Enhanced genetic algorithm-based fuzzy multi-objective approach to distribution network reconfiguration

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Abstract: An enhanced genetic algorithm (EGA)-based fuzzy multi-objective approach to solve a network reconfiguration problem in a radial distribution system is presented. Maximising the fuzzy satisfaction allows the operator to simultaneously consider the multiple objectives of the network reconfiguration to minimise power loss, violation of voltage and current constraints, as well as switching number, while subject to a radial network structure in which all loads must be energised. The optimisation technique of the EGA is then adopted to solve the fuzzy multi-objective problem efficiently. Test results verify the feasibility of applying the proposed method to manipulate the combinatorial optimisation network reconfiguration in distribution systems.

1 Introduction

Network reconfiguration modifies the network structure of distribution feeders by changing the open/close status of the sectionalising (normally closed) and tie (normally open) switches. This not only reduces the power loss, but also relieves the overloading of the network components. Hence, network reconfiguration is a vital task of distribution automation.

Reconfiguration has received considerable interest in recent years [1–10]. Related methods can be classified into mathematical and heuristic methods. Aoki *et al.* [1] developed a mathematical programming approach to solve optimal load allocation problems in distribution systems. Civanlar *et al.* [2] presented a computationally attractive solution procedure to reduce power loss through reconfiguration. Liu *et al.* [3] proposed two algorithms to minimise losses in distribution networks. Shirmohammadi *et al.* [4] applied optimal load flow analysis to network reconfiguration for loss minimisation. While formulating the loss reduction and load balancing as an integer programming problem, Baran *et al.* [5] proposed efficient load flow equations to calculate the power flow. In addition, related investigations [4, 6, 7] have attempted to reduce the search space by proposing heuristic methods to obtain solutions through intuitive rules based on the operator's experiences.

The reconfiguration is a complicated combinatorial, nondifferentiable and constrained optimisation problem owing to the enormous number of candidates switching combinations in distribution systems. Heuristics and experts' experience-based approaches can only obtain suboptimal solutions. To obtain global optimal or, at least, near global optimal solution, Chiang *et al.* [8, 9] proposed a two-stage solution methodology using the simulated annealing (SA) algorithm for the reconfiguration. Although SA has the potential to search the global optimal solution, tuning the control parameters of the annealing schedule is extremely difficult and requires a significant amount of computing effort. Simple genetic algorithm (SGA) [10] and hybrid genetic algorithm [11] approaches were presented to solve the reconfiguration, but they focus only on the loss minimum objective. The evolutionary programming [12] was proposed to solve the constrained multi-objective problem.

This study presents a fuzzy multi-objective problem formulation, not only to satisfy realistic objectives and soft constraints (not hard limits) of the reconfiguration, but also to supply rigorous mathematical and heuristic approaches within the problem-solving process. The fuzzy set theory provides an excellent framework for integrating the mathematical and heuristic approach into a more realistic formulation of the reconfiguration, while keeping an efficient computation. Owing to the non-commensurable characteristics of the objectives, a conventional approach that optimises a single objective function is inappropriate for this problem. The fuzzy decision [13] is therefore adopted to simultaneously consider the multiple objectives and to obtain a fuzzy satisfaction maximising decision. The EGA is considered to be an efficient method for solving the large-scale combinatorial optimisation problem, due to the ability to search global or near global optimal solutions and its appropriateness for parallel computing.

2 Problem formulation

This paper considers the following objectives in the reconfiguration:

(1) Minimisation of the system's power loss,
(2) Minimisation of the voltage constraint violation,
(3) Minimisation of the current constraints violation,
(4) Minimisation of the switching number,

subject to the radial network structure in which all loads must be energised.

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2.1 Fuzzy multi-objective formulation

The four objectives described in the preceding text are first fuzzified and, then, dealt with by integrating them into a fuzzy satisfaction objective function M through appropriate weighting factors as shown below:

$$\text{Max}\, M = w_1\mu_{\tilde{P}} + w_2\sum_{i=1}^{N_{bs}}\mu_{\tilde{V}_i} + w_3\sum_{i=1}^{N_{bh}}\mu_{\tilde{I}_i} + w_4\mu_{\tilde{S}} \quad (1)$$

where $\mu_{\tilde{P}}$ represents the membership value (MV) to minimise the total power loss; $\sum_{i=1}^{N_{bs}}\mu_{\tilde{V}_i}$ is the sum of MVs to minimise the voltage violation; $\sum_{i=1}^{N_{bh}}\mu_{\tilde{I}_i}$ is the sum of MVs to minimise the current violation; $\mu_{\tilde{S}}$ is the MV of minimisation of the switching number; N_{bs} is the number of busbars; N_{bh} is the number of branches, and w_i, $i = 1, 2, 3, 4$, are weighting factors. The membership functions (MFs) used to describe the four objectives are stated in the following.

2.2 MF for the power loss

Reconfiguration attempts to obtain the minimum power loss, while no violation of the constraint exists. A configuration with a larger power loss is given a lower MV. Because the exponential function meets this condition, it is selected for the MF of the power loss, as shown in Fig. 1, and is expressed as follows:

$$\mu_{\tilde{P}} = \exp(-(P_{loss} - P_{l,\min})/P_{l,\min}) \quad (2)$$

where $\mu_{\tilde{P}}$ denotes the MV of power loss P_{loss}, and the value of power loss $P_{l,\min}$ is the minimum power loss which can be obtained by minimising the single objective of the power loss.

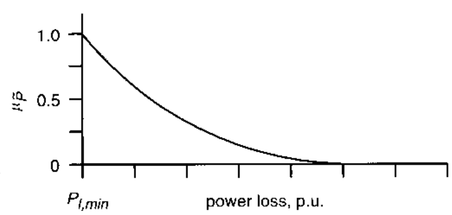

Fig. 1 *Membership function of the power loss*

2.3 MF for the busbar voltage

Selecting the trapezoid MF prevents undervoltage and overvoltage in each busbar, as described in the following:

$$\mu_{\tilde{V}_i} = \begin{cases} 0, & V < V_1 \\ \dfrac{V - V_1}{V_2 - V_1}, & V_1 \le V < V_2 \\ 1.0, & V_2 \le V < V_3 \\ \dfrac{V_4 - V}{V_4 - V_3}, & V_3 \le V < V_4 \\ 0, & V_4 \le V \end{cases} \quad (3)$$

Fig. 2 presents the MF for the voltage, where $\mu_{\tilde{V}_i}$ represents the MV of voltage V_i in busbar i; V_1, V_2, V_3 and V_4 are the specified voltage values.

2.4 MF for the branch current

The MF of the branch current is described as follows.

$$\mu_{\tilde{I}_i} = \begin{cases} 1.0, & I < I_1 \\ \dfrac{I_2 - I}{I_2 - I_1}, & I_1 \le I < I_2 \\ 0, & I_2 \le I \end{cases} \quad (4)$$

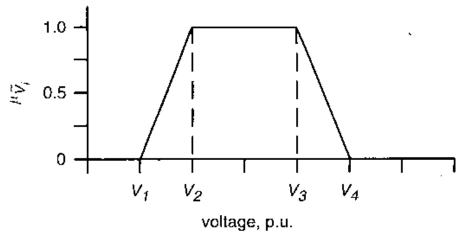

Fig. 2 *Membership function of the busbar voltage*

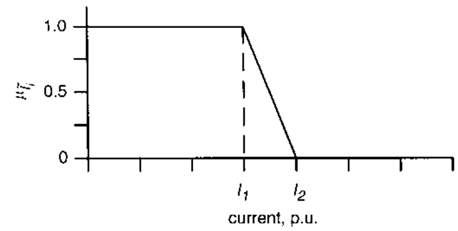

Fig. 3 *Membership function of the branch current*

Fig. 3 depicts the MF for the branch current, where $\mu_{\tilde{I}_i}$ represents the MV of current I_i flow in branch i; I_1 and I_2 are specified current values. The average current loading index (CLI_{ave}) and maximum current loading index ($CLI_{\max}$) evaluate the current loading of the network configuration, as described in the following:

$$CLI_{ave} = \frac{1}{N}\sum_{i=1}^{N_{bh}}\frac{I_{f,i}}{I_{c,i}} \quad (5)$$

$$CLI_{\max} = Max\left\{\frac{I_{f,i}}{I_{c,i}},\ i = 1, 2, \ldots, N_{bh}\right\} \quad (6)$$

where $I_{f,i}$ denotes the current in the branch i, $I_{c,i}$ is the line capacity of the branch i, and N_{bh} is the number of branches. Obviously, the minimum current loading index is equal to zero, indicating no current flow through this branch (i.e. tie line). The lower the CLI_{ave} implies a higher degree of load balance. The branch current $I_{f,i}$ can be calculated by the simplified power flow (11), as will be described later.

2.5 MF for the switching number

To reduce the operation, as well as extend the life of switches, the switching number is an essential consideration in the reconfiguration and should be kept as minimal as possible. A configuration with a larger switch number is assigned a lower MV. Because the exponential function satisfies this condition, it is used for the MF of the switching number, as shown in Fig. 4, and is written as follows:

$$\mu_{\tilde{S}} = \begin{cases} 1.0, & N_S \le N_{\min} \\ \exp(-(N_S - N_{\min})/N_{\min}), & N_{\min} < N_S \end{cases} \quad (7)$$

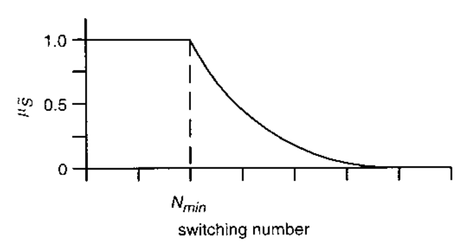

Fig. 4 *Membership function of the switching number*

where $\mu_{\tilde{S}}$ denotes the MV of switching number N_S, and N_{min} is the preselected switching number limit.

2.6 Simplified power flow equations

Consider the radial network in Fig. 5. The line impedances between branch i and branch $i+1$ are represented by $z_i = r_i + jx_i$, and load models are expressed as constant power sinks, $S_L = P_L + jQ_L$. By assuming that the losses on the lines between branches are significantly smaller than branch power terms, the following set of simplified power flow equations is used [5]:

$$P_{i+1} = P_i - P_{L,i+1} = \sum_{k=i+2}^{N_{bh}} P_{L,k} \tag{8}$$

$$Q_{i+1} = Q_i - Q_{L,i+1} = \sum_{k=i+2}^{N_{bh}} Q_{L,k} \tag{9}$$

$$V_{i+1}^2 = V_i^2 - 2(r_i P_i + x_i Q_i) \tag{10}$$

where the real power P_{i+1}, reactive power Q_{i+1} and busbar voltage V_{i+1} are the values at branch $i+1$, after determining the values of P_i, Q_i and V_i for branches $0, 1, \ldots, i$.

The P_i, Q_i and V_i can be used to calculate the branch current $I_{f,i}$:

$$I_{f,i} = \sqrt{(P_i^2 + Q_i^2)/V_i^2} \tag{11}$$

The total power loss on a distribution system can be calculated by summing up each branch power loss through the following equation:

$$P_{loss} = \sum_{i=1}^{N_{bh}} r_i (P_i^2 + Q_i^2)/V_i^2 \tag{12}$$

The multi-objective formulation in (1) is maximised using the EGA based approach. The following section briefly introduces the EGA.

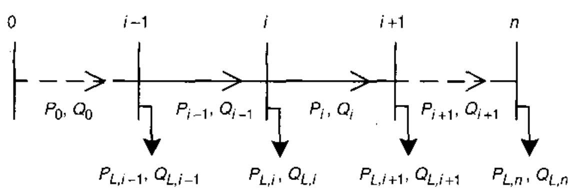

Fig. 5 *One line diagram of a radial distribution system*

3 The proposed EGA

The SGA [10, 14, 15] is a stochastic search mechanism based on the Darwinian principle of natural evolution. The evolutionary process causes initial solutions to move towards the optimal point over many generations. The roulette-wheel selection scheme used in SGA has the potential drawback that the best member of the population may fail to produce offspring in the next generation, possibly causing a stochastic error. The elitism and multiple-point crossover strategies [16] is embedded in the EGA to enhance the performance of the SGA. The EGA operations are described as follows.

3.1 Coding and decoding functions

A sequence of binary bits is called a string or an individual in the EGA, which corresponds to a set of genes [14, 15], i.e. a chromosome, in natural genetics. A coding function translates the decision variables into the binary strings, and a decoding function translates the binary strings back into the decision variables. The EGA conducts its operations according to these string representations, then a fitness function evaluates the fitness of the strings.

3.2 Initialisation

An initial population of strings is randomly generated from the initial conditions of the studied system. This scheme is intended to provide an extensive basis from which the EGA begins its search. Parameter settings are also given in the initialisation stage.

3.3 Fitness function

The individuals evolve according to their fitness to the environment. Fitness is defined as a non-negative figure of merit associated with a set of decision variables. For a maximisation problem, the larger the objective function value the individual implies a larger fitness.

3.4 Selection and elitism

The criterion to select the individuals is based on their fitness values [14, 15]. Individuals with a larger fitness value, i.e. better solutions to the problem, receive correspondingly larger numbers of copies in the mating pool. For example, assume there are m individuals within the population, each having a fitness value f_i, for $i = 1, 2, \ldots, m$. Then, in the mating pool, the number of individuals (n_i) with fitness f_i is proportional to the value calculated by

$$n_i = f_i \bigg/ \left(\sum_{j=1}^{m} f_j \right) \tag{13}$$

Elitism is an effective means of saving early solutions by ensuring the survival of the fittest strings in each generation [16]. The elitism puts the best string of the old generation into the new generation to improve convergence performance of the SGA.

3.5 Multiple-point crossover

Individuals in the mating pool are randomly taken in pairs, without replacement, after the pool has been constructed. The crossover operation used in the SGA [14, 15] is a single-point crossover, because one crossover site is selected. This simple crossover can be generalised to multiple-point crossover in which the number of crossover points N_c is specified. These two strings are then divided into segments by randomly setting N_c crossover sites. The segments of strings from the parents are exchanged with each other to generate their offspring. Multiple-point crossover can solve certain problems of feature combinations encoded on chromosomes that a single-point crossover cannot solve [16].

3.6 Mutation

The mutation diversifies the search and prevents the premature convergence that leads to nearly the same individuals within a population after several generations [14–16]. For each bit of the offspring, the mutation changes a 1 into a 0, or vice versa, according to a fixed mutation probability. The mutation probability must be sufficiently small to ensure not only that the crossover is the primary means of creating new offspring, but also that the EGA is not reduced to a random search. However, too small a mutation probability cannot avoid premature convergence.

The crossover and mutation are repeated until the mating pool is empty. Once the new generation is obtained, the evolving process repeats the genetic operations of selection, crossover and mutation, to generate the new individuals. The process stops when the average fitness is within a

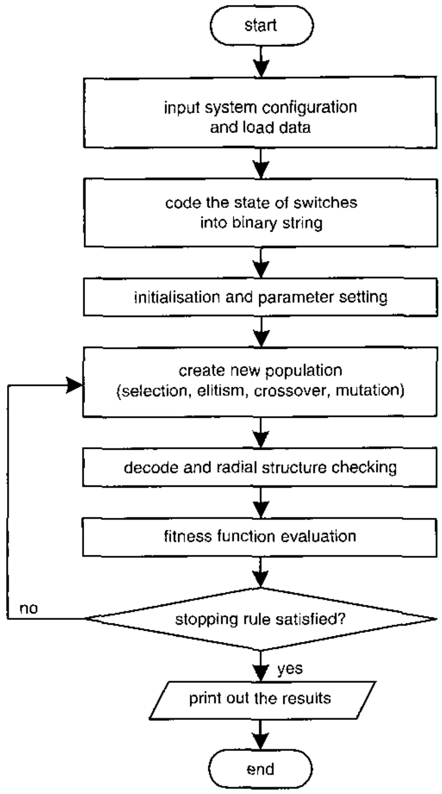

Fig. 6 *Flowchart of the reconfiguration solved by the EGA*

specified percentage of the best string fitness, or when the given count of total generations is reached.

4 Implementation of the proposed EGA

Fig. 6 displays the flowchart of the reconfiguration solved by the EGA. The EGA for the reconfiguration is implemented straightforwardly, except for handling the radial structure constraint. Detailed implementation is stated as follows.

4.1 Coding, decoding and radial structure checking

The binary decision variables denote the on/off status of switches to be determined in the reconfiguration. Where '0' denotes 'open' of the switch and '1' represents 'close'. The fitness value of each individual is evaluated by decoding the 1/0 status of switches to obtain the network configuration. The radial structure checking examines whether the configuration is radial. If the network is not radial, a switch of each loop is randomly opened to satisfy the radial structure constraint.

4.2 Fitness function, selection and elitism

The fitness function f of the reconfiguration is defined as follows:

$$f = M = w_1\mu_{\tilde{P}} + w_2\sum_{i=1}^{N_{bs}}\mu_{\tilde{V}_i} + w_3\sum_{i=1}^{N_{bh}}\mu_{\tilde{I}_i} + w_4\mu_{\tilde{S}} \quad (14)$$

The fitness value of individuals is estimated from the fuzzy values of the objectives considered (14). The larger the fitness of an individual implies a larger number of copies that are selected in the mating pool. Moreover, the elitism puts the best individual of the current generation into the new generation to further enhance the convergence performance of the SGA.

4.3 Multiple-point crossover and mutation

The crossover recombines an individual with another individual split at the same crossover sites based on the preselected crossover probability. The mutation randomly alternates a bit in the individual according to the mutation probability. The EGA optimisation process repeats until the specified maximum number of generations is reached.

5 Test results

The proposed EGA-based method was developed on a PC Pentium III-600 using Turbo C programming language. The proposed method was tested on a typical distribution system to evaluate its effectiveness.

5.1 Case study

The tested case is a 70-busbar and 74-branch radial distribution system [17], as shown in Fig. 7. The tie lines of the test system are 70, 71, 72, 73 and 74, which are opened in normal configuration. Table 1 summarises their impedance data. The system voltage is 12.66 kV, and kVA base was assumed at 1000 kVA. The total system loads are 3802.19 kW and 2694.6 kVAR. The lower busbar voltage limit is 0.9 p.u. The additional branch current constraints were set at 200 A, except for the upstream branches, 1–9, whose limits were 400 A, and 47–50 as well as 53–65 branches were 300 A.

The MFs were determined first. Through the single minimisation of power loss, the minimum power loss P_{Lmin} is 0.094023 p.u. (94.023 kW). The MF of the voltage used 0.9 p.u. for V_1, 0.95 for V_2, 1.0 for V_3 and 1.05 for V_4 (Fig. 2). For the branch current, I_1 was set at its 90% line capacity and I_2 at its specified capacity limit (Fig. 3). The reasonable switching number was set at 4 for N_{min}.

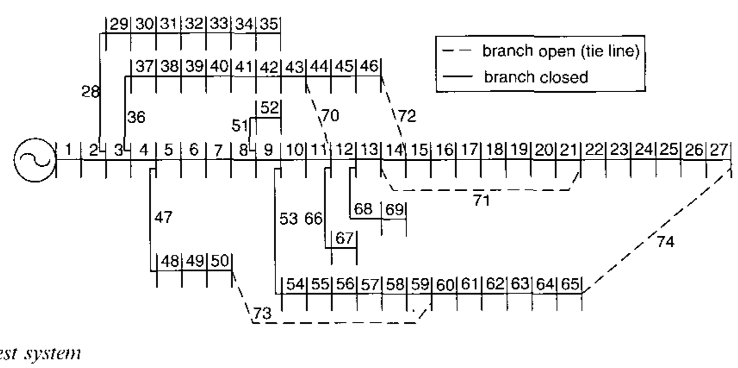

Fig. 7 *Diagram of the test system*

Table 1: Tie line data

Line number	Resistance, Ω	Reactance, Ω
70, 71	0.5	0.5
72, 74	1.0	1.0
73	2.0	2.0

Table 2: Optimal feeder reconfiguration

	Branch open	Switching number
Original configuration	70, 71, 72, 73, 74	—
After reconfiguration	13, 59, 70, 71, 74	4

Table 3: System state before/after network reconfiguration

	Power loss, kW	Voltage, p.u.	Current loading index
Original configuration	204.799	$V_{max} = 1.0$	$CLI_{ave} = 0.2201$
		$V_{min} = 0.9131$	$CLI_{max} = 0.9203$
After reconfiguration	113.406	$V_{max} = 1.0$	$CLI_{ave} = 0.1860$
		$V_{min} = 0.9288$	$CLI_{max} = 0.9203$

The proper weighting factors used are $w_1 = w_2 = w_3 = w_4 = 0.25$, in which these four objectives are assumed to be equally important. The weighting factors can be varied according to the preferences of different operators. The test results of the EGA are compared with the SGA [10] and the SA [8, 9]. The optimal configurations obtained by these three methods are all the same, as shown in Table 2. The case studied requires four switching numbers to achieve the optimal configuration.

Table 3 lists the power loss as well as the maximum and minimum voltages of the system before and after reconfiguration. The power loss before reconfiguration is 204.799 kW (5.39%) and that for the optimal configuration is 113.406 kW (2.98%). This finding indicates that 91.393 kW (2.41%) further reduction in power loss (or 44.71% improvement) is obtained. Also, the minimum voltage is upgraded. The CLI_{max} after reconfiguration is the same as that before reconfiguration, in which both occur at branch 1, i.e. is nearest the power source (Fig. 7). However, the CLI_{ave} after reconfiguration is smaller than that before reconfiguration, which arises from the reconfiguration transforming the original network structure into the optimal structure. Therefore, the proposed EGA can achieve the optimal load-balanced structure.

Fig. 8 presents the voltage profile of the system before and after reconfiguration. After reconfiguration, the voltage profile is obviously improved. Fig. 9 displays the current profile of the system before and after reconfiguration. Although the reconfiguration alters the current distribution, the more the load balancing is achieved (i.e. smaller CLI_{ave} obtained). Hence, optimal reconfiguration can improve the voltage profile and also provide a more load-balanced situation for distribution network operation by the proposed EGA.

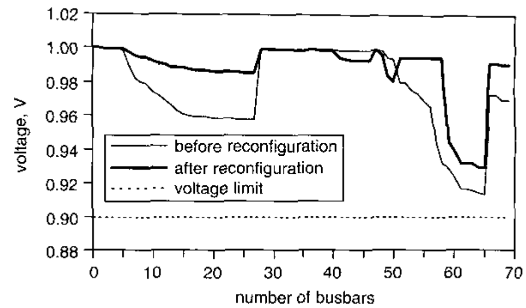

Fig. 8 *System voltage profile*

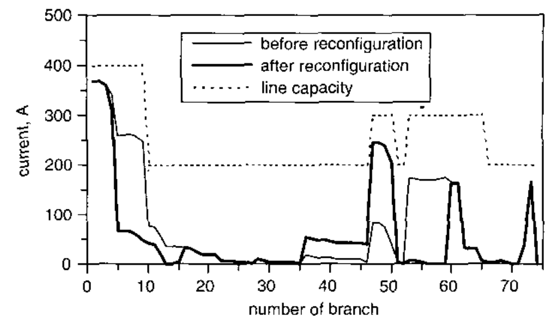

Fig. 9 *System branch current*

Table 4: Result comparisons of the EGA, SGA and SA

Methods	Average computing time, s	Number of global optimal reached in 100 runs
EGA	13	97
SGA [10]	11	91
SA [8, 9]	36	95

5.2 Performance comparisons of EGA, SGA and SA

Parameter settings of the EGA, as compared with the annealing schedule of the SA, can be more easily tuned to yield promising results [18] after some experiments. The optimal parameter settings of the EGA are as follows: population size of 60, maximum generation of 20, number of crossover sites (N_c) equal to 3, crossover probability equal to 0.6 and mutation probability equal to 0.001.

The parameters of SGA are set the same as EGA listed in the preceding text for comparison, except for single-point crossover operation used. The numbers of trials evaluated for the EGA and the SGA were 1200 (20 × 60) and that for the SA (after some experiments) was 12 000 (120 × 100), i.e. the maximum iteration number in the SA was set at 120 and the trial number per iteration was at 100. Table 4 displays the result comparisons of the EGA, SGA and SA. The average computing time of the EGA is close to that of SGA and far less than that of SA. The number of the global optimum reached in 100 runs with different random initial solutions of the EGA is superior to that of the SGA and the SA. Although the SA has the potential to obtain the global optimal solution, the features of its searching sequentially from a single point to another and possibly cycling around a local optimal solution diminish its performance in practice. The proposed EGA is a highly effective approach for the reconfiguration, owing to the high performance enhanced by the elitism and multiple-point crossover used in the EGA and inherent implicit parallelism of the SGA.

6 Conclusions

This study has presented an EGA-based fuzzy multi-objective approach to solve the network reconfiguration problem in a radial distribution system. The objectives considered attempt to maximise the fuzzy satisfaction of the minimisation of power loss, violation of voltage and current constraints, and the switching number is subject to radial network structure in which all loads must be energised. Owing to the high performance and implicit parallelism of the proposed method, the EGA can solve the fuzzy multi-objective problem efficiently. Test results confirm that the EGA-based approach can efficiently search the optimal or near-optimal network configuration. Results in this study further demonstrate the feasibility of applying the evolutionary optimisation algorithm to the network reconfiguration in actual distribution systems.

7 Acknowledgments

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