New Multiobjective Tabu Search Algorithm for Fuzzy Optimal Planning of Power Distribution Systems

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

***Abstract*—This paper presents a new multiobjective Tabu search (NMTS) algorithm to solve a multiobjective fuzzy model for optimal planning of distribution systems. This algorithm obtains multiobjective nondominated solutions to three objective functions: fuzzy economic cost, level of fuzzy reliability, and exposure (maximization of robustness), also including optimal size and location of reserve feeders to be built for maximizing the level of reliability at the lowest economic cost (for a given level of robustness). The main characteristics of the NMTS algorithm are: search of planning solutions using several objective functions simultaneously; partition of the space of solutions to diversify the search; intensification of the search by ranking lists of the best network nodes of the distribution system; and an elaborated Tabu list that stores visited network nodes, avoiding unwanted movements. The NMTS algorithm has been intensively tested in real distribution systems, proving its practical application in large power distribution systems.**

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

I. Introduction

ESSENTIALLY, in classical optimal planning of power distribution systems [1]–[6], single objective deterministic models minimize system expansion economical cost for deterministic demands of the system nodes, in a single-stage or in a multistage context subject to technical constraints [6] (power capacity limits of the substations and feeders, voltage drop limits at the system nodes, and radiality conditions of system operation). These models used diverse algorithms: mathematical algorithms such as "simplex" [1], "branch and bound" [2], "quadratic programming" [3], "Lagrange" methods [4], and heuristic algorithms such as "branch exchange" [5] and genetic algorithms [6].

A multiobjective deterministic model [7] simultaneously minimizes system expansion cost and maximizes network reliability to obtain the set of multiobjective nondominated solutions, using an evolutionary algorithm. Some other deterministic models have used only a single objective corresponding to the linear combination of a reliability cost function and the expansion cost [8], [9], using genetic algorithms [8], or other heuristic specialized algorithms [9].

Fuzzy models [10]–[12] provide a more realistic representation of the distribution system nodes demands since the intrinsic uncertainty of future demands is included in such models via suitable fuzzy variables. Multiobjective fuzzy models consider several fuzzy objective functions. Thus, in [10], a utility objective function is built (from such fuzzy functions) that is optimized using a genetic algorithm; in [11], various fuzzy objective functions are optimized using a simulated annealing algorithm.

This paper presents a new multiobjective Tabu search (NMTS) algorithm to solve the multiobjective fuzzy model of [12] as well as the corresponding multiobjective deterministic model for optimal planning of power distribution system. Thus, the present paper supplements [12], which described the multiobjective fuzzy model in detail, whereas the present paper describes the new Tabu search algorithm in detail.

The NMTS algorithm presents numerous original characteristics that allow it to obtain the multiobjective nondominated planning solutions resulting from a true *simultaneous* minimization of the fuzzy economic cost, maximization of the fuzzy reliability, and minimization the risk (exposure) of the system and also determining the optimal size and location of reserve feeders (feeders not usually operative except for failures in radial operating states of the system), that is, reserve feeders to be built for maximizing network reliability at the lowest economic cost (for a given level of risk). The solutions from the NMTS algorithm minimize the risk of surpassing the permitted lowest voltage limits at the network nodes as well as the risk of overloads in feeders and substations, which improves the system "robustness" for proper levels of electric service quality and security in the future.

Furthermore, the NMTS algorithm also obtains the multiobjective nondominated solutions of the above-mentioned deterministic model to minimize the deterministic economic cost and the deterministic reliability of the system (also obtaining the best sizing and locating of reserve feeders).

Intensive testing of the NMTS algorithm has been carried out with both complex multiobjective (fuzzy and deterministic) models in real distribution systems, thus demonstrating its practical applicability to large power distribution systems.

The NMTS algorithm could also be adapted to solve other multiobjective models for optimal planning of distribution systems.

Manuscript received November 16, 2004; revised June 7, 2005. This work was supported in part by the Ministerio de Educación y Ciencia of Spain and the FEDER Funds, in part by the Gobierno de La Rioja under Project DPI2005-07494 and Project ANGI2004/02, and in part by the European Union. Paper no. TPWRS-00600-2004.

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

J. A. Domínguez-Navarro is with the Department of Electrical Engineering, University of Zaragoza, 50018 Zaragoza, Spain (e-mail: jadona@unizar.es).

Digital Object Identifier 10.1109/TPWRS.2005.860946

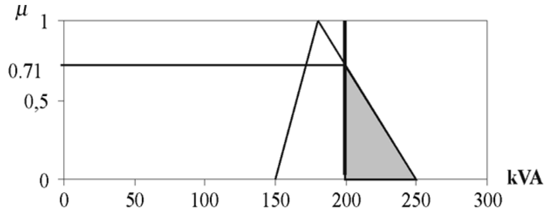

Fig. 1. Power flow transported by a feeder.

II. Summary of the Fuzzy Model of Multiobjective Optimal Planning

First, this section summarizes the basic concepts of fuzzy sets used for the fuzzy model; it then offers a brief presentation of this multiobjective fuzzy model (also referred to as possibilistic model) [12], as well as the corresponding multiobjective deterministic one; lastly, essentials of the technique for solving the multiobjective fuzzy model are indicated.

A. Basic Fuzzy Power Variables for Optimal Planning of Power Distribution Networks

These basic fuzzy power variables are fuzzy power demands at the distribution network nodes and fuzzy power flows throughout the distribution feeders. They are represented by triangular fuzzy numbers [13], [14], where a triangular fuzzy number $\tilde{p}$ is represented as $\tilde{p} = (p_1, p_2, p_3)$. A fuzzy power demand represents simultaneously a large set of possible values of the power demand in the future, at a given node on the distribution network, describing the intrinsic uncertainty of such future demand; a value of a membership function $\mu \in [0,1]$ is also associated to each value of this set of power demands of the triangular fuzzy number [13], [14].

Fuzzy power flows (also represented by fuzzy triangular numbers) are transmitted by the lines of the distribution network to supply the fuzzy power demands of the nodes. Such fuzzy power flows (and the fuzzy voltages at nodes) are calculated, in radial network operating states, by an iterative version of the algorithm of power flows, as in [15] and [16].

Fuzzy power flows in feeders (and in substations), (and fuzzy voltages at nodes) are subject to technical constraints of power capacity limits of feeders (and of substations), (and technical constraints of maximum allowable voltages drops at nodes). For example, in Fig. 1, the fuzzy power flow $\tilde{p} = \{150, 180, 250\}$ kVA is transported by a feeder with a power capacity limit of 200 kVA. Thus, above the degree of possibility 0,71 in Fig. 1, $\tilde{p}$ surpasses the 200-kVA limit, and then, from fuzzy set theory [13], [17], $\tilde{p}$ is "lower" than (or "equal" to) 200 kVA until degree of possibility of 0.71. Thus, $\tilde{p} \leq_{0.71} 200$.

Therefore, a classical technical constraint of feeder (or substations) power capacity limit in optimal power distribution planning is usually met for a given "degree of possibility" from the standpoint of fuzzy power flows (or voltage drop constrains from the standpoint of fuzzy voltages). Thus, above a given degree of possibility, there is a risk that the power capacity limit constraint of a feeder (or substation) will not be met; this is known as "exposure" [13] (similar ideas can be presented for exposure referring to fuzzy voltages). Thus, the exposure EX_{Ilk} associated with the power flow of the kth feeder 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. Then

$$\mathrm{EX}_{ILk} = \min\left\{\alpha_1 \,\middle|\, \tilde{x}^k \leq_{\alpha_1} x^k_{\max}\right\} \tag{1}$$

where $\min$ is the minimum of the values α_1 [17].

In Fig. 1, feeder exposure is 0.71. The corresponding robustness is $(1-0.71) = 0.29$, with robustness for the feeder capacity limit being a measure of the possibility of the feeder not being overloaded [13].

The exposure EX_{ISk} associated with the power flow in the kth substation 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. Then

$$\mathrm{EX}_{ISk} = \min\{\alpha_2 \,|\, \tilde{x}_k \leq_{\alpha_2} x_{\max,k}\}. \tag{2}$$

The exposure EX_{VDk} associated with the voltage of the kth node 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 $(V_{\min,k})$. Then

$$\mathrm{EX}_{VDk} = \min\left\{\alpha_3 \,\middle|\, V_{\min,k} \leq_{\alpha_3} \tilde{V}_k\right\}. \tag{3}$$

The exposure $\mathrm{EX}_{Il-\mathrm{RED}}$ of a considered distribution feeders network (composed by the set N_{Fe} of feeders) is

$$\mathrm{EX}_{IL-\mathrm{RED}} = \max\{\mathrm{EX}_{ILk} \,|\, k \in N_{\mathrm{Fe}}\}. \tag{4}$$

Similar concepts can be established for exposure $\mathrm{EX}_{IS-\mathrm{RED}}$ for substations and $\mathrm{EX}_{\mathrm{VD-RED}}$ for voltages of a considered power distribution network. Thus

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

where N_{Se} and N_{Ne} are, respectively, the sets of substations and nodes of the distribution network (the one that is being evaluated).

Then, the exposure EX of the considered network is

$$\mathrm{EX} = \max\{\mathrm{EX}_{IL-\mathrm{RED}}, \mathrm{EX}_{IS-\mathrm{RED}}, \mathrm{EX}_{\mathrm{VD-RED}}\} \tag{6}$$

where operator $\max$ represents the maximum [17] of the values of the set $\{\mathrm{EX}_{IL-\mathrm{RED}}, \mathrm{EX}_{IS-\mathrm{RED}}, \mathrm{EX}_{\mathrm{VD-RED}}\}$.

Further details about distribution system exposure and robustness concepts can be found in [12]–[14].

B. Other Fuzzy Values for Optimal Planning of Power Distribution Networks

Other triangular fuzzy variables are used in optimal planning for distribution systems to represent the economic cost associated with the distribution system expansion and failure rate and repair rate (for the reliability evaluation) used for the "expected nonsupplied energy" evaluations. This fuzzy "expected nonsupplied energy" can be obtained by an enumerative algorithm that simulates successive feeder failures and calculates their contribution to the "expected nonsupplied energy" of the system, as in [18].

C. Ranking Function "Removal"

The multiobjective fuzzy model considers the objective functions of economic cost and reliability (expected nonsupplied energy). Thus, corresponding triangular fuzzy values of these functions have to be compared and ranked to analyze diverse planning solutions (distribution networks patterns). The ranking function "removal" [14], [18]–[21] has been used for this, with the removal $R(\tilde{a})$ of a triangular fuzzy number $\tilde{a} = (a_1, a_2, a_3)$ being the value $R(\tilde{a}) = (a_1 + 2a_2 + a_3)/4$.

D. Fuzzy Model for Multiobjective Optimal Planning

Our multiobjective deterministic model for optimal planning of distribution systems contains integer variables (y) (decision variables to build and size up new proposed feeders and substations) and continuous variables (x) (power flows and voltages). Thus, a multiobjective optimization of the system-expansion economic cost $C(y,x)$ and the expected nonsupplied energy $E(x)$ is carried out subject to the usual technical constraints $g_r(y,x)\{\leq,=,\geq\}0$ representing the first and second of Kirchhoff's laws, the feeders and substations' power capacity limits, and the allowed voltage drop limits at the nodes (as well as the condition of power flows radiality in these systems). Then, this model is stated as [12]

$$\begin{aligned} &\mathrm{Min}[C(y,x), E(x)] \\ &\text{Such that: } (y,x) \in X \\ &\quad = \{(y,x) \,|\, g_r(y,x)\{\leq,=,\geq\}0, r \in R\} \end{aligned} \tag{7}$$

where R represents the set of the above-mentioned 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 Pareto optimality [22] with the simultaneous maximization of objectives $C(y,x)$ and $E(x)$.

Similarly, our multiobjective fuzzy model uses integer variables (y) and fuzzy continuous variables $(\tilde{x})$ in the multiobjective optimization of fuzzy planning cost $\tilde{C}(y,\tilde{x})$, fuzzy expected nonsupplied energy $\tilde{E}(\tilde{x})$, and exposure EX, subject to the fuzzy technical constraints $g_r(y,\tilde{x})\{\tilde{\leq},\cong,\tilde{\geq}\}0$. Then, this fuzzy model is stated as [12]

$$\begin{aligned} &\mathrm{Min} - f[\tilde{C}(y,\tilde{x}), \tilde{E}(\tilde{x}), \mathrm{EX}] \\ &\text{Such that: } (y,\tilde{x}) \in X_f \\ &\quad = \{(y,\tilde{x}) \,|\, g_r(y,\tilde{x})\{\tilde{\leq},\cong,\tilde{\geq}\}0, r \in R_f\} \end{aligned} \tag{8}$$

where R_f is the set of the fuzzy technical constraints, and $\mathrm{Min} - f[\tilde{C}(y,\tilde{x}), \tilde{E}(\tilde{x}), \mathrm{EX}]$ represents the multiobjective fuzzy minimization to obtain nondominated solutions using the α-Pareto optimality [17], [23], with a simultaneous minimization of objectives $\tilde{C}(y,\tilde{x}), \tilde{E}(\tilde{x})$ and EX.

E. Technique for Solving the Multiobjective Fuzzy Model When Using the NMTS Algorithm

A parametric technique (nondominated solutions generation method [17], [23]) has been used to solve the multiobjective fuzzy model, thus obtaining the set of nondominated solutions [23]–[25], with respect to the objective functions of fuzzy economic cost, fuzzy expected nonsupplied energy, and exposure. Therefore, a partition of the space of planning solutions is performed (to search this set of solutions) by including mathematical constraints in the aforementioned objective functions (using $R()$, the removal function) that enables the achievement of systematically successive planning solutions [22].

Let us define S_p as an element of the partition of the space of solutions. Thus

$$\begin{aligned} S_p = \{&s_{p,k} = (y_{p,k}, \tilde{x}_{p,k}) \in X_f \mid C_{\min}^p \\ &\leq R(\tilde{C}(s_{p,k})) \leq C_{\max}^p, E_{\min}^p \leq R(\tilde{E}(s_{p,k})) \\ &\leq E_{\max}^p, \mathrm{EX}_{\min}^p \leq \mathrm{EX}(s_{p,k}) \leq \mathrm{EX}_{\max}^p\} \end{aligned} \tag{9}$$

where values $C_{\min}^p, C_{\max}^p, E_{\min}^p, E_{\max}^p, \mathrm{EX}_{\min}^p, \mathrm{EX}_{\max}^p$ are values defined uniformly in the space of solutions.

To summarize, suitable optimizations are carried out for each element S_p of the partition, by successive minimizations of $R(\tilde{C}(y,\tilde{x})), R(\tilde{E}(\tilde{x}))$, and EX, in order to find proper planning solutions, subject to the above-mentioned mathematical constraints ($C_{\min}^p \leq R(\tilde{C}(y,\tilde{x})) \leq C_{\max}^p, E_{\min}^p \leq R(\tilde{E}(\tilde{x})) \leq E_{\max}^p$, and $\mathrm{EX}_{\min}^p \leq \mathrm{EX} \leq EX_{\max}^p$). The search for planning solutions is performed systematically in all elements of the partition and the obtained planning solutions compared among them in order to determine a set of nondominated solutions (as explained in more detail in Section III-C). Similar ideas can be affirmed for solving the multiobjective deterministic model (for two objective functions) when using the new Tabu search algorithm described in this paper.

III. New Tabu Search Algorithm for Multibobjective Optimal Planning

This section introduces the basic concepts of Tabu search [26]; afterward, fundamental concepts for the new Tabu search algorithm and this algorithm for multiobjective optimal planning of power distribution systems are described.

A. Basic Ideas of Tabu Search

A fundamental concept of the heuristic search is the local search. In this context, a solution is referred to as $\underline{s}$, the set of solutions as $\underline{S}$, and the objective function as $\underline{v(s)}$. Each solution $\underline{s} \in \underline{S}$ is associated with a set of neighboring solutions $\underline{N(s)} \subset \underline{S}$, called the neighborhood of $\underline{s}$. Each solution $\underline{s}' \in \underline{N(s)}$ may be reached directly from $\underline{s}$ by means of an operation called a "movement."

Tabu search [26] modifies the local search by introducing a memory mechanism that exploits the advantages deriving from the historical record or development of the search. Thus, Tabu search prohibits revisiting solutions stored in a Tabu list $\underline{TL}$ and that belong to $\underline{N(s)}$. In this way, searches are only performed in the set $\underline{N(TL,s)}$ (whose solutions are those of $\underline{N(s)}$ but having eliminated those stored in $\underline{TL}$). Tabu search has the following characteristics: 1) a short-term memory ("Tabu list"), which enables previously visited solutions to be avoided and local optimums to be exited, in order to intensify the search and 2) a long-term memory, which allows to visit zones that are distant and promising for diversifying the search.

TABLE I
TABU SEARCH METHOD

1. Initialization.

1.1. Selection of an initial solution. Initialize the current solution (to be stored in $\underline{s}_{now}$) with the initial solution

1.2. Initialize the Tabu List $\underline{TL}$, (which stores the solutions that have been reached previously) with the current solution.

1.3. Initialize the best solution (to be stored $\underline{s}_{best}$) with the current solution (stored in $\underline{s}_{now}$)

2. Search for a new solution.

2.1. Determine a new solution (to be stored in $\underline{s}_{new}$) of the $\underline{\text{Candidate-}N(TL,s_{now})}$ set, thus avoiding solutions stored in the Tabu List $\underline{TL}$.

2.2. Update the Tabu List $\underline{TL}$ with the new solution (stored in $\underline{s}_{new}$) and eliminate the oldest solution if the Tabu List is already full.

2.3. Acceptance criterion. For minimization of objective function $\underline{v}$, if $\underline{v}(\underline{s}_{new}) \leq \underline{v}(\underline{s}_{now})$ then this new solution (stored in $\underline{s}_{new}$) is the new current solution (to be stored in $\underline{s}_{now}$). If $\underline{v}(\underline{s}_{new}) \leq \underline{v}(\underline{s}_{best})$, the new solution (stored in $\underline{s}_{new}$) is the new best solution (to be stored in $\underline{s}_{best}$). If $\underline{v}(\underline{s}_{new}) > \underline{v}(\underline{s}_{now})$, the new solution will only be accepted if various iterations have been performed without any improvement in the objective function.

3. Stop criterion.

This process is repeated successively from step 2 until a specified stop criterion is fulfilled (maximum number of iterations or the objective function does not improve).

The basic algorithm of Tabu search can be followed in Table I. The search begins with a solution (stored in $\underline{s}_{now}$), and the best solution that is found at each moment (stored in $\underline{s}_{best}$) is $\underline{v}_{best} = \underline{v}(\underline{s}_{best})$. In each iteration, one solution is selected (stored in $\underline{s}_{new} \in \underline{\text{Candidate}}\text{-}\underline{N}(\underline{TL, s}_{now})$ corresponding to the most promising subset of $\underline{N}(\underline{TL, s}_{now})$). $\underline{TL}$ is gradually updated.

B. Fundamental Concepts in the New Tabu Search Algorithm for Power Distribution Optimal Planning

The NMTS algorithm for power distribution optimal planning uses basic ideas described in the previous Subsection A. We must now clarify some terms that are used to describe the algorithm. First, a feasible planning solution will be defined for distribution systems optimal planning. Then, we will describe the obtainment of the initial acceptable solution of the new Tabu search algorithm of this paper as well as the "movements" from a solution to another one. This will be followed by an explanation of the search process, the selection of the best movements to be performed, the treatment of the TL, and the acceptance criterion and stop criterion of the algorithm.

1) Structure of an Optimal Planning Solution: In the optimal planning of distribution systems, a search is performed for the best topology of feeders and substations (planning solution) in order to supply the power demanded by the demand nodes and to minimize one or more specified objectives: minimization of deterministic expected nonsupplied energy and minimization of deterministic economic cost (multiobjective deterministic model [12]); minimization of the removal of fuzzy economic cost, removal of fuzzy expected nonsupplied energy, and exposure (multiobjective fuzzy model [12]). These objective functions are subject to the technical constraint mentioned in Section II-D. Hence, in these multiobjective models, a feasible planning solution is formed by: 1) the localization and size of the selected feeders to be built; 2) the localization and size of the selected substations to be built; and 3) the optimal reserve feeders of the distribution system that maximize the reliability of the distribution network with minimal economic costs.

2) Initial Solution: A good acceptable initial solution (of the NMTS algorithm) is the one that minimizes the total length of the feeders (in the first instance, with only one size of feeder), which may be determined easily using the minimum spanning tree algorithm [27] modified accordingly (for various supply nodes). This solution fulfils the condition of radiality. Initially, it is accepted that feeder and substation power capacity limits and maximum voltage drop limits may be exceeded (these types of solutions are initially acceptable, despite being unfeasible, since new solutions without unfeasibilities are obtained in the optimization process).

3) Evaluation of A Planning Solution: In the multiobjective deterministic model, the objective functions $C(y, x), E(x)$ are obtained, and the technical constraints are analyzed by verifying whether or not they have been fulfilled. In the multiobjective fuzzy model, the objective functions $R(\tilde{C}(y, \tilde{x})), R(\tilde{E}(\tilde{x}))$, and EX are obtained.

The Tabu search algorithm uses integer variables to define the network topology (planning solution). Then, a power flow for radial distribution networks (deterministic [28] or fuzzy [15], [16]) enables to obtain the feeder flows, the voltages at the nodes, and the economic costs as well as to check the constraints (exposure for the fuzzy model). Also, the expected nonsupplied energy can be calculated, taking into account the reserve feeders (deterministic [29] or fuzzy [18]).

4) Neighborhood of A Solution: In a planning solution, neighboring solutions of the aforementioned solution are those that may be obtained from it by specific operations called "movements." The set of solutions (planning solutions) that are neighbors of another solution is referred to as a "neighborhood." Hence, the definition of the movements determines the corresponding neighborhood. We have defined the following as the simplest movements for modifying a solution.

a) Eliminate a substation in a network node.
b) Add a substation in a network node.
c) Change the size of a substation in a network node.
d) Eliminate a feeder that supplies power to a network node.
e) Add a feeder that supplies power to a network node.
f) Change the size of a feeder that supplies power to a network node.

The operations of eliminating, adding, and changing the size of a feeder can also be applied to reserve feeders that connect two network nodes. All the movements are associated with one network node, except movements on reserve feeders that are associated with two network nodes.

As indicated previously, we start from an initial radial distribution network. In order to maintain the radiality of the solutions obtained, a simple strategy was employed that consisted of eliminating first one feeder and then adding another feeder (which enabled this radiality to be maintained). The feeder that is eliminated (except when this is a reserve feeder) must be the feeder that supplies power to the node of the distribution network (network node). The feeder that is added has the same function, i.e.,

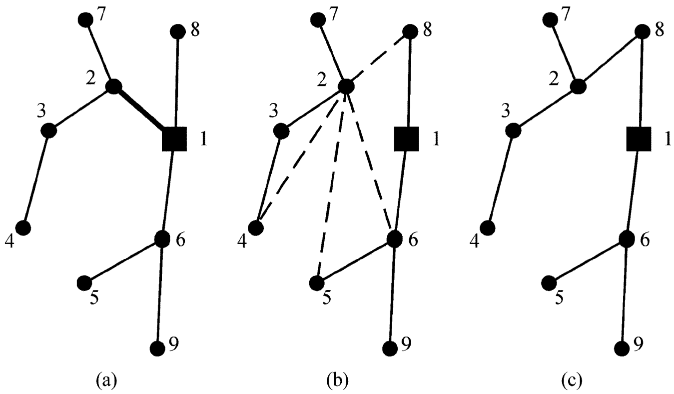

Fig. 2. Method for maintaining radiality.

it supplies power to the network node. Fig. 2 shows the method used for the exchange of a feeder.

Fig. 2(a) presents a radial solution of a distribution system formed by a substation on network node 1, various network nodes (nodes 2 to 9) with power demands and feeders that are represented by continuous segments. Fig. 2(a) shows the feeder (1, 2) that is to be eliminated. Fig. 2(b) shows that feeder (1, 2) has been eliminated, and it also shows (by dashed segments) other feeders (2, 8), (2, 4), (2, 5), and (2, 6) that can be connected to the network node 2. The feeder (2, 4) does not allow to supply power to all the network nodes; hence, it is the first one to fall from the candidate list. Fig. 2(c) shows that the final choice was feeder (2, 8), which maintains the radiality and connectivity of the network. The choice of one feeder or another is performed using an evaluation function (named "prospecting function," as described later), which can be different in each case, according to the objective function that we wish to study (minimize cost, minimize exposure, or improve reliability). The conductor size of the feeder that has been added will be the same as the size of the conductor of the eliminated feeder, since another movement is required in order to change the size of the conductor.

Another condition that must be imposed on the movements, in order to maintain radiality and connectivity, is that the elimination of a substation entails the elimination of all the feeders that leave the substation and the addition of feeders to supply the power demands of the nodes that are no longer able to be supplied from the eliminated substation.

Note that the conditions imposed on the movements achieve two effects: 1) the reduction of the memory that must be used to store completed movements (only the network node associated with the movement has to be stored); and 2) the maintenance of the condition of radiality (for all the movements performed).

5) Tabu List: The purpose of the TL is to prevent the search process from entering repetitive cycles that lead to the same solution. TL stores the network nodes on which movements have recently been performed; in this way, movements on network nodes, stored in TL, are forbidden; this avoids to visit nodes (that leads to solutions) explored recently (the longitude of TL is the closest integer to the square root of the number of network nodes).

6) Selection of "Elite Candidates": The evaluation of all the movements that can be performed in a network (planning solution) requires a prohibitive amount of time for the algorithm to be a success; therefore, a set of elite candidate nodes must be selected. To do so, for a current solution (of a given element of the partition), all the network nodes are evaluated using a "prospecting function" (a "prospecting function" for each objective function); this provides an idea of the success that will be achieved in the search (i.e., to obtain a better solution in the objective function to be improved); thus, the resulting order of network nodes is stored in a "list of elite candidate nodes" (a list of elite candidate nodes for each objective function) according to the aforementioned "prospecting function.". These prospecting functions are as follows.

a) *Prospecting function for cost.* Cost is evaluated using a function that calculates the difference between the cost of the feeder of the network node (feeder that supplies power to the node) and the lower cost of the next feeder to be connected to the node.
b) *Prospecting function for expected nonsupplied energy.* This function performs an approximate evaluation of the difference between expected nonsupplied energy before and after each movement (better improvements of expected nonsupplied energy are usually obtained by including movements of new reserve feeders in the network).
c) *Prospecting function for the degree of compliance with constraints.* This function, in the case of the multiobjective deterministic model, calculates in each network node the difference between the number of constraints that are not fulfilled with the current feeder and the number of constraints that are not fulfilled when changing this feeder (that supplies power to such node) or changing the size of its conductor to a larger one. In the case of the multiobjective fuzzy model, this function calculates in each network node the difference between the exposure of the current feeder and the exposure when changing the feeder or changing the size of its conductor to a larger one.

Once all the network nodes have been evaluated, the nodes are ordered by the prospecting function corresponding to the objective function to be minimized. In this way, we can determine which node is the most suitable in order to improve this objective function.

7) Obtainment of a Solution Using the Set of Candidate Nodes: Once the network node has been selected (belonging to the set of candidate nodes) on which we wish to perform a movement, each movement allowed in this node (demand node or substation node), or on the feeders that are connected to the node, produces a different solution. In order to determine the movement to be selected, and in order to obtain the next planning solution, each allowed movement is performed, and the objective function is evaluated directly. We then select the movement that achieves the best improvement of this function to be minimized.

8) Local Acceptance Criterion and Global Acceptance Criterion: For a given element of the partition of the solution space, with the local acceptance criterion, a new solution is accepted if its value is lower than the current value of the objective function (to be minimized) and if the corresponding mathematical constraints of the objective functions for the element of the partition are satisfied (see Section II-E).

As indicated later, the NMTS algorithm uses a set S_{ND} of current planning solutions "provisionally nondominated," i.e., the set of nondominated solutions at a given moment of algorithm execution. Then, for a given element of the partition, with the criterion of global acceptance, a new solution is always accepted if it is a provisionally nondominated solution. Then the set of S_{ND} is updated.

9) Local Stop Criterion and Global Stop Criterion: The global stop criterion of the search stops the NMTS algorithm if: 1) a specified number of global iterations (for example, 1000 iterations) has been carried out (one global iteration corresponds to one complete search in all the elements of the partition); or 2) if no provisionally nondominated solution has been found after a specified number of global iterations (for example, 20 iterations).

The local stop criterion stops the search in an element of the partition if, after a specified number of local iterations (for example, five iterations, where a local iteration corresponds to a movement for a new solution in the element of the partition), the obtained solutions are dominated. If this criterion stops the search in an element, a new search in a new element of the partition is carried out. Thus, this criterion allows diversification of the search when no provisionally nondominated solution is found in an element (during the specified number of iterations). Search diversification can be accentuated if we select network nodes that have not been visited yet or that have been received "few" visits. Each node stores the number of visits performed during the search process.

C. Tabu Search Algorithm for Multiobjective Optimal Planning of Power Distribution Networks

In the case of the fuzzy multiobjective model, the set S of solutions (where the NMTS algorithm carries out the search) contains set X_f (as well as certain solutions that are acceptable for the NMTS algorithm but unfeasible). Analogously, in the case of the multiobjective deterministic model, set S contains set X(as well as some solutions acceptable by the NMTS algorithm but unfeasible). The NMTS algorithm starts to calculate an acceptable initial solution of set S using the minimum spanning tree algorithm, which, thereafter, will be the current solution (stored in s_{now}). This solution will be the first "provisionally nondominated" solution that is stored in the set S_{ND}.

As indicated above, the search space is divided into elements of the partition (S_p denotes the pth element). These elements will be explored successively searching for "provisional nondominated" solutions (with respect to the current solutions of set S_{ND}). Normally, in a given element S_p, initially from a provisionally nondominated solution (of such element), the NMTS algorithm looks for new solutions (for such element). In a given local iteration, from the current solution (stored in s_{now}) of a given element S_p, by movements NMTS algorithm tries to find a solution that improves (successively) one or more objective functions. A new solution (stored in s_{new}) is not sought from among all the possible solutions (huge computational effort) but rather from among the solutions that can be obtained with movements in nodes of the neighboring set $N(TL, s_{now})$. This set is formed by network nodes that belong to the neighborhood of the solution stored in s_{now} and that are not prohibited by the constraints imposed by the TL. This set is still very big; hence, a set of candidates is selected, *Candidates*-$N(TL, s_{now})$, which is formed by the network nodes belonging to the set of elite candidate nodes selected by the prospecting function of a given objective function (in the multiobjective fuzzy model, the sets are *Candidates*-$N_{cost}(TL, s_{now})$, *Candidates*-$N_{eens}(TL, s_{now})$, and *Candidates*-$N_{\mathrm{ex}}(TL, s_{now})$, for the objective functions of fuzzy cost, fuzzy expected nonsupplied energy, and exposition, respectively. Similar concepts are stated for the multiobjective deterministic model). Each movement for a given objective function (for a given element S_p) leads to a new solution. (Note that the search is repeated for each objective function in order to improve each of them.) Thus, when a new solution (stored in s_{new}) has a better objective function value (to be minimized) than the current solution, then s_{now} is updated (for S_p) with the stored solution in s_{new} (local acceptance criterion). If additionally this new solution (stored in s_{new}) is provisionally nondominated (with respect to the solutions of the set S_{ND}), then it is stored in S_{ND} (global acceptance criterion), and the solutions of S_{ND}that are dominated by s_{new} are eliminated from S_{ND}. On the other hand, if this new solution (stored in s_{new}) is dominated, the search continues from that solution (for S_p). If the achieved solutions are dominated (along a given number of movements—local iterations), then the search in S_p is stopped (local stop criterion), and the search continues in another element of the partition.

As indicated above, the NMTS algorithm is stopped when the global stop criterion is fulfilled, i.e., if a given number of global iterations has been carried out or if no provisionally nondominated solution has been found after a specified number of global iterations.

Table II presents a description of the NMTS algorithm.

IV. Computational Results

The NMTS algorithm described in this paper has been intensively tested in large computational experiments for both multiobjective (deterministic and fuzzy) models and applied to real distribution systems of significant dimensions. A Spanish utility provided most of the data on distributions networks [12]. This section contains the main results of a multiobjective optimal planning case corresponding to an underground distribution network represented in Fig. 3. This figure shows an existing 10-kV feeder network (continuous segments) and the proposed routes (dashed segments) to build future 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 at node 181 is 15 MVA, and a future substation of two proposed sizes (31 MVA and 15 MVA) is proposed to be built at node 182.

In this section, first the sets of nondominated solutions (for this case) achieved by the NMTS algorithm are presented for

TABLE II
NMTS ALGORITHM

Step 1: Initialization process.

1.1. Select the multiobjective fuzzy model or the multiobjective deterministic model. Note that the objective functions are $R(\tilde{C}(y,\tilde{x}))$, $R(\tilde{E}(\tilde{x}))$ and *EX* for the fuzzy model. The objective functions are *C(y,x)* and *E(x)* for the deterministic model and the technical constraints must be satisfied (that are taken into account in step 2.2.4).

1.2. To search for an initial solution (acceptable for the NMTS algorithm) using the minimum spanning tree algorithm. Initialize s_{now} with the initial solution.

1.3. Generate the elements *Sp* of the partition of the solutions space.

1.4. Initialize the "provisionally nondominated" set of solutions S_{ND} using the solution stored in s_{now}

1.5. The Tabu List *TL* where the search history is stored is initialed empty.

Step 2: Search process.

2.1. Repeat the search for new nondominated solutions for each Sp element of the partition, until compliance with Local Stop Criterion in Step 2.2.

2.1.1. Choose a nondominated solution (stored in s_{now}) that belongs to a given element *Sp* of the partition and which has not been visited in recent global iterations (search diversification).

2.1.2. Search to improve the cost. *Choose:* Ordering of the network nodes (of the current solution stored in s_{now}) according to the prospecting function (of the objective function of cost) in the set *Candidates-*N_{cost}(*TL*, s_{now}). Choose the movement to be applied to the best ordered network node in candidate set *Candidates-*N_{cost}(*TL*, s_{now}); then apply this movement that leads to a new solution (stored in s_{new}).
Update: If the Local Acceptance Criterion is complied with, then update s_{now} with the new solution (stored in s_{new}). If the Global Acceptance Criterion is complied with, then update (using s_{new}) the set of "provisionally nondominated" solutions. Update the Tabu List, *TL*.

2.1.3. Search to improve expected non-supplied energy. *Choose*: Ordering of the network nodes (of the current solution stored in s_{now}) according to the prospecting function (of the objective function of expected non-supplied energy) in the set *Candidates-*N_{eens}(*TL*, s_{now}). Choose the movement to be applied to the best ordered network node in candidate set *Candidates-*N_{eenst}(*TL*, s_{now}); then, apply this movement that leads to a new solution (stored in s_{new}).
Update: If the Local Acceptance Criterion is fulfilled, then update s_{now} with the new solution (stored in s_{new}). If the Global Acceptance Criterion is complied with, then update (using s_{new}) the set of "provisionally nondominated" solutions. Update Tabu List, *TL*.

2.1.4. Search to improve the degree of compliance of constraints. *Choose*: ordering of the network nodes (of the current solution stored in s_{now}) according to the prospecting function (of the objective function of exposure for the multiobjective fuzzy model, or the prospecting function (described above in B.6) corresponding to the multiobjective deterministic model), in the set *Candidates-*N_{ex}(*TL*, s_{now}). Choose the movement to be applied to the best ordered network node in the candidate set *Candidates-*N_{ex}(*TL*, s_{now}); then, apply this movement that leads to a new solution (stored in s_{new}).
Update: If the Local Acceptance Criterion is complied with, then update solution s_{now} with the new solution (stored in s_{new}). If the Global Acceptance Criterion is complied with, then update (using s_{new}) the set of "provisionally nondominated" solutions. Update Tabu List *TL*.

2.2 Local Stop Criterion: The search in the current element *Sp* is stopped if, after a specified number of local iterations, the obtained solutions are dominated; then, the search continues (go to Step 2.1) from a provisionally nondominated solution of another element of the partition. Otherwise, a provisionally nondominated solution is found in *Sp* (before the specified number of iterations) and then the search continues (go to Step 2.1) in another element .

3. Global Stop Criterion. If the Global Stop Criterion is fulfilled (a specified number of global iterations have been carried out or no provisionally nondominated solution has been found after a specified number of global iterations) then the NMTS algorithm is stopped. Otherwise go to Step 2.

both multiobjective models; then, significant characteristics of the NMTS algorithm search are described.

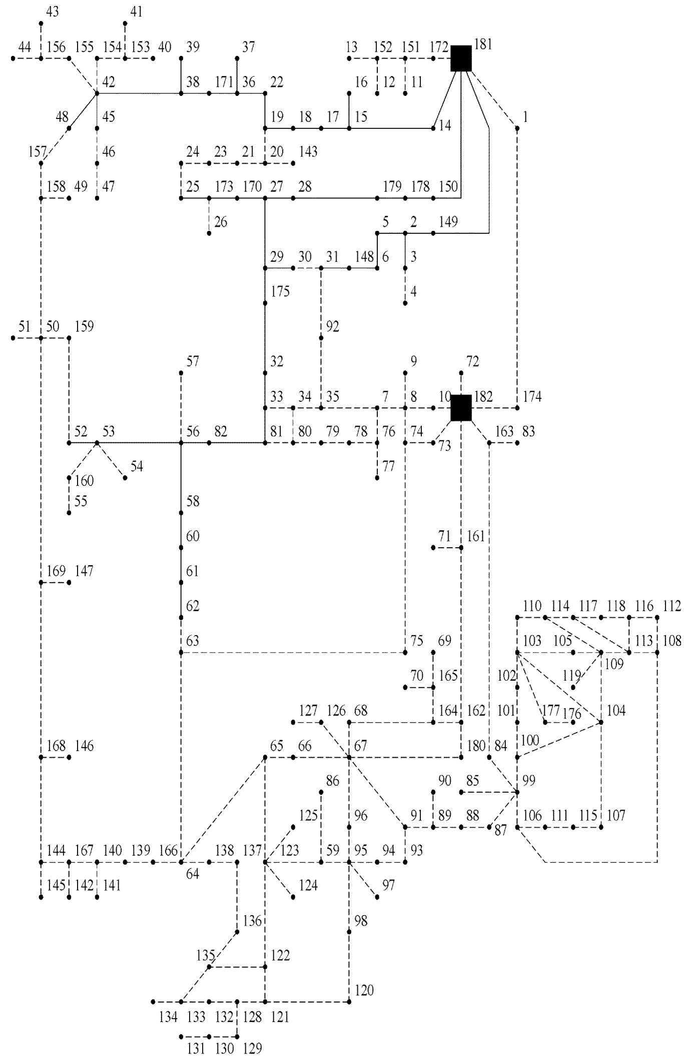

Fig. 3. Initial distribution system and proposed feeder routes.

A. Application of the NMTS Algorithm to Find the Set of Nondominated Solutions

The application of the NMTS algorithm determines the nondominated solutions obtained for the multiobjective fuzzy model and the multiobjective deterministic model of Section II.

The NMTS algorithm successively obtains a set of planning solutions when it is run. Thus, Figs. 4 and 5 show the set of these solutions achieved by the NMTS algorithm for the multiobjective deterministic model and for the multiobjective fuzzy model, respectively. In Fig. 4, the economic cost $C(y,x)$, in thousands of euros, is represented on the horizontal axis, and the expected nonsupplied energy $E(x)$, in kilowatthours, is represented on the vertical axis. In Fig. 5, the removal $R(\tilde{C}(y,\tilde{x}))$ of the fuzzy economic cost, in thousands of euros, is represented on the horizontal axis, and the removal $R(\tilde{E}(\tilde{x}))$ of the fuzzy expected nonsupplied energy, in kilowatthours, is represented on the vertical axis.

From the above-mentioned set of achieved planning solutions in Fig. 4, the corresponding nondominated ones are shown in Table III, i.e., 22 nondominated solutions obtained for the multiobjective deterministic model. In Table III, the number of the

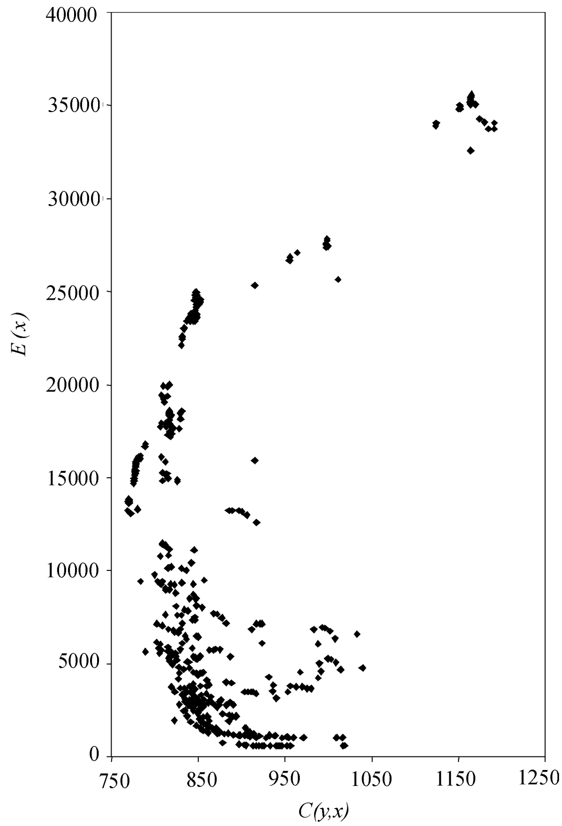

Fig. 4. Successive planning solutions obtained by NMTS algorithm for the multiobjective deterministic model.

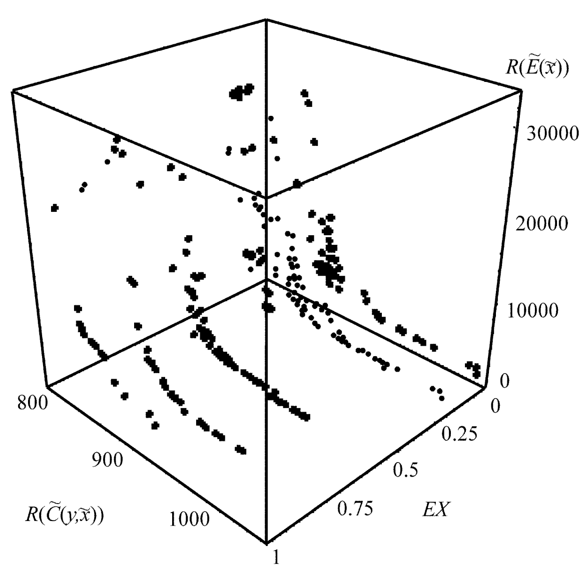

Fig. 5. Successive planning solutions obtained by NMTS algorithm for the multiobjective fuzzy model.

nondominated solution is denoted by the symbol ks, its economic cost is denoted by C_{ks}, and its expected nonsupplied energy by E_{ks}. From the set of achieved planning solutions in Fig. 5, the corresponding nondominated ones are shown in Table IV, i.e., 62 nondominated solutions obtained for the multiobjective possibilistic model. In Table IV, the number of the nondominated solution is denoted by the symbol *ks*, the removal of its fuzzy economic cost by $R(\tilde{C}_{ks})$, the removal of its fuzzy expected nonsupplied energy by $R(\tilde{E}_{ks})$, and its exposure by EX_{ks}.

TABLE III
NONDOMINATED SOLUTIONS OBTAINED BY NMTS ALGORITHM FOR THE DETERMINISTIC MODEL

ks	C_{ks}	E_{ks}	ks	C_{ks}	E_{ks}
1	768.52	13707.70	12	855.61	1392.83
2	768.62	13234.60	13	861.72	1298.15
3	772.50	13082.40	14	872.04	1250.13
4	783.64	9419.62	15	878.16	747.99
5	789.52	5640.65	16	897.06	672.94
6	805.17	5580.12	17	902.84	641.50
7	808.62	4284.71	18	905.04	612.90
8	828.32	1964.76	19	913.59	601.02
9	841.40	1889.63	20	920.32	592.54
10	848.29	1686.70	21	939.64	592.54
11	853.03	1563.67	22	943.81	592.54

TABLE IV
NONDOMINATED SOLUTIONS OBTAINED BY NMTS ALGORITHM FOR THE FUZZY MODEL

ks	$R(\tilde{C}_{ks})$	$R(\tilde{E}_{ks})$	EX_{ks}	ks	$R(\tilde{C}_{ks})$	$R(\tilde{E}_{ks})$	EX_{ks}
1	792.45	19608.70	0.20	32	907.63	2003.19	0.20
2	792.55	19425.70	0.20	33	911.63	1239.68	0.84
3	795.22	19162.60	0.09	34	920.59	1841.36	0.58
4	802.76	19568.60	0.00	35	926.41	1787.49	0.58
5	806.83	13995.80	0.20	36	926.61	1886.46	0.20
6	817.13	9863.47	0.56	37	930.61	1122.95	0.84
7	829.83	7109.44	0.20	38	932.43	1832.59	0.20
8	840.38	15901.10	0.04	39	932.99	2621.77	0.00
9	843.27	15720.10	0.04	40	936.44	1069.09	0.84
10	850.27	6817.68	0.59	41	937.17	2231.36	0.00
11	851.30	8539.93	0.00	42	937.98	1765.46	0.58
12	852.53	3499.96	0.59	43	938.00	1747.17	0.20
13	852.62	5889.97	0.58	44	938.64	1024.61	0.84
14	853.22	6878.54	0.20	45	941.82	2003.19	0.00
15	858.07	4618.73	0.58	46	944.10	1002.58	0.58
16	871.70	4920.28	0.00	47	944.78	1677.07	0.20
17	862.55	4094.62	0.58	48	950.88	986.86	0.58
18	864.49	3653.68	0.58	49	956.35	1655.04	0.20
19	871.13	3095.69	0.58	50	960.80	1886.46	0.00
20	875.53	4171.16	0.00	51	967.13	1832.59	0.00
21	875.84	4062.42	0.20	52	970.16	986.85	0.58
22	877.11	3496.03	0.00	53	974.34	986.84	0.58
23	878.07	2705.28	0.58	54	975.62	1655.03	0.20
24	882.72	2477.11	0.58	55	981.35	1747.17	0.00
25	885.31	2209.33	0.58	56	982.56	1655.02	0.20
26	888.01	2948.18	0.20	57	984.64	986.84	0.20
27	888.07	2572.96	0.20	58	988.13	1677.07	0.00
28	888.77	3462.70	0.00	59	999.70	1655.04	0.00
29	891.35	2047.14	0.58	60	1038.07	1655.03	0.00
30	901.61	1958.09	0.58	61	1045.01	1655.02	0.00
31	902.98	2231.36	0.20	62	1047.09	986.84	0.00

From the set of nondominated solutions achieved with the NMTS algorithm (for the multiobjective fuzzy model or the deterministic model), the planner can select the final nondominated solution, taking into consideration the most satisfactory objective functions values and taking into account his or her experience and professional point of view.

Furthermore, well-known methods [12], [17] can also be applied to select the final nondominated solution (from the set of nondominated solutions). Using a min–max approach [17] to select the final solution, from previous works [12], a final better planning solution is normally obtained from the set of nondominated solutions of the multiobjective fuzzy model, with a much lower expected nonsupplied energy and also with a substantially

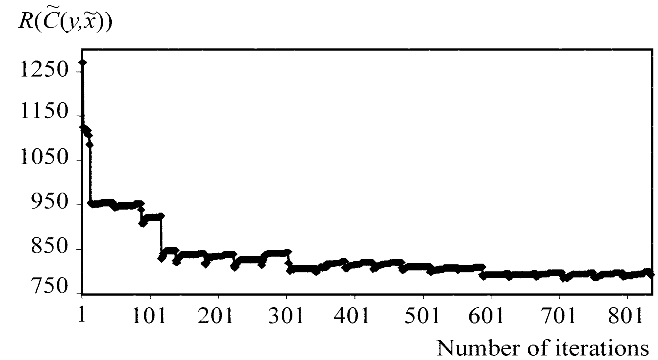

Fig. 6. Successive values of $R(\tilde{C}(y, \tilde{x}))$.

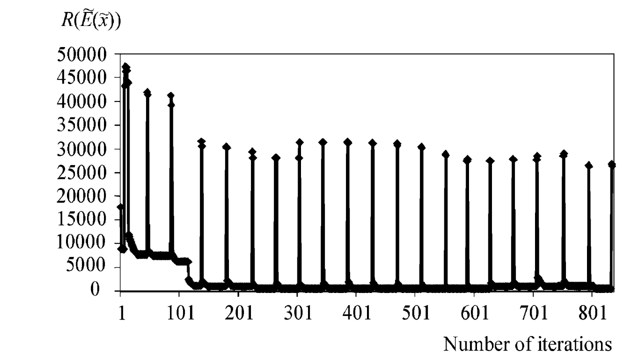

Fig. 7. Successive values of $R(\tilde{E}(\tilde{x}))$.

lower exposure (than the final planning solution of the set of nondominated solutions of the deterministic model); in other words, it is a more reliable and robust planning solution (with a very slight cost increase). Thus, from a technical standpoint, the final solution of the multiobjective fuzzy model is frequently much more satisfactory.

B. Characteristics of the Search of the New Tabu Search Algorithm

The NMTS algorithm performs an intensive search looking for optimizations of the three objective functions of the multiobjective fuzzy model. Thus, Fig. 6 shows the successive values of the removal of the objective function of fuzzy cost (of the multiobjective fuzzy model) on the vertical axis and the search iteration number on the horizontal axis. It reveals interesting aspects of the search, such as the provisional acceptance of solutions with higher removal of cost (to escape from local optima). Fig. 6 shows that there are iterations corresponding to search diversification movements, but this is clearer in Fig. 7. This figure shows the successive values of the removal of the objective function of expected nonsupplied energy on the vertical axis and the search iteration number on the horizontal axis. In Fig. 7, diversification movements are shown clearly since such movements have a more significant effect on this objective function. Fig. 8 shows the successive values of the objective function of exposure on the vertical axis and the search iteration number on the horizontal axis. It illustrates that movements often lead to nonsatisfied technical constraints (value 0 as exposure value) that are satisfied in subsequent iterations. It also shows that movements cause a wide search in the exposure values (between 0 and 1).

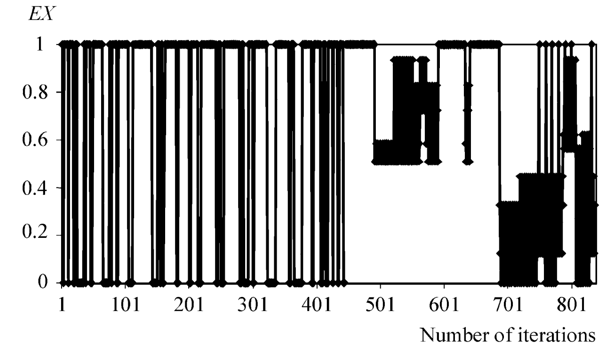

Fig. 8. Successive values of EX.

Similar comments can be made in relation to the characteristics of the search of the new Tabu search algorithm for the multiobjective deterministic model with respect to the objective functions of cost and expected nonsupplied energy.

V. Conclusion

This paper has presented an original metaheuristic algorithm (NMTS algorithm) for solving a novel multiobjective fuzzy model (and the corresponding multiobjective deterministic model) of power distribution optimal planning. A multiobjective optimization with minimization of the objective functions of fuzzy economic cost, fuzzy expected nonsupplied energy, and exposure is provided by the NMTS algorithm, which also determines the optimal location and size of the reserve feeders for maximizing the network reliability with the lowest cost for a given exposure level (robustness level). Thus, the NMTS algorithm obtains the set of nondominated multiobjective planning solutions. Later, this enables the planner to select the most satisfactory nondominated solution according to his or her experience.

Intensive testing has been carried out in real power distribution systems (with notably larger dimensions than other systems previously published) to validate the new algorithm (and the multiobjective fuzzy and deterministic models); these tests have also revealed its practical usefulness for application to large distribution networks. Often, the final solution achieved from the fuzzy model is much more satisfactory than the one from the deterministic model.

Significant characteristics of the NMTS algorithm (for both multiobjective models) are 1) intensification of the search for planning solutions using suitable prospecting functions to identify the best network candidate nodes (for each objective function); 2) diversification of the search through the discretization of the space of planning solutions using suitable elements of partition of this space; this also leads to a proper distribution of computational effort when searching among these elements; 3) the NMTS algorithm uses an original structure of movements on network nodes of the planning solutions, thus enabling the feasibility of the searched solutions to be maintained; 4) the design of the TL enables recently explored network nodes to be stored with a low utilization of computer resources; and 5) the NMTS algorithm achieves the set of nondominated solutions for both multiobjective models, i.e., the fuzzy and deterministic models.

Further research works about the improvement of the determination of fuzzy data and the possible effects of data uncertainty on planning solutions will be explored to expand the planning abilities of the fuzzy model presented in [12], which will be published in a future paper.

REFERENCES

[1] D. L. Wall, G. L. Thompson, and J. E. D. Northocote-Green, "An optimization model for planning radial distribution networks," *IEEE Trans. Power App. Syst.*, vol. PAS-98, no. 3, pp. 1061–1068, May/Jun. 1979.

[2] M. A. El-Kady, "Computer-aided planning of distribution substation and primary feeders," *IEEE Trans. Power App. Syst.*, vol. PAS-103, no. 6, pp. 1183–1189, Jun. 1984.

[3] M. Ponnavaikko, K. S. P. Rao, and S. S. Venkata, "Distribution system planning trough a quadratic mixed integer programming approach," *IEEE Trans. Power Del.*, vol. PD-2, no. 4, pp. 1157–1163, Oct. 1987.

[4] H. K. Youssef and M. A. Abu-El-Magd, "Novel optimization model for long range distribution planning," *IEEE Trans. Power App. Syst.*, vol. PAS-104, no. 11, pp. 3195–3202, Nov. 1985.

[5] H. Kuwabara and K. Nara, "Multi-year and multi-state distribution system expansion planning by multi-stage branch exchange," *IEEE Trans. Power Del.*, vol. 12, no. 1, pp. 457–463, Jan. 1997.

[6] I. J. Ramírez-Rosado and J. L. Bernal-Agustín, "Genetic algorithms applied to the design of large power distribution systems," *IEEE Trans. Power Syst.*, vol. 13, no. 2, pp. 696–703, May 1998.

[7] I. J. Ramírez-Rosado and J. L. Bernal-Agustín, "Reliability and costs optimization for distribution networks expansion using an evolutionary algorithm," *IEEE Trans. Power Syst.*, vol. 16, no. 1, pp. 111–118, Feb. 2001.

[8] V. Miranda, J. V. Ranito, and L. M. Proença, "Genetic algorithms in optimal multistage distribution network planning," *IEEE Trans. Power Syst.*, vol. 9, no. 4, pp. 1927–1933, Nov. 1994.

[9] Y. Tang, "Power distribution system planning with reliability modeling and optimization," *IEEE Trans. Power Syst.*, vol. 2, no. 1, pp. 181–189, Feb. 1996.

[10] V. Miranda and L. M. Proença, "A general methodology for distribution planning under uncertainty, including genetic algorithms and fuzzy models on a multi-criteria environment," in *Proc. IEEE/KTH Stockholm Power Tech Conf.*, Stockholm, Sweden, Jun. 1995, pp. 833–837.

[11] M. T. P. de Leão and M. A. Matos, "Fuzzy modeling independent producers for multicriteria electric distribution planning," in *Proc. IEEE/KTH Stockholm Power Tech Conf.*, Stockholm, Sweden, Jun. 1995, pp. 826–831.

[12] I. J. Ramírez-Rosado and J. A. Domínguez-Navarro, "Possibilistic model based on fuzzy sets for the multiobjective optimal planning of electric power distribution networks," *IEEE Trans. Power Syst.*, vol. 19, no. 4, pp. 1801–1810, Nov. 2004.

[13] J. T. Saraiva, V. Miranda, and L. M. V. G. Pinto, "Impact on some planning decisions from a fuzzy modeling of power systems," *IEEE Trans. Power Syst.*, vol. 9, no. 2, pp. 819–825, May 1994.

[14] W. Mielczarski, *Fuzzy Logic Techniques in Power Systems*. Heidelberg, Germany: Physica-Verlag, 1998.

[15] K. Kauhaniemi, "Fuzzy models and techniques for the calculation of radial distribution networks," in *Proc. IEEE/NTUA Athens Power Tech Conf.*, Athens, Greece, Sept. 5–8, 1993, pp. 423–428.

[16] A. D. Dimitrovski, "Iterative fuzzy load flow in radial distribution networks," in *Proc. 6th Int. Conf. Probabilistic Methods Applied Power Systems*, 2000, p. 6.

[17] Y. J. Lai and C. L. Hwang, *Fuzzy Multiple Objective Decision Making. Methods and Applications*. Berlin, Germany: Springer-Verlag, 1994.

[18] M. E. El-Hawary, *Electric Power Applications of Fuzzy Systems*. Piscataway, NJ: IEEE Press, 1998.

[19] D. Dubois and H. Prade, *Fuzzy Sets and Systems: Theory and Applications*, ser. Mathematics in Sciences and Engineering. New York: Academic, 1980, vol. 144.

[20] D. Dubois and H. Prade, *Théorie des Possibilités*. Paris, France: Masson, 1985.

[21] A. Kauffman and M. M. Gupta, *Fuzzy Mathematical Models in Engineering and Management Science*. Amsterdam, The Netherlands: Elsevier, 1988.

[22] A. Goicoechea, D. R. Hansen, and L. Duckstein, *Multiobjective Decision Analysis with Engineering and Business Applications*. New York: Wiley, 1982.

[23] R. Slowinski and J. Teghem, *Stochastic Versus Fuzzy Approaches to Multiobjective Mathematical Programming Under Uncertainty*. Dordrecht, The Netherlands: Kluwer, 1990.

[24] M. Zeleny, *Multiple Criteria Decision Making*. New York: McGraw-Hill, 1982.

[25] L. J. Cohon, *Multiobjective Programming and Planning*. New York: Academic, 1978.

[26] C. R. Reeves, *Heuristic Modern Techniques for Combinatorial Problems*. New York: Wiley, 1993.

[27] R. K. Ahuja, T. L. Magnanti, and J. B. Orlin, *Network Flows Theory, Algorithms, and Applications*. Englewood Cliffs, NJ: Prentice-Hall, 1993.

[28] D. Shirmohammadi, H. W. Hong, A. Semlyen, and G. X. Luo, "A compensation-based power flow method for weakly meshed distribution and transmission networks," *IEEE Trans. Power Syst.*, vol. 2, no. 2, pp. 753–762, May 1988.

[29] R. Billinton and R. N. Allan, *Reliability Evaluation of Power Systems*, 2nd ed. New York: Plenum, 1996.

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

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

Since 1992, he has been with the University of Zaragoza, where he is now a Professor Titular de Universidad. His current interest areas are applications of soft computing in electric power systems, power distribution networks planning, electric markets, and metaheuristic optimization.