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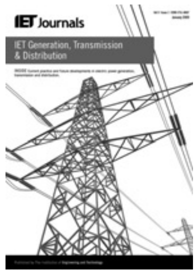

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Microgenetic multiobjective reconfiguration algorithm considering power losses and reliability indices for medium voltage distribution network

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Abstract: This study proposes and applies an evolutionary-based approach for multiobjective reconfiguration in electrical power distribution networks. In this model, two types of indicators of power quality are minimised: (i) power system's losses and (ii) reliability indices. Four types of reliability indices are considered. A microgenetic algorithm (μGA) is used to handle the reconfiguration problem as a multiobjective optimisation problem with competing and non-commensurable objectives. In this context, experiments have been conducted on two standard test systems and a real network. Such problems characterise typical distribution systems taking into consideration several factors associated with the practical operation of medium voltage electrical power networks. The results show the ability of the proposed approach to generate well-distributed Pareto optimal solutions to the multiobjective reconfiguration problem. In the systems adopted for assessment purposes, our proposed approach was able to find the entire Pareto front. Furthermore, better performance indexes were found in comparison to the Pareto envelope-based selection algorithm 2 (PESA 2) technique, which is another well-known multiobjective evolutionary algorithm available in the specialised literature. From a practical point of view, the results established, in general, that a compact trade-off region exists between the power losses and the reliability indices. This means that the proposed approach can recommend to the decision maker a small set of possible solutions in order to select from them the most suitable radial topology.

1 Introduction

The reconfiguration of the distribution network is a process that alters the feeder topological structure, changing the open/close status of sectionalisers and switches in an electrical distribution system, with the objective of minimising some system operating variable in the medium and long term. The first publication about the reconfiguration problem, in which the importance and the potential of this research line was observed, was presented by Merlin and Back [1]. Starting from this work, a new area of research was created with the aim of finding radial topologies with smaller power losses levels by using algorithms with reduced simulation times.

Several works on this topic have been analysed in a survey developed by Sarfi *et al.* [2]. From this review, new methodologies to face this optimisation problem have been developed, based mainly on artificial intelligence techniques: genetic algorithms [3, 4], dynamic programming [5], exhaustive search [6], simulated annealing [7] and ant colony optimisation [8].

Research in minimal loss reconfiguration has been guided in several ways; for example, a reconfiguration model for unbalanced distribution systems is developed in [9]. The work presented in [10] uses economical objective functions. In [11] the on-line reconfiguration is evaluated, taking into account the variability of demand through the characteristic load curves. In [12] the minimisation of the energy purchase cost is approached. On the other hand, the protection coordinations are considered as constraints in the reconfiguration problem studied in [13]; nevertheless, this work considers the reconfiguration problem from the perspective of system's abnormal operation, a problem that is known as service restoration.

Other important approaches based on reliability have been previously developed. For example, reconfiguration models that minimise a weighted sum of the reliability index, the expected interruption cost and the energy not supplied (ENS), are developed in [14, 15]. In general, these works show that the network's reconfiguration is an effective approach to increase the worth of distribution systems' reliability without extra costs, providing customers quality and financial benefits.

For these reasons, the aim of this work is to use the topology like a control variable to optimise two very important indices in primary distribution networks: (i) an index related to the efficient transport of energy and (ii) an index based on the quality of the client–supply–continuity. This problem can be solved through a multiobjective reconfiguration process using a multiobjective optimisation technique (an evolutionary algorithm, in our case). In this situation, the solution consists of finding the non-dominated solutions to the problem (such non-dominated solutions represent the best possible trade-offs between the two objectives considered). Such non-dominated solutions constitute the so-called Pareto optimal set. The image of the Pareto optimal set (i.e. the objective function values corresponding to the contents of the Pareto optimal set) is called the Pareto front.

There is also previous related work that considers multiobjective versions of the reconfiguration problem. For example, in [16] five objectives are minimised: the feeder losses, the load balancing among supply transformers, the worst voltage drop, the service interruption frequency and the balance service of important customers. All these goals are combined into one equation using weighting factors. On the other hand, in [17], several objectives are modelled with fuzzy sets so that they are evaluated in a single equation as well. The objectives considered include power losses, margin of feeders, margin of transformer, deviation of bus voltage, switching operation, branch current loading and feeder load balancing.

It is important to note that in all these works the objective functions are aggregated (i.e. they are combined into a single scalar value) and, therefore, the problem is solved through a single-objective optimisation technique. Consequently, the reconfiguration problem is not really tackled as a truly multiobjective optimisation problem, which leads to a loss of important technical and economical information that arises from analysing the trade-offs among the selected objectives. In contrast, in this paper, we do provide a truly multiobjective treatment of this problem, since instead of using an aggregating function, we adopt the definition of Pareto optimality (which aims to find the best possible trade-offs among all the objectives) for selecting solutions.

It is worth noting, however, that there exists previous work in electrical distribution network design, in which a real multiobjective treatment is adopted. For example, in [18] the non-dominated sorting genetic algorithm-II (NSGA-II), which is a well-known multiobjective evolutionary algorithm, is used as the search engine to find the trade-off region between the cost of the network (investment cost and energy losses) and the cost associated to the occurrence of faults (number of faults and non-delivered energy). The same problem is solved in [19], but in this case, the construction cost of the network and the non-supplied energy are considered as the objective functions. The problem is solved using two multiobjective evolutionary algorithms: the original non-dominated sorting genetic algorithm (NSGA) and the Pareto archived evolution strategy (PAES). Since both of these papers are focused on distribution network design, the objective functions associated to the power losses and reliability costs are evaluated in an approximated way.

As can be seen from the previous discussion, virtually no research has been carried out until now on the proper multiobjective reconfiguration of distribution power systems, incorporating the Pareto optimal criterion from a medium- and long-term planning perspective, as it is performed in this work.

This paper presents a multiobjective approach based on a microgenetic algorithm (μGA) that properly deals with the trade-offs between the power losses and the reliability indices, in order to obtain radial topologies of electrical distribution systems within a Pareto front. In this context, we have conducted our investigation on two standard test systems and a real primary 15 kV network. The protection and manoeuvre schemes, which play a very important role as constraints of this problem, were suitably considered because of the influence on the system's reliability. The performance of the μGA is assessed by comparing its obtained results (for the proposed electrical model) with respect to those found via exhaustive search and via another multiobjective evolutionary algorithm called Pareto envelope-based selection algorithm 2 (PESA 2). MATLAB was adopted for all the simulations reported in this paper.

2 Establishing the multiobjective problem of reconfiguration

Let us consider the 23 kV meshed network, which is provided with sectionalisers–fuses (SF) in lines 1, 2 and 5, and

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sectionalisers in lines 3 and 4 (S) as shown in Fig. 1. The universe of radial topologies is formed only by four possibilities (topologies). The data of line impedances, node powers and failure rates, are shown in Table 1. The repair and manoeuvre times are considered to be 1 and 0.5 h, respectively. For each topology, it is possible to calculate the power losses (PL), as the addition of the N_b square value of each current (i_b) multiplied by their respective resistance (R_b) (1) and the reliability indices according to (2)–(5), namely F (systems average interruption frequency index), T (system average interruption unavailability index), D (system average duration interruption index) and ENS (non-supplied energy), which are functions of the active (kW$_i$) and apparent (kVA$_i$) power values of the N_c system loads, as well of the failure rate (λ_i), repair time (r_i) and unavailability (U_i) for each load point. Table 2 shows these results. The reliability indices adopted by the Chilean law are defined by the Inter-American Committee of Regional Electricity-CIER

$$\mathrm{PL} = \sum_{b=1}^{N_b} R_b \cdot i_b^2 \tag{1}$$

$$F = \frac{\sum_{i=1}^{N_c} \mathrm{kVA}_i \cdot \lambda_i}{\sum_{i=1}^{N_c} \mathrm{kVA}_i} \tag{2}$$

$$T = \frac{\sum_{i=1}^{N_c} \mathrm{kVA}_i \cdot U_i}{\sum_{i=1}^{N_c} \mathrm{kVA}_i} \tag{3}$$

$$\mathrm{ENS} = \sum_{i=1}^{N_c} \mathrm{kW}_i \cdot U_i \tag{4}$$

$$D = \frac{T}{F} \tag{5}$$

$$U_i = \lambda_i \cdot r_i \tag{6}$$

These results show that the third radial topology presents the smallest value for the PL index. However, the fourth radial topology presents the smallest value for the ENS, F and T indices and the second radial topology presents the smallest values for the D index. Through these results, it is possible to observe that a commitment level exists between the objectives associated to the power losses and the reliability indices.

Table 1 Data for the test system

Line	Node	$R + jX$, p.u.	λ, f/yr	MW–MVAr[a]
L_1	1–2	0.03 + j0.03	0.2	3.4–1.4
L_2	1–3	0.02 + j0.02	0.3	10.0–4.0
L_3	2–4	0.02 + j0.02	0.2	6.7–2.7
L_5	4–5	0.01 + j0.01	0.1	10.0–4.0
L_4	3–4	0.01 + j0.01	0.2	

[a]Power at the end of the line.

Table 2 Result test system

	Loss, p.u.	F, f/yr	T, h/yr	ENS, MWh/yr	D, h/f
1	0.0028	0.73	0.49	14.71	0.67
2	0.0053	0.63	0.40	12.04	0.63
3	0.0022	0.50	0.38	11.53	0.77
4	0.0025	0.40	0.28	8.36	0.69

Furthermore, from a practical point of view, in this problem, it is necessary to consider an appropriate operation of the system regarding other electrical and topological variables such as

$$i_b \leq i_{\mathrm{máx}_b} \tag{7}$$

$$V_{\min} \leq V \leq V_{\max} \tag{8}$$

These are parts of the operational constraints of the proposed optimisation model. Equation (7) corresponds to the feeder thermal limits and to the maximum capacity of the substations, so that the system currents (i_b) do not exceed

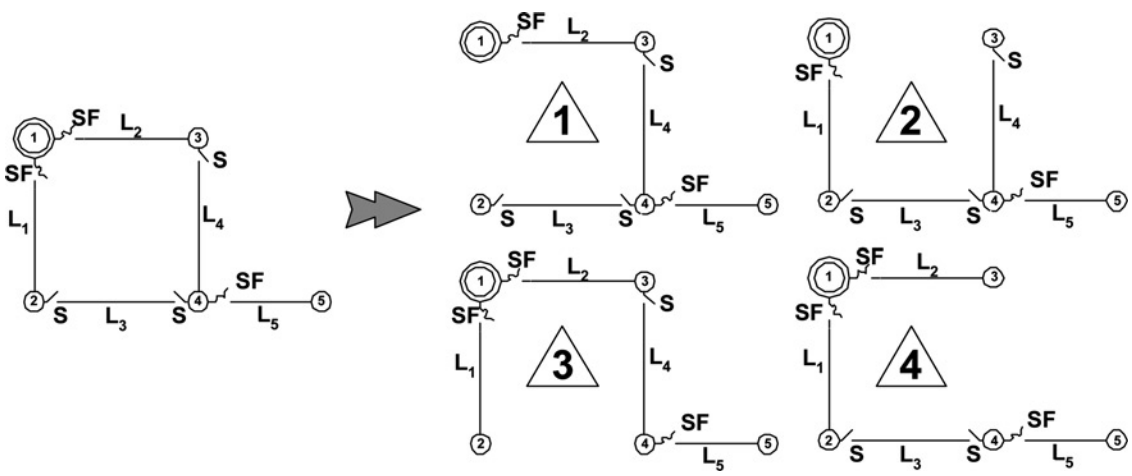

Figure 1 *Radial topologies for the test system*

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their maximum values ($i_{máx_b}$). Equation (8) considers voltage constraints in each node where these must be kept between their minimum (V_{min}) and maximum (V_{max}) allowable values.

3 Optimisation method for the proposed multiobjective reconfiguration problem

Nowadays, the inherent advantages of 'evolutionary multiobjective optimisation' are exploited in order to find the Pareto optimal set for the problem of our interest. In contrast with conventional techniques, an evolutionary algorithm is able to find more than one element of the Pareto optimal set in a single run, because of their population-based nature. Traditional mathematical programming techniques tend to generate Pareto optimal solutions one at a time. Furthermore, evolutionary algorithms are less susceptible to the shape or continuity of the Pareto front, whereas these are serious concerns when adopting mathematical programming techniques. Evolutionary multiobjective optimisation techniques can be roughly classified as follows [20]:

Techniques not based on Pareto optimality: linear and non-linear aggregating methods, vector-evaluated genetic algorithm (VEGA), lexicographic ordering, hybrids with the ε-constraint method and so on.

Techniques based on Pareto optimality: multiobjective genetic algorithm (MOGA), NSGA, NPGA, μGA, PAES, NSGA-II and SPEA2, among others.

Among these techniques, we decided to use the μGA proposed in [21] to solve the multiobjective optimisation problem of our interest. This technique was developed by one of the co-authors of this paper and its performance has been previously compared to other techniques that are representative of the state-of-the-art in evolutionary multiobjective optimisation.

3.1 Microgenetic algorithm

This technique improves the efficiency of the optimisation process, in comparison with other evolutionary algorithms, because it applies the concept of Pareto dominance to a very small set of possible solutions (a maximum of five individuals are used in the main population).

Fig. 2 shows a block diagram that describes the inner workings of the μGA. First, a set of solutions is randomly generated. This random population (which is called population memory) is divided into two parts: a replaceable portion (RM) and an irreplaceable one (IRM). The irreplaceable portion never changes during the evolutionary search, since it constitutes the source of diversity of the approach. In contrast, the replaceable portion is modified after each cycle of the μGA.

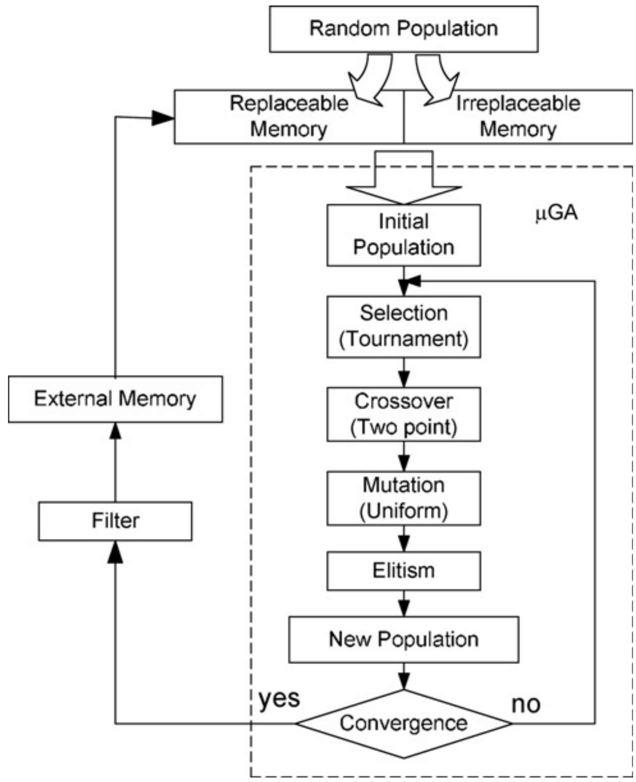

Figure 2 *μGA block diagram*

The population of the μGA at the beginning of each of its cycles is taken (with a certain probability) from both portions of the population memory (i.e. the replaceable and the non-replaceable portions).

During each cycle, the μGA applies the conventional operators of a simple genetic algorithm: tournament selection, crossover, mutation and elitism. The μGA is run for a certain (pre-defined) number of iterations, which defines the so-called nominal convergence. After this, two non-dominated solutions are chosen from the final population of the μGA and they are compared to the contents of the replaceable memory. Here, the aim is to replace two individuals from the replaceable memory that are dominated by these two solutions from the main population of the μGA. Over time, the replaceable memory will tend to have more non-dominated solutions, some of which will be used in the initial populations of the μGA.

The definition of Pareto dominance for two decision vectors $\boldsymbol{x}, \boldsymbol{y} \in F$ (F refers to the feasible region) is shown next.

A vector $\boldsymbol{x} = (x_1, x_2, \ldots, x_k)$ is said to dominate (in a Pareto sense) another vector $\boldsymbol{y} = (y_1, y_2, \ldots, y_k)$ (denoted by $\boldsymbol{x} \preceq \boldsymbol{y}$) if and only if

$$\forall i \in (1, \ldots, k),\ x_i \leq y_i \wedge \exists i \in (1, \ldots, k): x_i < y_i$$

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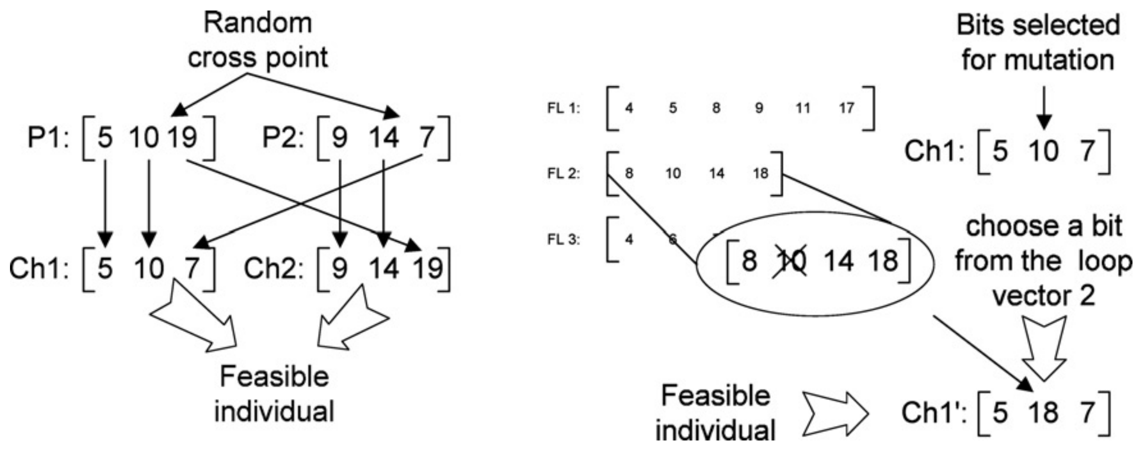

Figure 3 *Examples of encodings and genetic operators*

In words, a vector dominates another one (in a Pareto sense) when it is less or equal (assuming minimisation) with respect to all of its components and it is strictly less with respect to at least one of them. Note that if a solution $\boldsymbol{x}$ does not dominate another solution $\boldsymbol{y}$, and $\boldsymbol{y}$ does not dominate $\boldsymbol{x}$, then both are non-dominated with respect to each other (in other words, they are incomparable). For example, if we consider the minimisation of f_1 and f_2 and we have three vectors whose objective function values are the following: $\boldsymbol{A} = (2, 1)$, $\boldsymbol{B} = (3, 3)$, $\boldsymbol{C} = (1, 2)$, we can say that $\boldsymbol{A}$ dominates $\boldsymbol{B}$ ($\boldsymbol{A} \prec \boldsymbol{B}$) because $f_1(\boldsymbol{A}) < f_1(\boldsymbol{B})$ and $f_2(\boldsymbol{A}) < f_2(\boldsymbol{B})$. In the same way, we can say that $\boldsymbol{C}$ dominates $\boldsymbol{B}$ ($\boldsymbol{C} \prec \boldsymbol{B}$) because $f_1(\boldsymbol{C}) < f_1(\boldsymbol{B})$ and $f_2(\boldsymbol{C}) < f_2(\boldsymbol{B})$. However, as $f_1(\boldsymbol{C}) < f_1(\boldsymbol{A})$ and $f_2(\boldsymbol{A}) < f_2(\boldsymbol{C})$, we can say that these two solutions do not dominate among them.

Also, the μGA adopts an external archive in which the non-dominated solutions found along the evolutionary process are stored. This external archive is also used to spread the non-dominated solutions found. Further details of the mechanisms of the μGA can be found in [21].

4 Proposed approach

In this paper, a proper multiobjective distribution system reconfiguration model is proposed. This approach takes into account the power losses of the system (index of the energy transport efficiency) and reliability indices (F, T, ENS or D) (as quality indicators client–supply–continuity). The μGA technique is adapted to the proposed multiobjective reconfiguration model. For this sake, an efficient encoding and specialised genetic operators developed in some of our previous work were adopted [3]. In order to evaluate the objective functions and to verify the operational constraints of the network, specialised radial load flow and reliability algorithms are considered.

4.1 Encoding and genetic operators used

A great variety of encodings and genetic operators to solve the reconfiguration problem are available to be used with an evolutionary algorithm [3, 4]. However, not all of these proposals reach efficient results in the search of the best topologies.

The encoding and genetic operators adopted in this paper are based on some of our previous work presented in [3]. Such a proposal takes into account the fundamental loops vectors of a network, defined as a set of elements that form a closed-loop in a circuit, not containing any other closed-loop, in order to create a radial topology. These fundamental loops are obtained through a small routing algorithm that considers the system data. A string of integers (called chromosome) whose cardinality is the total number of lines to be disconnected from the network represents an individual of our μGA. To create radial topologies, one should select from the group of fundamental loop vector those elements that are to be disconnected (one per loop). In this technique, each position (gene) of the string represents a randomly selected element from each fundamental loops vector. These considerations allow limiting the generation of infeasible individuals used in the μGA, reducing the combinatorial search space. This methodology is very efficient and robust when applied to the large distribution systems [3, 4], for example, if we consider the system in Fig. 5*a*, it can be noticed that the number of fundamental

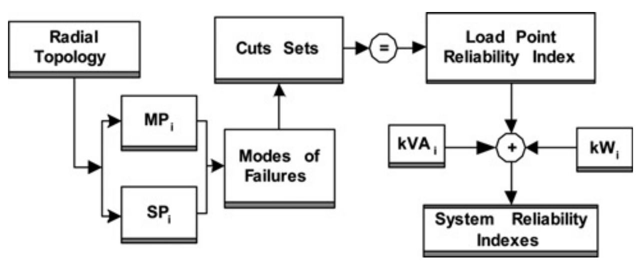

Figure 4 *Reliability block diagram*

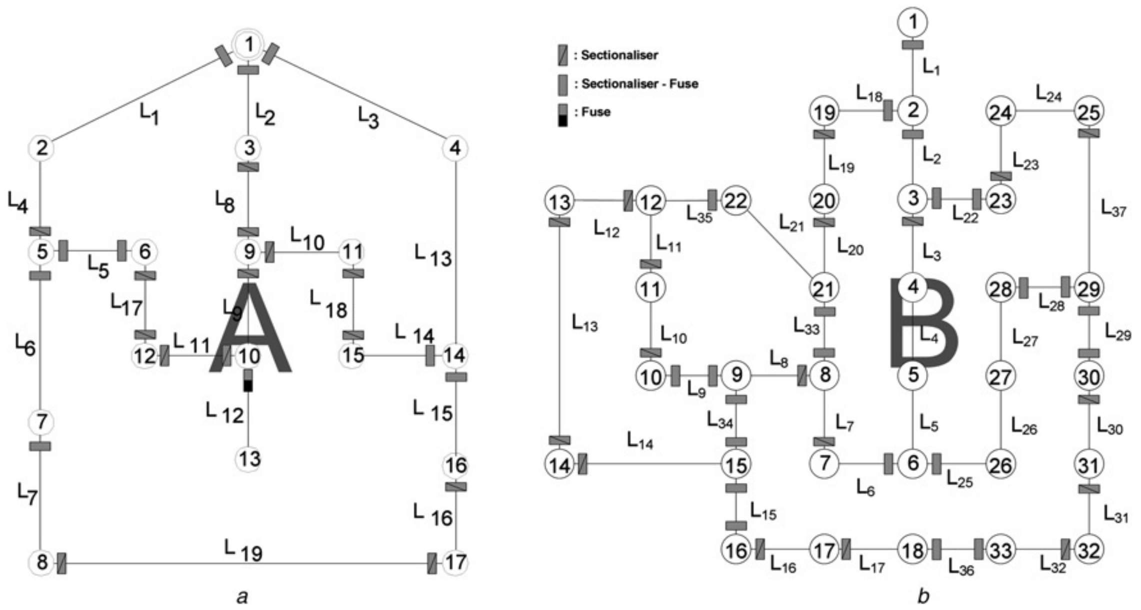

Figure 5 *System topologies*
a Civanlar
b Baran

loops (FL) is 3, which can be obtained by the branches number minus the buses number plus one. These grids are composed by the following lines

$$\begin{aligned}\boldsymbol{FL}_1 &= [L_1 \quad L_2 \quad L_4 \quad L_5 \quad L_8 \quad L_9 \quad L_{11} \quad L_{17}]\\ \boldsymbol{FL}_2 &= [L_2 \quad L_3 \quad L_8 \quad L_{10} \quad L_{13} \quad L_{14} \quad L_{18}]\\ \boldsymbol{FL}_3 &= [L_1 \quad L_3 \quad L_4 \quad L_6 \quad L_7 \quad L_{13} \quad L_{15} \quad L_{16} \quad L_{19}]\end{aligned} \tag{9}$$

From these vectors, the lines that cannot be open must be discarded; among them are L_1, L_2, L_3 and L_{13} so (9) is reduced to (10)

$$\begin{aligned}\boldsymbol{FL}_1 &= [L_4 \quad L_5 \quad L_8 \quad L_9 \quad L_{11} \quad L_{17}]\\ \boldsymbol{FL}_2 &= [L_8 \quad L_{10} \quad L_{14} \quad L_{18}]\\ \boldsymbol{FL}_3 &= [L_4 \quad L_6 \quad L_7 \quad L_{15} \quad L_{16} \quad L_{19}]\end{aligned} \tag{10}$$

From here, it is only necessary to select an element from each FL to form a radial network. In Fig. 3, an example of the encoding and the genetic operators used is shown. P1 and P2 are parents created by the previously described method; in this example, the crossover between both parents is done in a random selected position (second bit), to create two children (Ch1 and Ch2) as shown in Fig. 3. It can be noticed that both children are feasible individuals because they have not lost the radiality and connectivity conditions. For the mutation, in this example, the second bit of Ch1 has been randomly chosen to be modified; it is important to note that this second bit is not changed for any other element, but for some other that belongs, in this case, to the system's second loop. Finally, a new individual has been created (Ch1′) which is still feasible.

4.2 Objective function evaluation

In order to make better decisions in the optimisation process, the objective functions and constraints defined in this work (power losses and reliability indices) will be evaluated using specialised high-accuracy algorithms for each candidate that is selected by the evolutionary process.

First, a radial load flow based on a power summation method is used to evaluate the power losses of the systems. This load flow allows the evaluation of the system active losses and both voltage and current constraints.

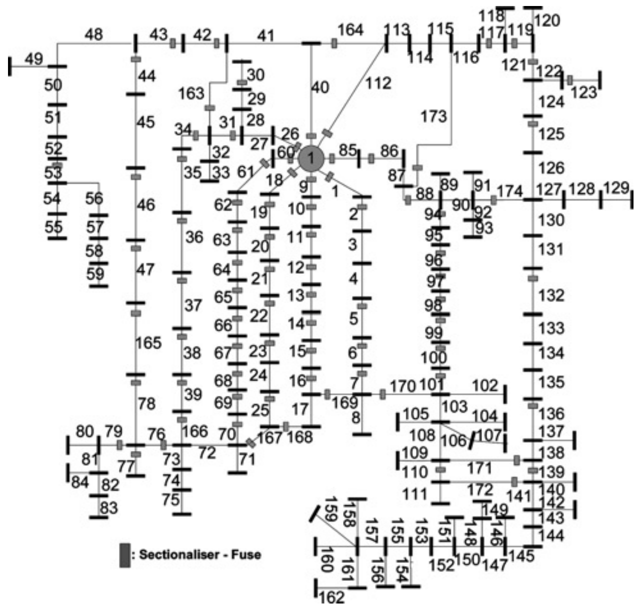

Figure 6 *Real system topology*

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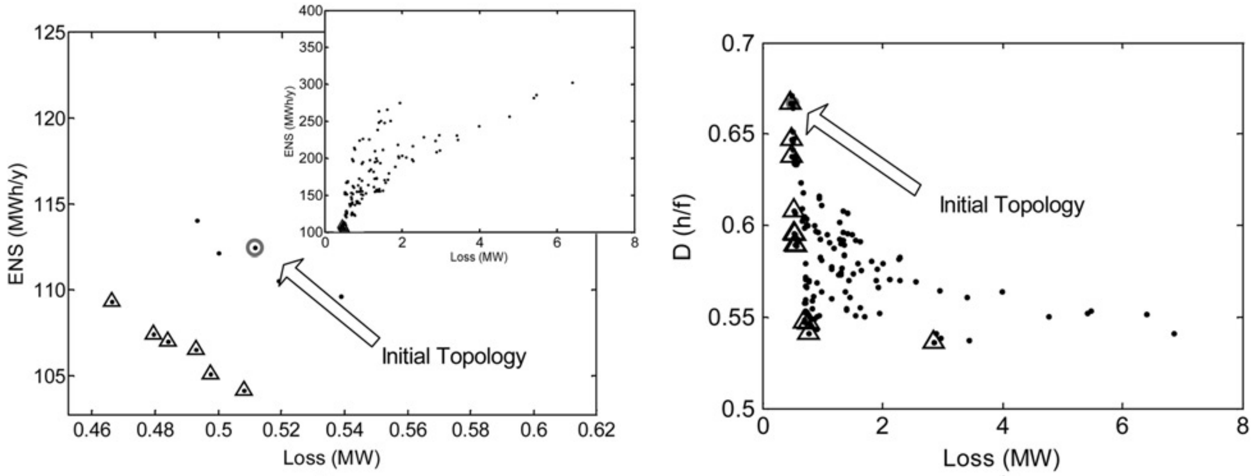
Table 3 Results of Civanlar systems

Topologies	Case 1		Case 2		Case 3		Case 4	
	PL, MW	*F*, f/yr	PL, MW	*T*, h/yr	PL, MW	ENS, MWh/yr	PL, MW	*D*, h/f
10-11-19	0.466	5.612	0.466	3.741	0.466	109.315	0.466	0.666
7-10-11			0.479	3.662	0.479	107.415	0.479	0.647
10-17-19	0.484	5.470			0.484	106.975		
10-11-16			0.493	3.636	0.493	106.500	0.493	0.638
7-10-17			0.498	3.591	0.498	105.075		
10-16-17			0.508	3.566	0.508	104.160		
11-14-19							0.512	0.608
7-11-14							0.518	0.596
7-14-17							0.540	0.595
11-14-16							0.548	0.589
14-16-17							0.567	0.589
7-9-14							0.684	0.547
9-10-16							0.776	0.546
9-14-16							0.775	0.541
4-9-14							2.857	0.536
individuals IRM	40		40		40		50	
cycles of process	60		60		60		100	



a

b

Figure 7 *Civanlar's system*

a Results for Case 3
b Results for Case 4

There are several alternatives for evaluating reliability indices in distribution systems. One of them is the algorithm presented in [15]. This approach uses the concept of 'main and secondary paths', in order to evaluate, efficiently, the basic reliability indexes. This method defines the main path (MP) of a load point as the group of all the existent elements among the source (main SS/EE) and the load point under study. On the other hand, the secondary path (SP) is conformed by all the elements taking part in the failure modes of the load point, except for the elements that belong to MP. In the MP and SP, it is necessary to carry out all the considerations, for the failure modes, in terms of the existent switching and protection elements. These considerations determine all order cut sets taking part in the reliability diagrams. Using the cut set, it is possible to calculate the failure rate ($\lambda = \sum_{i=1}^{N_C} \lambda_i$) and the unavailability ($U = \sum_{i=1}^{N_C} \lambda_i \cdot r_i$) of each load point. With these load point indicators, it is possible to determine the system indicators as in (2–(5) [22]. This algorithm allows a quick evaluation of any reliability index of the distribution networks, considering, in detail, the effect of the protection and manoeuvre elements. The block diagram of Fig. 4 shows the commented algorithm.

4.3 Description of the algorithm

The input data for the multiobjective reconfiguration program are the power system parameters: lines, loads, the location and rated values of capacitors banks, and the reliability parameters: failure rates, the repair times and time of the manoeuvres.

In order to start the evolutionary multiobjective optimisation process, the algorithm begins by giving a random population to the irreplaceable (or non-replaceable) memory. Regarding that, most of the CPU time spent by the algorithm is associated with the objective function evaluation and the verification of the constraints, for which a database was provided. The aim is to store the candidates that have been already evaluated. Therefore the objective function values are read from this memory if the procedure calls the candidates again, in order to avoid repeated calculations. In cases where the candidates do not meet the constraints, these are punished and later discarded by the evolutionary process.

The population size and the number of iterations to reach 'nominal convergence' within the multiobjective technique were 5 and 3, respectively. The percentage of the irreplaceable memory and the replaceable memory in the initial population in all simulations was 70 and 30%, respectively.

5 Applications

In this section, the proposed multiobjective method will be evaluated considering four multiobjective cases: (i) the PL and F index, (ii) the PL and T index, (iii) the PL and ENS and (iv) the PL and D index. Two networks called Civanlar and Baran systems are used as test systems [3].

Table 4 Results of Baran systems

Topologies	Case 1		Case 2		Case 3	
	PL, MW	F, f/yr	PL, MW	T, h/yr	PL, MW	ENS, MWh/yr
7-9-14-32-37	0.1396	3.136	0.1396	1.799	0.1396	6.645
7-10-14-32-37	0.1402	3.123	0.1402	1.792	0.1402	6.616
7-11-14-32-37	0.1413	3.110	0.1413	1.779	0.1413	6.566
7-11-14-36-37					0.1435	6.546
7-9-14-17-37	0.1476	3.078	0.1476	1.767	0.1476	6.478
7-10-14-17-37	0.1479	3.065	0.1479	1.760	0.1479	6.449
7-11-14-17-37	0.1484	3.052	0.1484	1.747	0.1484	6.399
7-10-14-16-37	0.1523	3.045				
7-11-14-16-37	0.1527	3.032	0.1527	1.736	0.1527	6.352
9-14-32-33-37	0.1600	3.026				
10-14-32-33-37	0.1637	2.997				
11-14-32-33-37	0.1676	2.970	0.1676	1.720	0.1676	6.319
10-14-17-33-37					0.1692	6.314
10-14-16-33-37					0.1724	6.301
11-14-17-33-37	0.1727	2.955	0.1727	1.709	0.1727	6.238
11-14-16-33-37	0.1759	2.952	0.1759	1.707	0.1759	6.225
11-13-16-33-37	0.1874	2.947				
individuals IRM	100		100		100	
Cycles of process	700		700		700	

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Table 5 Result of Baran systems

Solution	Topologies	Case 4		Solution	Topologies	Case 4	
		PL, MW	*D*, h/f			PL, MW	*D*, h/f
1	7-11-14-23-28	1.3484	0.5314	24	7-14-27-30-35	0.1806	0.5583
2	14-19-23-35-28	1.0787	0.5335	25	7-8-14-27-30	0.1780	0.5588
3	8-14-20-23-29	0.7177	0.5337	26	7-31-34-35-37	0.1772	0.5600
4	7-23-29-34-35	0.4217	0.5349	27	7-8-14-28-30	0.1758	0.5600
5	7-8-14-23-29	0.3515	0.5372	28	7-14-25-31-35	0.1712	0.5601
6	7-14-23-29-35	0.3368	0.5379	29	7-14-27-31-35	0.1642	0.5609
7	7-11-14-23-29	0.3062	0.5410	30	7-14-28-31-35	0.1616	0.5621
8	7-10-14-23-29	0.3017	0.5423	31	7-8-14-27-31	0.1599	0.5623
9	7-9-14-23-29	0.2973	0.5424	32	7-8-14-28-31	0.1572	0.5636
10	7-23-30-34-35	0.2704	0.5445	33	7-14-27-32-35	0.1554	0.5640
11	7-14-23-30-35	0.2439	0.5469	34	7-14-17-28-35	0.1549	0.5654
12	7-8-14-23-30	0.2413	0.5479	35	7-14-28-32-35	0.1521	0.5654
13	7-14-23-31-35	0.2382	0.5504	36	7-11-14-27-31	0.1501	0.5657
14	7-11-14-23-30	0.2266	0.5509	37	7-11-14-28-31	0.1474	0.5670
15	7-10-14-23-30	0.2244	0.5524	38	7-9-14-27-31	0.1470	0.5673
16	7-9-14-23-30	0.2223	0.5525	39	7-11-14-31-37	0.1458	0.5681
17	7-25-30-35-34	0.2131	0.5544	40	7-9-14-28-31	0.1443	0.5686
18	7-27-30-34-35	0.2071	0.5550	41	7-9-14-31-37	0.1427	0.5697
19	7-28-30-34-35	0.2050	0.5561	42	7-11-14-28-32	0.1418	0.5706
20	7-35-34-37-30	0.2032	0.5566	43	7-11-14-37-32	0.1413	0.5721
21	7-25-31-34-35	0.1883	0.5575	44	7-9-14-28-32	0.1401	0.5722
22	7-14-25-30-35	0.1865	0.5576	45	7-9-14-32-37	0.1397	0.5738
23	7-27-31-34-35	0.1814	0.5581				
individuals IRM	500						
cycles of process	2000						

Fig. 5 shows these networks, with their protection and manoeuvre schemes. Tables 8 and 9 show the data of these systems. The repair and manoeuvre times are considered to be 1 and 0.5 h, respectively.

The Civanlar system has an installed power of 28.47 MW and 5.9 MVAR. The initial operating condition considers the opening of lines 17, 18 and 19. The power losses indicator and the reliability indicators (*F*, *T*, ENS and *D*) are 0.511 MW, 5.740 f/yr, 3.828 h/yr, 112.43 MWh/yr and 0.667 h/f, respectively.

The Baran system has an installed power of 3.715 MW and 2.3 MVAR. The initial operating condition considers the opening of lines 33, 34, 35, 36 and 37. The power losses indicator and the reliability indicators (*F*, *T*, ENS and *D*) are 0.2028 MW, 3.177 f/yr, 1.819 h/yr, 6.695 MWh/yr and 0.5728 h/f, respectively.

On the other hand, a section of a real distribution network of a city, shown in Fig. 6, of 15 kV with 174 nodes, 163 lines, 8 sub-feeders and 75 sectionalisers is used to validate the proposed algorithm. The installed power of the system is 26 MVA. The topology adopted before for the reconfiguration process (open lines 163-164-165-166-167-168-169-170-171-172-173-174) has the power loss and ENS index of 0.183 MW and 140.6 MWh/yr, respectively.

The algorithm was implemented in MATLAB and the simulations were carried out in a PC with a Pentium IV processor, running at 1.7 GHz, and with 1 GB of RAM. The number of cycles (nominal convergence) as well as the other parameters for the μGA are specified according to the system's size. With the goal of assessing the global effectiveness and to validate the solutions that were found by the proposed algorithm in the search of the efficient solutions belonging to the Pareto front, an exhaustive evaluation (EE) process was carried out. This process was feasible only for the Civanlar and Baran systems.

On the other hand, with the purpose of illustrating the effectiveness of the optimisation technique adopted, another evolutionary multiobjective optimisation technique, called Pareto envelope-based selection algorithm 2 (PESA 2) [23], was implemented using the same type of encoding and genetic operators adopted by our proposed approach.

5.1 Civanlar system

The obtained numerical results of the multiobjective cases for the Civanlar system, using the proposed model, are shown in Table 3. The results show that 2, 5, 6 and 12 radial topologies

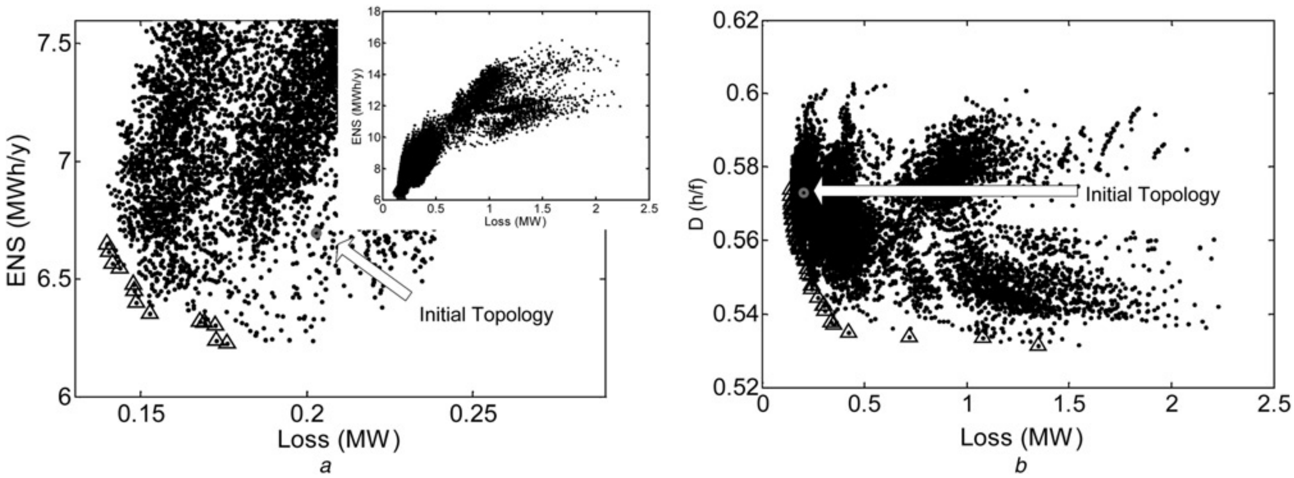

Figure 8 *Baran's system*

a Results for Case 3
b Results for Case 4

Table 6 Results of real system for Case 3

	Topologies	PL, MW	ENS, MWh/yr
1	6-70-78-99-163-164-166-168-171-172-173-174	0.1685	140.012
2	7-70-78-99-163-164-168-171-172-173-174-166	0.1685	138.420
3	7-70-78-100-163-164-166-168-171-172-173-174	0.1687	137.926
4	7-70-78-101-163-164-166-168-171-172-173-174	0.1691	137.377
5	7-78-101-163-164-166-167-168-171-172-173-174	0.1704	136.970
6	70-78-101-163-164-166-168-169-171-172-173-174	0.1795	132.706
7	78-101-163-164-166-167-168-169-171-172-173-174	0.1808	132.299
8	7-70-78-101-136-163-164-166-168-172-173-174	0.1908	128.795
9	7-78-101-136-163-164-166-167-168-172-173-174	0.1921	128.388
10	70-78-101-166-139-163-164-168-169-171-173-174	0.2665	115.698
11	78-101-139-163-164-166-167-168-169-171-173-174	0.2678	115.291
12	70-78-101-136-163-164-166-168-169-172-173-174	0.2687	113.349
13	78-101-136-163-164-166-167-168-169-172-173-174	0.2700	112.942

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belonging to the Pareto front exist in each case. Although these fronts are not composed of the same number of solutions, several efficient solutions are repeated in each of the different cases analysed (e.g. the radial topology obtained of opening lines 10, 11 and 16 appears in all cases except for Case 1). This means that its selection would be a good choice in the loss minimisation from the PL, T, ENS and D point of view. These results were validated through the EE. In Fig. 7, the results of the Cases 3 and 4 are shown. In that figure, a 'triangle' denotes a μGA solution whereas a 'point' denotes an EE solution. In these figures, the position associated to the system's initial configuration is also indicated.

If we focus on the analysis of the results for the third case, it can be observed in Fig. 7*a* that the initial topology (lines 17-18-19 are open) is far away from the Pareto frontier; this means that a considerable number of topologies have better indices of losses and ENS than this first one and, thus, they are better topologies. It is obvious that, from all this set of options, the best is to choose one from the Pareto frontier (Table 3). If we consider, for example, that the Pareto frontier selection criterion is to choose a solution located in the middle of the set, such as topology 10-17-19, a reduction of 5.2% in losses and a reduction of 4.8% in ENS are obtained, compared to the original configuration. This configuration can be achieved only by closing line 18 and opening line 10.

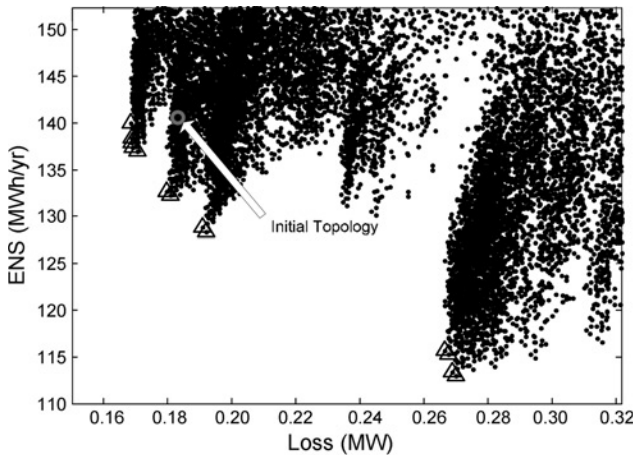

Figure 9 *Real system*
Results for Case 3

On the other hand, in the analysis of Case 4, it can be noticed in Fig. 7*b* that, from the point of view of the compromise between losses and the system average duration interruption index, the 17-18-19 topology privileges low losses over a better reliability index. If the topology 7-14-17 is chosen instead, the losses will be increased in 5.6%, but the average failure duration index will decrease in 10.8%. It is evident that this selection depends on the decision maker. Under other particular criterion, topology 11-14-19 can be selected, and thus losses would be increased only in 0.2%

Table 7 Comparative table for Civanlar and Baran systems for Case 3

Systems	Model	Performance	Total evaluations	Iterations	Time, s
Civanlar	proposed model using μGA	average	48	38	2.34
		best	42	18	1.78
		worst	56	62	3.07
		std. dev.	4.5	15.7	0.41
	proposed model using PESA 2	average	77	60	4.04
		best	70	19	1.75
		worst	83	80	5.21
		std. dev.	4.5	18.8	1.04
Baran	proposed model using μGA	average	474	555	134
		best	385	309	105
		worst	639	818	158
		std. dev.	80	173	17
	proposed model using PESA 2	average	651	231	185
		best	573	108	120
		worst	736	528	340
		std. dev.	58	117	63

but the reliability index would improve in 8.8%. This can be done by closing lines 17 and 18, and opening lines 11 and 14.

5.2 Baran system

For the Baran system, the numerical results using the proposed model for the multiobjective cases are shown in Tables 4 and 5. In the simulations corresponding to each case, the Pareto front is formed by 14, 10, 13 and 45 radial topologies, respectively. In the Baran system's results, the Pareto frontiers for each case are composed of efficient topologies that are repeated. Therefore they are more representative of the proposed objectives. In all these results, the proposed method found all the possible topologies. This was validated upon applying the EE. In Fig. 8, the results of Cases 3 and 4 are shown. Once again, a triangle denotes a μGA solution whereas a point denotes an EE solution. The position associated to the system's initial configuration is indicated in these figures too.

As in the Civanlar system analysis, if we focus on the results of the third case, it can be observed in Fig. 8*a* that the initial topology (lines 33-34-35-36-37 are open) is far away from the Pareto frontier; thus again, a significant number of topologies have better indices of losses and ENS than the first one and, therefore, they constitute better topologies. As before, from all these available options, the best is to select one from the Pareto front (Table 4). Considering the same Pareto frontier selection criterion as mentioned before, taking topology 7-11-14-17-34, a reduction of 26.8% in losses and a reduction of 4.4% in ENS are obtained, compared to the original configuration. This can be achieved by closing lines 33, 34, 35 and 36, and opening lines 7, 11, 14 and 17.

On the other hand, in the analysis of Case 4, it can be noticed in Fig. 8*b* that, from the point of view of the compromise between losses and system's average duration interruption index, the original topology privileges low losses over a better reliability index (even if losses are not minimal, this point is located in the left part of the feasible solutions set). If the same previous criterion is used and topology 7-27-31-34-35 is chosen, both power losses and reliability index (*D*) drop in 10.5 and 2.5%, respectively. In this case, lines 33, 36 and 37 must be closed and lines 7, 27 and 31 must be opened.

Table 8 Civanlar system data

Line no.	*n*1	*n*2	*R*, p.u.	*X*, p.u.	Imax, p.u.	EPM	λ, f/yr	Repair time, h	Manoeuvre time, h	End bus load	
										MW	MVAr
1	1	2	0	0.0001	0.20	1	0	1	0.5	0.0	0.0
2	1	3	0	0.0001	0.20	1	0	1	0.5	0.0	0.0
3	1	4	0	0.0001	0.20	1	0	1	0.5	0.0	0.0
4	2	5	0.075	0.10	0.20	22	3.50	1	0.5	2.0	1.6
5	5	6	0.080	0.11	0.10	333	3.00	1	0.5	3.0	0.4
6	5	7	0.090	0.18	0.10	3	1.50	1	0.5	2.0	−0.4
7	7	8	0.040	0.04	0.10	3	3.50	1	0.5	1.5	1.2
8	3	9	0.110	0.11	0.20	222	1.10	1	0.5	4.0	2.7
9	9	10	0.080	0.11	0.12	2	2.80	1	0.5	5.0	1.8
10	9	11	0.110	0.11	0.10	2	1.10	1	0.5	1.0	0.9
11	10	12	0.110	0.11	0.10	222	0.80	1	0.5	0.6	−0.5
12	10	13	0.080	0.11	0.10	1	2.00	1	0.5	4.5	−1.7
13	4	14	0.110	0.11	0.10	0	0.50	1	0.5	1.0	0.9
14	14	15	0.090	0.12	0.10	3	1.00	1	0.5	1.0	−1.1
15	14	16	0.080	0.11	0.10	3	1.50	1	0.5	1.0	0.9
16	16	17	0.040	0.04	0.10	2	4.40	1	0.5	2.1	−0.8
17	6	12	0.040	0.04	0.10	222	4.00	1	0.5	0.0	0.0
18	11	15	0.040	0.04	0.10	222	5.00	1	0.5	0.0	0.0
19	8	17	0.090	0.12	0.10	222	1	1	0.5	0.0	0.0

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Table 9 Baran system data

Line no.	n1	n2	R, p.u.	X, p.u.	Imax, p.u.	EPM	λ, f/yr	Repair time, h	Manoeuvre time, h	End bus load	
										kW	kVAr
1	1	2	0.0058	0.0029	0.5	1	0.05	1	0.5	100	60
2	2	3	0.0308	0.0157	0.4	3	0.30	1	0.5	90	40
3	3	4	0.0228	0.0116	0.2	2	0.22	1	0.5	120	80
4	4	5	0.0238	0.0121	0.2	0	0.23	1	0.5	60	30
5	5	6	0.0511	0.0441	0.2	0	0.51	1	0.5	60	20
6	6	7	0.0117	0.0386	0.2	3	0.11	1	0.5	200	100
7	7	8	0.0444	0.0147	0.2	2	0.44	1	0.5	200	100
8	8	9	0.0643	0.0462	0.2	2	0.64	1	0.5	60	20
9	9	10	0.0651	0.0462	0.2	333	0.65	1	0.5	60	20
10	10	11	0.0123	0.0041	0.2	2	0.12	1	0.5	45	30
11	11	12	0.0234	0.0077	0.2	2	0.23	1	0.5	60	35
12	12	13	0.0916	0.0721	0.2	2	0.91	1	0.5	60	35
13	13	14	0.0338	0.0445	0.2	222	0.33	1	0.5	120	80
14	14	15	0.0369	0.0328	0.2	2	0.36	1	0.5	60	10
15	15	16	0.0466	0.0340	0.2	333	0.46	1	0.5	60	20
16	16	17	0.0804	0.1074	0.2	2	0.80	1	0.5	60	20
17	17	18	0.0457	0.0358	0.2	2	0.45	1	0.5	90	40
18	2	19	0.0102	0.0098	0.2	3	0.10	1	0.5	90	40
19	19	20	0.0939	0.0846	0.2	2	0.93	1	0.5	90	40
20	20	21	0.0255	0.0298	0.2	2	0.25	1	0.5	90	40
21	21	22	0.0442	0.0585	0.2	2	0.44	1	0.5	90	40
22	3	23	0.0282	0.0192	0.3	333	0.28	1	0.5	90	50
23	23	24	0.0560	0.0442	0.3	2	0.56	1	0.5	420	200
24	24	25	0.0559	0.0437	0.3	0	0.55	1	0.5	420	200
25	6	26	0.0127	0.0065	0.2	3	0.12	1	0.5	60	25
26	26	27	0.0177	0.0090	0.2	0	0.17	1	0.5	60	25
27	27	28	0.0661	0.0583	0.2	2	0.66	1	0.5	60	20
28	28	29	0.0502	0.0437	0.2	333	0.50	1	0.5	120	70
29	29	30	0.0317	0.0161	0.2	333	0.31	1	0.5	200	600
30	30	31	0.0608	0.0601	0.2	2	0.60	1	0.5	150	70
31	31	32	0.0194	0.0226	0.2	2	0.19	1	0.5	210	100
32	32	33	0.0213	0.0331	0.2	2	0.21	1	0.5	60	40
33	8	21	0.1248	0.1248	0.2	333	1.24	1	0.5		
34	9	15	0.1248	0.1248	0.2	333	1.24	1	0.5		
35	12	22	0.1248	0.1248	0.2	33	1.24	1	0.5		
36	18	33	0.0312	0.0312	0.2	333	0.31	1	0.5		
37	25	29	0.0312	0.0312	0.2	2	0.31	1	0.5		

5.3 Real system

Finally, the numerical results of the proposed multiobjective process for a real system in Case 3 are shown in Table 6. The parameters used to simulate this system are 500 individuals and 2000 cycles. In this case, it is very difficult to perform the EE to compare the results given by the proposed model. For this reason, this procedure was not used (more than 17 billion evaluations would be needed with an estimated CPU time of 1000 years). Therefore Fig. 9 only shows the solutions of the proposed method corresponding to the third case. Moreover, the position associated to the system's initial configuration is indicated with some of the evaluation performed by the optimisation algorithm in order to have an idea of the space explored by the algorithm.

As in the Baran and Civanlar systems, if we consider as an example that the Pareto front selection criterion is to choose one that is located in the middle of the set, topology 78-101-163-164-166-167-168-169-171-172-173-174 can be chosen (number 7 in Table 6). This topology has a losses reduction of 1.2% and an ENS reduction of 5.9% compared to the original values. This can be done by closing lines 165 and 170, and by opening lines 78 and 101, which are adjacent to the lines that were closed.

The time taken for the simulation was approximately 2.5 h to evaluate 3920 candidates. This system was evaluated increasing the number of generations (to 10 000) without finding new efficient solutions.

5.4 Analysis of results

In this paper, a multiobjective μGA reconfiguration problem, considering the power losses and reliability indices, was proposed and analysed. Our experiments show that a reduced trade-off region exists between the power losses and the F, T and ENS indices. From a practical point of view, this result is very important because it makes simpler for the operation or planning engineers to choose a radial network operation topology. However, these Pareto regions are not always formed by the same topologies. This implies the necessity of using this kind of tool with the specific priorities established by each distribution company regarding the reliability indices.

On the other hand, when the power losses and the D index are considered, the trade-off region can be conformed by a considerably high number of solutions. Therefore in this case, it could be necessary to use a special criterion in order to filter out solutions from the Pareto frontier, which are representative of the decision-maker's interests. From a practical point of view, the index D is not a good index to be used as an objective function because, among other things, its minimisation implies not only the minimisation of T but also the maximisation of F.

5.5 Computational efforts

As shown by the exhaustive search procedure, all solutions belonging to the Pareto frontier were found by the proposed algorithm; this shows the effectiveness of the implemented technique. In Table 7, we provide information regarding the number of evaluations, the number of iterations and the simulation times for the ten runs performed. The goal was finding the 6 and 13 efficient solutions of the Civanlar and Baran systems, respectively, using the proposed μGA and PESA-2 for comparative purposes.

In the first place, the proposed model for the Civanlar system only required evaluating 48 candidates on average; this is a 36% from a total set of 134 topologies. In the case of the Baran system, from a universe of 18 000 topologies, an average of only 474 evaluations were required, which represents a 2.6% of the total (Table 7).

When comparing the two heuristic optimisation techniques, it can be noticed that, for both the Civanlar and the Baran systems, the μGA required a lower number of evaluations; this means a 60% reduction for the Civanlar system and a 37% for the Baran system. A similar relation is obtained when comparing simulation times, where the μGA requires only 2.34 s for the simulation of the Civanlar system, that is, a 72% reduction in time compared to PESA 2 and a 38% reduction when simulating the Baran system.

Only for the Baran system, PESA 2 found the results with a lower number of iterations: 231 against 555 for the μGA. However, the most significant factors, from our point of view, are the number of evaluations and the simulation times.

On the other hand, although the μGA, as well as any other heuristic optimisation technique, does not ensure to find the entire Pareto frontier, in this problem, the reduced number of efficient solutions belonging to the Pareto frontier allows us to claim that it is very likely to obtain, with a relatively low computational effort, all (or many of the) efficient solutions belonging to the Pareto front. However, when using any heuristic search technique, the quality of the solutions obtained depends on the number of iterations (i.e. CPU time) performed. This explains why an adequate exploration technique enhances the solutions produced while reducing the corresponding simulation times.

6 Conclusions

In this paper, a proposed multiobjective reconfiguration, considering power losses and reliability indices for medium voltage distribution systems, was studied. Consequently, this paper extends and illustrates a procedure for optimal distribution reconfiguration calculating the configuration-Pareto frontier of several objectives.

The μGA technique, adapted to the reconfiguration problem, searches for Pareto optimal solutions using a very

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small population size and a set of special operators that allow performing a very efficient search. The multiobjective problem was formulated taking into account two objectives to be minimised: the total power losses and a reliability index. The feeder thermal limits, maximum capacity of substations and voltage limits were considered as optimisation constraints.

The results of this model show trade-off regions containing a reduced number of efficient solutions considering F, T and ENS. This significantly facilitates the decision-making process of engineers, when they need to choose a single radial topology for the distribution system. Furthermore, the number of solutions belonging to the Pareto front is increased when the system's average interruption repair duration index (D) is considered.

This procedure and the resulting indices permit to quantitatively assess the selection of configurations under two important distribution engineers' criteria of power quality, when specific demand and topological possibilities are known. This ability can be quite useful to system planners involved in assessing the need to reconfigure networks in order to improve the losses and reliability conditions of the overall system.

The results of the investigations show that the μGAs and the multiobjective system reconfigurations enhance the classical overall-mono-homogenised objective system reconfiguration responses.

The degree of enhancement achieved by the network's reconfiguration solutions depends on the degree of commitment of each system objective.

The basic concepts presented in this paper can be extended to include other operational objectives that intervene in the system as well as other power quality and reliability indices that are used in practice.

Finally, the technique's effectiveness was verified by comparing results to an exhaustive search and another multiobjective optimisation technique called Pareto envelope-based selection algorithm 2. This comparison showed a better effectiveness of our proposed approach in the search of efficient solutions for the optimisation problem of our interest.

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