| Open switches | Switch 33 | Switch 7 | Switch 7 |
| | Switch 34 | Switch 10 | Switch 9 |
| | Switch 35 | Switch 14 | Switch 14 |
| | Switch 36 | Switch 33 | Switch 32 |
| | Switch 37 | Switch 37 | Switch 33 |
| Power loss (MW) | 0.202674 | 0.141541 | 0.139532 |

and 32 load points. The five initially-open switches are '33', '34', '35', '36' and '37'. The total system load is 3.715 MW, while the initial system power loss is 0.202674 MW. The system base is $V = 12.66$ kV and $S = 10$ MVA.

Results on the two study systems are listed in Tables 3 and 4. The test results are also compared with those in Ref. [7], in which the solution was stated global optima. It can be observed that the results in this paper are even better than those in Ref. [7]. Thus, we can say that the global optima have been found in this paper.

## 6. Conclusions

An improved method to study distribution network reconfiguration using GA is presented in the paper. The DNRC model, in which the objective is to minimize the distribution system loss, is formed. In the application of GA to the DNRC, some improvements of algorithms are made on chromosome coding, fitness function and mutation pattern. The genetic string used in the paper is shortened to minimize the required memories and to ensure search efficiency. The proposed process of adaptive mutation not only prevents premature convergence, but also leads to a smooth convergence. From several case studies and comparison with other methods, it can be concluded that the global optima have been found by the proposed algorithm. The validity and effectiveness of the proposed methodology have also been demonstrated.

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