Possibilistic Model Based on Fuzzy Sets for the Multiobjective Optimal Planning of Electric Power Distribution Networks

Ignacio J. Ramírez-Rosado, *Member, IEEE,* and José Antonio Domínguez-Navarro, *Member, IEEE*

***Abstract*—This paper presents a new possibilistic (fuzzy) model for the multiobjective optimal planning of power distribution networks that finds out the nondominated multiobjective solutions corresponding to the simultaneous optimization of the fuzzy economic cost, level of fuzzy reliability, and exposure (optimization of robustness) of such networks, using an original and powerful meta-heuristic algorithm based on Tabu Search. This model determines the optimal location and size of the future feeders and substations in distribution networks with dimensions significantly larger than the ones usually presented in papers on the matter. The model also allows to determine the optimal reserve feeders (location and size) that provide the best distribution network reliability at the lowest cost for a given level of robustness (exposure). The model and the algorithm have been intensively tested in real distribution networks, which proves their practical application to large power distribution systems.**

***Index Terms*—Fuzzy sets, multiobjective optimization, planning, power distribution systems, Tabu search.**

I. Introduction

The CLASSICAL optimal planning of distribution networks [1]–[6] determines basically the most economical planning solution (single objective optimal economic cost solution) with the best size and location for future substations and/or feeders to meet the future demand represented using deterministic values. In this classical planning, an objective function of economic cost associated with the expansion of the distribution network (in a single-stage or a multi-stage planning [2], [4], [5]) is optimized, subject to a set of technical constraints [2], [6] (power capacity limits of the substations and feeders, voltage drop limits at the demand nodes of the distribution system, and radiality conditions of the power network operation). In the past, deterministic planning models used conventional optimization algorithms such as "branch and bound" [1], [2], and more recently they have used other methods based on more efficient meta-heuristic techniques of local search such as, for example, "branch exchange" [3], [4] and genetic algorithms [5], [6].

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I. J. Ramírez-Rosado is with the Department of Electrical Engineering, University of La Rioja, Logroño 26004, Spain (e-mail: ignacio.ramirez@die.unirioja.es).

J. A. Domínguez-Navarro is with the Department of Electrical Engineering, University of Zaragoza, Zaragoza, Spain (e-mail: jadona@posta.unizar.es).

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In the field of the multiobjective optimal planning of distribution networks based on deterministic demand, very few works have analyzed the network reliability maximization simultaneously with the minimization of the economic cost [7]. Furthermore, sometimes this optimal planning has been carried out using a single objective corresponding to the linear combination of a reliability cost function and the economic cost [5], [8]. Usually, the papers on multiobjective distribution planning based on deterministic demand have not been tested in real distribution networks of significant dimensions (except in [7]) to obtain the set of multiobjective nondominated solutions [9], [10] with a true simultaneous optimization of objectives.

The abovementioned deterministic planning models (single objective or multiobjective models) can only represent one value of future demand at each node of the distribution network and, therefore, they cannot represent directly the intrinsic uncertainty associated with the future demand. This future demand can be better defined using fuzzy variables that represent possibility distributions of the demand values in the future [11]–[14], providing a more realistic representation of such demand. Relatively few fuzzy models for the optimal planning of distribution networks [12]–[14] have been published. No model of multiobjective fuzzy planning for distribution systems seems to have considered a true *simultaneous* optimization of the economic cost and reliability taking into account the optimal size and location of reserve feeders (feeders that are not usually operative except for failures in the distribution network in a radial operating state). These optimal reserve feeders provide the best network reliability at the lowest economic cost. In the fuzzy planning of distribution systems, we can introduce the concept of risk (exposure) associated with the assessment of the possibility that the power flows in the feeders and substations surpass their power capacity limits [12]–[14]. This concept has a substantial advantage (compared to the deterministic models) since the planner can evaluate the "risk" associated with a given planning solution using the "exposure" value of such solution (distribution network) linked to the future possibility of overloading the feeders and/or substations. That is, this "risk" is an advantageous and important concept in order to evaluate the "robustness" of the distribution network in terms of future security in the operation of the network. Only a fuzzy planning model for distribution systems [13] has considered the risk (exposure) of surpassing the allowed voltage drop limits, but it has not been applied to distribution networks of significant dimensions. This exposure, associated with the voltage drop limits, is also interesting for the planner in terms of robustness of the distribution network in order to obtain an appropriate level of electric service quality in the future.

This paper presents an original possibilistic (fuzzy) model based on nonlinear optimization for the multiobjective optimal planning of power distribution systems in a single stage or multi-stage optimal planning (for the latter, using the pseudo-dynamic methodology [2]). The possibilistic model determines the multiobjective nondominated solutions that manage *simultaneously* to minimize the (fuzzy) economic cost, maximize the (fuzzy) reliability and minimize the risk (exposure), whereby the risk of surpassing the power capacity limits of the feeders and substations is minimized and, furthermore, the risk of surpassing the allowed voltage drop limits at the network nodes is also miminized. This new multiobjective possibilistic (fuzzy) model also determines the optimal size and location of the reserve feeders that should be built to maximize the network reliability at the lowest economic cost (for a given level of risk). This model has been applied to distribution systems significantly larger and more complex to optimize than most of the ones usually presented in the papers on distribution system optimal planning, using an original meta-heuristic algorithm of multiobjective optimization based on the technique of Tabu Search [15]. The model and the algorithm have been intensively tested in real distribution networks, which proves their practical application to large power distribution systems.

II. Possibilistic Model of Multiobjective Planning

In the first section, several fundamental concepts related to the possibilistic (fuzzy) model are presented, as well as the mathematical comparisons of fuzzy numbers. Afterwards, the possibilistic multiobjective model is described, and finally the formal mathematical method (Section II-C) used to solve the multiobjective optimization problem is discussed. This method can be implemented by diverse algorithms, and in this paper we have used the abovementioned original algorithm described in Section III.

A. Fundamental Concepts

1) Fuzzy Variables: The power demand at each node can be represented using a value d_1 (the "most favorable" demand), a value d_3 (the "most unfavorable" demand), and a value d_2 (demand with the highest possibility of existence in the future that corresponds to the value 1 of the membership function μ [11]), as shown in Fig. 1.

This description of the demand is associated with a triangular possibility distribution (fuzzy), $\tilde{d} = (d_1, d_2, d_3)$, and represents simultaneously a large set of possible future values of demand at a given node. Other important variables are the power flows in the feeders and substations, the economic cost ("fixed" and variable cost) associated with the expansion of the distribution system, the failure rate and repair rate for the reliability evaluation (using the "expected nonsupplied energy"), and the voltages at the network nodes. All these magnitudes, with intrinsic uncertainties, are also represented by triangular possibility (fuzzy) distributions. The abovementioned fuzzy (possibilistic) power flows and fuzzy voltages are calculated in radial operating states of the network using an iterative version of the algorithm of power flows as in [16]–[18]. The fuzzy "expected nonsupplied energy" is obtained through an enumerative algorithm that simulates successive feeder failures and calculates their contribution to the "expected nonsupplied energy" of the system as in [19], [20]. Furthermore, the objective functions of economic cost and reliability, and the technical constraints [21], are represented using possibility distributions, too [22], [23]. Note that the possibilistic model represents simultaneously, using fuzzy (possibilistic) variables, an extensive set of situations (scenarios) of future demand (very large set of future demand values at each node of the network). Therefore, often the technical constraints of power capacity limits in the feeders and substations, and the allowed voltage drop limits at the network nodes, will not be strictly met in all the future situations considered simultaneously. If they were met in all the future situations, then the planning solutions would have no "risk" associated, that is, the "exposure" (to the risk) would be zero. If such technical constraints were only met in a subset of these future situations, we would be assuming a certain level of risk, that is, a certain exposure to this risk [11]. The possibilistic multiobjective model presented in Section II-B optimizes simultaneously the economic cost associated with the distribution network, the exposure and the reliability of the network.

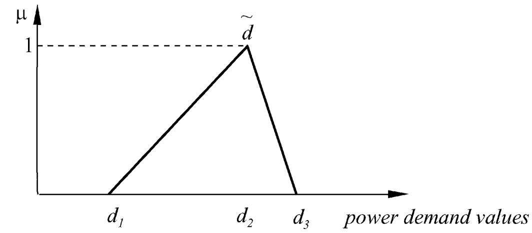

Fig. 1. Fuzzy representation of power demand.

2) Comparison of Objective Function Values: As we have mentioned before, possibility distributions (triangular fuzzy numbers) are used to represent several magnitudes (i.e., demand, power flow, voltage, etc.). The fuzzy (possibilistic) variables are denoted by the symbol ($\sim$) in the possibilistic model. The nonlinear objective function associated with the economic cost and the one associated with the expected nonsupplied energy correspond to fuzzy values. These fuzzy values must be compared and ranked to assess several planning solutions. The ranking function "removal" [22], [23] allows to determine and compare these values. For example, in Fig. 2, the removal of the fuzzy value $\tilde{a}$ for an α-cut $= h_1$ is defined [22], [23] as $R_{h_1}(\tilde{a}) = \left(a^l_{h_1} + 2a_2 + a^u_{h_1}\right)/4$. (The symbols h_2 and $a_{\max}$ in Fig. 2 will be used later). Thus, for two fuzzy values $\tilde{a}$ and $\tilde{b}$, we can study whether $R_{h_1}(\tilde{a}) \le R_{h_1}(\tilde{b})$ is true or not, that is, $\tilde{a}$ and $\tilde{b}$ can be compared. Therefore, we can compare the fuzzy values of the objective functions abovementioned.

3) Fuzzy Constraints: In Fig. 3, let us represent the right-hand side of the fuzzy number $\tilde{c}$ by c^u_h and the left-hand side by c^l_h (with a similar representation for the fuzzy number $\tilde{e}$). The relationship $\tilde{c} \le_{h_3} \tilde{e}$ is satisfied if the left-hand side satisfies $c^l_h \le e^l_h$ and the right-hand side satisfies $c^u_h \le e^u_h$ for any α-cut $h \in [h_3, 1]$. Then, according to [22]–[24], a fuzzy constraint $\tilde{c} \tilde{\le} \tilde{e}$ can be satisfied in different ways. We have considered that a fuzzy constraint is satisfied up to the level h_3 if $\tilde{c} \le_{h_3} \tilde{e}$, that is, we have applied "Soyster's criterion" [22]–[24].

The possibilistic (fuzzy) power flows of the model can be "larger" than the power capacity limits of the distribution elements from a β-level up to a zero-level. For example, in Fig. 2,

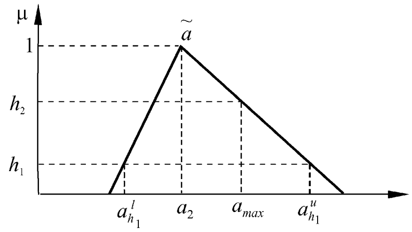

Fig. 2. Fuzzy variables.

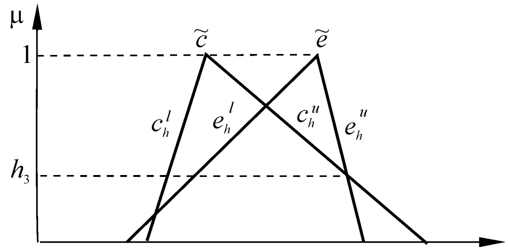

Fig. 3. Fuzzy constraint.

let us assume that the fuzzy number $\tilde{a}$ represents the fuzzy power flow $\tilde{x}$ carried out through a feeder, and that the power capacity limit of such feeder is $a_{\max}$ Then, the relationship $\tilde{x} \leq_{h_2} a_{\max}$ implies that the fuzzy power flow $\tilde{x}$ is "lower" than (or "equal" to) the power capacity limit for any α-cut $h \in [h_2, 1]$. ($\beta = h_2$ in Fig. 2).

This β-level is a measurement of the corresponding risk accepted by the planner and is called "exposure". Furthermore, a measurement of the so-called "robustness" of the distribution system planning solution is the value $(1 - \beta)$ [11]. If the level of robustness is forced to increase, then the number of feasible planning solutions (that meet the power capacity limits) decreases. Usually, if an objective function is minimized, then there is a planning solution for each specified level of robustness. Similar concepts of "exposure" and "robustness" can be extended to fuzzy node voltages with respect to the lowest voltage limits allowed at the network nodes [21].

B. Possibilistic Model for Multiobjective Planning

The multiobjective deterministic planning of a power distribution network can be modeled as a problem of multiobjective optimization with integer variables (y) (decision variables to build and size up new proposed feeders and substations) and continuous variables (x) (power flow and voltage), where the economic cost $C(y, x)$ associated with the expansion and expected nonsupplied energy $E(x)$ is minimized, subject to the usual technical constraints $g_r(y, x) \{\leq, =, \geq\}\ 0$ that represent the first and second law of Kirchhoff, the power capacity limits of the feeders and substations, and the allowed voltage drop limits at the nodes (subject to the condition of radiality of the power flows in these distribution networks). In mathematical terms, it can be expressed as [21]

$$\begin{aligned}&\mathrm{Min}[C(y,x), E(x)]\\&\text{Such that :}\\&(y,x) \in X = \{(y,x) | g_r(y,x)\{\leq, =, \geq\}0, r \in R\}\end{aligned} \tag{1}$$

where R represents the set of the abovementioned technical constraints (r refers to the rth constraint); and $\mathrm{Min}[C(y,x), E(x)]$ represents the multiobjective deterministic minimization to obtain the nondominated solutions using the optimality of Pareto [9], [10] with the simultaneous maximization of the objectives $C(y,x)$ and $E(x)$.

If the different magnitudes are represented by fuzzy (possibility) distributions, then the possibilistic (fuzzy) model of multiobjective optimal planning will include, in a similar way, integer variables (y) and fuzzy continuous variables $(\tilde{x})$, where the fuzzy planning cost $\tilde{C}(y, \tilde{x})$ and the fuzzy expected nonsupplied energy $\tilde{E}(\tilde{x})$ are miminized subject to the fuzzy technical constraints $g_r(y, \tilde{x}) \{\tilde{\leq}, \cong, \tilde{\geq}\}\ 0$. Furthermore, the exposure EX (mathematically defined later) is included in the possibilistic model. It considers the exposure associated with the power capacity limits of the feeders and substations as well as the exposure associated with the voltage drop limits at the network nodes. Thus, the possibilistic model can be expressed as [21]

$$\begin{aligned}&\mathrm{Min}-f[\tilde{C}(y,\tilde{x}), \tilde{E}(\tilde{x}), EX]\\&\text{Such that :}\\&(y,\tilde{x}) \in X_f = \{(y,\tilde{x}) | g_r(y,\tilde{x})\{\tilde{\leq}, \cong, \tilde{\geq}\}0, r \in R_f\}\end{aligned} \tag{2}$$

where R_f is the set of the fuzzy technical constraints and $\mathrm{Min}-f[\tilde{C}(y,\tilde{x}), \tilde{E}(\tilde{x}), EX]$ represents the multiobjective fuzzy minimization to obtain nondominated solutions using the optimality of α-Pareto [22], [24] with a simultaneous minimization of the objectives $\tilde{C}(y,\tilde{x})$, $\tilde{E}(\tilde{x})$ and EX.

Note that, in the next paragraphs, the objective functions of the model contain fuzzy variables and fuzzy coefficients. Therefore, the model will be called "possibilistic" model [22]–[24]. The terms of the objective function of economic cost $\tilde{C}(y,\tilde{x})$ of (3) represent fuzzy variable costs associated with existing feeders and substations; fuzzy fixed costs associated with future feeders and substations; and fuzzy variable cost associated with future feeders and substations [21]. This function contains possibilistic (fuzzy) variables $\tilde{x}$

$$\begin{aligned}&\tilde{C}(y,\tilde{x}) =\\&= \sum_{(i,j)\in N_{FE}} (\tilde{C}v_{ij})_E \left[(\tilde{x}_{ij})^2_E + (\tilde{x}_{ji})^2_E\right] + \sum_{k\in N_{SE}} (\tilde{C}v_k)_E (\tilde{x}_k)^2_E +\\&\quad + \sum_{(i,j)\in N_{FF}} \sum_{\Omega\in N_\Omega} \left\{(\tilde{C}f_{ij})_\Omega (y_{ij})_\Omega\right\} +\\&\quad + \sum_{k\in N_{SF}} \sum_{\Omega'\in N_{\Omega'}} \left\{(\tilde{C}f_k)_{\Omega'} (y_k)_{\Omega'}\right\} +\\&\quad + \sum_{(i,j)\in N_{FF}} \sum_{\Omega\in N_\Omega} \left\{(\tilde{C}v_{ij})_\Omega \left[(\tilde{x}_{ij})^2_\Omega + (\tilde{x}_{ji})^2_\Omega\right]\right\} +\\&\quad + \sum_{k\in N_{SF}} \sum_{\Omega'\in N_{\Omega'}} \left[(\tilde{C}v_k)_{\Omega'} (\tilde{x}_k)^2_{\Omega'}\right]\end{aligned} \tag{3}$$

where

N_{FE}	set of routes (between nodes) associated with the existing feeders in the initial network;
N_{FF}	set of proposed feeder routes (between nodes) to be built;
N_Ω	set of proposed feeder sizes to be built;

N_{SE} set of nodes associated with the existing substations in the initial network;

N_{SF} set of nodes associated with the proposed locations to build substations;

$N_{\Omega'}$ set of proposed substation sizes to be built;

(i,j) route between the nodes i and j;

$(\tilde{x}_k)_{\Omega'}$ fuzzy power flow, in kVA, supplied from the node $k \in N_{SF}$ associated with a substation of size Ω';

$(\tilde{x}_{ij})_{\Omega}$ fuzzy power flow, in kVA, carried through the route $(i,j) \in N_{FF}$ associated with a feeder of size Ω;

$(\tilde{x}_k)_E$ fuzzy power flow, in kVA, supplied from the node $k \in N_{SE}$ associated with an existing substation in the initial network;

$(\tilde{x}_{ij})_E$ fuzzy power flow, in kVA, carried through the route $(i,j) \in N_{FE}$ associated with an existing feeder in the initial network;

$(\tilde{C}v_{ij})_E$ fuzzy variable cost coefficient of an existing feeder in the initial network, on the route $(i,j) \in N_{FE}$;

$(\tilde{C}v_{ij})_{\Omega}$ fuzzy variable cost coefficient of a feeder of size Ω to be built on the route $(i,j) \in N_{FF}$;

$(\tilde{C}f_{ij})_{\Omega}$ fuzzy fixed cost of a feeder of size Ω to be built on the route $(i,j) \in N_{FF}$;

$(\tilde{C}v_k)_E$ fuzzy variable cost coefficient of an existing substation in the initial network, at the node $k \in N_{SE}$;

$(\tilde{C}v_k)_{\Omega'}$ fuzzy variable cost coefficient of a substation of size Ω', at the node $k \in N_{SF}$;

$(\tilde{C}f_k)_{\Omega'}$ fuzzy fixed cost of a substation of size Ω',at the node $k \in N_{SF}$;

$(y_k)_{\Omega'}$ 1, if a substation of size Ω' associated with node $k \in N_{SF}$ is built. Otherwise, it is equal to 0;

$(y_{ij})_{\Omega}$ 1, if a feeder of size Ω associated with route $(i,j) \in N_{FF}$ is built. Otherwise, it is equal to 0.

In (3), notice that the fuzzy mathematical operations are algebraic operations with fuzzy numbers [20], [22].

The objective function of the expected nonsupplied energy $\tilde{E}(\tilde{x})$ is the following fuzzy function:

$$\tilde{E}(\tilde{x}) = \sum_{(i,j)\in N_F} \left(\tilde{P}_{NS\_TOTAL}(i,j) \cdot \tilde{u}_{ij}\right) \tag{4}$$

where

N_F $N_{FE} \cup N_{FF}$;

$\tilde{u}_{ij}$ fuzzy constants obtained considering other suitable reliability fuzzy constants (several reliability related fuzzy parameters, such as the fuzzy failure rate and fuzzy repair rate of the distribution feeders, as well as the length of the corresponding feeders) associated with a feeder on the route $(i,j) \in N_F$;

and $\tilde{P}_{NS\_TOTAL}(i,j)$ is the fuzzy expected nonsupplied power, in kVA, associated with a possible feeder failure on route $(i,j) \in N_F$, taking into account the reserve feeders.

As mentioned above, the multiobjective possibilistic model includes the minimization of the exposure EX (a new objective function). Thus, in future situations (scenarios) of demand (large set of values of future demand at each node of the network considered simultaneously), it minimizes the risk of surpassing the technical constraints of the power capacity limits of the elements of the network and the allowed voltage drop limits, taking into account the best reserve feeders. In the multiobjective deterministic model, this risk is not evaluated since there is only one future situation (a single deterministic value of future demand at each node of the network). However, with the multiobjective possibilistic model, the planner works simultaneously with the representation of a significant set of future demand situations (scenarios). Then, he/she can select an exposure level (risk) acceptable for the planning solution from his/her experience and professional point of view.

For each planning solution (distribution network belonging to the set X_f), the exposure of the network EX is mathematically defined as

$$\begin{aligned} EX &= \max\{EX_{IL-RED}, EX_{IS-RED}, EX_{VD-RED}\} \\ EX_{VD-RED} &= \max\{EX_{VDk} | k \in N_{Ne}\} \\ EX_{IS-RED} &= \max\{EX_{ISk} | k \in N_{Se}\} \\ EX_{IL-RED} &= \max\{EX_{ILk} | k \in N_{Fe}\} \end{aligned} \tag{5}$$

where the operator max represents the maximum [22]–[24] of the values of the set $\{EX_{IL-RED}, EX_{IS-RED}, EX_{VD-RED}\}$; N_{Ne}, N_{Se}, and N_{Fe} are, respectively, the sets of nodes, substations and feeders of the planning solution (the one that is being evaluated); and EX_{VDk}, EX_{ISk}, and EX_{ILk} are, respectively, the exposure associated with the node k-th, the substation k-th and the feeder k-th [21], for this planning solution. Then, in (5), EX_{ILk} represents the exposure associated with the power flow of the feeder k-th, that is, the lowest α_1-level at which the fuzzy power flow ($\tilde{x}^k$) of the feeder is "lower" than (or "equal" to) the power capacity limit ($x^k_{\max}$) of the feeder. Thus

$$EX_{ILk} = \min\left\{\alpha_1 | \tilde{x}^k \le_{\alpha_1} x^k_{\max}\right\} \tag{6}$$

where min is the minimum of the values α_1 [22]–[24].

Furthermore, EX_{ISk} represents the exposure associated with the power flow in the substation kth, that is, the lowest α_2-level at which the fuzzy power flow ($\tilde{x}_k$) in the substation is "lower" than (or "equal" to) the power capacity limit ($x_{\max,k}$) of the substation. Thus

$$EX_{ISk} = \min\left\{\alpha_2 | \tilde{x}_k \le_{\alpha_2} x_{\max,k}\right\}. \tag{7}$$

Finally, EX_{VDk} represents the exposure associated with the voltage of the node kth, that is, the lowest α_3-level at which the fuzzy voltage ($\tilde{V}_k$) of the node is "higher" than (or "equal" to) the allowable lowest voltage limit ($V_{\min,k}$). Thus

$$EX_{VDk} = \min\left\{\alpha_3 | V_{\min,k} \le_{\alpha_3} \tilde{V}_k\right\}. \tag{8}$$

C. Resolution Method of the Possibilistic Model

This method is developed in two phases. In the first phase, the set of nondominated planning solutions is obtained (with respect to the objective functions of fuzzy economic cost, fuzzy expected nonsupplied energy, and exposure) using a parametric method based on an optimization by goals [10]. In the second phase, a solution of the set of nondominated solutions is selected using a suitable max-min approach [22].

Phase 1: Search of the Set of Nondominated Solutions: Each planning solution k obtained with the multiobjective possibilistic model has an associated fuzzy value for the objective function of fuzzy planning cost $\tilde{C}_k(y,\tilde{x}) = \tilde{C}_k$, a fuzzy value for the fuzzy expected nonsupplied energy $\tilde{E}_k(\tilde{x}) = \tilde{E}_k$ and a deterministic value for the exposure EX_k. The evaluation and comparison of these different fuzzy values is carried out using the removal function $R(\ )$ [22], [23], mentioned in Section II-A. The "removal" of the objective function $\tilde{E}(\tilde{x})$ (fuzzy expected nonsupplied energy) can range from 0 to RE, where $RE = \max\left\{R(\tilde{E}(\tilde{x}))\right\}$ is the maximum "removal" value of the fuzzy expected nonsupplied energy when the objective function of economic cost is optimized. The exposure EX can range from 0 to 1. Thus, a partition of the space of planning solutions is carried out by limiting the values of two objective functions using mathematical constraints that lead systematically to successive planning solutions (parametric method [10]), as shown in the next paragraph. Let us consider the mathematical constraints

$$R(\tilde{E}(\tilde{x})) \le E_{meta}; \quad EX \le EX_{meta} \tag{9}$$

where $E_{meta} \in [0, RE]$ and $EX_{meta} \in [0,1]$.

Then, the following optimization is successively solved each time, by varying systematically the values of E_{meta} and EX_{meta}:

$$\begin{aligned} &\mathrm{Min}[R(\tilde{C}(y,\tilde{x}))] \\ &\text{Such that :} \\ &R(\tilde{E}(\tilde{x})) \le E_{meta}; EX \le EX_{meta} \\ &(y,\tilde{x}) \in X_f = \left\{(y,\tilde{x}) | g_r(y,\tilde{x})\left\{\tilde{\le}, \tilde{\cong}, \tilde{\ge}\right\} 0, r \in R_f\right\} \end{aligned} \tag{10}$$

where $\mathrm{Min}[R(\tilde{C}(y,\tilde{x}))]$ represents the minimization of the removal of the objective function $(\tilde{C}(y,\tilde{x}))$ to obtain the optimal solution [22], [24].

The planning solutions obtained with this method are compared among themselves to determine a set of nondominated solutions.

Phase 2: Selection of the Best Multiobjective Planning Solution: After analyzing the set of nondominated solutions, the planner can select the final nondominated solution, considering the most satisfactory values of the three objectives and according to his/her experience and professional point of view. In this paper, a max-min approach is used to select the best (final) multiobjective planning solution. Each solution k in the set of nondominated solutions has an associated vector of values $(\tilde{C}_k, \tilde{E}_k, EX_k)$ that can be normalized using the following expression:

$$\left(\frac{C_{\max} - R(\tilde{C}_k)}{C_{\max} - C_{\min}}, \frac{E_{\max} - R(\tilde{E}_k)}{E_{\max} - E_{\min}}, \frac{EX_{\max} - EX_k}{EX_{\max} - EX_{\min}}\right) \tag{11}$$

where $C_{\max}$, $E_{\max}$ and $EX_{\max}$ are the "removal" values of the maximum values obtained for the objective function of fuzzy economic cost, for the function of fuzzy expected nonsupplied energy and for the exposure function, respectively, and $C_{\min}$, $E_{\min}$ and $EX_{\min}$ are the "removal" values of the minimum values obtained. Note that the result of this normalization gives the vector (1, 1, 1) for the ideal point $(C_{\min}, E_{\min}, EX_{\min})$ and the vector (0, 0, 0) for the anti-ideal point $(C_{\max}, E_{\max}, EX_{\max})$, that is, it represents the level of satisfaction for each objective function. Afterwards, a max-min approach, shown in (12), at the bottom of the page, is applied to select the best (final) multiobjective planning solution (that is, the most satisfactory solution using the aforementioned approach). The definition of the well-known max-min operator can be found in [20], [22], and [24].

III. Summary of the Algorithm of Multiobjective Tabu Search

The basics of the original Tabu Search algorithm will be briefly described and, afterwards, due to the lack of space, only a summary of the application of such an algorithm to our multiobjective optimization problem will be presented.

A. Basics of the Tabu Search [21]

1) Evaluation of a Planning Solution : The Tabu Search algorithm uses integer variables (Section II-B), i.e., variables that define the network topology (planning solution). For a given planning solution (topology and fuzzy demand), the fuzzy radial power flows [16]–[18] can be determined (using possibility distributions), as well as the corresponding fuzzy voltages at the network nodes and the fuzzy planning economic cost. The exposure associated with this solution can also be obtained considering the power flows and the power capacity limits of the feeders and substations, as well as the node voltages and allowed voltage drop limits. The fuzzy expected nonsupplied energy can be calculated taking into account the reserve feeders [21].

2) Movements for the Search of a New Planning Solution: A solution is defined when the feeders and substations (to be built) are determined. We can obtain a new solution from a given one by applying certain changes to its topology. To find new solutions, the following topology changes are allowed: 1) remove a feeder by introducing a new one (with guarantee of a radial operating state of the power network); 2) change the size of a selected feeder; 3) remove or include a substation; and 4) change the size

$$\max\left\{\min_k\left[\left(\frac{C_{\max} - R(\tilde{C}_k)}{C_{\max} - C_{\min}}, \frac{E_{\max} - R(\tilde{E}_k)}{E_{\max} - E_{\min}}, \frac{EX_{\max} - EX_k}{EX_{\max} - EX_{\min}}\right)\right]\right\} \tag{12}$$

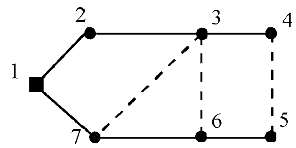

Fig. 4. Illustrative example.

of a given substation. These changes (called "movements") preserve the operation radiality of the new networks (planning solutions in the "neighborhood" of the present solution). For example, in Fig. 4 we are going to explain the abovementioned movements 1) and 2). An elementary electric network is represented in Fig. 4 with a substation at node 1 and six demand nodes (nodes 2–7). The continuous segments are the feeders that compose the current radial solution and the dashed segments are additional feeder routes that could be part of new solutions. The search of a new solution starts in the aforementioned radial solution. Then, the search process selects a node, for instance node 3 in the current solution. This process only allows to carry out movements that preserve the radiality. Therefore, the allowed movements (associated with node 3) are: change the size of the feeder on the route (2,3), or remove the feeder from this route by introducing a new feeder (preserving the radial operating state) that supplies power to node 3 [feeder on the route (7,3) or feeder on the route (6,3)].

3) Tabu List: The elements of the power network associated with movements in the last m iterations are stored in a list of length m. Furthermore, the movements on such elements are "forbidden". Thus, the search is diversified. The length m of the Tabu list is defined as the closest integer to $\sqrt{N_{iv}}$ [15], where N_{iv} is the number of components that correspond to N_{FF} and N_{SF} (Section II-B).

4) Neighborhood of a Planning Solution: The set of solutions that can be obtained from a given solution (by applying movements) are the "neighborhood" of the solution. Since the neighborhood is usually composed of a large set of solutions (with a considerable computational effort to evaluate them), a subset of movements is selected to obtain some solutions ("elite candidates") of such neighborhood that seem to be better than the current solution (without a previous evaluation of these "elite candidates"). The movements that lead to the "elite candidates" are selected using a local approach aimed at improving the optimization objectives. Obviously, the movements on elements belonging to the Tabu list are forbidden [15].

B. Application of the Tabu Search to Our Multiobjective Optimization Problem [21]

The new meta-heuristic algorithm is a multiobjective original version of the Tabu Search technique [15]. The flow chart in Fig. 5 shows a brief description of the new algorithm, which will be presented in detail in a future paper. This algorithm is based on a local search with suitable procedures to avoid local minima. The two main procedures are: a short-term memory (Tabu list) that avoids the repetition of movements carried out in the last iterations (steps 6 and 8), and a long-term memory that provides regions of unexplored solutions within the search space (step 3). The algorithm begins with an initial solution belonging to the set of the planning solutions (step 1). Afterwards, still in step 1, the partition (in search regions) of the solutions space is created as it has been explained in Phase 1 of Section II-C. In each search region, the movements that improve the objectives are applied. From the neighborhood of the current solution, the set of elite candidates is selected (step 4). Then, these elite candidates are evaluated. In step 5, if there are nondominated solutions, then such solutions are stored in the set of nondominated solutions; otherwise, the best one is chosen (step 7). The systematization of the Tabu Search is reinforced by keeping in a "Tabu list" the element that has given (through the corresponding movement) the aforementioned best solution in step 8 (or the nondominated solutions in step 6). In the following iteration, the movements on elements stored in the Tabu list are forbidden (step 4). Thus, we avoid going back to solutions already visited (recent local optima). The local search is repeated as long as it improves the current solution (step 9). The global search is repeated until there are no more unexplored regions (step 10). Afterwards, the corresponding set of nondominated solutions is obtained from all the obtained planning solutions, (step 2). Finally, the best solution from the set of nondominated solutions is selected as it has been explained in Phase 2 of Section II-C.

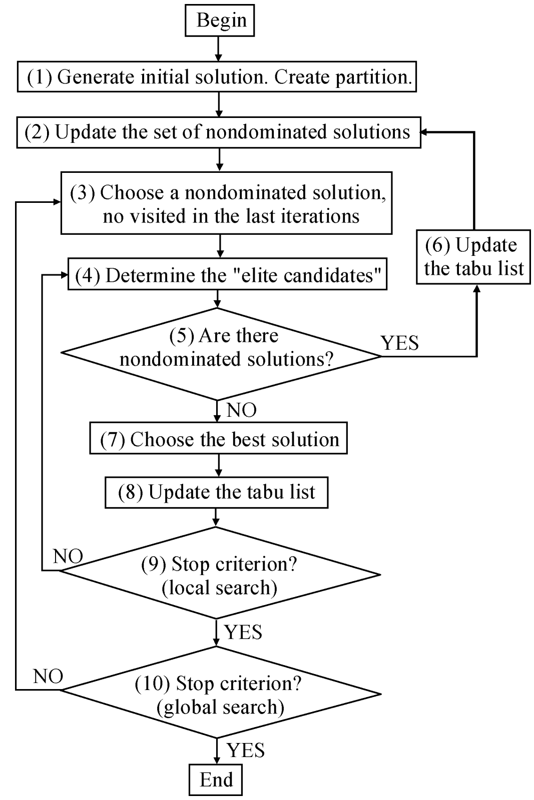

Fig. 5. Tabu Search flowchart.

IV. Computational Results

The possibilistic model of multiobjective planning and the new algorithm of multiobjective optimization (Tabu Search) have been intensively validated in large computational experiments and applied to real distribution networks of significant dimensions. Most of the data on the distribution systems have been provided by a Spanish electric utility.

In this paper, only the main data and results of a case of multiobjective optimal planning are presented due to the lack

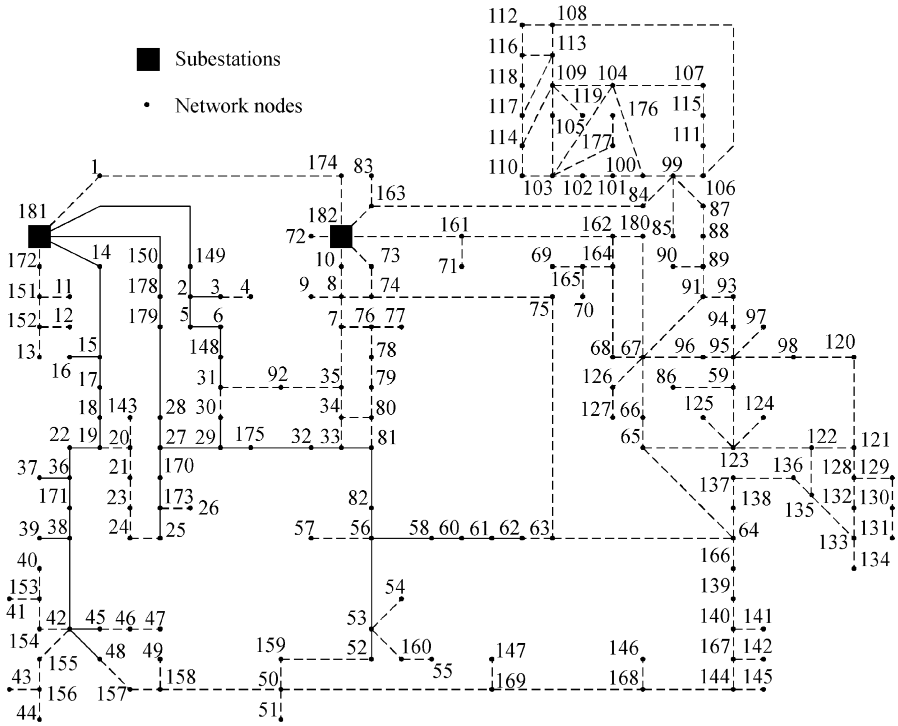

Fig. 6. Existing and future proposed distribution network.

TABLE I
POWER DEMAND REQUIREMENTS IN KVA

n	d_1	d_2	d_3	n	d_1	d_2	d_3	n	d_1	d_2	d_3	n	d_1	d_2	d_3	n	d_1	d_2	d_3	n	d_1	d_2	d_3	n	d_1	d_2	d_3	n	d_1	d_2	d_3
1	373	415	519	20	233	259	324	39	54	60	75	58	0	0	0	77	15	20	29	96	78	104	156	115	22	43	76	134	130	259	454
2	373	415	519	21	373	415	519	40	17	19	23	59	194	259	389	78	194	259	389	97	64	85	127	116	34	68	118	135	415	830	1452
3	134	149	186	22	75	83	104	41	8	9	12	60	64	86	128	79	311	415	622	98	311	415	622	117	43	87	152	136	83	166	290
4	149	166	207	23	149	166	207	42	0	0	0	61	0	0	0	80	490	653	980	99	118	158	236	118	54	108	189	137	183	365	639
5	213	237	296	24	233	259	324	43	34	37	47	62	43	57	85	81	127	169	254	100	249	332	498	119	44	88	154	138	156	311	544
6	218	242	302	25	373	415	519	44	84	93	117	63	46	61	92	82	194	259	389	101	491	982	1719	120	130	259	454	139	9	19	33
7	588	653	817	26	34	37	47	45	60	67	83	64	124	166	249	83	34	45	67	102	69	139	243	121	110	220	384	140	30	60	105
8	299	332	415	27	373	415	519	46	113	126	157	65	311	415	622	84	19	26	38	103	14	27	47	122	207	415	726	141	14	28	49
9	233	259	324	28	197	219	274	47	149	166	207	66	490	653	980	85	110	147	221	104	4	8	14	123	130	259	454	142	23	47	82
10	111	123	154	29	323	359	448	48	233	259	324	67	272	363	544	86	156	207	311	105	0	0	0	124	25	50	87	143	47	93	163
11	45	50	62	30	322	357	447	49	42	47	58	68	194	259	389	87	174	232	348	106	68	135	237	125	104	207	363	144	0	0	0
12	45	50	62	31	210	233	291	50	25	28	35	69	9	12	19	88	194	259	389	107	0	0	0	126	83	166	290	145	37	75	131
13	8	9	12	32	373	415	519	51	28	37	56	70	47	62	93	89	0	0	0	108	62	125	218	127	160	319	559	146	5	9	16
14	233	259	324	33	0	0	0	52	194	259	389	71	93	124	187	90	53	70	105	109	98	195	342	128	23	46	80	147	9	19	33
15	103	115	144	34	373	415	519	53	8	11	17	72	86	114	171	91	127	169	254	110	0	0	0	129	32	64	111	148	82	164	288
16	114	127	159	35	747	830	1037	54	41	54	81	73	194	259	389	92	91	122	183	111	19	38	67	130	130	259	454				
17	0	0	0	36	373	415	519	55	28	37	56	74	182	243	364	93	194	259	389	112	69	138	241	131	13	27	47				
18	59	66	82	37	233	259	324	56	194	259	389	75	194	259	389	94	223	298	447	113	19	37	65	132	57	114	200	176	44	176	353
19	294	327	408	38	0	0	0	57	124	166	249	76	311	415	622	95	311	415	622	114	34	68	118	133	123	246	431	177	44	176	353

of space. Fig. 6 shows the existing 10-kV feeder network (continuous segments) and the proposed routes (dashed segments) to build future underground feeders of three proposed sizes (3×150 Al, $3 \times 1 \times 400$ Al, and parallel circuits $3 \times 1 \times 400$ Al). These are also the sizes of the existing feeders. The size of the existing substation is 15 MVA and a future substation of two proposed sizes (31 MVA and 15 MVA) is proposed to be built at node 182. Table I gives the power demand, in kVA, of the distribution system nodes (n) from node 1 to node 148, node 176 and node 177. From node 149 to 175 and from node 178 to 182, the power demands are zero. In Table I, the demand is represented by triangular fuzzy numbers $\tilde{d}$ (note that (d_1, d_2, d_3) have been described in Section II-A). The value d_2 represents the demand, in kVA, with the highest possibility of existence in the future (and it also represents the deterministic demand of the deterministic model).

The application of Phase 1, defined in Section II-C, determines the nondominated solutions obtained with the two planning models (deterministic and possibilistic models). Fig. 7 shows the 22 nondominated solutions obtained with the multiobjective deterministic model. The economic cost $C(y,x)$, in thousands of Euros, is represented on the horizontal axis and the expected nonsupplied energy $E(x)$, in kWh, is represented on the vertical axis. Fig. 8 shows the 61 nondominated solutions obtained with the multiobjective possibilistic model, where the removal $R(\tilde{C}(y,\tilde{x}))$ of the planning economic cost, in thousands of Euros, the removal $R(\tilde{E}(\tilde{x}))$ of the expected nonsupplied energy, in kWh, and the exposure (EX) are shown. Due to the lack of space, Table II only shows a sample of the nondominated solutions obtained with the deterministic model and Table III gives a sample of the ones obtained with the possibilistic model. In Table II (and in Table III), the symbol

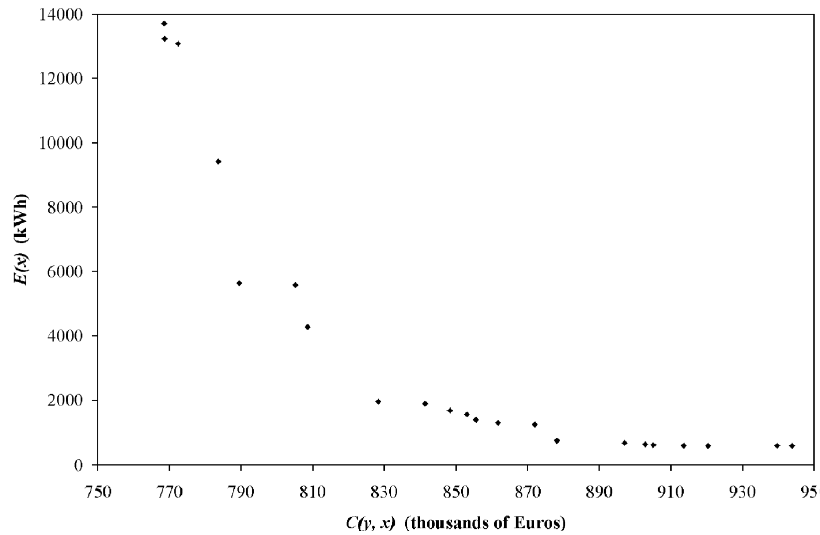

Fig. 7. Nondominated solutions obtained with the multiobjective deterministic model.

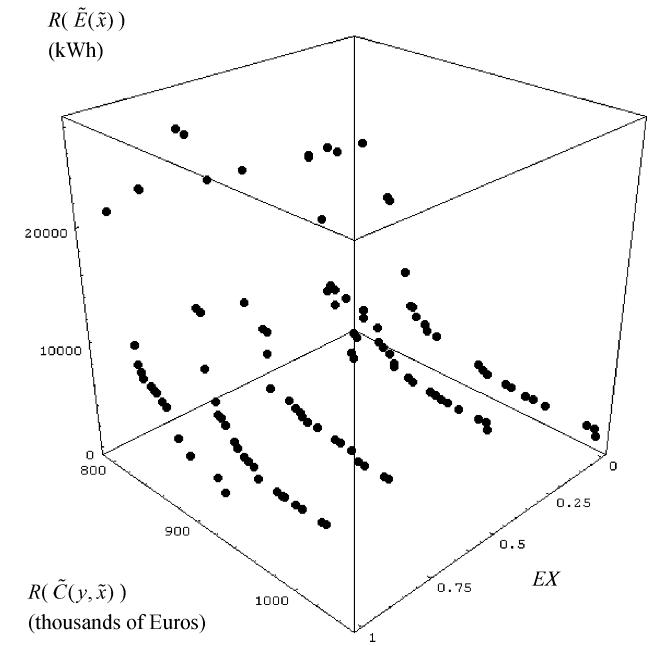

Fig. 8. Nondominated solutions obtained with the multiobjective possibilistic model.

TABLE II
SAMPLE OF NONDOMINATED SOLUTIONS OBTAINED WITH THE DETERMINISTIC MODEL

ks	C_{ks}	E_{ks}	*Cnk*	*Enk*	*Max-min*
6	805.17	5580.12	0.79	0.59	0.59
7	808.62	4284.71	0.77	0.69	0.69
8	828.32	1964.76	0.66	0.86	0.66
9	841.40	1889.63	0.58	0.86	0.58
10	848.29	1686.70	0.54	0.88	0.54
11	853.03	1563.67	0.52	0.89	0.52
12	855.61	1392.83	0.50	0.90	0.50
13	861.72	1298.15	0.47	0.91	0.47
14	872.04	1250.13	0.41	0.91	0.41

TABLE III
SAMPLE OF NONDOMINATED SOLUTIONS OBTAINED WITH THE POSSIBILISTIC MODEL

ks	$R(\tilde{C}_{ks})$	$R(\tilde{E}_{ks})$	EX_{ks}	$\tilde{C}nk$	$\tilde{E}nk$	*EXnk*	*Max-min*
13	852.62	5889.97	0.58	0.76	0.74	0.31	0.31
14	853.22	6878.54	0.20	0.76	0.68	0.77	0.68
15	858.07	4618.73	0.58	0.74	0.80	0.31	0.31
16	862.55	4094.62	0.58	0.72	0.83	0.31	0.31
17	864.49	3653.68	0.58	0.72	0.86	0.31	0.31
18	871.13	3095.69	0.58	0.69	0.89	0.31	0.31
19	871.70	4920.28	0.00	0.69	0.79	1.00	0.69
20	875.53	4171.16	0.00	0.67	0.83	1.00	0.67
21	875.84	4062.42	0.20	0.67	0.83	0.77	0.67
22	877.11	3496.03	0.00	0.67	0.87	1.00	0.67

ks denotes the number of the nondominated solution obtained with the deterministic model (and the possibilistic model, respectively). Thus, for example, in Table II the nondominated solution number 7 obtained with the deterministic model is denoted by $ks = 7$.

In order to select the best multiobjective planning solution (Phase 2 defined in Section II-C), the values of the objective functions of Tables II and III are normalized using the following expressions:

$$\left(\frac{C_{\max} - C_{ks}}{C_{\max} - C_{\min}}, \frac{E_{\max} - E_{ks}}{E_{\max} - E_{\min}}\right) = (Cnk, Enk) \tag{13}$$

$$\left(\frac{C_{\max} - R(\tilde{C}_{ks})}{C_{\max} - C_{\min}}, \frac{E_{\max} - R(\tilde{E}_{ks})}{E_{\max} - E_{\min}}, \frac{EX_{\max} - EX_{ks}}{EX_{\max} - EX_{\min}}\right) = = (\tilde{C}nk, \tilde{E}nk, EXnk). \tag{14}$$

Then, the max-min approach (Section II-C) is applied: the result of the application of the "$\min$" operator is given in the column "*Max-min*" (Tables II and III), and, afterwards, the result of the "$\max$" operator indicates that best solution obtained with the multiobjective deterministic model is solution number 7 (Table II) and that the best one obtained with the multiobjective possibilistic model is solution number 19 (Table III). Fig. 9 shows this nondominated solution number 19, where the reserve feeders are represented by dashed segments.

Thus, comparing the two distribution network topologies of the mentioned best multiobjective planning solutions (obtained

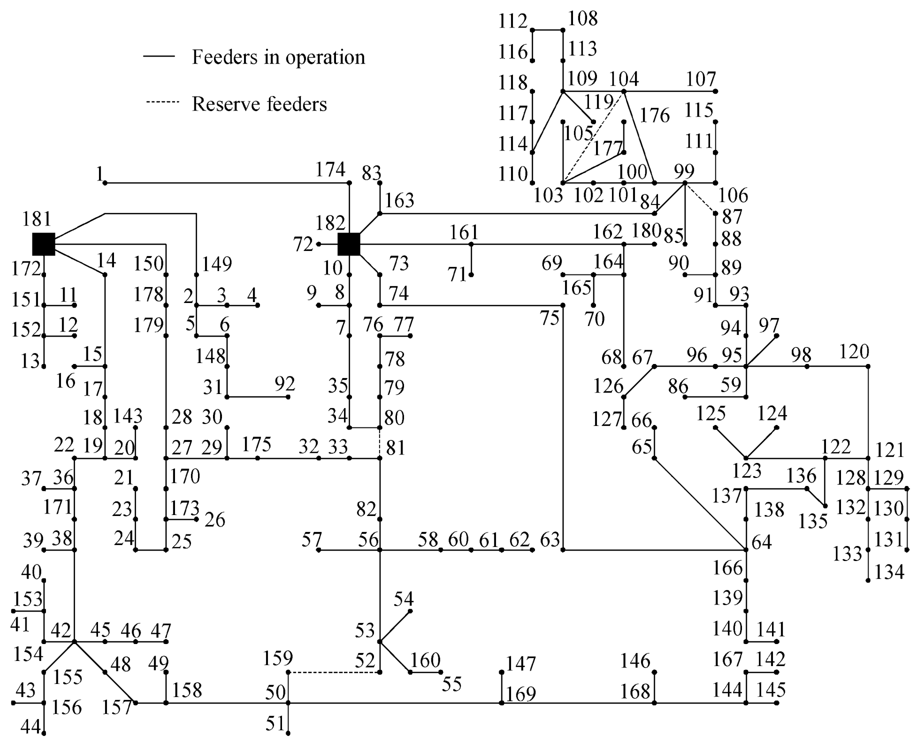

Fig. 9. Solution obtained with the multiobjective possibilistic model.

with the possibilistic and deterministic models), we get 48 topological differences between such solutions (17 different feeder routes, and 31 feeder routes with built feeders that have different size for the two topologies).

If the best multiobjective planning solutions obtained with the deterministic model (deterministic solution) and the possibilistic model (possibilistic solution) are compared, there is only a very slight increase in the fixed cost (3.61%) of the possibilistic solution vs. the deterministic one. However, the technical features of the former are much better than the ones of the latter. Thus, the expected nonsupplied energy improves significantly (30.79%) in the possibilistic solution compared with the deterministic one. Furthermore, the possibilistic solution has an associated zero exposure value (completely robust solution) whereas the deterministic solution has an associated exposure of 0.20. Therefore, the multiobjective possibilistic model is preferred since it provides a better planning solution with a much lower expected nonsupplied energy and, also, with a substantially lower exposure, that is, it is a more reliable and robust planning solution (with a very slight cost increase). Thus, from a technical point of view, the solution of the multiobjective possibilistic model is much more satisfactory, as it improves significantly the reliability of the power distribution network and, according to the concept of robustness used in this paper, it also creates an expectation of more robustness of the future electric service quality and operation security of the distribution network.

V. Conclusions

This paper has presented a new possibilistic (fuzzy) model of multiobjective optimal planning for electric power distribution systems of significant dimensions, using an original meta-heuristic algorithm of multiobjective Tabu Search based on nonlinear optimization. The model considers a fuzzy explicit representation of the uncertainties associated with the future demand, as well as a fuzzy representation of the uncertainties associated with the expansion cost of the distribution network, the power flow in the feeders and substations, the network node voltages, and the reliability (expected nonsupplied energy). This original possibilistic model provides a true *simultaneous* minimization of the economic cost, expected nonsupplied energy and exposure, subject to several fuzzy technical constraints imposed by the Kirchhoff's laws, the power capacity limits of the feeders and substations, and the allowed voltage drop limits at the distribution network nodes (subject to the condition of radial network operation). The possibilistic model also allows to find out the optimal location and size of the reserve feeders that maximize the network reliability at the lowest cost for a given exposure level (robustness level). Furthermore, the corresponding multiobjective deterministic model has been presented (and the computational results obtained with both deterministic and possibilistic models have been compared). An original meta-heuristic algorithm of multiobjective optimization has been created to solve the possibilistic model (and the deterministic one). This algorithm uses sophisticated heuristic strategies to avoid local optima. The algorithm determines the set of nondominated multiobjective planning solutions. Afterwards, the planner can select the most satisfactory nondominated solution on the basis of his/her experience and professional point of view. In this paper, a max-min approach has been proposed to select the best nondominated planning solution.

The new algorithm and the possibilistic model have been intensively tested in real power networks of significantly larger dimensions than the ones usually presented in papers on optimal planning of distribution systems, proving their practical application to large power distribution systems.

The multiobjective possibilistic model allows to consider *simultaneously* a very large set of future demand scenarios (a large set of future demand values at each node of the distribution network, resulting in an improved representation of the intrinsic uncertainty of the future demand in the planning process), whereas the corresponding multiobjective deterministic model can only consider one planning scenario (only one value of future demand at each node of the network). The computational results have shown that the network topologies obtained with the possibilistic model are notably different from the ones obtained with the deterministic model. Moreover, the possibilistic model provides more satisfactory planning solutions than the deterministic model, with a significant improvement of the distribution network reliability as well as a very large improvement of the robustness (exposure), that is, leading to an expectation of more robustness of the future electric service quality and operation security of the distribution network.

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Ignacio J. Ramírez-Rosado (M'87) received the Ph.D. degree in electrical engineering from the University of Zaragoza, Zaragoza, Spain, in 1986.

He was a Visiting Research Associate and a Fulbright Researcher at the Department of Electrical and Computer Engineering, University of Missouri-Columbia, under the Fulbright Program (1984–1985). He was Professor Titular de Universidad and the Subdirector of the Departamento de Ingeniería Eléctrica e Informática, University of Zaragoza. In 1998, he moved to the University of La Rioja, La Rioja, Spain, where he is presently a Full Professor of the Department of Electrical Engineering. He has been responsible for several research projects in the power systems area, mainly in network planning, load forecasting, and regional energy planning. His current areas of interest are integrated electricity resources planning and operation and applications of novel computational techniques and intelligent systems to electric power systems.

José Antonio Domínguez-Navarro (S'98–A'99–M'04) received the Ph.D. degree in electrical engineering from the University of Zaragoza, Zaragoza, Spain, in 2000.

In 1992, he joined the University of Zaragoza, where he is presently Professor Asociado. He has been involved in some research projects in the area of optimization of power distribution networks. His current interest areas are applications of soft computing in electric power systems, power distribution networks planning, electric markets, and meta-heuristic optimization.