Multi-objective Evolutionary Algorithms for Decision-Making in Reconfiguration Problems Applied to the Electric Distribution Networks

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Abstract: In this work the performance of three multiobjective optimization techniques based on evolutionary programming, applied to distribution network reconfiguration problems, are evaluated. The proposed model takes into account the power losses and the reliability index as minimization objectives. Due to their proven ability to find the commitment solution sets in multi-objective problems and due to the adaptability of techniques based on the Genetic Algorithms applied to reconfiguration processes the following algorithms were chosen: Microgenetic Algorithms, Non-Dominated Sorting Genetic Algorithm 2 and Strength Pareto Evolutionary Algorithm 2. The results of this research show the effectiveness of the SPEA 2 to solve this problem.

Keywords: Evolutionary algorithms, Multiobjective, Reconfiguration.

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1. Introduction

The reconfiguration of a distribution network is a process that alters feeder topological structure, changing the open/close status of sectionalizers and interrupters in the system. The objective of this process is to find the radial structure of the system which minimizes some previously defined objective.

The first publication on the reconfiguration problem was presented by Merlin and Back [1]. In this paper a heuristic topology search was proposed for power loss minimization based on a meshed network.

In order to finding better results for loss minimization, a series of research studies have been carried out based on this first publication. These are summarized in the study by Sarfi, Salama and Chikhani [2]. Several techniques have been used to solve these mono-objective optimization problems, for example, dynamic programming [3], Colored Petri nets [4], Annealing Simulation [5], Ant Colonies [5] and genetic algorithms [6]. Moreover, a group of publications which focus on other important objectives for distribution network planning & operation, such as the cost functions [7], non-supplied energy [8] or [9], were Brown minimizes fault frequency and duration indices.

Additionally, there exist approaches which take where the reconfiguration problem is recognized as a multi-objective problem, using several indices. However, this group of works transforms this multi-objective problem into one optimization mono-objective problem using weighting factors or fuzzy logic [10]. Thus, they do not really consider the real multi-objective dilemma.

In this research area, as in other engineering applications, there exists today a tendency to optimize problems from a broader perspective using a multi-objective approaches [12]. Hence, in recent years there has been growing development of new optimization techniques based on artificial intelligence [13] and more specifically on evolutionary algorithms [14].

The studies presented in [16] and [17] approach the network configuration problem from a planning perspective, in order to find an efficient solution set over various objectives. In [16], two first generation techniques, called NSGA and SPEA, are compared. They take into account network construction costs and the cost of non-supplied energy. Paper [17] uses NSGA 2 to minimize network construction costs and costs associated to possible faults.

Following the above, the goal of this paper is the study of the performance of three important evolutionary techniques for multi-objective optimization reconfiguration. The techniques are Microgenetic Algorithms (uGA), Non-Dominated Sorting Genetic Algorithm 2 (NSGA 2) and Strength Pareto Evolutionary Algorithm 2 (SPEA 2). They were chosen due to 1) their proven ability for finding commitment solution sets to multi-objective problems and 2) the adaptability of genetic algorithms to solving problems with complex, non-differentiable, discrete and mainly combinatorial objective functions; as those involved in reconfiguration problems.

2. The Optimization Problem: Multi-Objective Reconfiguration

As mentioned in the introduction, reconfiguration is a process for which distribution network topology is used to optimize network operation. Figure 1 show, for a small example network, its four operational possible radial topologies. Using the data in Table 1 and considering reparation and maneuver times equal to 1 and 0.5 hours, respectively, it is possible to calculate the losses and a reliability indicator such as energy non-supplied (ENS), for each radial topology. The results shown in Table 2 were obtained by applying equations (1) and (2) to the example system. The dependency between the radial topologies of the system and the chosen indicators are shown. It is also possible to observe a commitment between the solutions associated with the power losses and non-supplied energy objectives. These results may also be seen in large real systems. Therefore, due to the significance of the indicators (preferred for the distribution companies), the comparison and development of techniques which solve this problem becomes a necessity.

Furthermore, under a practical viewpoint, in this problem it is essential to consider an appropriate operation of the system with regard to other electric and topological variables. This study has considered operational constrains such as the feeder thermal limits (3). Equation (4) considers voltage constrains in each node. Equation (5) describes the radial constraints of the primary distribution system.

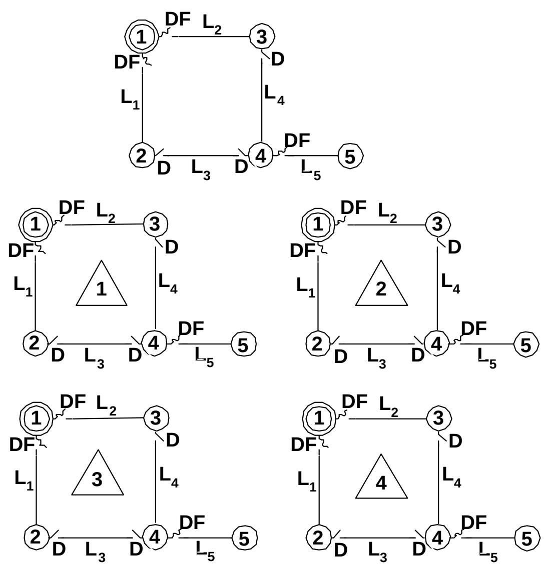

Figure. 1. Example system

$$PL = \sum_{b=1}^{Nb} R_b \cdot i_b^2 \quad (1)$$

$$ENS = \sum_{i=1}^{Nc} kW_i \cdot U_i \quad (2)$$

$$i_b \le i_{m\acute{a}x_b} \quad (3)$$

$$V_{\min} \le V \le V_{\max} \quad (4)$$

$$N_{branch} = N_{nodes} - 1 \quad (5)$$

to all of its components and strictly less with respect to at least in one of them. Note that if a solution x does not dominate another solution y, and y does not dominate x, then both are non-dominated with respect to each other (in other words, they are incomparable). In the special case of non-dominated solutions which are found on the lower limits (for minimization) of the region of possible solutions, these are known as the global Pareto front.

Nowadays, the inherent advantages of

Table 1. Example system data

Line	Node	R+j X (p.u)	λ (f/yr)	MW- MVAr
L1	1 – 2	0.03+j 0.03	0.2	3.4 – 1.4
L2	1 – 3	0.02+j 0.02	0.3	10.0 – 4.0
L3	2 – 4	0.02+j 0.02	0.2	6.7 – 2.7
L5	4 – 5	0.01+j 0.01	0.1	10.0 – 4.0
L4	3 – 4	0.01+j 0.01	0.2	

Table 2. Example system results

	PL (p.u)	ENS (MWh/yr)
1	0.0028	14.71
2	0.0053	12.04
3	0.0022	11.53
4	0.0025	8.36

“Evolutionary Multiobjective Optimization” are being used in order to find the Pareto optimal set for this kind of problem. As opposed to conventional techniques, an evolutionary algorithm is able to find more than one element of the Pareto optimal set in a single run. 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.

3. Multi-Objective Optimization Evolutionary Algorithms

The purpose of multi-objective optimization algorithms is to find efficient solution sets under the concept of Pareto dominance. This definition establishes when one solution, from the universe of possible solutions, is better than another. Pareto dominance defined for two decision vectors, assuming minimization, x, y ∈ F (where F is the region of possible solutions), indicates the following:

A vector $x = (x_1, x_2, \ldots, x_k)$ is said to dominate (in the Pareto sense) vector $y = (y_1, y_2, \ldots, y_k)$ (denoted $x \prec y$) if and only if:

$$\forall i \in (1,\ldots,k), x_i \le y_i \wedge \exists i \in (1,\ldots,k) : x_i < y_i \quad (6)$$

In other words, a vector dominates another one (in a Pareto sense) when it is less than or equal (assuming minimization) with respect

Thus, in the literature there exists a considerable number of evolutionary techniques for multi-objective optimization, which may be grouped, according to Coello 18, in two categories 1) Techniques not based on Pareto optimality: linear and nonlinear aggregating methods, Vector Evaluated Genetic Algorithm (VEGA), Lexicographic ordering, hybrids with the ε-constraint method, etc., and 2) Techniques based on

Pareto optimality: Multiobjective Genetic Algorithm (MOGA), NSGA, NPGA, uGA, Pareto Archived Evolution Strategy (PAES), NSGA-II, and SPEA2, among others.

In this study we are interested in evaluating the performance of methods based on Pareto optimal and especially the second generation methods.

A general description of the three chosen methods is given below, followed be their comparison.

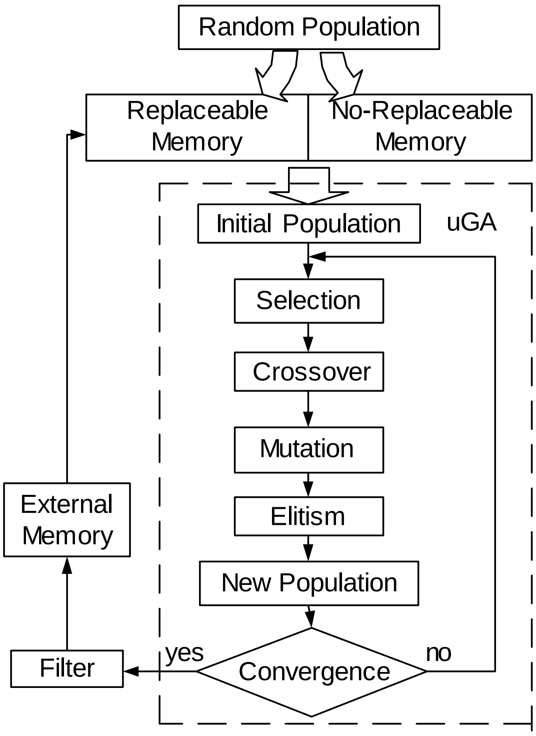

Figure 2. Block diagram of uGA

3.1 Microgenetic algorithms (uGA)

This technique bases its search mechanism, faced to other evolutionary techniques, on the non-dominance checking reduction of candidates. It also considers geographic positioning in order to maintain diversity in the Pareto front, and finally, it exhibits a strong elitist sense in order to obtain a Pareto front with higher quality solutions at a lower computational cost.

The main objective of this technique is to use population memory, which is made up of replaceable memory (RM) and non-replaceable memory (NRM) (see Figure 2). All those solution vectors which are found by the uGA cycle are saved in the RM. The NRM remains fixed, with the aim of preserving the search diversity throughout the process.

Then, through selection in tournaments, using dominance as the comparison method, a reduced set of individuals is chosen from the RM and the NRM to be used in the uGA. The operators of the uGA follow the same methodology as traditional Genetic Algorithms, thus the elitism is developed considering a non-dominated vector in arbitrary form to be copied intact in the second generation.

Once this process is finished, a filter is used to separate non-dominated individuals to a history file and to compare the candidates with those from the RM in terms of dominance. Thus, cycle after cycle fitness improves, converging on the global Pareto front.

To this is added a process called adaptive meshing, whose aim is to evaluate and if necessary, add candidates obtained from the uGA to an external solution file. Using a determined schema it is possible to compare dominance of the possible candidate, using only the coordinates closest to the schema, thus reducing dominance checking. More detail of this technique is found in [19].

3.2 Non-dominated sorting genetic algorithm 2

This algorithm, proposed in [20], is an improved version of its predecessor NSGA, from which it inherited its principal structure. It attaches different characteristics for solving three aspects of the original algorithm which have been frequently criticized by the research community: non-dominated ordering, absence of elitism and the necessity to specify additional parameters for conserving front diversity. In order to solve these problems the NSGA 2 algorithm classifies the population by front. The individuals from the first front are the non-dominated, the second front is comprised of the non-dominated in the absence of the first front, and thus successively. Each individual is assigned an indicator which depends on its front; the lowest index corresponds to the first front. In order to avoid the necessity of parameters for dispersion, the front incorporates a calculation of crowding distance. For this calculation, the mean distance of two points are taken around the solution along all the objectives, this allows the estimation of the size of the biggest cuboid which contain no other point.

The selection is made through a binary tournament, using a comparison operator which allows selection of the individuals with the lowest range of dominance, and in the case of a draw the individual with highest crowding distance. Figure 3 shows a block diagram of the NSGA 2.

the fitness of individuals is assigned. It considers an index called "raw fitness" for each individual in the population as well as those of the external file; this index represents the number of individuals which are dominated by and the number which dominate that particular individual.

Here it is possible to find two individuals with the same raw fitness value; in this case the SPEA 2 uses a technique of density estimation which examines the distance from each individual to its k^{th} closest neighbor, obtaining a second indicator which is inversely proportional to the calculated distance, and

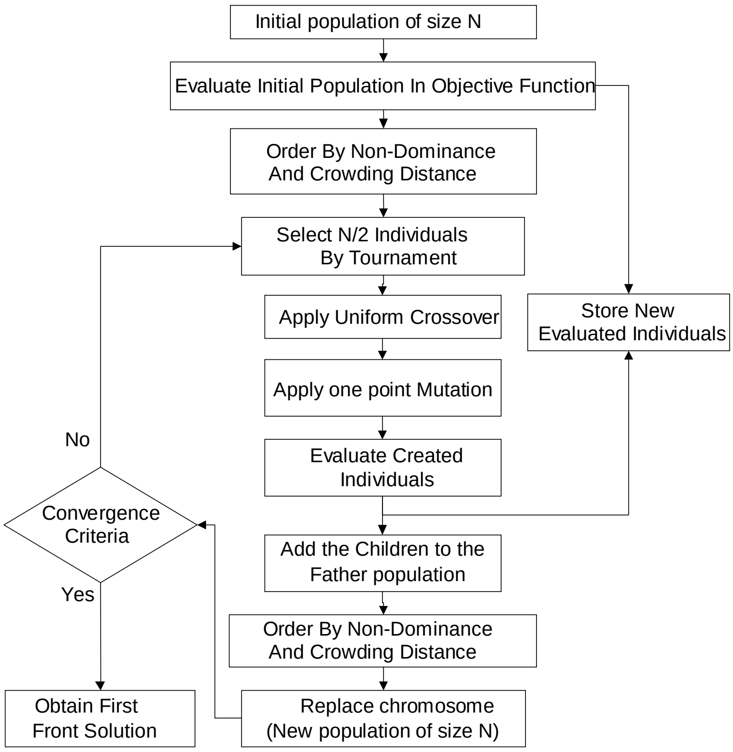

Figure 3. Block diagram of NSGA 2

3.3 Strength pareto evolutionary algorithm 2

This method of multi-objective optimization comes from its predecessor the SPEA with the aim of improving performance. As with the SPEA it has a fixed size population and an external file for storing non-dominated solutions obtained in each generation; solutions which come from both the population and the file of the preceding generation. It is distinct from other evolutionary techniques mainly in the way

which is then added to the raw fitness of each individual. Under these indicators the non-dominated individuals have a zero raw fitness value. Once the fitness of each individual in the population and the external file has been determined, the non-dominated elements are copied to the external file of the next generation. If the size of the new external file is less than the preceding one, the new file is then completed by copying the first dominated individuals (from lowest to highest fitness) present in the population and in the current file. In the opposite case, if the size of the current external file is exceeded by that which follows, a truncation mechanism is called to, which proceeds to delete the elements with the least distance from another in each iteration, until the already established size is reached. Once the new external file has been established, it is passed to the tournament selection process, where a binary tournament is used to determine which individuals belong exclusively to the file, to which will then be applied crossover and mutation; the elements created will form the next generation. Figure 4 shows a block diagram of the algorithm, more detail of this technique may be found in [21].

used at constant power and for the NSE calculation a reliability algorithm was used. It is based on the concept of principal and secondary path [22].

4.1 Codification and genetic operators

The codification strategy and genetic operators used were developed in [6], achieving great adaptability to the reconfiguration problem. This methodology allows a more efficient solution search, achieving results better than other strategies [23].

The codification is based on a vector of real

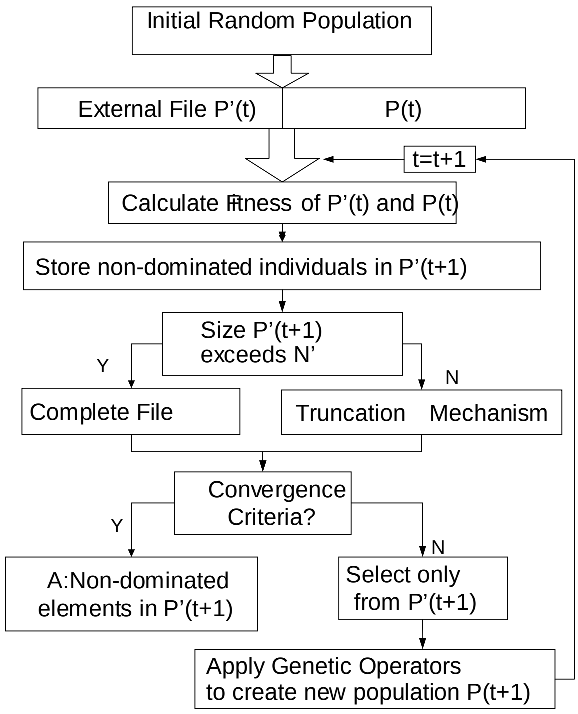

Figure 4. Block diagram of SPEA 2

4. Implementation

This section presents some details about implementation techniques and parameters used to testing the algorithms. In general there are two aspects which are common to the implementation of the optimization techniques.

The first is related to the application of a special codification strategy and of genetic operators, common to the three techniques. Secondly, the evaluations of the objective functions (the fitness of the candidates) were carried out under the same algorithms. In the case of power losses calculations and constraint verifications a fast load flow was

numbers which identify the maneuver elements which may be found on lines associated to the fundamental loops system. Using this strategy it is possible to create radial topologies simply and easily, also, using the loops information it is possible to apply the special crossover and mutation operators without losing the radial characteristic which is a requisite of the evaluated candidates. More detail on the codification and genetic operator strategies may be found in the aforementioned reference.

4.2 Implementation of uGA

In the case of the uGA, one-point crossover was used, with a crossover probability of

95%. The mutation used was established in a randomly chosen bit of the string, with a probability of 30%. A population of 5 and 3 generations were used in the internal uGA, following the recommendation of the authors [19]. The number of individuals in the population and the number of iterations used to simulate the systems depended on the size of the problem.

4.3 Implementation of the NSGA 2

In this case uniform crossover was used with an occurrence probability of 50%. Mutation was carried out at one point with probability of 1%. The number of individuals in the population and the number of iterations used to simulate the systems depended on the size of the problem.

4.4 Implementation of the SPEA 2

In this case the crossover was implemented on one random point of the string. The mutation was carried out at a random point of the chromosome, with a probability of 30%. The size of the population, the external file and the number of generations were established according to the size of the simulated system.

5. Applications and Results

Several indices may be used to measure the performance of these algorithms; however, this study has focused on three indicators, which are described below.

Error rate (ER): This measures what percentage of the "n" vectors of the obtained Pareto front (PFo) does not belong to the real Pareto front (PFr). When ER approaches zero, this means that the found Pareto front is closer to PFr.

$$ER = \frac{\sum_{i=1}^{n} e_i}{n}, \quad e_i = \begin{cases} 0 & \text{if vector i} \in \text{PF}_\text{r} \; i = (1, \ldots, n) \\ 1 & \text{otherwise} \end{cases}$$

Number of evaluations (NE): This indicator reflects the number of individuals which must be evaluated in order to find the resulting Pareto front for each technique. For this, a memory was implemented in the three algorithms for storing the values of the objective functions of the already evaluated candidates. This may also be used to avoid evaluating a candidate more than once.

Simulation Time: Although this indicator is associated with the number of evaluations performed, it is possible to prove some differences due to the differing evolutionary procedures. Hence, it is expressed as the total simulation time (TST) and as the simulation time per evaluation (STE), the latter being the ratio of TST and NE.

The networks used to compare the responses are two IEEE testing systems whose details may be found in the references Civanlar et al. [24] and Baran M., Wu F., [25], see Figures 5 and 6. In addition, a real 15 kV, 174 lines and 163 nodes distribution network was used.

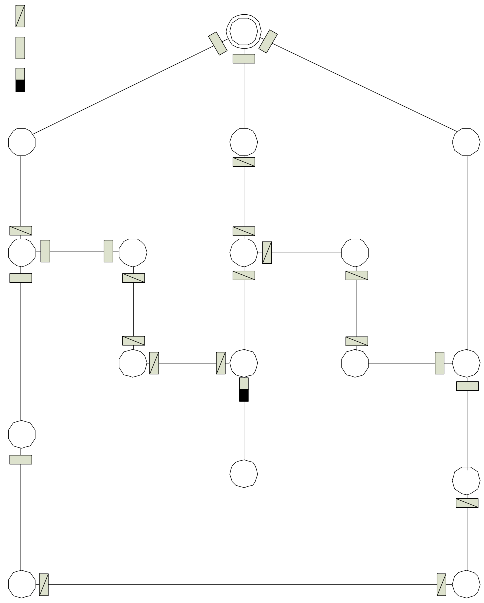

Figure 5. Civanlar test system

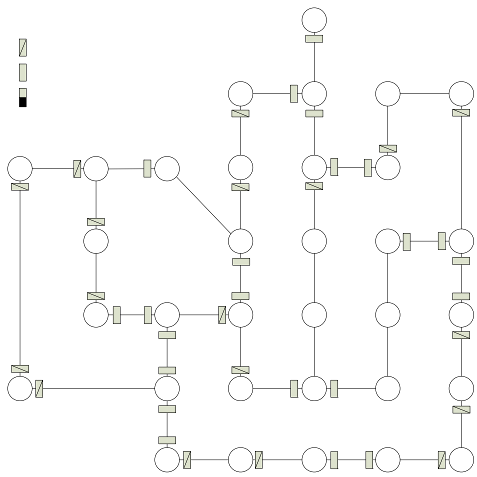

Figure 6. Baran test system

The three techniques were implemented in MATLAB using a Pentium IV, Quad Core computer with 4 Ghz RAM. The simulation parameters used for each algorithm are shown in Table 3.

Table 3. Simulation parameters

uGA	Civanlar	Baran	Real
Population uGA	5	5	5
Generations uGA	3	3	3
Individuals NRM	30	100	500
Process cycles	100	500	2500
% RM and NRM in The population	70/30	70/30	70/30
NSGA 2			
Population	10	15	50
Generations	100	160	350
Crossover Probability	90	90	95
Mutation Propability	9	9	20
SPEA 2			
Population	16	30	90
File Size	8	15	20
Generations	20	30	200

In order to evaluate the ER, it was necessary to carry out an exhaustive search (ES) of all possible solutions to find the PFr; this may only be done at a high computational cost when using the Civanlar and Baran systems, which required 134 and 16,133 evaluations respectively. For the real system a universe of 25,000 evaluations was used, which is less than the estimated universe of all possible solutions. Tables 4 and 5 show the results of the Civanlar and Baran systems,

Table 4. Results of the Civanlar System

Topologies	PL (MW)	ENS (MWh/yr)
10 – 11 – 19	0.47	109.32
7 – 10 – 11	0.48	107.42
10 – 17 – 19	0.48	106.98
10 – 11 – 16	0.49	106.50
7 – 10 – 17	0.50	105.08
10 – 16 – 17	0.51	104.16

Table 5. Results of the Baran System

Topologies	PL (MW)	ENS (MWh/yr)
7-9-14-32-37	0.1396	6.645
7-10-14-32-37	0.1402	6.616
7-11-14-32-37	0.1413	6.566
7-11-14-36-37	0.1435	6.546
7-9-14-17-37	0.1476	6.478
7-10-14-17-37	0.1479	6.449
7-11-14-17-37	0.1484	6.399
7-11-14-16-37	0.1527	6.352
11-14-32-33-37	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	6.238
11-14-16-33-37	0.1759	6.225

and figures 7, 8 and 9 show the solutions of the ES (dots) and the solutions found by the evolutionary algorithms (triangles), the latter of which coincide for all techniques.

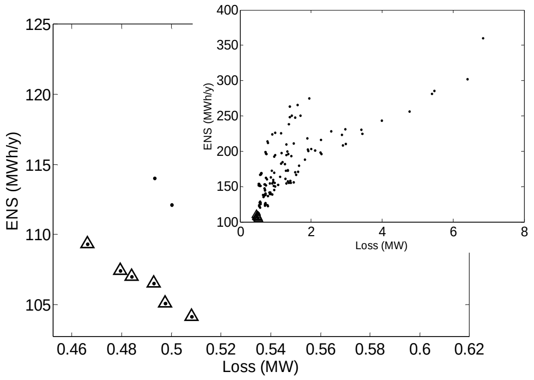

Figure 7. Results of the Civanlar system

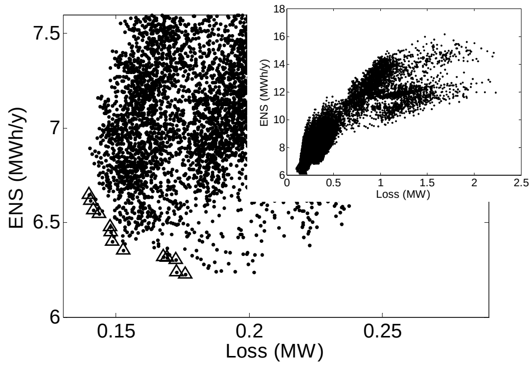

Figure 8. Results of the Baran system

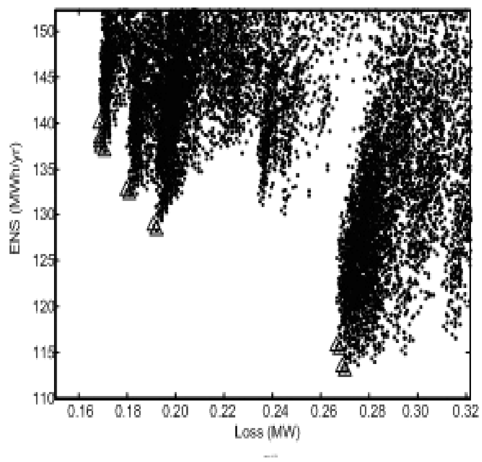

Figure 9. Result of the Real system

The results of the algorithm performance evaluating indicators are shown in table 6. These results are the average of the performance indicators over 10 runs for each system. In the case of NE, the percentage of evaluations with respect to the universe of possible solutions is also shown.

Table 6. Performance indicators

Civanlar	**uGA**	**NSGA 2**	**SPEA 2**
ER	0	0	0
NE	72 (53%)	70 (52%)	67 (50%)
TST (s)	4.6	3.4	2.1
STE (ms)	64	49	31
Baran			
ER	0	0	0
NE	653 (4%)	235 (1.4%)	231 (1.4%)
TST (s)	71	20	19
STE (ms)	108	85	82
Real			
ER	0	0	0
NE	3344	1504	1423
TST (min)	79	33	21
STE (s)	1.47	1.32	0.88

As can be seen, the algorithms in the evaluated systems have an ER of zero, which means that they are able to reach FPr (or the best front found, in the case of the real system) without losing solutions. However, significant differences are seen for the indices NE, TST and STE, where it is possible to observe that in all cases the uGA requires the evaluation of a greater number of individuals in order to achieve the same results as the other methods. In some cases this implies the necessity for two or three times the TST in the optimization process. In addition, the STE is also highest in the uGA, which implies that the optimization procedure is a little more costly than the other techniques.

As can be seen, all the algorithms achieved an ER of zero, which means that they were able to reach FPr (or the best found Pareto front, in the case of the real system) without losing solutions. On the other hand, in all cases, Civanlar, Baran and real systems, it is possible to note a marked advantage to the SPEA 2 over the NSGA 2, since it is able to converge on the Pareto front more quickly, evaluating fewer individuals and having a lower value of STE.

6. Conclusions

This study compared the performance of three important evolutionary techniques of multi-objective optimization applied to the distribution network reconfiguration problem.

The results show that the three multi-objective techniques are highly efficient in finding the Pareto front since they require the evaluation of a reduced number of candidates in order to identify all the solutions belonging to the real front. Moreover, the NSGA 2 and the SPEA 2 require only half the evaluation and simulation time of those of the uGA, in order to find the same solutions.

Additionally, the SPEA 2 has advantages over the NSGA 2 in all systems; being more efficient in the search for solutions. Consequently, it is recommended using the SPEA 2 in this application, since the reconfiguration problem is focused on systems of large size.

From the implementation viewpoint, the uGA is a very simple algorithm to program due to the philosophy of its conception, whereas the NSGA 2 and the SPEA 2 have similar levels of difficulty in terms of implementation, though slightly more complex than the uGA.

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