An Approach Based on the Strength Pareto Evolutionary Algorithm 2 for Power Distribution System Planning

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Abstract. The vast majority of the developed planning methods for power distribution systems consider only one objective function to optimize. This function represents the economical costs of the systems. However, there are other planning aspects that should be considered but they can not be expressed in terms of costs; therefore, they need to be formulated as separate objective functions. This paper presents a new multi-objective planning method for power distribution systems. The method is based on the Strength Pareto Evolutionary Algorithm 2. The edge-set encoding technique and the constrain-domination concept were applied to handle the problem constraints. The method was tested on a real large-scale system with two objective functions: economical cost and energy non-supplied. From these results, it can be said that the proposed method is suitable to resolve the multi-objective problem of large-scale power distribution system expansion planning.

1 Introduction

A power distribution system is a network that consists of substations (electrical power source nodes), lines (electrical conductors connecting nodes and carrying power) and customers (power demand nodes). System planners must ensure that there is adequate substation capacity, line capacity and acceptable level of reliability to satisfy the power demand forecasts within the planning horizon. Planning these systems involves various tasks [1]; the main of these are: 1) To find the site of substations and lines, 2) To determine substations and lines sizes (substations and lines capacities) and 3) To determine the electrical power flow in substations and lines. These tasks have to be done simultaneously optimizing various objectives such as economical costs and reliability of the systems, and considering three main technical constraints: voltage drop limit, substation and line capacity limit and radial configuration (spanning tree configuration).

The vast majority of the developed planning methods consider only one objective function to optimize [2]. The objective function of these methods represents the economical costs of the system such as, investment, energy losses and interruption costs. However, there are other planning aspects that should be considered in the planning methods but they can not be expressed in terms of costs. For instances, environmental and social impact can be very important in some cases and they can not be expressed as economical costs. Reliability of the system is another planning aspect that have been expressed in terms of costs and considered in some planning methods but, it is required information about the economical impact of power interruptions on customers and suppliers. This information might be difficult to obtain in some cases. Therefore, some planning aspects to be considered need to be formulated as separate objective functions.

There are few multi-objective methods that have been proposed to resolve the problem of power distribution systems expansion planning with more than one objective function separately formulated. In [3], a planning method is proposed to optimize three objective functions: economical cost, energy non-supplied (a reliability index) and total length of overhead lines. This method generates a set of Pareto-optimal solutions using the ε-constrained technique. This technique transforms two objectives into constraints, by specifying bounds to them (ε), and the remaining objective, which can be chosen arbitrarily, is the objective function to optimize. In other words, the multi-objective problem is transformed into a single-objective optimization problem, which is resolved by classical single-objective algorithms. The bounds ε are the parameters that have to be varied in order to find multiple solutions.

Another planning method that uses the ε-constrained technique is reported in [4]. This method resolves the single-objective problems using a simulated annealing algorithm. The disadvantage of this technique is that the solution of the resulting single-objective problem largely depends on the chosen bounds ε. Some values of ε might cause that the single-objective problem has no feasible solution. Thus, no solution would be found. In addition, several optimization runs are required to obtain a set of Pareto-optimal solutions.

In [5], it is reported a planning method that uses the weighting technique to obtain non-dominated solutions. This technique consists in assigning weights to the different objective functions and combining them into a single-objective function. The Pareto-optimal solutions are identified by changing the weights parametrically with several optimization runs. One difficulty with this technique is that it is difficult to find a uniformly distributed set of Pareto-optimal solutions. In addition, many weight values can lead to the same solution and, in case of non-convex objective space, certain solutions can not be found.

In [6], a multi-objective optimization method based on genetic algorithms is presented. This method is able to find a set of approximate Pareto-optimal solutions in one single simulation run due to its population approach. The method is formulated to find the site and size of substations and lines optimizing two objective functions: economical cost and energy non-supplied. The drawback of this method is that the genetic algorithm has to be run several times in order to obtain solutions closer to the optimal ones. Moreover, the method uses genetic operators that generate many illegal solutions and its encoding technique has low heritability, making the algorithm inefficient and ineffective.

In this paper, we propose a new multi-objective planning method for optimal power distribution system expansion planning. The method is based on the Strength Pareto Evolutionary Algorithm 2 (SPEA2) [7]. The edge-set encoding technique [9] and the constrain-domination concept [11] were used to handle the problem constraints. The method was tested on a real large-scale system and some studies were carried out to analyze the effect of constraints and non-convex regions of the search space on the performance of the proposed method.

2 Problem Formulation

In this paper, the planning problem is formulated as the problem of selecting the number, site and size of substations and lines such that the investment cost, the cost of energy losses and the energy non-supplied index are minimum; maintaining the radiality of the network and at the same time not violating the capacity and voltage drop constraints in any part of the network. Fig. 1 shows a power distribution system for planning.

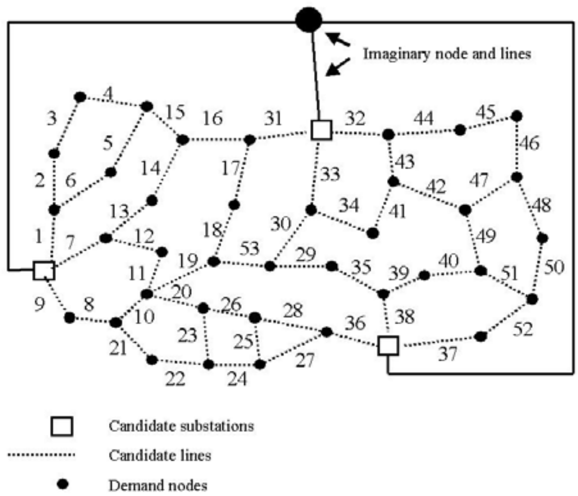


Fig. 1. A power distribution system for planning. The imaginary node and lines are used to manipulate problems with more than one substation and to represent the systems as spanning trees.

The candidate substations and lines are the possible components to be selected. The candidate components and power demand nodes are known beforehand.

The mathematical formulation of the planning problem is expressed as follows:

$$Minimize \quad F_{\cos t} = \sum_{t \in Nt} \sum_{s \in Ns} \{(FC_t)_s (X_t)_s + (Coeff)(PW)(3{I_t}^2 R_t)_s\} + \sum_{l \in Nl} \sum_{c \in Nc} \{(FC_l)_c (X_l)_c + (Coeff)(PW)(3{I_l}^2 R_l)_c\} \quad \textbf{(1)}$$

$$Minimize \quad ENS = \sum_{l=1}^{N_L} PF_l \; \lambda_l \; r_l$$

Subject to the conditions:

$V_{min} \le V_j \le V_{max}$	(Voltage drop constraint)
$I_l \le Imax_l$	(Line capacity constraint)
$T_t \le Tmax_t$	(Substation capacity constraint)
$\Sigma l = n\text{-}1$	(Radiality constraint)

Where:

F_{cost}	= Total economical cost (in Millions)
ENS	= Energy non-supplied index (in Megawatt-hour)
$(FC_t)_s$	= Investment cost of substation t to be built with size s
$(X_t)_s$	= 1 if substation t with size s is built. Otherwise, it is equal to 0.
I_t	= Current through substation t
R_t	= Resistance of the transformer in substation t
$(FC_l)_c$	= Investment cost of line l to be built with size c
$(X_l)_c$	= 1 if line l with size c is built. Otherwise, it is equal to 0.
I_l	= Current through line l
R_l	= Resistance of line l
$Coeff$	= Cost factor = (8760)(Cost of energy)(Loss factor)
PW	= Present worth factor = $[(1+d)^p-1]/[d(1+d)^p]$; p = planning years; d = discount rate
Nt	= Number of proposed substations
Ns	= Number of proposed sizes for substations
Nl	= Number of proposed lines
Nc	= Number of proposed sizes for lines
V_j	= Voltage in node j
PF_l	= Power flow on line l (in Megawatts)
λ_l	= Failure rate of line l (in failures/km*year)
r_l	= Failure duration of line l (in hours)
N_L	= Number of lines in the system
$V_{min,max}$	= Voltage drop limit (Permissible levels of voltage)
$Imax_l$	= Current capacity limit of line l
$Tmax_t$	= Power capacity limit of substation t
Σl	= Number of selected lines
n	= Number of nodes

3 A Multi-objective Planning Method for Power Distribution Systems

A multi-objective planning method is proposed to resolve the problem of power distribution system expansion planning. The method is based on Strength Pareto Evolutionary Algorithm 2 (SPEA2) [7].

3.1 SPEA2

SPEA2 uses a regular population and an archive (external set). The overall algorithm is as follows [7]:

Step 1 (Initialization): Generate an initial population P_o and create the empty archive $A_o = 0$. Set $t = 0$.
Step 2 (Fitness assignment): Calculate fitness values of individuals in P_t and A_t.
Step 3 (Environmental selection): Copy all non-dominated individuals in P_t and A_t to A_{t+1}. If size of A_{t+1} exceeds the archive size N_A then reduce A_{t+1} by means of a truncation operator; otherwise if size of A_{t+1} is less than N_A then fill A_{t+1} with dominated individuals in P_t and A_t.
Step 4 (Termination): If $t \geq G$ (where G is the maximum number of generations) or another stopping criterion is satisfied then set $\bar{A}$ (non-dominated set) to the set of the non-dominated individuals in A_{t+1}. Stop.
Step 5 (Mating selection): Perform binary tournament selection with replacement on A_{t+1} in order to fill the mating pool.
Step 6 (Variation): Apply recombination and mutation operators to the mating pool and set P_{t+1} to the resulting population. Increment generation counter ($t = t + 1$) and go to Step 2.

Fitness Assignment
The fitness assignment is a two-stage procedure. First, each individual i in the archive A_t and the population P_t is assigned a strength value $S(i)$, representing the number of solutions it dominates (the symbol $\succ$ corresponds to the Pareto dominance relation):

$$S(i) = |\{ j \mid j \in P_t + A_t \wedge i \succ j \}| \quad \textbf{(2)}$$

Second, the raw fitness of an individual i is determined by the strengths of its dominators in both archive and population:

$$R(i) = \sum_{j \in P_t + A_t,\, j \succ i} S(j) \quad \textbf{(3)}$$

Additional density information is incorporated to discriminate between individuals having identical raw fitness values. The density information technique proposed in [7] is an adaptation of the *k-th* nearest neighbor method [8]. Thus, the fitness of an individual i is defined by:

$$F(i) = R(i) + D(i) \tag{4}$$

Where $D(i)$ is the density information.

Environmental Selection

In the environmental selection, the first step is to copy all non-dominated individuals from the archive and population to the archive of the next generation A_{t+1}. In this step, there can be three scenarios: 1) The non-dominated set fits exactly into the archive ($|A_{t+1}| = N_A$), 2) The non-dominated set is smaller than the archive size ($|A_{t+1}| < N_A$) and 3) The non-dominated set exceeds the archive size ($|A_{t+1}| > N_A$).

In the first case, the environmental selection is completed. In the second case, the best N_A-$|A_{t+1}|$ dominated individuals in the previous archive and population are copied to the new archive. Finally, in the third case, an archive truncation procedure is invoked which iteratively removes individuals from A_{t+1} until $|A_{t+1}| = N_A$. The truncation procedure is as follows:

At each iteration, an individual i is chosen for removal if:

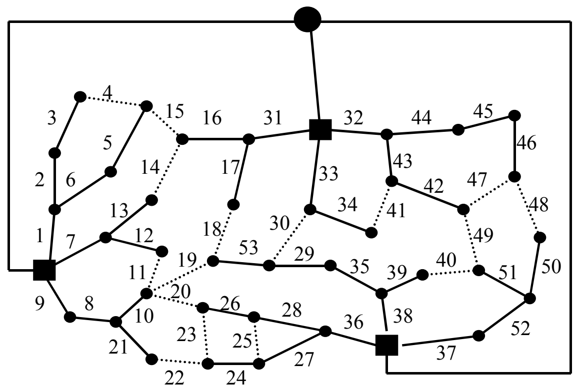
- $\sigma_i^k = \sigma_j^k$ for every value of k in the range $0 < k < |A_{t+1}|$ and $j \in A_{t+1}$ or
- $\sigma_i^q = \sigma_i^q$ and $\sigma_i^k < \sigma_i^k$ for every value of q in the range $0 < q < k$ and any value of k in the range $0 < k < |A_{t+1}|$.

3.2 The Proposed Multi-objective Planning Method

The proposed multi-objective planning method for power distribution system expansion planning is based on SPEA2. In the following sections, the main components of the method are described.

Encoding and Genetic Operators

It is proposed that the distribution system topologies be represented directly as sets of their lines (edge-set encoding technique), and special recombination and mutation operators be used. This encoding technique and genetic operators were proposed in [9] for the degree-constrained minimum spanning tree problem and they were adapted for power distribution system planning in [10]. For example, Fig. 1 shows a power distribution network with 37 demand nodes, 3 candidate substations and 53-numbered candidate lines. A potential solution for this network is encoded as the set of numbers that represent the lines that form the solution (Fig. 2). The imaginary node and lines are used to manipulate problems with more than one substation and to represent the networks as spanning trees. Therefore, each solution can be encoded with an array containing the lines of the solution.



Encoded solution =

{9,8,21,10,1,2,6,5,3,7,12,13,31,32,17,16,33,34,44,45,46,43,42,37,52,50,51,
38,39,36,27,28,24,26,35,29,53}

Fig. 2. An example of a direct encoding of a solution.

The recombination operator to create offspring consists on two steps: In the first step, a set of lines contained in both parents is selected to initialise the offspring. In the second step, lines are randomly and successively selected from the rest of the lines contained either in parent 1 or parent 2 (but not in both) to be included in the offspring (only lines that do not introduce cycles are included). Fig. 3 shows an example of a recombination operation for two parent solutions of the network in Fig 1. Figs. 3a) and 3b) are the parent solutions 1 and 2, respectively. Fig. 3c) is the offspring initialised with lines contained in both parents. In this phase, the offspring has components disconnected. In the second step, the disconnected components are connected with lines contained either in parent 1 or parent 2; as it is shown in figure 3d).

The mutation operator is described as follows (see Fig. 4): In a first step, a candidate line currently not in the offspring is randomly chosen and inserted in the offspring, e.g. in Fig. 4a) the line 30 (darker line) is inserted. A cycle will be formed with this action so, in a second step, a random choice among the lines in the cycle (triple lines) is then made (excluding the new line inserted and the imaginary lines), and the chosen one is removed from the offspring. In Fig. 4b) the line 41 is removed.

The recombination operation is controlled by a recombination probability parameter (*Prc*): the probability parameter is set to a real number in the range [0.0, 1.0] then, a real number is obtained by a random number generator. If the obtained number is smaller than *Prc*, the recombination is executed; otherwise one of the parents is randomly chosen and copied to the offspring population. Mutation operation is applied to every individual in the offspring population: exactly one line in an individual is changed. The size of the mating pool is equal to the population size and, in each iteration the old population is replaced with the offspring population.

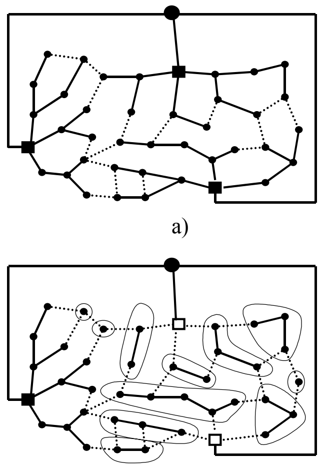

a) b) c) d)

Fig. 3. An example of a recombination operation for two parent solutions of the network in Fig. 1.

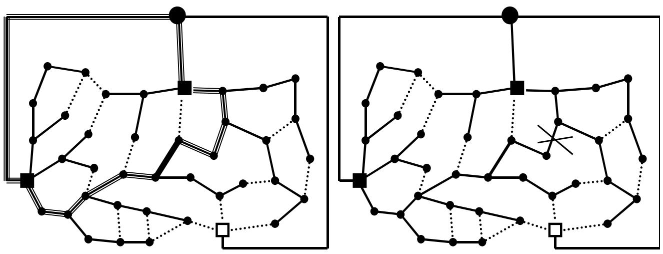

a) b)

Fig. 4. An example of a mutation operation for the offspring in Fig. 3.

Fitness Function

The fitness function is defined by the strategy formulated in SPEA2 algorithm. In this paper, the application of a different domination definition from the conventional one is suggested in order to handle the constraints of power system planning problems. This new concept of domination is called constrain-domination [11].

Selection Mechanism

The binary tournament selection is the selection mechanism used in the phase where solutions are selected for recombination (step 5 of SPEA2). This mechanism selects two solutions randomly and picks out the solution with better fitness value. Using the concept of constrain-domination in the fitness function formulation, one of the following scenarios is created each time this selection mechanism is applied:

- If both solutions are feasible, the solution closer to the Pareto-optimal front is chosen
- If both solutions are infeasible, the solution with the smaller constraint violation is chosen
- If one solution is feasible and the other is not, the feasible one is chosen
- If both solutions are feasible and close to the Pareto-optimal front, the solution with the smaller density of individuals in its neighborhood is chosen.

4 Case Studies

The proposed method was tested on a real large-scale system presented in [6] (Fig. 5).

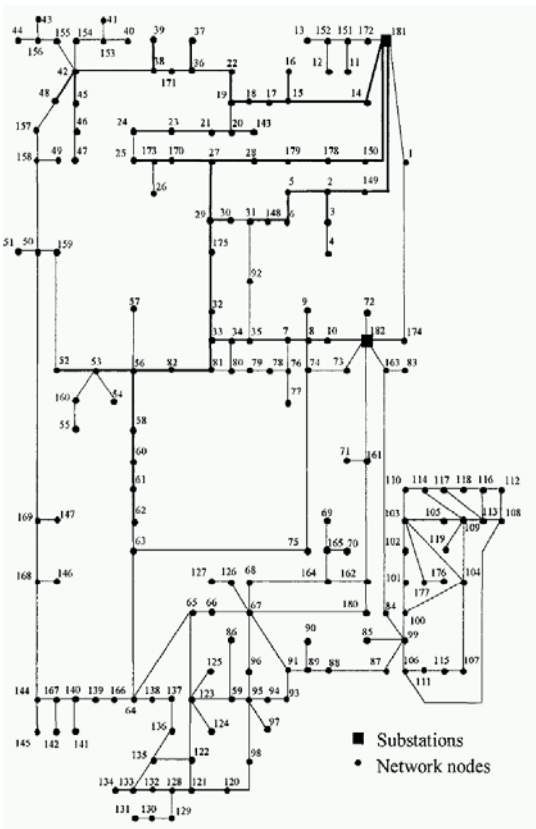


Fig. 5. Power distribution network for the case studies. The darker lines represent the existing lines and the proposed routes are represented by thin lines.

The system has 45 existing demand nodes and 44 existing lines with one power substation of 40 MVA. 163 routes were considered for new lines to connect 137 new demand nodes and one substation in node 182. This future substation was proposed with two sizes of 8 MVA and 40 MVA. For the new lines, two conductor sizes were considered. The proposed conductors and substation sizes have different investment cost. The substation size of 40 MVA costs 300 millions (unit of money), whereas the other substation size costs 136 millions. Similarly, the conductor with the bigger size costs more but, it has less failure and failure duration rate than the other conductor.

The parameter values of the algorithm used to resolve the problem were: population size of 200; external archive size of 50; recombination probability of 0.8 and the maximum number of generations was 500. The tests were done using a PC compatible 1 GHz Pentium with 128 Mb of RAM, WindowsME and a Visual C++ compiler.

In this case, the problem was to find a set of Pareto-optimal solutions (or a set of approximate Pareto-optimal solutions) considering two objective functions to optimize: the economical cost function and the energy non-supplied function.

Fig. 6 shows the set of approximate Pareto-optimal solutions found by the proposed method.

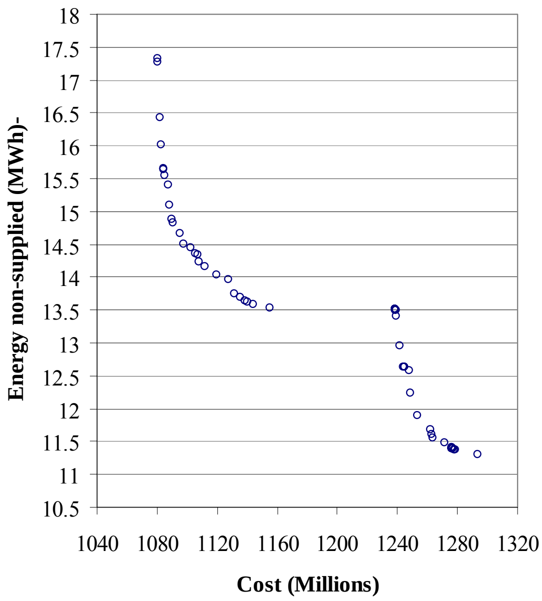


Fig. 6. Approximate Pareto-optimal solutions found by the proposed planning method to the problem of Fig. 5.

Because of two substation sizes are proposed with different costs for the new substation, the Pareto front is divided into two fronts. The left front contains solutions with the new substation size of 8 MVA; and the other front contains solutions with the new substation size of 40 MVA.

Solutions with the substation size of 40 MVA provide more reliability (in terms of energy non supplied) than solutions with the substation size of 8 MVA because a bigger substation size can supplied more power; therefore, the total power demand is more equally shared between the existing and new substation and it experiences less interruption rate. However, in this case, the substation size of 40 MVA is more expensive. Similarly, in each front, there are solutions with better reliability than others but they have higher costs. This is because the energy non-supplied is a function of the configuration and the types of conductors in the system. In this case, the cheaper conductor has the higher failure rate.

The solutions shown in Fig. 6 produce conflicting scenarios between the both objective functions. If both objectives are equally important, none of these solutions is the best with respect to both objectives. However, this set of solutions can help the system planner to evaluate the solutions considering other criteria. The planner can assess the advantages and disadvantages of each of these solutions based on other criteria which are still important; and compare them to make a choice.

Fig. 6 is different from the figure that depicts the solutions for the same problem reported in reference [6]. In this reference, the Pareto front is not divided into two fronts and it is not clear if the two proposed substation size have different fixed cost or not. Also, it is not mentioned which substation size was selected for each solution or what is the effect of the substation size on the set of non-dominated solutions.

In addition to the above study, more studies were carried out to analyze the effect of constraints and non-convex regions of the search space on the performance of the proposed method. These studies are reported as cases B, C, D and E. Case A corresponds to the original problem of reference [6](Fig. 6).

To analyze the effect of the constraints, the method was applied on the same problem of reference [6] with different levels of constraints. Fig. 7 shows the solutions found by the proposed method to the problem with the permissible level of voltage drop changed from the original 3.0 percent to 1.0 percent (case B). In Fig. 8, it is shown the solutions for the problem with the capacity limit of lines reduced by 50 percent (case C). Finally, Fig. 9 shows solutions to the problem with the proposed substation size of 40 MVA changed for a substation size of 9 MVA (the cost does not change) (case D).

Figs. 7 and 8 show that the proposed method was able to converge to one of the Pareto fronts previously found for the original problem. This Pareto front corresponds to the solutions with the new substation size of 40 MVA, which satisfy the new constraints. The other Pareto front of the original problem now lies on the infeasible region.

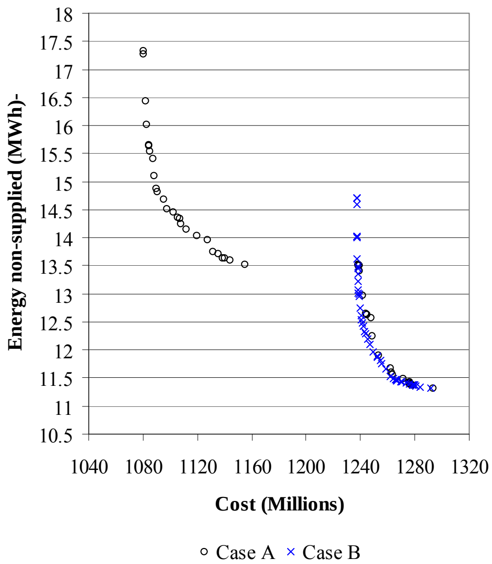


Fig. 7. Approximate Pareto-optimal solutions to the original problem (case A) and to the problem with the permissible level of voltage drop changed from 3.0 percent to 1.0 percent (case B)

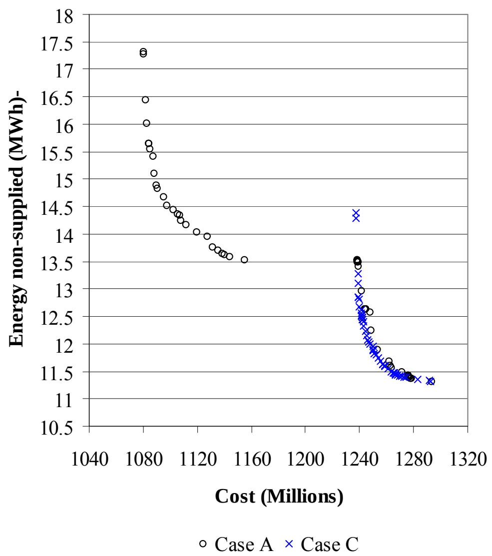


Fig. 8. Approximate Pareto-optimal solutions to the original problem (case A) and to the problem with the capacity limit of lines reduced by 50 percent (case C)

These solutions of the cases B and C were expected since, as it was mentioned early, solutions with the bigger substation size have the total power demand more shared between the existing and the new substation; therefore, the lines carry less amount of current and the voltage drop is lower.

In case D, Fig. 9 shows that the method converged to two Pareto fronts. One of these Pareto fronts is the same one found for the original problem, which corresponds to the solutions with the new substation size of 8 MVA. The other Pareto front is different from the one of the original problem since the second proposed substation size has been changed for a smaller one.

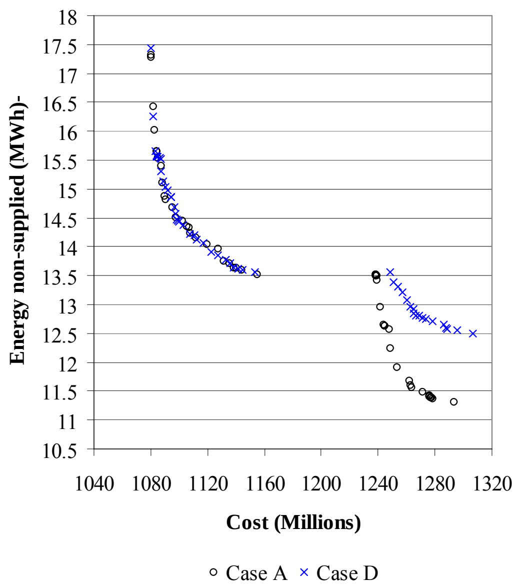


Fig. 9. Approximate Pareto-optimal solutions to the original problem (case A) and to the problem with the new proposed substation size of 40 MVA changed for a substation size of 9 MVA (case D)

Similarly, the solutions of case D were expected. Because of one of the proposed substation size was not changed, the method converged to the corresponding Pareto front. The other Pareto front is different from the one of the original problem because the substation size of 9 MVA has less capacity to supply energy; therefore, more power demand is satisfied by the existing substation and, as a consequence, the energy non-supplied index increases.

To analyze the effect of non-convex regions of the search space on the performance of the proposed method, the method was applied on the same original problem [6] with the cost of the new substation size of 40 MVA reduced from 300 millions to 200 Millions. Fig. 10 shows the solutions found by the method to this case (case E).

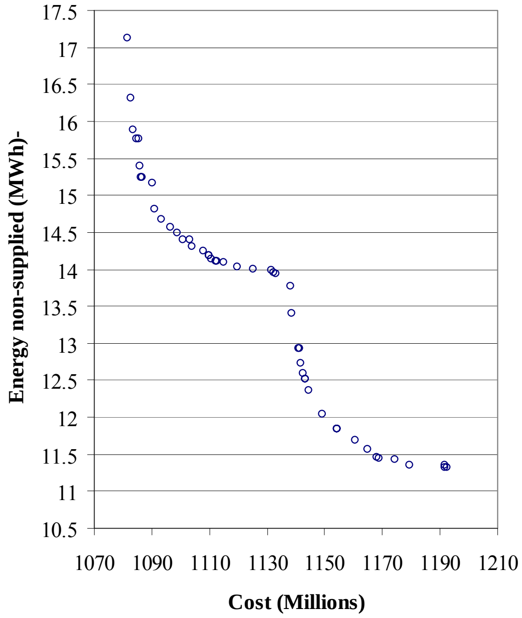


Fig. 10. Approximate Pareto-optimal solutions to the problem with the cost of the new proposed substation size of 40 MVA reduced from 300 millions to 200 millions (case E)

In this case E, there is a non-convex region in the Pareto front. The presence of several alternatives to build lines and substations with different economical and electrical characteristics can produce this type of scenarios.

5 Conclusions

Traditionally, the planning problem has been formulated to minimize the economical costs of the system being treated. However, a distribution system involves other aspects such as reliability, environmental and social impact. If solutions to a planning problem are described only in terms of economical costs, it might be difficult to qualify the solutions. If instead the solutions are described in terms of other aspects, there would be more information available to help the planner to compare and select options.

Evolutionary algorithms (EAs) are ideal candidates to be applied on problems considering more than one objective since EAs work with a population of solutions; however, this property of EAs has been little exploited.

In this paper, a new multi-objective method for large-scale power distribution system expansion planning was introduced. The method is based on SPEA2 algorithm. The method has been tested on several multi-objective optimization problems. Some of these are presented in this paper. From the results we concluded that:

- The proposed method was able to find a set of approximate Pareto-optimal solutions, despite the complexity of these problems. One of the difficulties in these problems is that the Pareto-optimal front is not continuous.
- The constraints can cause complications for some planning methods to converge to the Pareto-optimal front and to maintain a diverse set of Pareto-optimal solutions. In these cases, it can be said that the proposed method was success in tackling these difficulties.
- Many multi-objectives optimization methods face difficulties in solving problems with non-convex search space. In one case reported here, the proposed method was able to find solutions in the non-convex region.

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