

Reconfiguration of distribution network for loss reduction and reliability improvement based on an enhanced genetic algorithm



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ABSTRACT

Electrical distribution network reconfiguration is a complex combinatorial optimization process aimed at finding a radial operating structure that minimizes the system power loss or/and maximizes the system reliability while satisfying operating constraints. In this paper, a distribution network reconfiguration method is presented for both the indices of power loss reduction and reliability improvement. The enhanced genetic optimization algorithm is used to handle the reconfiguration problem so as to determine the switch operation schemes. Based on the information of a single loop caused by closing a normally open switch, we improve the algorithm on crossover and mutation operations of original Genetic Algorithms. The effectiveness of the proposed method is demonstrated on 33-bus, 69-bus, and 136-bus radial distribution systems.

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Introduction

Motivation

As one of the most important content in distribution automation research, network reconfiguration of distribution feeders is performed to improve system operating conditions and reduce system cost. It is a process that alters feeder topological structure, changing the open/close status of sectionalizing switches and tie switches in system. Majority of works reported in the existing literatures aim at minimizing real power loss in distribution network or balancing load distribution. It has, however, been reported in the technical literature that approximately 80% of the customer interruptions occur due to the problems in distribution networks [1,2]. Therefore, reliability is also an essential criterion for reconfiguration problem.

Traditionally, network reconfiguration for loss reduction problem is formulated as a multiobjective problem when considering other parameters related to the system reliability [3]. Due to the nonlinear characteristics of electrical behavior constraints and large number of switching elements in distribution networks, reconfiguration problem generally is a highly complex combinatorial and constrained nonlinear mixed integer optimization

problem. To find an appropriate solution for this kind of problem, meta-heuristic methods are frequently used [4–8].

One of these methods, the genetic algorithm (GA), is highlighted in this paper. One of the most principal difficulties is the radiality constraint in GA operators (mutation, selection, and crossover), which ensures that the network topology operation should be radial. Nevertheless, this paper presents an approach based on an enhanced genetic algorithm (EGA). It properly deals with the radiality constraint to generate feasible solution in GA operators. Therefore, it explores the search space more efficiently, producing better solutions for distribution reconfiguration problem.

This paper deals with the above mentioned proposals to find efficient solutions. The main contribution is the new algorithm that, always, generates radial topologies after the implementation of the genetic operators. This proposal is incorporated in a specialized genetic algorithm allowing the appropriated control of the diversity. However, the proposal of this genetic algorithm is only a collateral contribution. The algorithm presented is set up to solve the reconfiguration problem, and it can also be generalized to solve other problems of the same family, such as multiobjective reconfiguration and reconfiguration with variable demands.

Prior work

It is satisfied with the application of GA to solve the optimization problem with discrete random variables and nonlinear

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objective functions. It has been clearly demonstrated to be both feasible and advantageous, as GA or the enhanced GA approach can efficiently identify the optimal or near optimal network configurations [9,10]. Moreover, it has been found using GA to resolve the planning problem of large-scale power distribution networks is more suitable and efficient than several other methods [11,12]. In spite of that, its main drawback is the slow convergent velocity and the required running time.

In order to acquire better solutions and mitigate the computational burden, considerable efforts have been made to solve the problem. Researchers mainly set about from two aspects: topology coding strategies and genetic operator(crossover and mutation) modifying method.

For GA, the topology coding strategies must permit the genetic operators to be performed in an efficient way. Practically, all the evolutionary algorithms use a codification vector which, after being decoded, represents a radial distribution network topology. The binary coding strategy is the most simple but the least effective in terms of space memory or GA operators success. It takes a string formed by the binary status (closed/open) of each network switch [13,14] as the distribution configuration. The arc number(binary string) and the switch position in each open branch are considered for the feasible radial system in [11]. The topology string is simplified by only the opened switch number in [15]. Based on the concept of path(a set of branches from node to the source), the topology string is composed of all the paths in [16], where the state of each path is represented by a binary variable. It should be noted that only a path to the source for each node is considered for a radial configuration. An encoding scheme with real numbers is adopted in [17–19] based on the concept of fundamental loops or the cut set of each loop. A Prufer number encoding/decoding scheme based on the spanning tree concept is given in [20], which can avoid the tedious “mesh check” algorithm. Actually, a complex strategy could reduce considerably the convergence time on the one hand. On the other hand, a simple strategy would decrease the exploration effectiveness in the research field [19].

A great majority of the GA applications to the reconfiguration problem use the traditional crossover and mutation techniques [11,21,22,20], in which the crossover operator always do not generate a new radial topology. New radial topologies can be always generated by the mutation operator. Therefore, the proposals in [23–25] are implemented using only the mutation operator and avoiding using the crossover operator. A process is developed to change the crossover and mutation probability in [14,15]. In [26], an accentuated crossover process is presented, in which the information of the fundamental loops is used to form a codification vector whose size is equal to the number of branches out of the tree. This information, along with the information of the loops, allows the recombination operator to be implemented in an adequate way. This type of operator is efficient, but the radiality of the generated topologies must be checked. In [20], the combination of two prufer numbers generates another prufer number, that after being decoded, represents another radial topology. Some radial topologies generated could be unfeasible, because there are radial topologies for the interconnected graph, but not for the electrical system. In [19], a theoretical approach based on the graph and matroid theories (graphic matroid in particular) is proposed to deal with the crossover and mutation operator, it also needs the information of fundamental loops. When applied to complex distribution networks, the loop identification could be much more difficult. By far, there is no efficient algorithms to list automatically the fundamental loops for a given graph. Therefore, we need explore more efficient algorithm to solve the problem avoiding to find fundamental loops and perform mesh check.

There is also previous related work that considers multiobjective versions of the reconfiguration problem. For example, five objectives are combined into one equation using weighting factors in [27]. Several objectives are modeled with fuzzy sets in [28] so that they are evaluated in a single equation as well. The objectives considered include power losses, voltage drop, margin of transformer, balance service of important customers, switching operation, branch current loading and feeder load balancing. In [29], the original non-dominated sorting genetic algorithm (NSGA) is employed as the search engine to find the trade-off region between the construction cost of the network and the non-supplied energy. With the enhanced technique non-dominated sorting genetic algorithm-II (NSGA-II), the cost of the network and the cost associated to the occurrence of faults are considered as the objective functions in [30]. In [31], a microgenetic algorithm (uGA) is presented to handle the reconfiguration problem with power losses and reliability indices as two objective functions.

This paper, therefore, proposes an enhanced GA for automated reconfiguration of an existing distribution network to determine the optimal topology which yields the minimum power loss or/and the maximum system reliability. The coding strategy uses the open switch number representation. An approach based on the information of a single loop caused by closing a normally open switch is to perform the GA operators.

Paper organization

This paper is organized as follows: Section “Problem formulation” gives a mathematical model for the distribution network reconfiguration problem. A description of the EGA algorithm is presented in Section “Reconfiguration method”. Simulation results of test cases are presented in Sections “Case studies” discusses and concludes this paper.

Problem formulation

Power loss of radial distribution network

The power flows are calculated by the following set of recursive equations derived from the single-line diagram in Fig. 1 [32,33].

From Fig. 1, the voltage phasers at buses i and $i + 1$ are $V_i \angle \delta_i$ and $V_{i+1} \angle \delta_{i+1}$, respectively. The current \tilde{I}_{i+1} from bus i to bus $i + 1$ (neglecting the shunt flow) is given by

$$\tilde{I}_{i+1} = \frac{V_i \angle \delta_i - V_{i+1} \angle \delta_{i+1}}{R_{i+1} + jX_{i+1}} \quad (1)$$

Here, R_{i+1} and X_{i+1} are the resistance and reactance of the branch from bus i to bus $i + 1$. The load power consumption is given by

$$P_{i+1} - jQ_{i+1} = \tilde{V}_{i+1} * \tilde{I}_{i+1} \quad (2)$$

From (1) and (2), the voltage magnitude of V_{i+1} at node $i + 1$ is given by

$$V_{i+1} = \left\{ \left[\left(P_{i+1} R_{i+1} + Q_{i+1} X_{i+1} - \frac{|V_i|^2}{2} \right)^2 - (R_{i+1}^2 + X_{i+1}^2) (P_{i+1}^2 + Q_{i+1}^2) \right]^{1/2} - \left(P_{i+1} R_{i+1} + Q_{i+1} X_{i+1} - \frac{|V_i|^2}{2} \right) \right\}^{1/2} \quad (3)$$

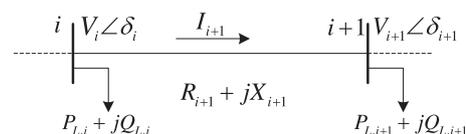


Fig. 1. single-line diagram for power flow calculation.

Here, P_{i+1} and Q_{i+1} represent the total real and reactive powers at bus $i + 1$. They are

$$P_{i+1} = \sum_{j=i+1}^{N-1} P_{L,j} + \sum_{j=i+1}^{N-1} P_{loss,j} \quad (4)$$

$$Q_{i+1} = \sum_{j=i+1}^{N-1} Q_{L,j} + \sum_{j=i+1}^{N-1} Q_{loss,j} \quad (5)$$

where N is the number of buses in the system, $P_{loss,i}$ and $Q_{loss,i}$ are the real and reactive power loss in the branch from bus i to bus $i + 1$, $P_{L,i}$ and $Q_{L,i}$ are the real and reactive load powers at bus i .

$$P_{loss,i} = \frac{R_i(P_i^2 + Q_i^2)}{|V_i|^2} \quad (6)$$

$$Q_{loss,i} = \frac{X_i(P_i^2 + Q_i^2)}{|V_i|^2} \quad (7)$$

By summing up the losses of all branches of the feeder, total real power loss of the feeder can be determined as

$$P_{Tloss} = \sum_{i=1}^{N_l} k_i P_{loss,i} \quad (8)$$

Here, N_l is the total number of branches in the radial distribution system, k_i is a binary variable that represents the topological status of the branches.

Reliability of distribution network

In our studies, the system average interruption frequency index (SAIFI), the system average interruption duration index (SAIDI), the system average service unavailability index (ASAI), and the expected energy not supplied (EENS) are used as the typical quantities to evaluate distribution network reliability [34]. All these indices are obtained from the annual outage rate and annual outage duration at each load point of the system. λ_i is the annual outage rate (number of outage/year) and U_i is annual outage duration (sum of outage time/year) at the i load point.

$$\lambda_i = \sum_{j=1}^3 \sum_{k \in E_{i,j}} \lambda_{i,k} \quad (9)$$

$$U_i = \sum_{k \in E_{i,3}} \lambda_k t_{r,k} + \sum_{k \in E_{i,2}} \lambda_k t_{s,l} \quad (10)$$

Here, $\lambda_{i,k}$ and $U_{i,k}$ represent the annual outage rate and duration caused by the fault of branch k . The value can be determined according to the location of the load point and fault branch k . The branch failure can affect the load point in 3 ways, we denote the fault set for load point i in this case as $E_{i,j}$ ($j = 1, 2, 3$).

- If the fault branch k and load point i lie in different power supply paths (e.g., for $i = 9$ and $k = 10$ in Fig. 2), the fault does not affect the continuity of supply for the considered load point. If they lie in the same power supply path, but the fault branch is in the downstream of the load point (e.g., for $i = 9$ and $k = 15$ in Fig. 2), the fault has no affect on the continuity of supply for the considered load point as well. Hence,

$$\lambda_{i,k} = 0, U_{i,k} = 0 \quad (11)$$

- If the fault branch is in the upstream of the load point in the power supply path, there exist one or more opened branches which once closed will make the fault branch and the considered load point in a loop (e.g., for $i = 9$ and $k = 8$ in Fig. 2), then the load point is left unsupplied for a time equal to the operate time of the normally open switch. Hence,

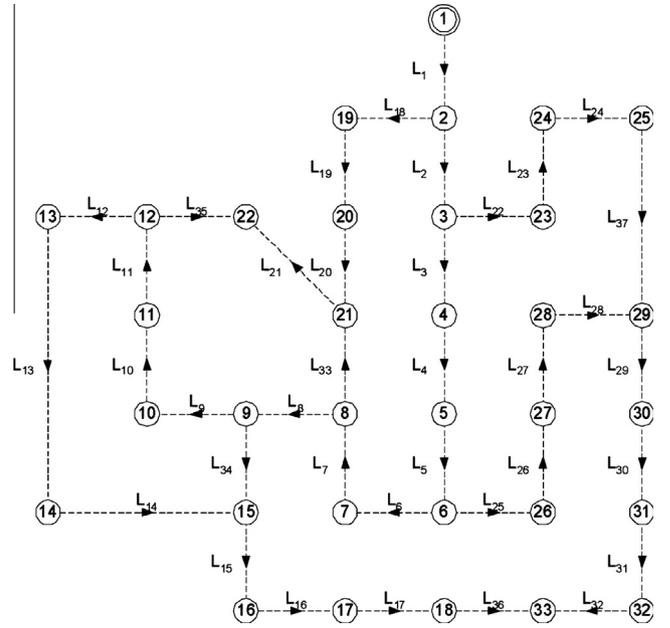


Fig. 2. 33-bus system topology. (The optimal topology for minimum power loss is {L7, L9, L14, L32, L37}.)

$$\lambda_{i,k} = \lambda_k, U_{i,k} = \lambda_k t_{s,l} \quad (12)$$

- If the fault branch is in the upstream of the load point in the power supply path, but there exist no opened branches which once closed will make the fault branch and the considered load point in a loop (e.g., for $i = 9$ and $k = 1$ in Fig. 2), then the load point is left unsupplied for a time equal to the repair time of the fault branch. Hence,

$$\lambda_{i,k} = \lambda_k, U_{i,k} = \lambda_k t_{r,k} \quad (13)$$

Taking the load point $i = 9$ as example in Fig. 2, it lies in the following power supply path. According to above analysis, the branch faults fall into 3 fault sets as

$$\overbrace{L1}^{E3}, \overbrace{L18, L19, L20, L33, L8, L34, L15, L16, L17, L36}^{E2}, \overbrace{L32}^{E1}$$

Mathematical model for distribution network reconfiguration

The purpose of distribution network reconfiguration in this paper is to find a radial operating structure that minimizes the system power losses and maximizes the system reliability while satisfying operating constraints. From a practical point of view, the simulation result is a trade-off between the power losses and the reliability indices. Thus, the problem can be formulated as follows:

$$\begin{cases} \text{Min} f_c = P_{Tloss}(k) \\ \text{Max} \text{Rel} = \frac{1}{N_b} \sum_{i=1}^{N_b} \text{Rel}_i(k) \end{cases} \quad (14)$$

subject to:

- (1) Radial network constraint:

The distribution system cannot deviate from the radial structure.

- (2) Voltage constraints:

Voltage magnitude at each node must lie with their permissible ranges to maintain power quality.

$$V_{i,\min} \leq |V_i| \leq V_{i,\max}, i \in [1, 2, \dots, N_b] \quad (15)$$

where $V_{i,\min}$ and $V_{i,\max}$ are the minimum and maximum voltage limits of bus i .

(3) Current constraints:

Current magnitude of each branch (feeder, laterals, and switches) must lie with their permissible ranges.

$$k_i I_i \leq I_{i,\max}, i \in [1, 2, \dots, N_l] \quad (16)$$

where $I_{i,\max}$ is the maximum current limit of branch i .

4) Kirchhoff's current and voltage laws:

$$g_i(I, k) = 0, g_v(V, k) = 0 \quad (17)$$

Here, $g_i(I, k)$ and $g_v(V, k)$ represent the Kirchhoff's voltage and current laws, respectively.

Reconfiguration method

The real number of open switches encoded genetic algorithm is adapted to handle the above problem. The system power loss is computed by the method discussed in Section "Power Loss of radial distribution network", and the system reliability indices (SAIFI, SAIDI, ASAI, and EENS) are evaluated by the method described in Section "Reliability of distribution network". A discussion regarding the GA algorithm is presented in the following section.

About GA

GA is an artificial intelligence method simulating natural evolution, which uses three main operators of selection, crossover and mutation to produce individuals with better fitness. The general structure of the algorithm used can be summarized as follows [35,36].

- step 1: Generate the initial population and find the fitness and unfitness for each individual in it.
- step 2: Select two individuals as parents using tournament selection.
- step 3: Apply genetic operators depending on the problem (crossover, mutation, etc.) to generate a single descendant.
- step 4: Local search optimization: improve the resulting descendant with information about the nature of the problem.
- step 5: Include the descendant in the population, only if it passes a substitution test.
- step 6: If the stop criterion was satisfied, stop. Otherwise, return to step 2.

Enhanced GA with information of single loop

- (1) Codification and Feasible Population: In this paper, the individuals are represented by a string of whole numbers (chromosome) whose dimension is the total number of switches to be disconnected from the network. Consequently, the length of the string is equal to the number of the system loops.
- (2) Crossover: The traditional crossover process randomly selects two parents (chromosomes) for a gene exchange with a given crossover rate. For the reconfiguration problem, it means one or several edges are exchanged between two spanning trees for a given distribution network graph. The exchange property of spanning trees has been proved by Kruskal. It is shown in Fig. 3.

Denote T_1 and T_2 as two feasible radial structure of the distribution system, if

$$\begin{aligned} \mathbf{e} &= E(T_1) \setminus E(T_2) = \{e_1, e_2, e_3, \dots, e_t\} \\ \mathbf{f} &= E(T_2) \setminus E(T_1) = \{f_1, f_2, f_3, \dots, f_t\} \end{aligned}$$

there exists a sequence $f_{j_1}, f_{j_2}, f_{j_3}, \dots, f_{j_t}$ of \mathbf{f} , such that $T_2 + e_i - f_{j_i}$ is also a feasible radial structure of the distribution system.

Let $loop(T_i, S_j)$ represent the single loop formed by closing the open switch S_j in tree T_i . It can easily be known that $loop(T_1, f_i)$ or $loop(T_2, e_i)$ is always a single loop, where $f_i \in \mathbf{f}$ and $e_i \in \mathbf{e}$.

For a given graph, to list the fundamental loops could be much more complex, but if there is only a single loop in the graph, to find it would be rather easy according to the graph theory. Based on the Kruskal theorem and the information of the single loop, the crossover operator for the distribution network reconfiguration problem is defined as follows:

- step 1: Select two parents P_1 and P_2 using tournament selection.
- step 2: Determine the sets \mathbf{e} and \mathbf{f} .
- step 3: Choose the pointcuts x and y randomly.
- step 4: Determine the mapping relationship.
 - (a) If $P_1(x) \notin \mathbf{f}$, there exist no feasible exchange gene in P_2 for P_1 . If $P_1(x) \in \mathbf{f}$, find the single loop in P_1 by closing $P_1(x)$.
 - (b) Find the intersection of $loop(P_1, P_1(x))$ and P_2 , it is the set of feasible exchange gene.
 - (c) Select a gene randomly from this set as the mapping branch with $P_1(x)$.
 - (d) Refresh the sets \mathbf{e} and \mathbf{f} .
 - (e) Repeat the above process to the pointcut y and determine the mapping relationship.
- step 5: Exchange the genes between P_1 and P_2 according to the mapping relationship.

In Fig. 3, the basic step for a crossover operation is shown between two chromosomes. Each chromosome represents a spanning tree for the distribution network in Fig. 3. Taking Fig. 3(f) as example, we illustrate the partially mapped crossover.

Fig. 3(a) and (b) are selected as two parents P_1 and P_2 , where

$$\begin{aligned} P_1 &= \{s_3, s_4, s_9, s_{10}, s_{12}\} \\ P_2 &= \{s_2, s_3, s_6, s_8, s_{12}\} \end{aligned}$$

According to Kruskal Theorem,

$$\begin{aligned} \mathbf{e} &= \{s_2, s_6, s_8\} \\ \mathbf{f} &= \{s_4, s_9, s_{10}\} \end{aligned}$$

Two pointcuts x and y are randomly chosen between the first and the third gene in P_1 . Firstly, s_3 is considered. As $s_3 \notin \mathbf{f}$, there exist no feasible exchange gene in P_2 with s_3 .

The second gene is s_4 . According to the definition of $loop(T_i, S_j)$,

$$\begin{aligned} loop(P_1, s_4) &= \{s_1, s_2, s_4\} \\ loop(P_1, s_4) \cap P_2 &= \{s_2\} \end{aligned}$$

Therefore, the first mapping set is (s_4, s_2) . The sets \mathbf{e} and \mathbf{f} would be refreshed as

$$\begin{aligned} \mathbf{e} &= \{s_6, s_8\} \\ \mathbf{f} &= \{s_9, s_{10}\} \end{aligned}$$

For the third gene $s_9, s_9 \in \mathbf{f}$, thus

$$\begin{aligned} loop(P_1, s_9) &= \{s_7, s_8, s_9, s_{11}\} \\ loop(P_1, s_9) \cap P_2 &= \{s_8\} \end{aligned}$$

Therefore, the second mapping set is (s_9, s_8) . The above crossover process is shown in Fig. 4.

- (3) Mutation: The mutation operator can allow GA to avoid local optima and to explore new research area as it introduces new information into the knowledge base. Select one or multiple genes in the chosen parent randomly, the single loop is formed by closing the branch in the corre-

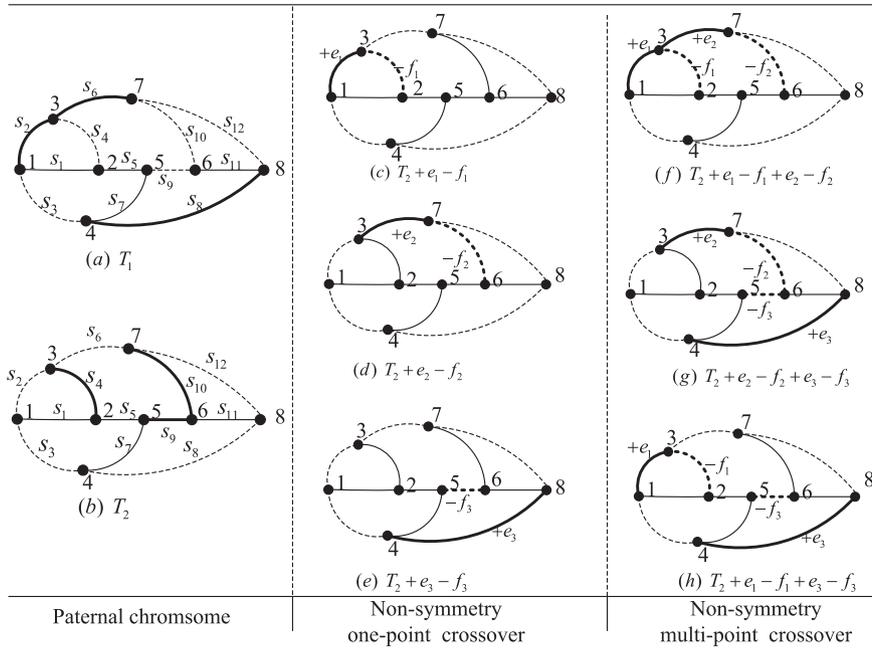


Fig. 3. Branch exchange between two spanning trees. Exchanging one branch for trees T_1 and T_2 , there will be 3 new feasible trees as (c)–(e); Exchanging two branches for trees T_1 and T_2 , there will be 3 new feasible trees as (f)–(h).

sponding tree. with a depth-first graph search algorithm we can determine the single loop. A new gene is randomly chosen in this loop to replace the first selected (see Fig. 5).

At the end of the process, the generated individuals are evaluated using the power loss function or the reliability function, taking into account the operational constraints. Their aptitudes are compared with the results of their parents. Naturally, the individuals with the best aptitude is selected.

(4) Crossover rate and mutation rate.

To gain a satisfying convergence, crossover rate and mutation rate are established by sort-based adaptive algorithm.

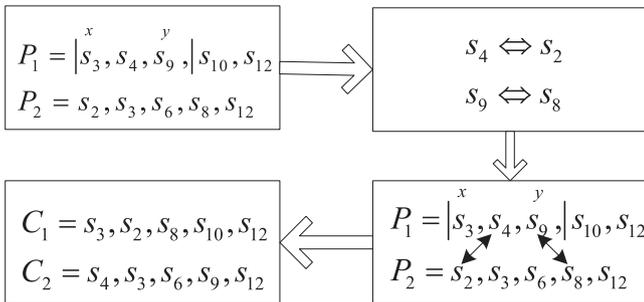


Fig. 4. Crossover process based on the information of a single loop.

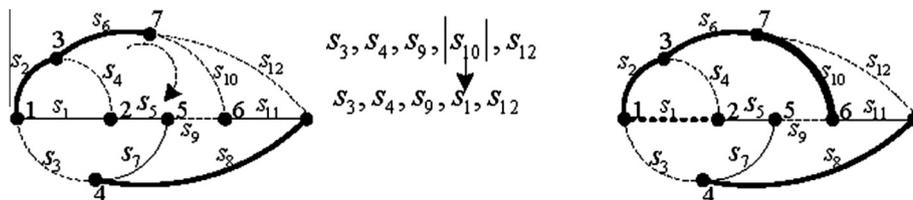


Fig. 5. Mutation process based on the information of a single loop.

$$P_c = \begin{cases} P_{c1} - \frac{2(P_{c1}-P_{c2})}{Pop} (\frac{Pop}{2} - rank'(C) + 1), & rank'(C) \leq \frac{Pop}{2} \\ P_{c1}, & rank'(C) > \frac{Pop}{2} \end{cases} \quad (18)$$

$$P_m = \begin{cases} P_{m1} - \frac{2(P_{m1}-P_{m2})}{Pop} (\frac{Pop}{2} - rank(C) + 1), & rank(C) \leq \frac{Pop}{2} \\ P_{m1}, & rank(C) > \frac{Pop}{2} \end{cases} \quad (19)$$

Here, Pop represents the population size; $rank(C)$ represents the sequence number of individual C in population; $rank'(C)$ represents the one with low sequence number in the crossover individuals; P_{c1} and P_{m1} are crossover rate and mutation rate of the individuals whose fitness value is below average value respectively; P_{c2} and P_{m2} crossover rate and mutation rate of the individuals who have the top fitness value. To control the crossover rate P_c and mutation rate P_m in a reasonable level would help access to the tradeoff between population diversity and search efficiency.

Case studies

In order to ascertain the effectiveness of the proposed algorithm, results for 33-bus, 69-bus, and 136-bus systems, have been obtained. The algorithms of GA and EGA in this paper are performed in MATLAB R2010a with LENOVO M4350-N000 2.66 GHz. For all these systems, the substation voltage is considered as 1 p.u. and all the tie and sectionalizing switches are considered as candidate switches for reconfiguration problem.

Table 1
Parameter for GAs.

Parameter	Population	Generation	P_{c1}	P_{c2}	P_{m1}	P_{m2}
Value	30	100	0.6	0.9	0.1	0.01

Case 1

The proposed method for maximizing reliability and minimizing system power loss is first applied to the modified 33-bus, 12.66 kV, radial distribution system shown in Fig. 2. It consists of 5 normally open switches and 32 normally closed switches. The normally open switches are s33, s34, s35, s36 and s37, and the normally closed switches are s1 to s32. The line data and load data of this system are given in [37], and the total real and reactive power loads on the system are 3715 kW and 2300 kVar, respectively. The initial power losses of this system are 210.99 kW and 143.02 kVar. Table 1 shows the chosen values of the parameters for the presented EGA. These values are chosen after 100 runs of the algorithm.

The simulation results for the 33-bus system are show in Table 2. It shows the results of reconfiguration for maximum reliability, for minimum power loss, and for maximum reliability and minimum power loss with varying weights. In Table 2, the units of SAIDI, SAIFI, EENS, power loss, and time are respectively hours/

year, times/year, MW h, KW, and seconds. It should be noted that the time consumption is calculated by the mean operation time of 30 runs with the presented algorithm. The value of $w1$ and $w2$ are 0.5×1000 and 0.5×8760 .

In order to show the efficiency of the described method, an original GA has been implemented and applied to the system. It selects the real number coding strategy as well as the EGA, which uses the open switches number representation. But the genetic operations are only performed by the mutation operator with $p_m = 0.01$. The convergence results of system indices for GA and EGA are shown in Fig. 6. The EGA curves are plotted randomly from 30 runs of the presented algorithm with different objectives, and the GA curves are plotted for the best results from 30 runs of the original GA.

A Pareto front is shown in Fig. 7, which is drawn with the objective of minimizing the indices of power loss and EENS for different reconfiguration schemes. Decision makers can choose their desired reconfiguration schemes based on the requirement of the indices of reliability or power loss or a tradeoff between them.

Case 2

Other 2 test distribution systems, namely 69-bus and 136-bus systems, are used to validate the proposed methodology. Since there is no access to the reliability data of these systems, we take

Table 2
Optimal solution for 33-bus system with different objective.

Item	Initial Case	Min SAIDI	Min SAIFI	Min EENS	Min Loss	$w1 * EENS + w2 * Loss$
Solution	33, 34, 35, 36, 37	10, 13, 16, 28, 33	10, 13, 16, 28, 33	10, 13, 16, 28, 33	7, 9, 14, 32, 37	7, 9, 14, 32, 37
Loss	210.99	164.41	164.41	164.41	139.55	139.55
SAIDI	1.247	1.047	1.047	1.047	1.259	1.259
SAIFI	2.445	2.158	2.158	2.158	2.467	2.467
EENS	3.846	3.302	3.302	3.302	3.867	3.867
Time (EGA)	-	0.52	0.43	0.46	0.60	0.62
Time (GA)	-	3.32	3.44	4.56	5.06	5.24

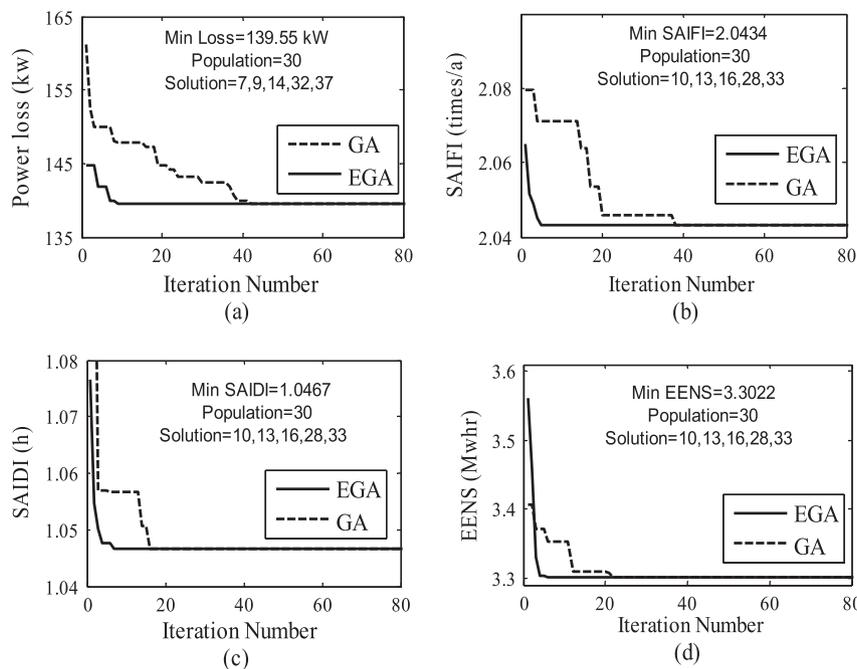


Fig. 6. Convergence results of various system indices for GA and EGA.

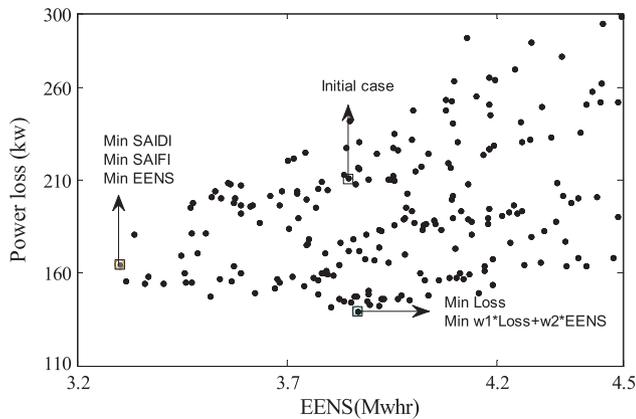


Fig. 7. A Pareto front for power loss vs EENS.

Table 3
Reconfiguration results for 69-bus system with different methods.

Method	Solution found	Power loss (KW)	Time (s)
[37]	15, 59, 62, 70, 71	99.62	34.31
[39]	11, 14, 21, 56, 62	106.67	15.27
[40]	14, 56, 62, 70, 71	99.71	33.43
[41]	15, 59, 62, 70, 71	99.62	27.25
GA	15, 59, 62, 70, 71	99.62	16.12
EGA	15, 59, 62, 70, 71	99.62	8.31

the reconfiguration for minimum power loss as example to ascertain the effectiveness of the proposed algorithm.

The next test system is a 12.66 kV radial distribution system with 69 buses and 5 loops. The system data of the initial configuration can be accessed in [38]. The total active and reactive system loads are 3802.19 kW and 2694.60 kVar, respectively, and the initial real power loss is 225.0 kW. The final configurations and system real power losses are shown in Table 3, which are summarized and compared to methods presented in [37,39–41]. The power loss of final configuration obtained by EGA is 139.55 kW, which is comparable to [37,41] but less than other methods. Table 3 also represents the effectiveness of our method, which could have achieved the optimal configuration in the 14th iteration with 8.31 s compared to other methods. 30 runs for each method were performed in order to calculate the average computational time in MATLAB.

The last test system is a 13.8 kV real distribution system with 136 buses and 156 branches [35]. The initial real power loss is 320.36 kW for total loads of 18313.8 kW and 7932.5 kVar. The results of other methods applied on this system are shown in Table 4. The power loss of final configuration obtained by EGA is 280.19 kW. Table 4 also shows that the proposed method have

Table 4
Reconfiguration results for 136-bus system with different methods.

Method	Solution found	Power loss	Time
[39]	135, 136, 138, 143, 144, 145, 146, 148, 150, 155 135, 136, 138, 143, 144, 145, 146, 148, 150, 155	293.29	367.44
[41]	7, 35, 51, 90, 96, 106, 118, 126, 135, 137, 138, 141, 142, 144, 145, 146, 147, 148, 150, 151, 155	280.19	402.36
GA	7, 35, 51, 90, 96, 106, 118, 126, 135, 137, 138, 141, 142, 144, 145, 146, 147, 148, 150, 151, 155	280.19	381.45
EGA	7, 35, 51, 90, 96, 106, 118, 126, 135, 137, 138, 141, 142, 144, 145, 146, 147, 148, 150, 151, 155	280.19	33.98

achieved the optimal configuration in the 34th iteration with 33.98 s compared to other methods. 30 runs for each method were performed in order to calculate the average computational time in MATLAB. In EGA, the percentage of illegal individuals is lower than GA, the best solution can be identified in less iterations with fewer time. Hence, the convergence characteristics of the best results for EGA are better than GA.

Conclusions

In this paper, the network reconfiguration problem for loss reduction and reliability improvement is formulated to be solved by using enhanced GA. The effectiveness of the proposed method is demonstrated on 33-bus, 69-bus, and 136-bus radial distribution systems. Results show that the proposed algorithm can converge to optimum solution quickly with better accuracy compared to other methods mentioned. It is to be noted that although the results presented in this section correspond to radial distribution systems, the procedure described in Section “Reconfiguration method” is valid for meshed systems as well.

The main contribution is improving the crossover operator of GA and avoiding to find fundamental loops of distribution networks. When applied to complex distribution networks, the loop identification could be much more difficult. By far, there is no efficient algorithms to list automatically the fundamental loops for a given graph. In our algorithm, we need only one loop to improve the effectiveness of genetic operations. Based on the information of a single loop caused by closing a normally open switch, all resulting individuals after GA operators are radial structures. Therefore, we would not need to perform mesh checks to validate each resulting topology (to detect any loop in the network or any not energized node).

Other major contribution of this paper is to incorporate reliability evaluation methods into the distribution system reconfiguration problem. The simulation result for case 1 is a trade-off between the power losses and the reliability indices, as the proposed method worked effectively which show that the power loss is reduced, the reliability is increased. Further tests are performed to emphasize the efficiency of proposed method.

The experimental results show that the proposed method can solve the feeder reconfiguration more effectively and stably with less iteration and fewer time.

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