GENETIC ALGORITHMS APPLIED TO THE DESIGN OF LARGE POWER DISTRIBUTION SYSTEMS

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Abstract: This paper presents the application of a new genetic algorithm for the optimal design of large distribution systems, solving the optimal sizing and locating problems of feeders and substations using the corresponding fixed costs as well as the true non-lineal variable costs. It can be also applied to single stage or multistage distribution designs.

The genetic algorithm has been tested with real size distribution systems achieving optimal designs in reasonable CPU times compared with respect to the dimensions of such distribution systems. On the other hand, these distribution systems present significantly larger sizes than the ones frequently found in the technical literature about the optimal distribution planning.

Furthermore, original operators of the genetic algorithm have been developed in order to obtain global optimal solutions, or very close ones to them. An integer codification of the genetic algorithm has been also used to include several relevant design aspects in the distribution network optimization.

Keywords: Power distribution systems, optimal design, genetic algorithms.

1. INTRODUCTION

The optimal power distribution system design has been frequently solved by using classical optimization methods during the last two decades for single stage or multistage design problems [1-7]. The basic problem has been usually considered as the minimization of an objective function representing the global power system expansion costs in order to solve the optimal sizing and/or locating problems for the feeder and/or substations of the distribution system. Some models [1] considered a simple linear objective function to represent the actual non-linear expansion costs, what leads to unsatisfactory representations of the real costs. On the other hand, mixed-integer models [2-7] achieved a better description of such costs by including fixed costs associated to integer 0-1 variables, and linear variable costs associated to continuous variables.

The most frequent optimization techniques to solve these models have been the branch and bound ones. These kinds of methods need large amounts of computer time to achieve the optimal solution, especially when the number of integer 0-1 variables grows for large power distribution systems.

The model of reference [8] contained the non-linear variable expansion costs and used dynamic programming that requires excessive CPU time for large distribution systems.

Other authors [9-10] proposed a distribution planning heuristic method, that is faster than classical ones but the obtained solutions are sometimes local optimal solutions. This model takes into account linearized costs of the feeders, that is, a linear approximation of the non-linear variable costs.

On the other hand, genetic algorithms [17-18] have solved industrial optimization problems [19] in recent years, achieving suitable results.

Genetic algorithms have been applied to the optimal multistage distribution network design [11] and to the street lighting network design [12]. In these works, a binary codification was used, but this codification makes difficult to include some relevant design aspects in the mathematical models. However the integer codification introduced in this paper surpasses these limitations.

In previous works [13] the authors have used a binary codification for a genetic algorithm, which was applied to the optimal design of distribution systems. The results obtained in these works have shown good possibilities of the genetic algorithms to look for solutions for the distribution networks design. Such results were compared with respect to the ones of the classical optimization methods, improving significantly the CPU times when the same solutions were achieved by the genetic algorithm and such classical methods.

This paper presents a new genetic algorithm for the optimal distribution system design. It can solve single stage or multistage problems (in this last case, under the "pseudodynamic methodology" [2, 7]). The algorithm has been tested with real dimensions distribution systems that have larger dimensions than the ones usually found in the technical literature. Novel operators of the genetic algorithm have been developed, that allow for getting out of local optimal solutions and obtaining the global optimal solution or solutions very close to such optimal one. This algorithm

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considers the true non-linear variable cost and it also obtains the distribution nodes voltages and an index that gives a measure of the distribution system reliability. As above mentioned, the new algorithm includes an integer codification, which allows for more flexibility, taking into account several design aspects as, for example, different conductor sizes, different sizes of substations, and suitable building of additional feeders for improving the network reliability. At the present time, this last aspect is being applied to the multiobjective distribution planning [14-16], to be presented in a future paper, where two objective functions referring to the costs and the reliability of the distribution network are simultaneously optimized.

2. GENETIC ALGORITHMS

The genetic algorithms [17-18] are part of the evolutionary algorithms family which are computational models inspired in the Nature. Genetic algorithms are usually considered as functions optimizers [17].

The first assumption usually established is that any variable of the optimization problem can be codified or represented by means of bit strings. Each one of the codified possible solutions for the studied problem is an individual. For example, if the number 47 is a possible solution then it can be codified as follows 000101111 where a binary codification has been used.

The genetic algorithms work with a set of individuals (codified solutions) that constitutes a population. Such population is able to evolve in a given environment by application of the processes of selection, reproduction, crossover and mutation. The strongest individuals (solutions) survive during the optimization process.

The first step of any genetic algorithm is to generate the initial population. A binary string of length L is associated to each member (individual) of the population. The string is usually known as a chromosome and represents a solution of the problem. A sampling of this initial population creates an intermediate population. Thus some operators (reproduction, crossover and mutation) are applied to this new intermediate population in order to obtain a new one. The process, that starts from the present population and leads to the new population, is named a generation when executing a genetic algorithm.

Reproduction is an operator that obtains a fixed number of copies of solutions according to their scores. If the score increases then the number of copies increases too. A score value is associated to a given solution according to its distance to the optimal solution (closer distances to the optimal solution mean higher scores).

The universal stochastic method (used in this work for the reproduction operator) considers a roulette wheel with a fixed number of boxes. Figure 1 shows this roulette wheel and Table 1 gives the associated values. In this case the population consists of four solutions (individuals). The total number of boxes of the roulette wheel is equal to the number of copies of the solutions. Figure 1 shows the roulette wheel with sixteen boxes for the four solutions. The score of a given solution determines the number of boxes associated to such

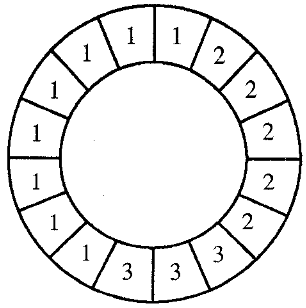

Fig.1. Roulette Wheel

TABLE 1

n	S	C
1	0.506	8
2	0.301	5
3	0.192	3
4	0	0

n=Solution number
S=Score
C=Copies

solution. Thus, in Table 1, eight copies (boxes) correspond to the first solution, five copies to the second solution, etc.

Crossover is an operator used by genetic algorithms for the search process. It leads to a mixture of solutions. For example, if the following solutions,

1001011110110   0101010011101

are crossed, then two new solutions are obtained, which are,

1001010011101   0101011110110

The mixture is performed by choosing a point of the strings randomly and switching their segments to the left of this point. The new strings belong to the next generation of possible solutions. The strings to be crossed are selected according to their scores using the roulette wheel. Thus, the strings with larger scores have more chances to be crossed with other strings because all the copies in the roulette wheel have the same probability to be selected. For example, in Figure 1 the solution number 1 has eight copies and its probability to be selected is 0.5, since there are sixteen boxes.

The crossover rate(C) is the factor that determines the number of crossed strings in a generation. If the population size is N, then N*C strings suffer the described mixture process.

The mutation operator is defined by a random bit value change in a chosen string with a low probability of such change. The mutation adds a random search character to the genetic algorithm, and it is necessary to avoid that, after some generations, all possible solutions were very similar ones. All strings and bits have the same probability of mutation. For example, in the string 10011101101 if the mutation affects to the bit number six, the string obtained is 10011001101. The mutation rate (M) is the number that determines the mutations that are carried out in a generation. If L is the string length (in our example it is twelve), then M*N*L bits change their value in each generation. Generally M is a small number.

3. PROBLEM FORMULATION

In this paper, the optimal design model is basically a mixed-integer non-linear one for the optimal sizing and location problems of feeders and substations, that can be used for single stage or for multistage planning (under a "pseudodynamic methodology" [2, 7]), where it is assumed that the existing distribution network is expanded from an initial state throughout a given planning period.

The model contains an objective function that represents the investment costs of future feeders and substations as well as the true non-linear variable costs associated to the operation of the distribution system.

The objective function to be minimized is:

$$\sum_{(i,j)\in N_F}\sum_{a\in N_a}\left\{(CF_{ij})_a(Y_{ij})_a+(CV_{ij})_a\left[(X_{ij})_a^2+(X_{ji})_a^2\right]\right\}+$$
$$\sum_{k\in N_S}\sum_{b\in N_b}\left[(CF_k)_b(Y_k)_b+(CV_k)_b(X_k)_b^2\right]+$$
$$\sum_{(i,j)\in N_{FE}}(CV_{ij})_E\left[(X_{ij})_E^2+(X_{ji})_E^2\right]+\sum_{k\in N_{SE}}(CV_k)_E(X_k)_E^2 \qquad (1)$$

where,

N_{FE} = set of routes (between nodes) associated with existing feeders in the initial network.

N_{FP} = set of proposed feeder routes (between nodes) to be built.

N_{FR} = set of routes (between nodes) associated with selected routes for building feeders. Only the feeder size is a variable.

$N_F = N_{FP} \cup N_{FR}$

N_a = set of proposed feeders sizes to be built.

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

N_{SP} = set of nodes associated with proposed locations for building substations.

N_{SR} = set of nodes associated with selected locations for building substations. Only the substation size is a variable.

$N_S = N_{SP} \cup N_{SR}$

N_b = set of proposed substation sizes to be built.

(i,j) = route between nodes i and j.

$(X_k)_b$ = Power flow, in kVA, supplied from node $k \in N_S$ associated with a substation size b.

$(X_{ij})_a$ = Power flow, in kVA, carried through route $(i,j) \in N_F$ associated with a feeder size a.

$(X_k)_E$ = Power flow, in kVA, supplied from node k associated with an existing substation in the initial network.

$(X_{ij})_E$ = Power flow, in kVA, carried through route (i,j), associated with an existing feeder in the initial network.

$(CV_{ij})_E$ = Variable cost coefficient of an existing feeder in the initial network, on route (i,j).

$(CV_{ij})_a$ = Variable cost coefficient of a feeder to be built with size a, on route (i,j).

$(CF_{ij})_a$ = Fixed cost of a feeder to be built with size a, on route (i,j).

$(CV_k)_E$ = Variable cost coefficient of an existing substation in the initial network, in the node k.

$(CV_k)_b$ = Variable cost coefficient of a substation with size b, in the node k.

$(CF_k)_b$ = Fixed cost of a substation to be built with size b, in the node k.

The minimization of the objective function is subject to technical constraints, that are the Kirchhoff's current law for the nodes of the distribution system, and the power capacity limits of the feeders and the power supply limits of substations.

Thus, the Kirchhoff's current law is

$$D_k-(X_k)_E-\sum_{b\in N_b}(X_k)_b=\sum_{i\in N_{kP}}\sum_{a\in N_a}\left[(X_{ik})_a-(X_{ki})_a\right]+$$
$$\sum_{i\in N_{kE}}\left[(X_{ik})_E-(X_{ki})_E\right] \qquad (2)$$

where:

D_k = Power demand of node k.

N_{kP} = set of proposed nodes to be connected to node k.

N_{kE} = set of nodes that are connected to node k.

The power capacity limits and supply limits constraints are:

For a future feeder:

$$0\le(X_{ij})_a\le(U_{ij})_a(Y_{ij})_a \quad ; \quad 0\le(X_{ji})_a\le(U_{ij})_a(Y_{ij})_a \qquad (3)$$
$$\forall(i,j)\in N_{FP} \quad ; \quad \forall a\in N_a$$

For an existing feeder:

$$0\le(X_{ij})_E\le(U_{ij})_E \quad ; \quad 0\le(X_{ji})_E\le(U_{ij})_E \qquad (4)$$
$$\forall(i,j)\in N_{FE}$$

For a selected route for building a feeder:

$$0\le(X_{ij})_a\le(U_{ij})_a \quad ; \quad 0\le(X_{ji})_a\le(U_{ij})_a \qquad (5)$$
$$\forall(i,j)\in N_{FR} \; ; \; \forall a\in N_a$$

For a future substation:

$$0\le(X_k)_b\le(U_k)_b(Y_k)_b \; ; \; \forall k\in N_{SP} \; ; \; \forall b\in N_b \qquad (6)$$

For an existing substation:

$$0\le(X_k)_E\le(U_k)_E \; ; \; \forall k\in N_{SE} \qquad (7)$$

For a selected node for building a substation:

$$0\le(X_k)_b\le(U_k)_b \quad ; \; \forall k\in N_{SR} \; ; \; \forall b\in N_b \qquad (8)$$

where:

$(Y_k)_b = 1$, if substation with size b associated with node k $\in (N_{SP})$ is built. Otherwise, it is equal to 0.

$(Y_{ij})_a = 1$, if feeder with size a associated with route $(i,j) \in (N_{FP})$ is built. Otherwise, it is equal to 0.

$(U_{ij})_a$ = Power capacity limit of a feeder with size a associated with route $(i,j) \in N_F$.

$(U_{ij})_E$ = Power capacity limit of an existing feeder in the initial network, associated with route $(i,j) \in N_{FE}$.

$(U_k)_b$ = Power capacity limit of a substation of size b associated with node $k \in N_S$.

$(U_k)_E$ = Power capacity limit of an existing substation in the initial network, associated with node $k \in N_{SE}$.

The above described model is a mixed-integer non-linear one that includes the true non-linear variable costs to find out the optimal solution. Furthermore, these costs can be linearized what leads to the corresponding mixed-integer linear model [6-7]. The proposed genetic algorithm of this paper has been applied to solve design problems of real dimensions distribution systems using these two models, that is, using the true non-linear variable costs and the linear ones. Furthermore, the design models can include voltage drop constrains [6-7].

4. THE PROPOSED ALGORITHM

A new genetic algorithm has been applied to the mentioned mixed-integer models for the optimal distribution systems design. The algorithm allows to find out the optimal feeders and substations to be built for the future expansion of an existing distribution network in order to meet its future power demand requirements, taking into account the voltage drop limits in the demand nodes. Furthermore, the algorithm also obtains an index used to evaluate the power distribution system reliability for radial operation of the network even though such network can present a non-radial topology, that is, with feeders "in reserve" that are not usually in operation but that can be used for reconfigurations of the network.

New concepts and original aspects of the implemented genetic algorithm are going to be presented in the following paragraphs.

A non-binary codification has been selected because of its simplicity and its capabilities to include much more information than a binary alphabet. Furthermore, the possibility of including new design aspects makes this codification more flexible. For example, the following strings

021002210101   10

can represent a distribution system topology. In the first string there are seven distribution network routes with built feeders and five routes without built feeders (zero indicates that the corresponding feeder has not been installed). Four built feeders have the size number 1 and the remaining three ones have the size number 2. The second string represents the possible locations for two substations where there is only a built substation (with size 1). Therefore, this kind of codification includes several feeder and substation sizes.

In order to evaluate the solutions, the variable costs associated to a topology that represents an individual (that is, a solution of the distribution system) have to be obtained from the results of the corresponding transhipment problem. Since these computations have to be carried out many times in each generation, the algorithm should work very fast. Traditional simplex algorithms are not efficient enough to overcome this problem and, therefore, we decided to use the algorithm proposed by Grigoriadis [20], achieving important CPU time savings compared with respect to the traditional methods. This algorithm, described in [21], was tested and its efficiency was proved for solving large minimum-cost network flow problems.

During crossover and mutation some strings are replaced by new ones. Thus, some criteria used for the elimination of strings are the following ones:

Regarding crossover: Higher number of copies in the roulette wheel leads to lower replacement probability in the next generation.

Regarding mutation: A mutated string is replaced by the new string obtained by the mutation operator. This avoids that some strings become very similar to other strings.

In order to keep the best configurations (solutions) when moving from one generation to the next one, a protection technique, named "elitist" one in the specialized literature, has been used.

Common genetic algorithms can present an early convergence to solutions what difficulties the process to find out the optimal solution. An original "mutation factor" (developed by the authors) is introduced in order to try to solve this problem. If the mutation factor is f_m, then a string of length L will undergo L/f_m mutations. Thus, a multiple mutation is applied in order to try to avoid local optimal solutions. However, in large distribution systems, it is possible to fall into a local optimal solution even though we use the multiple mutation technique. In order to overcome this limitation, a new operator, called, by the authors, "epidemy" has been implemented allowing the algorithm to achieve the global optimal solution or very close ones to such optimal solution. This operator eliminates all the solutions except those with the best scores. In the algorithm the number of solutions to be saved can be specified as well as the gap between generations when this operator is applied. The eliminated solutions are then replaced by new generated ones in order to refresh the information processed by the algorithm and to get out of local optimal solutions.

The novel characteristics described above are the most important ones of the developed algorithm.

The planner specifies the size of the population as well as the number of generations to be carried out, increasing this number with the dimension of the distribution system. The size of the population must be large enough to obtain sufficient kinds of topologies so that the algorithm can achieve the optimal solution, getting out of local optimal solutions. Furthermore, the rate of mutation and the rate of crossover has to be specified.

After the execution and the selection of some solutions, the program can be restarted with such solutions that become now the initial population. This is useful when dealing with large distribution systems or when the planner looks for better solutions.

5. COMPUTATIONAL RESULTS

The genetic algorithm has been tested with large distribution systems of different sizes. A PC compatible 150 MHz Pentium with 16 Mb of RAM, the Linux 3.0 operating system and the gcc compiler has been used.

Before applying the algorithm to large distribution networks, some tests were carried out in order to determine the best values for the parameters that control the genetic algorithm.

The optimal design processes of diverse distribution systems with several dimensions were studied from the point of view of results and computation times, which indicated that a suitable population can include around 150 individuals. Any increase in this parameter did not lead to better results. The best crossover rate was around 0.3, the best mutation rate around 0.02 and the mutation factor was between 10 and 50, depending on the distribution network.

Table 2 shows relevant characteristics of three real dimensions distribution systems used for testing the genetic algorithm. Most data of the distribution networks have been provided by a Spanish electric utility. Notice that the large numbers of 0-1 variables of the three distribution networks indicate that the dimensions of such networks surpass the dimensions of the ones usually described in the technical

TABLE 2
CHARACTERISTICS OF THE DISTRIBUTION SYSTEMS

CASE	1	2	3
Nodes of the network	201	201	417
Existing routes	106	43	88
Proposed routes	121	184	385
Number of variables 0-1	318	370	674
Best linear objective function value	1274	1304	2492
Best non-linear objective function value	1214	1251	2412
CPU time for the "linear solution"	0.79	3.14	15.1
CPU time for the "non-linear solution"	1.2	3.56	15.25

literature about the optimal distribution planning. The CPU times, in hours, for the "non-linear solution" (using the non-linear mixed-integer model) and for the "linear solution" (from the linear model) can be considered as low CPU times from the point of view that classic enumerative algorithms are not able to solve these real dimensions problems, in reasonable CPU times, in practice. In Table 2, the objective function values are given in millions of pesetas.

Only the main data and results of case 2 of Table 2 will be presented in this paper due to the lack of space. Figure 2 shows the existing 10 kV distribution system of case 2 and the routes proposed to build future underground feeders with two feeder sizes (3x150Al and 3x1x400Al). The existing feeders are represented by continuous lines and the proposed routes by dashed lines. The existing feeder 104-107 correspond to a feeder "in reserve" that is not connected to the initial system. Table 3 gives the power demand requirements of the distribution network nodes that have to be met in the future. Figure 3 shows the best distribution network design solution obtained by the optimization process carried out with the genetic algorithm (using the non-linear model). This genetic algorithm used a population of 150 individuals, a crossover rate of 0.3, a mutation rate of 0.02 and a mutation factor of 30. Table 4 gives the values of voltage levels at the end-nodes of the distribution system represented in Figure 3. Figure 4 shows the cost values evolution of the best solution of each generation obtained by the algorithm. The vertical axis of Figure 4 represents the cost values (objective function values) for the generations represented in the horizontal axis. Dashed lines correspond to the objective function values which distance from the best solution is 1%, 0.5% and 0.2%. It can be observed the typical evolution of the genetic algorithm: First, the objective function value improves very fast and later this improvement slows down when the number of generations increases. Therefore, we can achieve very good solutions in significant lower CPU times than the one for the best solution. For example in case 2, good solutions, with distances of 1%, 0.5% and 0.2% from the best solution, can be obtained in 0.52, 0.78 and 2.14 hours respectively for the mixed-integer non-linear model (with actual non-linear variable costs).

The program can be also used to achieve the best solution for the mixed-integer linear model (with linear variable costs). In the case 2, feeders 48-20, 29-38, 38-48, 21-52, 25-29, 52-25 and 32-21 are built with feeder size 3x150Al using

TABLE 3
POWER DEMAND REQUIREMENTS, IN kVA.

Node #	Power Demand	Node #	Power Demand	Node #	Power Demand	Node #	Power Demand
1	0	52	135	102	79	152	67
2	135	53	0	103	86	153	86
3	0	54	47	104	216	154	216
4	0	55	135	105	135	155	62
5	127	56	13	106	61	156	135
6	57	57	86	107	42	157	0
7	92	58	55	108	24	158	3
8	0	59	0	109	0	159	1
9	135	60	67	110	86	160	58
10	135	61	79	111	135	161	216
11	86	62	135	112	42	162	11
12	55	63	86	113	135	163	142
13	75	64	106	114	30	164	18
14	79	65	134	115	71	165	41
15	0	66	86	116	0	166	171
16	0	67	114	117	0	167	0
17	86	68	58	118	0	168	23
18	33	69	63	119	0	169	87
19	13	70	190	120	88	170	23
20	1	71	134	121	274	171	30
21	216	72	43	122	0	172	114
22	86	73	132	123	55	173	135
23	86	74	54	124	55	174	80
24	86	75	0	125	55	175	55
25	135	76	55	126	55	176	135
26	116	77	49	127	55	177	216
27	0	78	90	128	86	178	0
28	86	79	147	129	135	179	86
29	270	80	216	130	69	180	91
30	86	81	23	131	117	181	59
31	86	82	135	132	135	182	135
32	50	83	3	133	86	183	71
33	134	84	58	134	86	184	96
34	216	85	114	135	0	185	91
35	135	86	23	136	94	186	0
36	86	87	23	137	9	187	186
37	0	88	23	138	135	188	0
38	0	89	5	139	39	189	0
39	107	90	23	140	61	190	146
40	135	91	0	141	170	191	23
41	78	92	23	142	351	192	23
42	64	93	20	143	117	193	23
43	0	94	135	144	22	194	23
44	135	95	129	145	105	195	23
45	135	96	8	146	42	196	0
46	135	97	71	147	92	197	23
47	96	98	54	148	56	198	0
48	86	99	18	149	86	199	0
49	0	100	86	150	135	200	58
50	135	101	132	151	113	201	0
51	135						

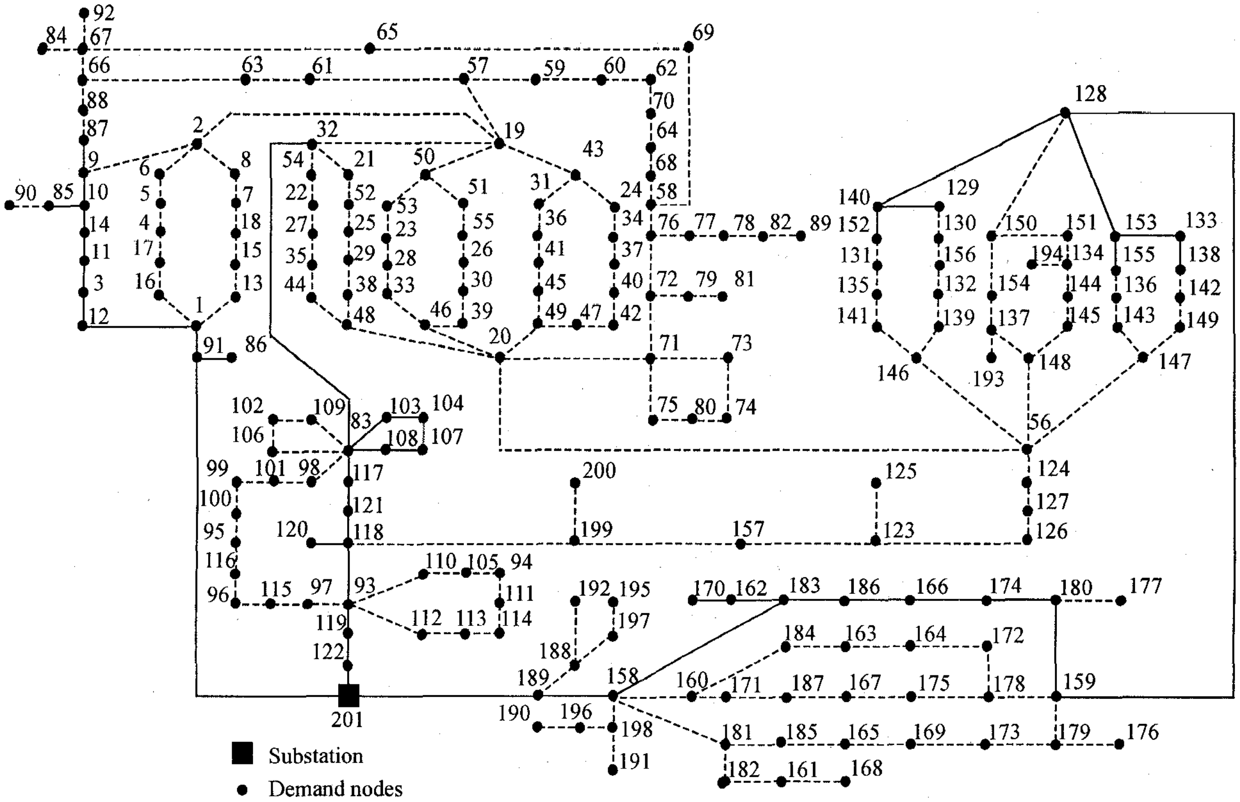

Fig.2 . Existing feeders and proposed routes (Distribution system of the case 2).

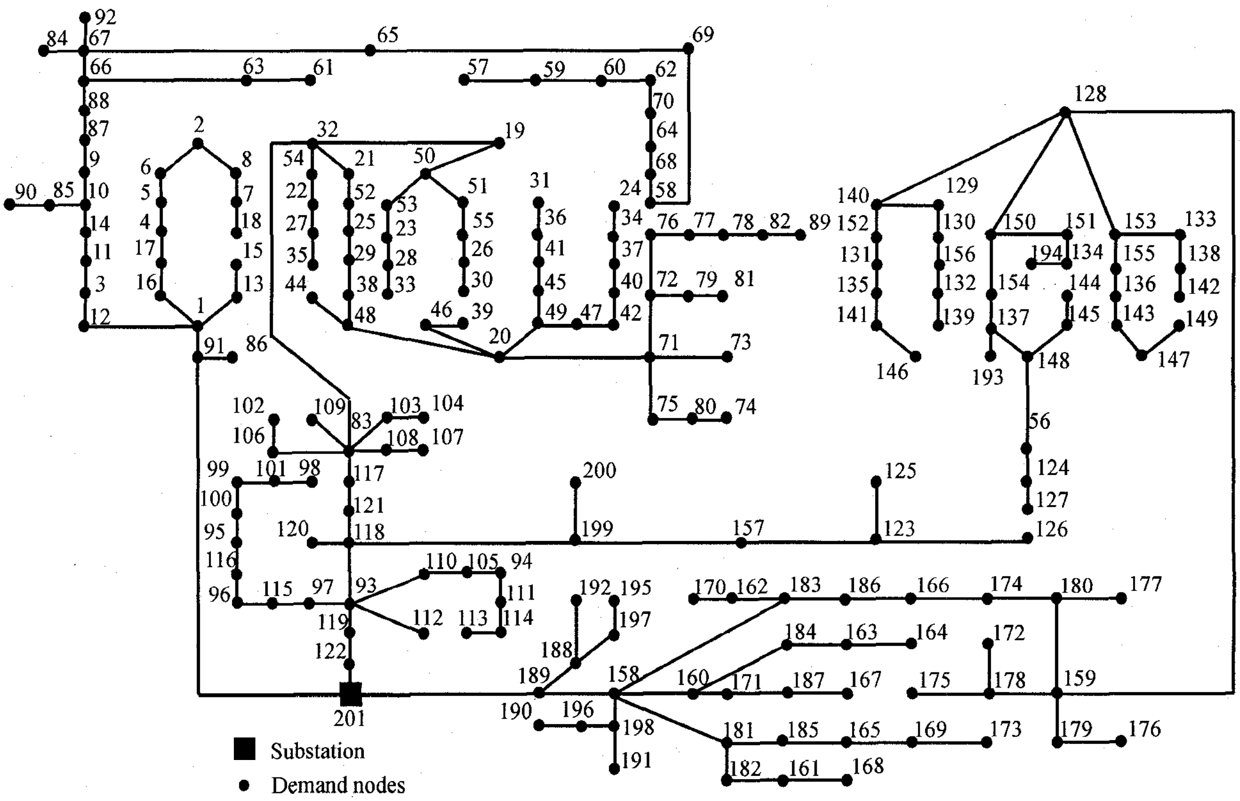

Fig.3 . Optimal design of the distribution system of the case 2. Mixed-integer non-linear model.

the linear variable costs model and, however, with size 3x1x400Al using the non-linear one. Furthermore, in the case 1, as well as in the case 3, there are some differences between the topologies (and the feeder sizes) obtained using the true non-linear costs and the linear costs. Thus, the non-linear mixed-integer model achieves lower global costs than the linear one even thought causing the investment costs to increase. All this illustrates the influence of the costs modelling in the distribution network topology achieved by the optimization process.

TABLE 4
VOLTAGE LEVELS AT THE END-NODES, IN kV

Node #	Voltage Level	Node #	Voltage Level	Node #	Voltage Level	Node #	Voltage Level
15	9.93	81	9.76	120	9.90	172	9.85
18	9.91	84	9.82	125	9.90	173	9.95
24	9.76	86	9.96	126	9.90	175	9.85
30	9.82	89	9.75	127	9.78	176	9.85
31	9.77	90	9.86	139	9.78	177	9.87
33	9.82	92	9.82	142	9.78	190	9.96
35	9.83	98	9.91	144	9.78	191	9.96
39	9.78	102	9.84	146	9.78	192	9.98
44	9.79	104	9.84	149	9.78	193	9.78
57	9.80	107	9.84	164	9.95	194	9.79
61	9.82	109	9.85	167	9.95	195	9.98
73	9.76	112	9.93	168	9.95	200	9.90
74	9.76	113	9.92	170	9.92		

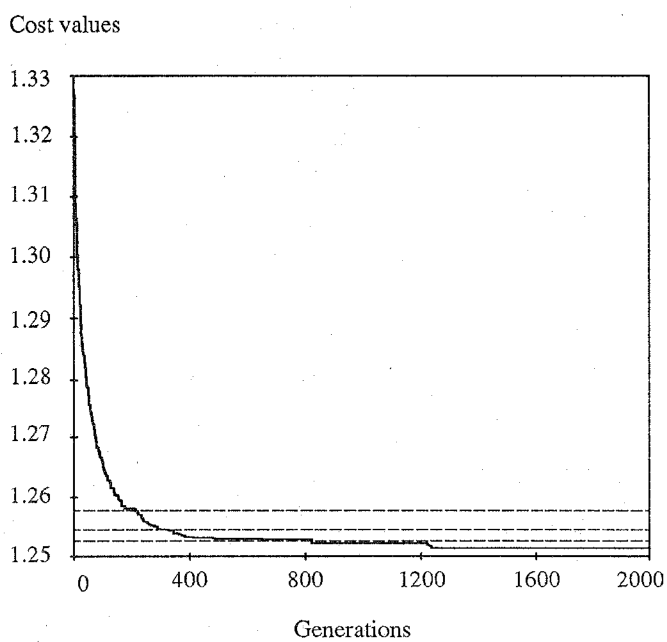

Fig. 4. Evolution of the cost values of the best solution from the genetic algoritm.

6. CONCLUSIONS

In this paper, a new and efficient genetic algorithm has been presented for the optimal design of large power distribution systems corresponding to a mixed-integer non-linear model as well as a mixed-integer one, that consider non-linear variable costs and linearized costs respectively.

These models represent the optimal sizing and locating problems of feeders and substations and they can be used for single stage or multistage distribution systems design.

The developed genetic algorithm is a good alternative to the classical branch and bound algorithms to solve mixed-integer models for large distribution networks design due to the corresponding large amounts of CPU time savings that can be achieved by such genetic algorithm. Thus, this genetic algorithm has obtained optimal designs for real dimensions distribution systems in reasonable CPU times compared with respect to the dimensions of such systems, using the above mentioned non-linear or linearized costs. Furthermore, the distribution systems used to test the new genetic algorithm have considerable larger dimensions than the ones usually presented in the technical literature about the optimal planning of distribution networks.

The results of tested practical problems have shown the influence of the costs modelling in the network topology designed for the distribution system. Thus, the non-linear variable cost model achieves lower global expansion costs than the linear one even though causing the investment costs to increase.

Novel operators of the genetic algorithm have been developed in order to obtain the global optimal solution or very close ones to such optimal solution. Also, the genetic algorithm binary codification of previous works of the authors have been replaced by an integer codification that allows for including several relevant design aspects in the optimization process as, for example, feeders and substation sizing, and suitable building of additional feeders in order to improve the distribution system reliability. At the present time, this last aspect is being applied to the multiobjective distribution planning that will be presented in a future paper.

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