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DECISION STRATEGIES BASED ON METAHEURISTICS FOR DISTRIBUTION NETWORKS PLANNING

M. A. Matos (1, 2), I. J. Ramírez-Rosado (3), M. T. Ponce-de-Leão (1, 2) and J. A. Domínguez-Navarro (4).

(1) FEUP - Faculdade de Engenharia U.P., Porto, Portugal
(2) INESC-Porto – Instituto de Engenharia de Sistemas e Computadores, Porto, Portugal
(3) Departamento de Ingeniería Eléctrica, Universidad de La Rioja, Spain.
(4) Departamento de Ingeniería Eléctrica (C.P.S.), Universidad de Zaragoza, Spain.

Abstract: The classical distribution network planning problem involves deciding network investments to meet future demand at minimum cost while meeting technical restrictions. The decision whether to construct facilities and branches leads to a mixed integer programming problem with a great number of decision variables. The great deal of uncertainty associated with data that cannot be modeled using probabilistic methods leads to the use of fuzzy models to capture the uncertainty. In addition several criteria must be taken into account resulting in a fuzzy multiobjective problem. However this problem has reached maturity and researchers have recognized [1, 3, 7 e 8], that the problem must be dealt with as a decision problem were uncertainty and risk must be explicitly modeled.

The combinatorial nature of the problem limits the use of traditional mathematical tools to limited size problems. This contribution presents a basic description of the application of two meta-heuristic methods to deal with the combinatorial decision problem taking into account uncertainties in loads and investment costs. These heuristic methods, SIMULATED ANNEALING and TABU SEARCH, will be evaluated and compared taking into account their performances and the quality of solutions provided. We will focus on the simplicity and versatility of these methods, its analogies and its conceptual differences. A case study allows a compared analysis and stands out for the advantages over traditional methods.

Keywords: Power Distribution Networks, TABU search, Simulated annealing, Decision-Aid Systems.

I. INTRODUCTION

The objective of planning of power distribution networks is to determine the size and location of future substations and feeders satisfying some technical constraints. Single objective models minimize an objective function of the network expansion costs [2]. Multi-objective models [3, 9] are based on multiple criteria (investment costs, reliability, etc.). The cost of a given plan includes not only investment costs in new substations and branches but also operating costs (power losses) and reliability related costs. Thus, the problem has multiple objectives, and it is not generally possible to obtain an optimal solution, due to the conflict among evaluation criteria. Moreover, recent trending in the business of electricity make the quality issue a priority concern. This feature is included in the models through the evaluation of non-supplied energy.

The uncertainty associated to future events namely investment, operation costs and injections cannot be forgotten. Loads and an increasing number of independent generation units connected to the distribution network, introduces additional difficulties to the planning problem. In recent years, uncertainty of these injections has been modeled by possibility distributions that represent "typical" situations, as defined by experts' declarations or clustering studies [4].

To deal with the combinatorial nature of the problem, different heuristic techniques based on local search such as branch exchange [10] have been used to accelerate the search process, but they tend to fall on local minima for single objective optimization. Efficiency in dealing with this problem has been reached more recently by the use of meta-heuristic based methods [6] based on different techniques to escape local minima.

Another important issue when dealing with this kind of problems consists on setting up a decision aid system concerning the general problem of selecting investments (new facilities) in order to optimize the considered criteria. This system must be able to cope with the combinatorial nature of the problem while incorporating all the uncertainties associated to data.

In this paper we compare two decision aid systems to deal with the problem. The strategies support on different meta-heuristics. In section II and III, the operational models formulated as multiobjective ones are presented. In section II the Tabu-Search methodology is described. Each solution is evaluated by investment costs, non-supplied energy costs and exposure, which is a measure of the corresponding risk accepted by the planner. In section III a Simulated Annealing methodology is presented. In this approach two main ideas conduct the process: (1) each solution consists on a plan of investments for the stages of the study period and (2) using the robustness concept, which evaluates the ability of a certain plan to accommodate all the uncertainties, the constraints of the basic problem can be relaxed. This is accomplished by introducing a new objective function. This formulation leads to a problem without fuzzy restrictions.

To address the multiobjective problem, both strategies follow a procedure in two steps. First, using the ε-constraint method they generate a representative sample of the non-dominated solution set [3]. The multiobjective problem turns into an equivalent set of mathematical optimization problems. Second, a decision-aid process, supporting the Planner in making his final decision takes place. Section IV presents an extension of this second stage suggesting the Planner formal procedures that allow zooming actions and drive trough the solutions, generated by first stage. The output of this phase will be a representative set of solutions or plans the decision maker will be able to inspect more in detail and achieve his final decision.

Section V presents a case study, based on a realistic situation, and all the steps for the problem as well as the description of the generation of efficient alternatives are presented in detail. The list of alternatives corresponds, in fact, to efficient expansion plans for the stage into consideration. Simultaneously the simulation of the decision process (where

the Planner can choose the preferred plan) is presented and discussed.

II. TABU SEARCH IN COMBINATORIAL MULTIPLE OBJECTIVE OPTIMIZATION

The implemented algorithm is a version of the Tabu Search technique. Tabu Search strategies have been used and constitute a powerful algorithm with excellent computing performances being able to be easily applied to complex multiobjective models.

Basic algorithm of Tabu Search.

The proposed algorithm basically works with distribution network planning solutions in radial operation states taking advantages of its properties (simple calculations referred to Kirchhoff laws and radiality constraints). In opposition to other algorithms, this one is able to consider reserve feeders that improve the reliability of the electric system.

An initial solution is achieved by a shortest-path algorithm. Afterwards, topological changes in the distribution network solution are allowed (named movements) that are: 1) To eliminate one feeder and to include another (keeping the radial operation state). 2) To change the size of a selected feeder. 3) To eliminate or to include one substation. 4) To change the size of a given substation. 5) To eliminate one reverse feeder and to include another. 6) To change the size of a selected reverse feeder.

Starting from the initial solution, the search process begins. The actual movement is carried out using a selected node, or a feeder connected to this node (feeder that carries some power flow towards such node). Thus, the corresponding node number is stored in a “tabu list” in order to avoid the selection of this node in the following movements. Afterwards, each one of the allowed movements is evaluated by using a local function. This allows for choosing the best movement that is finally evaluated by several objective functions of the planning model. If the corresponding solution is better than the one obtained previously, then the algorithm stores this solution as the best present solution. Otherwise, it goes back to the beginning of the search. The solution search finishes when the objective function values do not improve for a given limit of the number of iterations.

The selection of the node is carried out by using some heuristic strategies which are: To select the node with the largest fixed cost value or variable cost value of the feeders connected to it, or to select the node with the worst voltage value. The “tabu list” prevents the algorithm from selecting the nodes already chosen.

Tabu Search is rather different from the other methods. Its strategy emphasizes intelligent search, based on a more systematic form of guidance. The random aspects of the search are almost forgotten. One of the key aspects of Tabu Search is the idea of neighborhood. It explores a neighborhood of the present visited solution to identify changes of high quality from a candidates' list. These changes also preserve the radiality of the new network. The systematic guidance is enhanced storing the last visited solutions in a tabu list. Tabu Search keeps the solutions recently visited in order to avoid local minima. The solutions previously visited are penalized in the evaluation. It also keeps the number of times that each solution is reached, in order to visit the unexplored regions of the search space. The basic algorithm can be stated as follows:

Step 1. Initialization. A) Selection of an initial solution $x_{now} \in X$. B) Initialise the best with the initial solution $x_{better} = x_{now}$;. C) Initialize the tabu list H with x_{now}.

Step 2. Search:

- A) Determine a neighborhood of x_{now}, $N(x_{now})$.
- B) Select a subset $Candidates\_N(x_{now}) \subset N(x_{now})$.
- C) Evaluate each solution $x_{new} \in Candidates\_N(x_{now})$ and choose the best according to the several functions $c_i(H, x_{new})$.
- D) Store the best solution x_{new} as x_{now} ($x_{now} = x_{new}$).
- E) IF x_{now} is better than x_{better} THEN $x_{better} = x_{now}$.
- F) Update the history of the search H with x_{now}.

Step 3. Stop.

IF termination criterion is verified THEN end the search

ELSE return to step 2.

Optimization with multiple objectives.

The Tabu-Search strategy was used to deal with the multiple objective problem. The process was divided in two phases. In the first phase, the method is able to determine the whole surface of non-dominated solutions (fuzzy economic costs, fuzzy energy not supplied and exposure) by means of a parametric method based on the optimization by goals. In the second phase a solution set of non-dominated solutions is chosen. The next paragraphs present a detailed explanation of the process.

Phase 1. Search of the set of non-dominated solutions.

The axis of each objective (fuzzy total cost of planning, fuzzy energy not supplied and exposure) is divided into intervals from their minimum value till their maximum value. This way, the space of solutions is divided into “cubes” [3]. In each cube, the algorithm “tabu search” looks for the optimal solution when minimizing the total cost, while the constraints, about the maximum allowed non supplied fuzzy energy and about the maximum allowed exhibition, are set. The “tabu search” algorithm finds the optimal solutions in each cube. Later on, the found solutions are compared to select all the non-dominated solutions. This way we obtain an approximation of the set of non-dominated solutions.

Phase 2. Selection of the best solution.

The selection of the best solution is made with the criterion of max-min. Each solution k of the surface of nondominated solutions is represented by (C_k, E_k, EX_k), where the value C_k is obtained for the function of fuzzy total economic cost of planning, the value E_k is obtained for the function of fuzzy energy non supplied and the value EX_k is obtained for the function of exposure. Then, it is normalized according to the following expression:

$$\left(\frac{C_{max} - C_k}{C_{max} - C_{min}}, \frac{E_{max} - E_k}{E_{max} - E_{min}}, \frac{EX_{max} - EX_k}{EX_{max} - EX_{min}} \right) \qquad (1)$$

where C_{max} and E_{max} are the maximum values of the function of fuzzy total economic cost of planning and of the function of fuzzy energy non supplied respectively, and C_{min} and E_{min} the minimum values of the function of fuzzy total economic cost of planning and of the function of fuzzy energy non suplied respectively. Of similar form, EX_{max} and EX_{min} are the values maximum and minimum of the function of exposure of the planning solution.

This normalization type leads to the (1, 1, 1) in the ideal point (C_{min}, E_{min}, EX_{min}) and to the (0, 0, 0) in the point anti-ideal (C_{max}, E_{max}, EX_{min}), that is to say, it determines the degree of satisfaction of each fuzzy function objective. The selected solution, x_k, is obtained using:

$$\max_k \left\{ \min \left[\left(\frac{C_{max} - C_k}{C_{max} - C_{min}}, \frac{E_{max} - E_k}{E_{max} - E_{min}}, \frac{EX_{max} - EX_k}{EX_{max} - EX_{min}} \right) \right] \right\} \quad (2)$$

Set of Solutions

The case under study is a 10 kV distribution network with nodes and 58 branches. Details of data can be obtained from the authors.

The final set of solutions is found by the search process as described. The limits are successively reduced in a systematic way so that all the solution space is covered.

Table I presents a set of non-dominated solutions for the studied problem. The columns present the attributes for the efficient solutions. These attributes were evaluated by the removal of the normalized fuzzy values of each objective. The cost column (COST) presents the removal value for investment and operation cost in million of pesetas. The non-supplied energy column (NSE) presents the removal values of the normalized energy in kWh. In the exposure columns (EXP) each solution is evaluated by the removal of exposure. This index represents the degree of the risk of surpassing technical limits for a given scenario [15].

TABLE I – Representative solution set

N	Cost	NSE	EXP	*Max-min*
1	392.62	4348.93	0.47	*0.09*
2	394.37	4379.08	0.46	*0.08*
3	394.44	4190.34	0.46	*0.12*
4	397.28	4773.81	0.00	*0.00*
5	398.14	3384.94	0.47	*0.29*
6	398.28	4365.62	0.00	*0.09*
7	398.63	3022.60	1.00	*0.00*
8	398.85	3289.82	0.47	*0.31*
9	398.86	4208.93	0.00	*0.12*
10	400.26	3550.16	0.13	*0.26*
11	401.03	2276.45	0.00	*0.52*
12	401.11	1687.78	1.00	*0.00*
13	401.93	2213.22	0.00	*0.54*
14	404.08	1152.64	0.00	*0.69*
15	404.70	1140.75	0.00	*0.67*
16	405.25	958.31	0.00	*0.66*
17	408.23	509.75	0.00	*0.57*
18	412.54	323.93	0.00	*0.46*
19	423.45	286.64	0.24	*0.16*
20	424.98	258.50	1.00	*0.00*
21	429.31	0.00	0.00	*0.00*
Minimum	*392.62*	*0.00*	*0.00*	*0.00*
Maximum	*429.31*	*4773.81*	*1.00*	*0.69*

Table I also presents an extra column with the title max-min and two extra lines that point out the maximum and minimum value for each column. If we apply the max-min rule solution 14 will be selected.

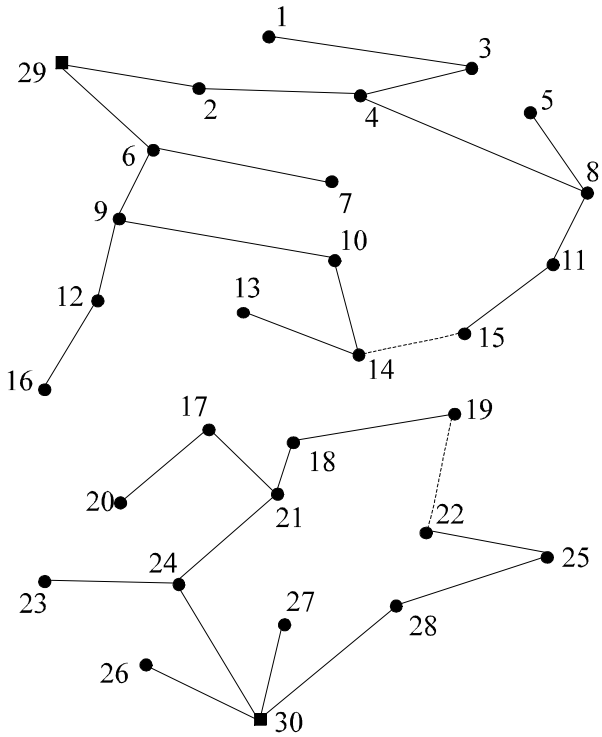

Figure 1 – Solution 14 *(obtained from the set of efficient solutions)*

This subject will be discussed in section IV where the selection of a final set of solutions derived from a formal methodology where DM will be able to include his preferences will be discussed.

III. SIMULATED ANNEALING STRATEGY TO SOLVE THE COMBINATORIAL MULTIOBJECTIVE PROBLEM

Simulated annealing (SA) [13] appears like a flexible meta-heuristic which adequately solves a great number of combinatorial problems. SA is a simple framework that takes advantage of relaxing optimality to escape from local minima. The flexibility and simplicity of this framework render this meta-heuristic adequate to model particular and, often, complex constraints, providing solutions in acceptable computation time.

This section describes a second strategy to handle the problem. First we will describe the phase of generating the efficient solutions and then we will propose a methodology to deal with the second phase, which, in fact, is a multiattibute problem derived from the first phase.

Generation of the set of efficient solutions

As in the first approach, the model addresses a network with n nodes and m potential branches, in a multi-period study with h periods. Substations are represented by artificial branches to an auxiliary node.

A sensitivity matrix $\mathbf{A_i}$ describes the network in each period *i*, relating the vector of fuzzy flows $\tilde{\mathbf{x}}_\mathbf{i}$ with the fuzzy injections $\tilde{\mathbf{d}}_\mathbf{i}$. The usual branch limit and maximum voltage drop constraints are considered. However the use of fuzzy variables (flows and voltage) soften the constraints allowing some violations within certain limits. A constraint violation

degree is evaluated by a robustness index β that reflects the degree of satisfaction of the fuzzy constraints (i.e. β=1 if the constraint is fully satisfied). Figure 2 illustrates the robustness, β=1-α, concerning the maximum limit, I_{max} of a branch.

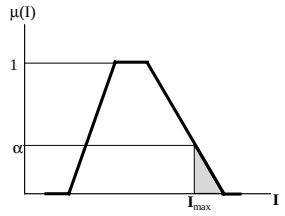

Figure 2: Robustness

A new objective function, maximizing robustness, joins the three original objective functions; minimization of investment costs, minimization of losses (fuzzy) and maximization of reliability (fuzzy). Simultaneously constraints are relaxed. Nevertheless, the new operational problem, although non-fuzzy, is a multiobjective combinatorial one. This leads to hard or even impossible resolutions in reasonable time.

SA for a single objective function

In the SA strategy, the analogy between the electric distribution planning problem and the Metropolis method (physical process) can be stated as follows:

The **alternative solutions or configurations** of the combinatorial electric distribution planning problem are equivalent to the physical system **states**

The network configurations (alternative solutions) **attributes** are equivalent to the different states' **energy**.

The **control parameter,** which is such that about half the new configurations found are accepted at the start of the process, is equivalent to the **temperature parameter**.

Some decisions had to be set to tune the general parameters. To solve small size problems we had already tried other methods (such as the one proposed by Aoki et al., 1989). The features of that approach were useful to tune the model for small size problems. Then, we successively tuned the parameters for larger problems until reaching a general rule.

TABLE II - Keystone decisions for process convergence

Decisions	
General (temperature lowering)	**Problem Specifications**
T_0 (initial temperature)	i_0 (initial solution)
L_k (iteration number)	Neighborhood generation
T_k (temperature function)	Evaluation of solutions.
Stop criteria	

The SA cooling schedule consists of: the initial value, the decrement function, the number of iterations for each temperature and the freezing temperature.

The temperature or control parameter (T_0) should be large enough to prevent being stuck in local optimum and should not be so high that leads to excessive computation time. This second issue appears to be of lesser importance as in planning problems we do not usually need answers in real time.

The choice of the initial control parameter was such that about half the configurations were accepted and is highly dependent of the nature of the problem.

$$T_0 = -\Delta C_i / ln(0.5) \qquad (3)$$

where T_0 is the initial temperature parameter
ΔC_i is the cost difference between solution *i* and solution *i-1*

The number of iterations, (the time during which a constant temperature is maintained) was set approximately 10 times the average number of possible neighbors. This value can be easily obtained during the process of calculation of the initial temperature, as in this process all the possible neighbors must be explored. This number is highly dependent on the problem size and desired accuracy.

The quality of results do not benefits from a continuous reduction scheme while the computing time is less when using a geometric schedule, thus:

$$T_i = \beta^i T_0 \qquad (4)$$

where T_i is the temperature parameter during period *i*
β^i is the temperature decreasing parameter in period *i*

An average value for β^i was also defined. From our experience we derived a value between 0.85 and 0.92. Larger values yield high computation times, and smaller values, below 0.85, lead to poorer solutions.

The freezing point is determined where the number of acceptances is very small. This point is highly dependent on the problem size and must be determined for each problem.

An auxiliary algorithm that finds a shortest spanning tree generates the initial solution; the weights used for the edges usually are the edges (branches) costs, although other criteria could be used.

A **neighborhood** generation mechanism is then created. To eliminate a great number of trials, only feasible solutions, **S´,** from the solution space **S** are considered. This procedure consists of choosing all possible combinations of connected trees that result from removing a branch to the loop created by each edge of the co-tree entering the initial configuration.

The **alternatives** (network configurations) are evaluated according to the criteria to be optimized. As each solution consists of a network configuration, it is very simple to proceed to its **evaluation** using an auxiliary package developed for fuzzy load flow calculation for radial networks.

SA and a multiobjective heuristic

A modified SA procedure was combined with the ε-constraint search to form a methodology for solving the multiobjective planning problem. In practice the initial multiobjective problem was split into several single objective problems successively solved to generate non-dominated solutions.

To apply the ε-constraint method the bounds for each objective function must be evaluated in advance and the SA acceptance function must be modeled to integrate the ε-constraint method. To implement the method we changed the acceptance function adding a constraint to allow partial optimizations which is equivalent to reducing the solution space to be optimized.

$$s'' \subseteq s' \tag{5}$$

Equation (6) illustrates the new acceptance function constraining the solution space:

when considering an objective k, $k \in \{1,...,l\}$ for each objective $m \in \{1,...,l\}$

$$P_c(\text{acceptj}) = \begin{cases} 1 & \text{if } f_k(j) \tilde{\leq} f_k(i) \\ e^{\frac{(f_k(i)-f_k(j))}{c}} & \text{if } f_k(j) \tilde{>} f_k(i) \\ 0 & \text{if } f_k(j) \tilde{>} f_k(i) \wedge \exists f_m(j) | \varepsilon_{mMin} \tilde{>} f_m(j) \tilde{>} \varepsilon_{mMax} \end{cases} \tag{6}$$

$c \in \Re^+$

The whole implementation mainly consists of iteratively applying the algorithm using several modified acceptance functions, where each function reflects the limits chosen for the ε-constraint method. The output of this phase is a list of alternative plans that cover the whole decision region, regarding the different attributes' scales. Figure 3 presents the configuration of one of the efficient alternatives.

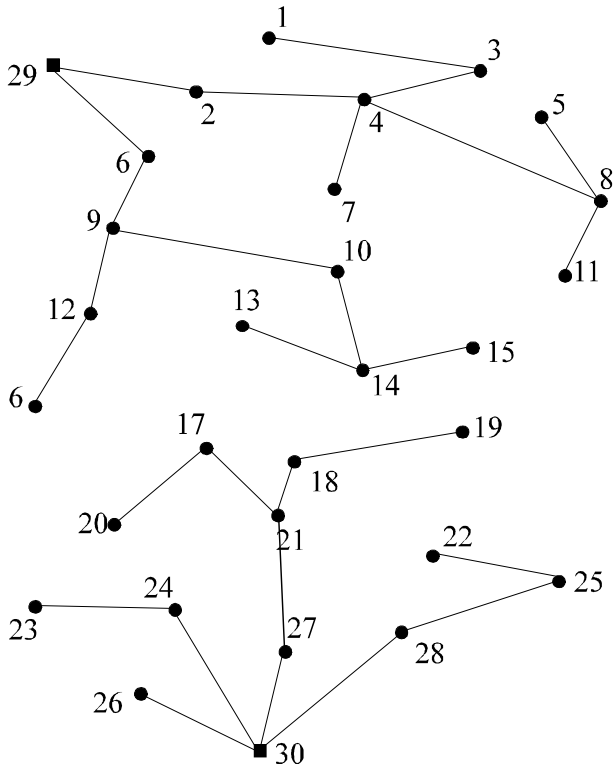

Figure 3 – Configuration for alternative 36.

Phase two consists on a decision-aid process for the fuzzy multiattribute problem that results from the first phase and will be discussed on the next section.

Table III presents an efficient reduced set of alternatives for the proposed distribution problem.

TABLE III – Reduced set of solutions obtained with procedure 2

N	Cost	Losses (kWh)			NSE (kWh)			R
6	311.2	43.9	87.8	131.7	1433.2	2866.4	4299.6	0.76
11	311.3	40.1	87.3	120.5	1432.0	2866.1	4298.5	0.5
15	316.0	40.5	79.0	98.6	1360.0	3356.0	4587.0	0.87
18	302.3	44.5	57.8	67.9	1295.0	2866.5	3905.1	0.47
21	301.8	42.5	57.1	65.9	1195.2	2666.5	3705.6	0.67
22	316.8	39.6	79.2	118.8	1619.7	3239.3	4859.0	1.00
25	317.6	39.7	79.4	119.1	1292.5	2585.0	3877.5	0.00
26	302.5	44.5	57.8	67.9	1195.2	2666.5	3705.6	0.7
27	301.8	44.5	57.8	67.9	1195.2	2666.5	3705.6	0.68
28	320.0	40.0	80.0	120.0	1170.0	2340.0	3510.0	1.00
30	301.4	44.5	57.8	67.9	1195.2	2666.5	3705.6	0.3
31	320.8	40.1	80.2	120.3	1835.0	3670.0	5505.0	0.00
33	300.5	44.5	57.8	67.9	1195.2	2666.5	3705.6	0.25
36	323.3	40.4	80.8	121.2	576.3	1152.6	1729.0	1.00

The column costs represents, only, investment costs, the column losses and non-supplied energy present the equivalent triangular fuzzy numbers and the last column presents robustness as defined. In figure 3 the configuration for alternative 28 is presented.

IV. PROPOSED DECISION PROCESSES

The first phase achieves a representative set of the whole space of nondominated solutions. From this phase, the selection of the final planning solution can be a direct procedure. A prescriptive process, as the max-min method, could be used. Alternatively, from such phase, the formal inclusion of decision maker preferences can be included as explained in this paper.

In order to help the planner selecting his preferred solution, a linguistic model (based in fuzzy sets) is now described. The aim is reducing the amount of information presented to the planner, allowing him to deal with a high-level description of the alternatives, instead of the detailed enumeration of the attributes' values. Of course, in the final stage, the "true" values will appear again.

In order to deal with inferences, fuzzy logic allows the use of fuzzy predicates (pretty, tall, old), fuzzy quantifiers (very little, little, medium, large, very large), fuzzy true values (quite true, very true, false) and various other kinds of fuzzy modifiers. Fuzzy sets can be handled with many of the basic fuzzy set operations. Furthermore, these sets can be modified by special operations corresponding to linguistic terms, which are often called linguistic hedges.

In general, fuzzy quantifiers are represented in fuzzy logic by fuzzy numbers, which are manipulated in terms of the operation of fuzzy arithmetic.

Classical decision making deals with a set of alternatives comprising the decision space. A decision can be taken under conditions of certainty when the outcome for each action can be ordered when a utility can be evaluated for the alternative. Fuzzy decision making attempts to deal with the vagueness inherent in subjective or imprecise determinations of preferences and decisions must be taken under conditions of uncertainty.

Decision process 1

In the first step fuzzy membership functions are defined for each attribute The attributes are previously normalized. In this case, with the purpose of illustration, the value 1 corresponds to best satisfaction and the value 0 to complete dissatisfaction. For the attribute costs correspond to the minimum and maximum evaluating values of the solutions' attribute cost.

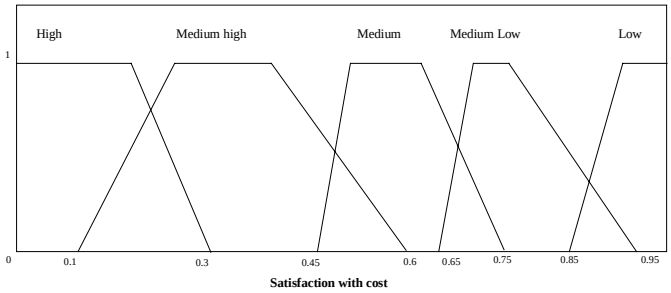

Figure 4 - Graduating descriptor for cost

A second step follows were we translate, in terms of fuzzy sets, the linguistic descriptor of the decision maker. In the figure 4 we present the graduating descriptors for the attribute cost. In fact, these descriptors can be interpreted as the degree of membership to a fuzzy set "satisfaction with cost".

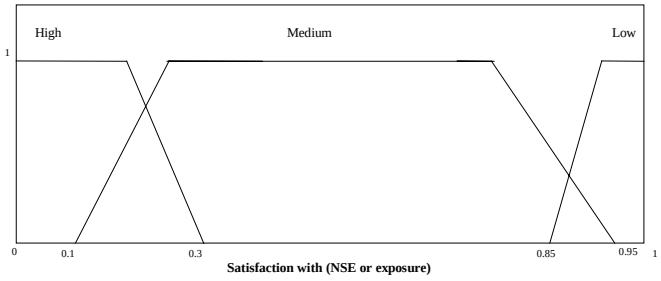

Figure 5 - Graduating descriptor for NSE and exposure

Figure 4 and 5 present the descriptors for cost, non-supplied energy and exposure of solutions.

TABLE IV – Set of TS solutions evaluated by satisfaction

Satisfaction							
N	Cost	NSE	Exp	N	Cost	NSE	Exp
1	1.00	0.09	0.43	12	0.77	0.65	0.00
2	0.95	0.08	0.44	13	0.75	0.54	1.00
3	0.95	0.12	0.44	14	0.69	0.76	1.00
4	0.87	0.00	1.00	15	0.67	0.76	1.00
5	0.85	0.29	0.43	16	0.66	0.80	1.00
6	0.85	0.09	1.00	17	0.57	0.87	1.00
7	0.84	0.37	0.00	18	0.46	0.93	1.00
8	0.83	0.31	0.43	19	0.16	0.94	0.76
9	0.83	0.12	1.00	20	0.12	0.95	0.00
10	0.79	0.26	0.87	21	0.00	1.00	1.00
11	0.77	0.52	1.00				

The rules for deduction are evaluated by means of the compositional rule of inference. This rule is no more than a fuzzy generalization of the traditional *modus ponens* rule of logical inference [14].

$$\mu_{P\circ M}(x,y) = \sup_{y\in Y} \min\left(\mu_P(x,y), \mu_M(y,z)\right) \qquad (7)$$

x fuzzy value for variable
y membership value as defined
z modified possibility values

A new set, presented in Table V, results from the composition of the values in table IV with he appropriate function in Figure 4 and 5, using the max-min fuzzy composition rule that is presented in (7). With this procedure we qualitatively evaluate the solutions that will be object of a filtering action to eliminate dominated solutions.

Table V shows the qualitative classification to each attribute as a result of the composition of table IV values with figure 1 and 2 graduating descriptors. All solutions in bold are qualitatively efficient.

This classification allows us to aggregate similar alternatives, based on these linguistic descriptors, with the belief that they will be indifferent to the decision maker DM (for instance alternatives 1 and 2: low cost, high NSE, medium exposure).

The same reasoning leads to a filtering process named "qualitative dominance". For instance, 19 qualitative dominates 20 because the small advantage of 20 in NSE (0.95 to 0.94) is ignored, and 19 is better on the other attributes. So, 20 can be discarded.

TABLE V – Qualitative classification of alternatives regarding the attributes

	Satisfaction										
	Cost					NSE			exposure		
	H	MH	M	ML	L	H	M	L	H	M	L
1	0	0	0	0	1	1	0	0	0	1	0
2	**0**	**0**	**0**	**0**	**1**	**1**	**0**	**0**	**0**	**1**	**0**
3	0	0	0	0	1	1	0	0	0	1	0
4	0	0	0	0,5	0,2	1	0	0	0	0	1
5	0	0	0	0,6	0	0,1	1	0	0	1	0
6	0	0	0	0,6	0	1	0	0	0	0	1
7	0	0	0	0,6	0	0	1	0	1	0	0
8	0	0	0	0,6	0	0	1	0	0	1	0
9	0	0	0	0,6	0	1	0	0	0	0	1
10	0	0	0	1	0	0,45	1	0	0	0,5	0,1
11	0	0	0	1	0	0	1	0	0	0	1
12	0	0	0	1	0	0	1	0	1	0	0
13	**0**	**0**	**0**	**1**	**0**	**0**	**1**	**0**	**0**	**0**	**1**
14	0	0	0,55	0,45	0	0	0,8	0	0	0	1
15	0	0	0,55	0,45	0	0	0,8	0	0	0	1
16	0	0	0,6	0,4	0	0	0,5	0	0	0	1
17	0	0,2	1	0	0	0	0,4	0,4	0	0	1
18	0	0,75	0	0	0	0	0,1	1	0	0	1
19	**1**	**0,45**	**0**	**0**	**0**	**0**	**0,1**	**1**	**0**	**1**	**0**
20	1	0,1	0	0	0	0	0	1	1	0	0
21	1	0	0	0	0	0	0	1	0	0	1

Table VI presents the final set of efficient solutions obtained with this procedure.

TABLE VI – Final set obtained with procedure 2

N	Cost	NSE	satisfaction
2	Low	high	medium
13	medium low	medium	low
19	high	low	low

Decision for process 2

Another different set of efficient alternatives was obtained with the stategy presented in paragraph III. Table III presents a reduced set of the efficient alternatives obtained with this strategy. This set consists on a group of alternatives selected from the list generated by the SA methodology. As it can be seen triangular fuzzy numbers for losses and non-supplied energy evaluate attributes. Column R represents the robustness of the solutions evaluated as defined in section III and illustrated in figure 2.

The methodology for evaluating the reduced set of alternatives could consist of identifying a restricted number of solutions using the procedure adopted on the previous section. Although other systematic procedures could also be used. An example of this could be the method presented in [14] were Macro-solutions (MS) are evaluated after a clustering process on the initial set of solutions. In that method each MS M_i is considered as a fuzzy set of alternatives where:

$$M_i = \{(z, u(zM_i)) | z \in Z\}$$

$u : z - [0,1]$ is the membership of z in M_i

Apart from this reduction, all the decisions to be taken during this phase are subjective and depend on the utility economical policy.

Table VII presents a reduced set of alternatives from those obtained in Table III. This set consists on a group of alternatives presenting high degree of membership to robust solutions.

TABLE VII – Final set from procedure 2

N	Cost	Losses (kWh)			NSE (kWh)			R
22	317	39,6	79,2	118,8	1619,7	3239,3	4859,0	1
28	320	40,0	80,0	120,0	1170,0	2340,0	3510,0	1
36	323	40,4	80,8	121,2	576,3	1152,6	1729,0	1

The inclusion of decision maker preferences led us to two reduced final sets presented in table VI and VII. From this final reduced sets we will select two solutions for comparing purposes and respectively represented in table VIII and IX.

Table VIII – Solution from reduced set departing with TS methodology

N	Cost	NSE	EXP
13	402	2213	0.00

Small differences among efficient solutions, presented in selected reduced sets, were found. In the following tables two solutions are compared; solution 13 from the first methodology and 36 from the second procedure proposed.

Table IX - Solution from reduced set departing with SA methodology

N	Cost	Losses (kWh)			NSE (kWh)			R
28	320	40,0	80,0	120,0	1170,0	2340,0	3510,0	1

Note that in the first solution the column cost refers to investment and operation costs while in the second these costs are evaluated separately. As noticeable both solutions present similar attributes. Differences between both configurations can be seen in figures 1 and 3.

V. CONCLUSIONS

Two methodologies designed to cope with the fuzzy combinatorial distribution planning problem were presented. These methodologies were based on two meta-heuristics, Tabu-Search techniques and Simulated Annealing. Both proved efficient in generating non-dominated solutions.

From the results we would like to point out the main added value extracted from this comparison; Meta-heuristics prove undoubtedly efficient in providing solutions when the problems are combinatorial. Distribution planning problem is an example of this.

Comparisons are always difficult nevertheless some important conclusions can be pointed out from a deep analysis to the results obtained. Both seem able to produce a representative set of solutions from the solution space. This can be stated from the diversity of solutions obtained.

We can find in literature different procedures to include uncertainty with no probabilistic behavior. The description of both methods prove this. The first method extracts fuzziness in the end of first step and provides a set of efficient solutions evaluated by deterministic values. The second procedure keeps fuzziness till the second step including it, as an extra criteria, in the decision problem through the attribute robustness. The output of this phase is a set of efficient solutions evaluated by fuzzy attributes.

Although, slightly different in the evaluating process, both methods generate efficient solutions assuring the whole decision space is covered. Generated solutions are evaluated in the attributes' space. Moreover, as stated from the results presented in table VI and VII, both lead to the selection of equivalent solutions, in what concerns configuration and therefore the evaluating attributes.

The first phase achieves a representative set of the whole space of nondominated solutions. From this phase, the selection of a the final planning solution can be a direct procedure. Alternatively, from such phase, the formal inclusion of decision maker preferences can be included as explained in this paper. Human reasoning is imprecise in nature, and the development of tools for handling with uncertainty is an important issue in the design of efficient systems. To note that this final set obtained after representing the decision maker preferences does not include the solution obtained with the max-min method.

The final step consists on helping the decison maker to include his preferences and reach the final decision. Both procedures lead to similar solutions even though the technical evaluations are made following different procedures.

As a final conclusion we think that the proved maturity reached by these methodologies stimulates the improvement of these models and justifies the investment in developing complete decision aid systems, allowing the decision maker to include his preferences, to be included, as a planning package,

in commercial software for Distribution Management Systems.

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