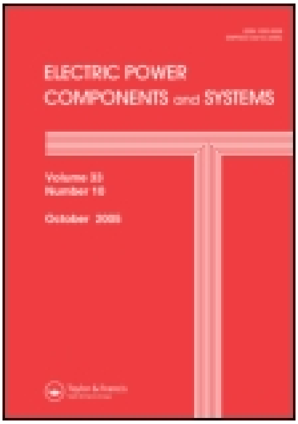

Electric Power Components and Systems
Publication details, including instructions for authors and subscription information:
http://www.tandfonline.com/loi/uemp20

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Version of record first published: 30 Nov 2010.

Electric Power Components and Systems, 30:151–165, 2002

1532-5008/02 $12.00 + .00

Grounding Grid Design Using Evolutionary Computation-Based Methods

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In this paper, a new method for designing grounding grids by means of evolutionary computation techniques is proposed. The aim being pursued is to minimize the cost of the grounding system while meeting the safety restrictions required by the standard regulations. The utilization of evolutionary computation (in particular, genetic algorithms and evolution strategies) allows us to build unequally spaced networks that, as is well-known, produce a more uniform surface potential distribution than equally spaced networks.

1. Introduction

An effective grounding grid design is one of the problems that must be solved when a new substation is projected. The objective of a grounding system is to provide a way to ground for currents generated by some fault or disturbance. This makes it possible to detect the faults to ground ensuring the actuation of protections and to limit the overvoltages that may appear in the system. It is known that the circulation of these currents in the ground produces voltages between different points of the earth that may be dangerous for people.

Safety requirements mean, in practice, ensuring that the magnitude and duration of the current conducted through the body of a person who is exposed to a gradient potential do not cause ventricular fibrillation. Therefore, step and touch voltage at any point of the installation should not exceed the maximum allowable values.

Usually, grounding systems of substations take the form of grids of horizontal buried conductors, supplemented by a set of vertical rods [1]. The cost of the grounding system depends on the type and size of the conductors and is approximately proportional to their total length. The type and size of the wires are chosen according to the maximum expected magnitude and duration of the fault current.

Standard procedures for designing equally spaced grounding grids are well known [1]. A number of authors have worked on developing different expressions for calculating ground resistances and step and touch voltages in this type of grid [2–5]; however, this kind of configuration is not the best solution from the point of

Manuscript received in final form on 13 February 2001.
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view of the uniformity of the earth surface potential. Due to the higher density of draining current in the vicinity of the grid perimeter, the mesh potential is higher in the meshes near the corner. The distribution of earth surface potential could be substantially improved if a grounding grid with unequally spaced conductors is built [6–8]. In this way, with the same number of wires (the same cost), a more uniform density of leaking current and potential distribution, and therefore a lower step and touch voltage, are obtained.

Hence, with the same safety requirements, an unequally spaced grid needs fewer wires than an equally spaced grid and is more economical.

In this paper, a new way for solving this problem is proposed using an approach based on evolutionary computation. Although here only rectangular grids are considered for simplicity, the method is fully applicable to systems with any other shape.

Other elements of the ground system (such as ground rods, connecting leads to the structures, etc.) having a great influence on the system performance are not included in this paper for simplicity; however, these elements can be easily included with the methodology we are proposing.

2. Grounding Grid Design Problem

The objective of the grounding grid design is to find a structure of buried wires that ensures the safety of people and equipment, using the smallest possible number of wires. Both objectives are in conflict, and a compromise solution must be found.

So, we can express the problem as the search for an arrangement of buried wires observing the following objectives:

1. Step and touch voltages at any point of the installation must be lower than maximum values required by the regulation.
2. The total length of conductors (therefore, the cost) should be as low as possible.

Mathematically, the problem may be expressed as the minimization of the cost function

$$C = \sum_{i=1}^{n} L_i, \tag{1}$$

where L_i is the length of wire i and n the total number of wires making up the ground network.

The minimization of the function C must satisfy the constraints

$$V_p < V_{p_{\max}} \quad \text{and} \quad V_c < V_{c_{\max}}. \tag{2}$$

Besides these two fundamental objectives, the following conditions are introduced in the design with the aim of simplifying the problem:

a) A continuous conductor loop surrounding the perimeter of the substation is assumed. This loop encloses the total are of the installation.
b) The grounding grid is made up of N wires arranged in parallel in both directions of the plane: n_x wires along the x direction and n_y wires along the y direction, and $n_x + n_y = N$. The choice of N, n_x and n_y, and the determination of the different positions of the wires is the problem that must be solved.

To solve this problem, two different algorithms are proposed: the first one is a genetic algorithm (GA) [9] and the second one is an evolution strategy (ES) [10, 11]. Both techniques are algorithms which imitate the principles of natural evolution as a method to solve parameter optimization problems.

3. Grounding Grid Design by Means of Genetic Algorithms (GAs)

The basic structure of a genetic algorithm is as follows:

1. The process starts with the random generation of an initial population of individuals (chromosomes).
2. A fitness value is assigned to each individual as a measure of its goodness as a solution for the problem.
3. According to its fitness value, and in a proportional way, each individual has a probability of participating as parent in the generation of the next population.
4. Taking into account such probabilities, parents are randomly selected to produce new individuals by means of basic operators of *reproduction*, *crossover*, and *mutation*.
5. Repeating the process from step 2, subsequent generations are obtained until a satisfactory solution is achieved.

The reproduction operator is a process by which one individual parent is used to obtain a descendant that is identical to the original.

Crossover combines two parent individuals to generate two offspring by swapping corresponding segments of the parents. In this case, the single-point crossover is used. By this operator, once the two parents V_i and V_j are chosen, a random number l between 1 and N is generated. The first offspring chromosome is obtained by appending the last $N - l$ bits of V_i to the first l bits of V_j. The second offspring chromosome is formed by appending the last $N - l$ bits of V_j with the first l bits of V_i (Fig. 1).

The mutation operator simply changes a randomly chosen bit in the parent chromosome.

In the application of a genetic algorithm [9–12] for designing an optimal grounding grid [13], we work with a population of M possible solutions (candidate grids or chromosomes). The representation of each possible grid is made by means of a string of bits V. This string is made of two substrings V_x and V_y with lengths N_x

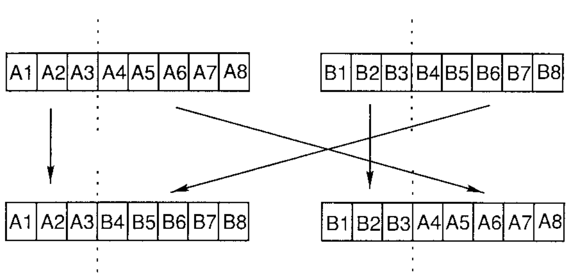

Figure 1. Crossover operator.

and N_y, respectively. Each substring represents the conductors arranged in each possible direction. N_x and N_y are the maximum number of wires parallel to the y and x axes, respectively, forming the grid. Hence, the minimum possible distance between any two wires parallel to the y axis is

$$D_x = \frac{L_x}{N_x}, \tag{3}$$

and to the x axis

$$D_y = \frac{L_y}{N_y}, \tag{4}$$

where L_x and L_y are the total dimensions of the grid. Each bit corresponds to one possible situation of a wire in the grounding grid. If the grid has a conductor in the i position, the respective bit value is 1. Otherwise, the bit value is 0 (Fig. 2).

First of all, a population is generated in a random way. Starting from this population, and by means of the basic crossover and mutation operators, the following new populations are generated. In each generation, all of the individuals are analyzed to evaluate their fitness as optimum solution to the problem.

The model used in the analysis of the grounding grids is independent of the genetic algorithm. In this case, a typical matrix method [14–16] for studying grounding systems at low frequency is used.

The objective function to be minimized is the cost. The constraints of step and touch voltages which must be strictly observed could be introduced by assigning a null value to the fitness function for the grids which do not meet them; however, it is possible that some individuals of the population which do not meet the constraints, hold useful information for the following generations. For this reason, in this work, constraints are considered by means of a penalty term, proportional to the step and/ or touch voltage excess over the limit values.

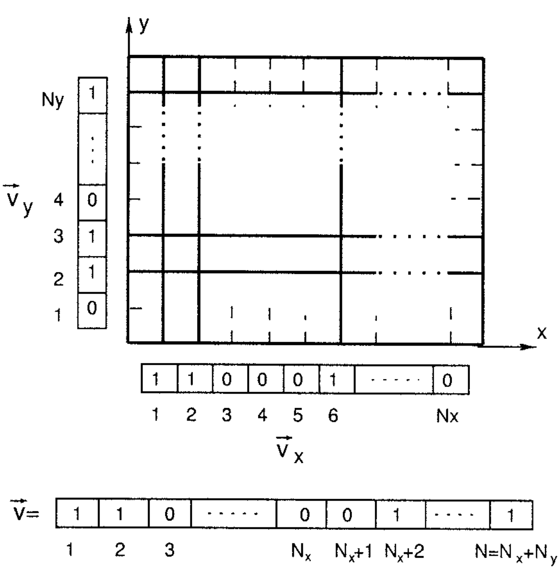

Figure 2. Representation of individuals.

On the other hand, there will be several grounding grids with the same number of conductors (the same cost) observing the restrictions and thus being possible solutions to the problem. So, we must include a new condition to decide which solutions are better. For this, a new term is introduced in the cost function. This term penalizes the grids generating a less uniform distribution of potential on the earth surface.

So, the following new cost function is defined:

$$F_i = C_i + K_d \times D_i + K_r \times (\Delta V_{c_i} + \Delta V_{p_i}), \tag{5}$$

with

$$\Delta V_{c_i} = \begin{cases} \dfrac{V_{c_i} - V_{c\max}}{V_{c\max}} & \text{if } V_{c_i} > V_{c\max} \\ 0 & \text{otherwise} \end{cases},$$

$$\Delta V_{p_i} = \begin{cases} \dfrac{V_{p_i} - V_{p\max}}{V_{p\max}} & \text{if } V_{p_i} > V_{p\max} \\ 0 & \text{otherwise} \end{cases},$$

where

C_i material cost of the grid i
D_i measure of the nonuniformity of the potential distribution on the earth surface (the more uniform the potential is, the lower D_i is)

K_d and K_r are constants.

The value of K_d must be chosen in such a way that grids having a higher material cost never have a function F lower than grids with lower material cost. So, it will depend on the definition of the D_i function and the minimum step of the cost function C_i.

Assigning a relatively low value to K_r at the beginning, solutions with step and touch voltages higher than the maximum limits have a certain degree of fitness. As the calculation process progresses, K_r is increased so that, at the end, solutions which do not meet the constraints have practically null fitness. Good results were obtained by increasing K_r in an exponential way with the number of iterations.

The fitness function for each individual is defined as the inverse function of the objective function:

$$f_i = 1/F_i. \tag{6}$$

When first running the genetic algorithm, usually there are a few individuals that stand out greatly from the rest of a mediocre population. If the fitness function 6 is used directly for the distribution of selection probabilities, then these few individuals take up a large percentage of this distribution. This tends to lead to undesirable premature convergence. In contrast, as the algorithm progresses, even with some diversity among the population, the viability of the best individual may be near the average for the population. In such a situation, almost all the individuals have the same probability of being selected, and the algorithm becomes a random choice among them. In order to avoid both situations, fitness scaling is recommended [9].

In our case, we have opted for a linear scaling according to

$$f^{esc} = Af + B, \tag{7}$$

where the constants A and B are chosen in each iteration on the basis of the following conditions:

- The average value for both functions must coincide: $f^{esc}_{med} = f_{med}$.
- The range of variation for the scaled function should be small when beginning the algorithm and increase as the various generation succeed each other.
- In no case can the value of f^{esc} be negative.

From the scaled function, and proportional to it, each individual is assigned a probability of being chosen for participation in the subsequent population. In this algorithm, the fittest grid in the current generation is always retained in the next generation.

4. Grounding Grid Design by Means of Evolution Strategies (ESs)

A second evolutionary algorithm to solving the optimum grounding grid design problem has been developed: this is a (μ, λ)-ES [10, 11]. In a (μ, λ)-ES, from an initial population of μ individuals, a new population of λ offspring ($\lambda > \mu$) is generated through the successive application of crossover and mutation operators. Among the λ offspring, the best μ individuals are chosen to form the next generation. The process is repeated, progressively improving the quality of the solutions.

Usually, in ESs, each individual is represented by a pair of real-number vectors, $(\vec{x}, \vec{\rho})$. The first one, $\vec{x}$, represents a point in the search space, while the second one, $\vec{\rho}$, is a vector of standard deviations used to define the mutation operator.

The function to be optimized is evaluated for all individuals, with the aim of *selecting* in a deterministic way the μ best ones.

In contrast to GAs, mutation is the most characteristic operator of ESs. In accordance with the biological observation that smaller changes occur more often than larger ones, mutation is realized by adding to vector $\vec{x}$, a vector of random Gaussian numbers with mean of zero and standard deviations $\vec{\rho}$:

$$\vec{x}' = \vec{x} + \vec{N}(0, \vec{\rho}). \tag{8}$$

One of the characteristics defining a modern ES is the capability of the algorithm to adapt the mutation parameters (vector $\vec{\rho}$) throughout the successive generations. The mechanism of adjustment of the variances was introduced by Schwefel [10], who considered $\vec{\rho}$ as a part of the genetic information of an individual. Consequently, it is subject to recombination and mutation as well. Those individuals with better adjusted strategy parameters are expected to perform better.

The recombination (crossover) operator consists of the two following basic steps:

- The totally random preselection of the two individuals who are going to be recombined.
- The recombination of such individuals to produce one or more offspring.

The recombination of the parents to obtain offspring can be performed in different ways, depending on the particularities of the problem to be solved. Typically, there are two kinds of recombination:

- Discrete: where each component of the new offspring randomly comes from the first or the second preselected parent.
- Intermediate: where the components of the new offspring are obtained as the average of the components of the parents.

Based on the described ESs, we proposed a new algorithm to obtain the optimum grounding grid. Because of their particular characteristics, the use of the above evolution strategies will allow us directly to use a real-type codification for the individuals (grounding networks). This means the disappearance of the discretization for the space of solutions which we were obliged to have with the binary codification in the genetic algorithm. Thus, a finer adjustment can be obtained in the optimum solution search. What follows is a description of the main characteristics of the proposed algorithm.

Each grounding grid or individual of the population is represented by two vectors of equal length, $\vec{c}$ and $\vec{p}$: vector $\vec{c}$ codifies the physical characteristics of the grid while vector $\vec{p}$ contains the corresponding variances determining the mutation. Furthermore, vector $\vec{c}$ consists of two parts: a first sub-vector $\vec{x}$ of length n_x, whose components express the distance to origin from the conductors parallel to y axis (Fig. 3), and a second sub-vector $\vec{y}$ of length n_y representing the distance to origin from the conductors parallel to x axis. So, vector $\vec{c}$ (and then, also $\vec{p}$) have dimension $n_x + n_y$, where n_x and n_y are the numbers of conductor parallel to y and x axes, respectively. Both n_x and n_y are variable parameters, and their values, like the disposition of conductors, are obtained through the iterative process.

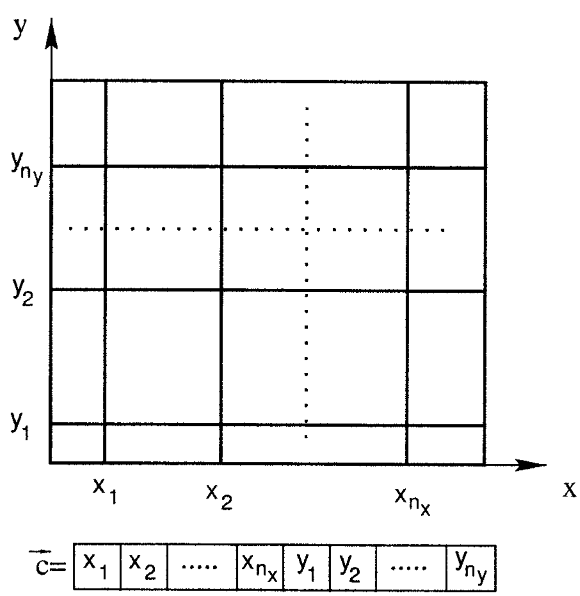

Figure 3. Codification of grounding grids.

As above, the objective function to be minimized is the cost of the grid, which can be considered as proportional to the total length of the conductors. In general, this cost function may be expressed as

$$C = \sum_{i=1}^{n} L_i. \tag{9}$$

Because of the very nature of the problem, several different grounding grids with the same cost can exist. In these cases, the selection process must take into account the condition of uniformity of the earth surface potential. According to this condition, a solution is considered to be better when the distribution of potential generated on the earth surface is more uniform. In the same way, only solutions meeting the imposed constraints of touch and step potentials are accepted.

The algorithm starts by randomly generating a population of μ individuals who will act as parents in the first iteration. Starting from the initial group, and by means of recombination and mutation techniques, a new population of λ ($\lambda > \mu$) offspring (grounding grids) is obtained. All of these grids are analyzed with the aim of selecting from among them the best μ solutions (process of *selection*), which will be the parents of the next generation. This iterative process is repeated until the population converges to an acceptable solution.

The recombination operator used is a discrete type crossover. It is performed by recombining two individuals $\vec{p}_1$ and $\vec{p}_2$ randomly chosen among the μ possible parents. This recombination is carried out separately in conductors parallel to each axis. For conductors parallel to y axis (conductor whose positions are defined by vectors $\vec{x}_1$ and $\vec{x}_2$), a coordinate r_x is randomly selected. A new grid may be built by combining the conductors before and after r_x, randomly from $\vec{x}_1$ or $\vec{x}_2$. The process must be repeated for conductors parallel to x axis (conductors whose positions are defined by vectors $\vec{y}_1$ and $\vec{y}_2$). A graphical explanation of the recombination

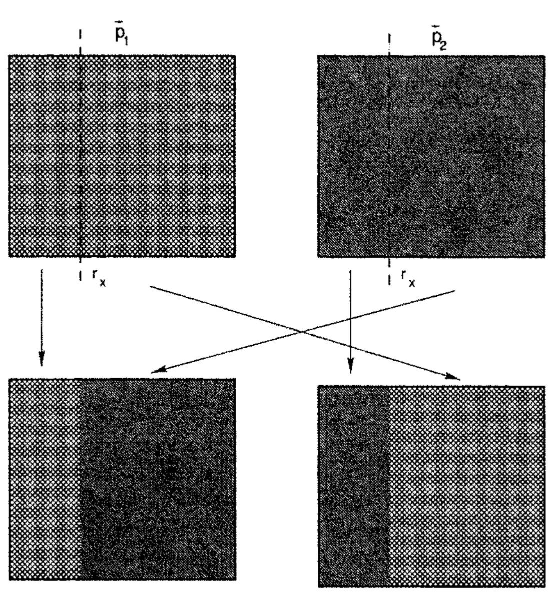

Figure 4. Recombination of conductors parallel to the y axis.

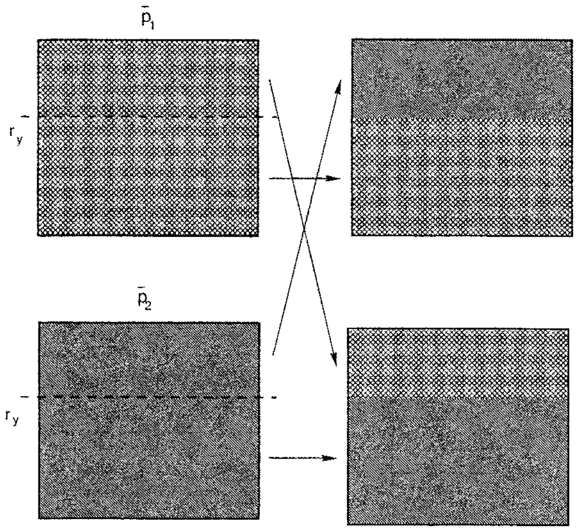

Figure 5. Recombination of conductors parallel to the x axis.

operator can be seen in Figures 4 and 5. Once the recombination has been carried out, the Gaussian mutation operator is applied to the new individual as was shown previously. In a first step, the mutation is performed in the vector of standard deviations. With the new vector $\vec{\rho}$, the vector of coordinates is mutated (8).

5. Practical Application

The proposed algorithms have been applied in the design of different practical cases. In this paper we are showing some results (two cases).

The system we are studying is a substation grounding grid covering a total area of 80 $\times$ 60 m. The main design parameters are assumed to be known and are the following:

- Constant resistivity of values: $\rho = 200\ \Omega \times m$ (case 1) and $\rho = 100\ \Omega \times m$ (case 2).
- Surface resistivity $\rho_{sup} = 3000\ \Omega \times m$.
- Copper wire of diameter 14 mm.
- Depth: 0.5 m (case 1) and 1.0 m (case 2).
- Fault current $I_f = 5000$ A during a time of 0.5 s.
- With the above values and according to the standards, the maximum permissible touch voltage is $V_{c_{max}} = 792$ V.

As the grounding grid has a rectangular shape, a symmetrical arrangement for the conductors is established in each direction. This allows the codifying of each grid with half the number of bits, decreasing the computation time.

5.1. Solved with GA

As has been said, the proposed GA works in a discrete space of solutions. The discretization degree is determined by the maximum number of conductors adopted

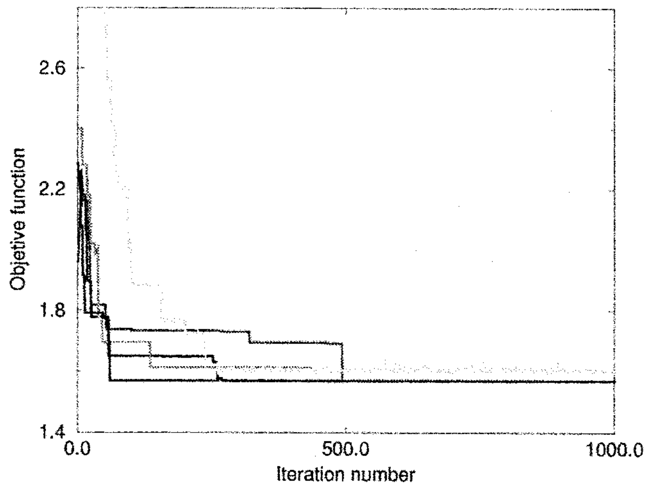

Figure 6. GA1: Cost of the grid against generations.

in both directions. In this case, we have $N_x = 79$ and $N_y = 59$. So, the most expensive grid that can be obtained is made up from 80 $\times$ 60 meshes, with a minimum distance of 1 m between any two wires.

Case 1. The algorithm was run several times, and the evolution of the cost function throughout the computation is shown in Figure 6. As can be seen in Figure 7, the least expensive solution consists of 13 $\times$ 8 meshes.

To emphasize the advantages of the unequally spaced grid, an equally spaced grid with the same number of wires (the same cost) was analyzed. While in the unequally spaced grid, the touch potential is 785 V; in the equally spaced grid, this potential is 1180 V. The minimum equally spaced grid necessary to obtain a touch voltage similar to the unequally spaced grid is made from 25 $\times$ 20 meshes. So, the saving obtained with the proposed grid is approximately 50%.

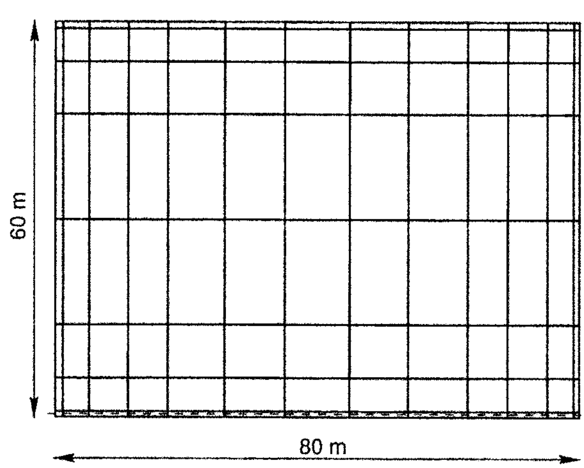

Figure 7. GA1: Grid obtained.

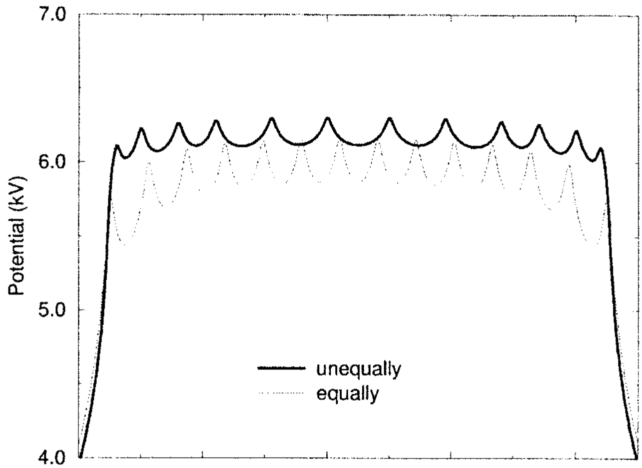

Figure 8. GA1: Surface potentials.

Figure 8 shows the potential profile on the earth surface computed along the dashed line in both cases. The potential profile in the unequally spaced grid is more uniform.

Case 2. In the second case, due to the lower earth resistivity, a simpler grounding grid was obtained (Fig. 9). In addition, a faster convergence of the algorithm is achieved, as can be seen in Figure 10. Comparing the proposed grid with the minimum equally spaced grid necessary, the saving is approximately 15%.

5.2. Solved with ES

The same problem was solved with the ES proposed.

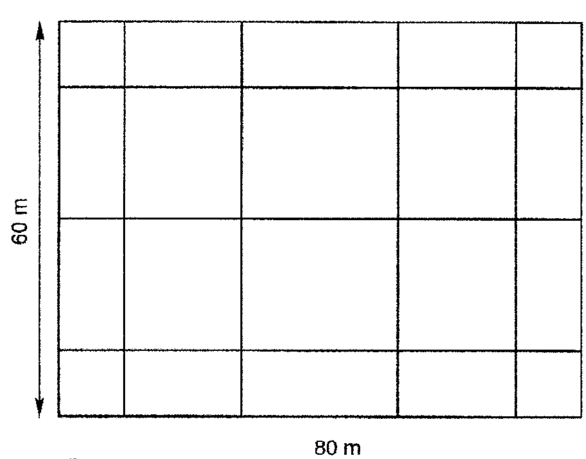

Figure 9. GA2: Grid obtained.

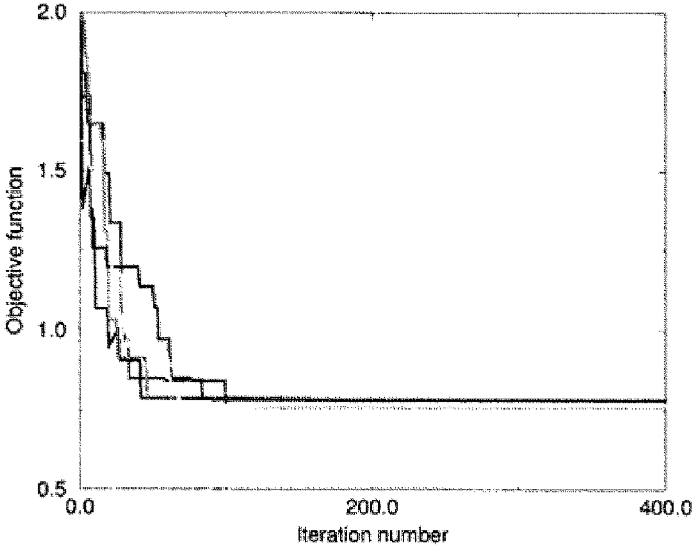

Figure 10. GA2: Cost of the grid against generations.

Case 1. As above, the algorithm was executed a number of times with very similar results in all cases. The evolution of the cost function is shown in Figure 11, and the best solution can be seen in Figure 12.

The grid obtained with the ES is a little less expensive than the grid computed with the GA. This is due to the finer adjustment of the position of conductors that can be achieved with the real codification used in the ES.

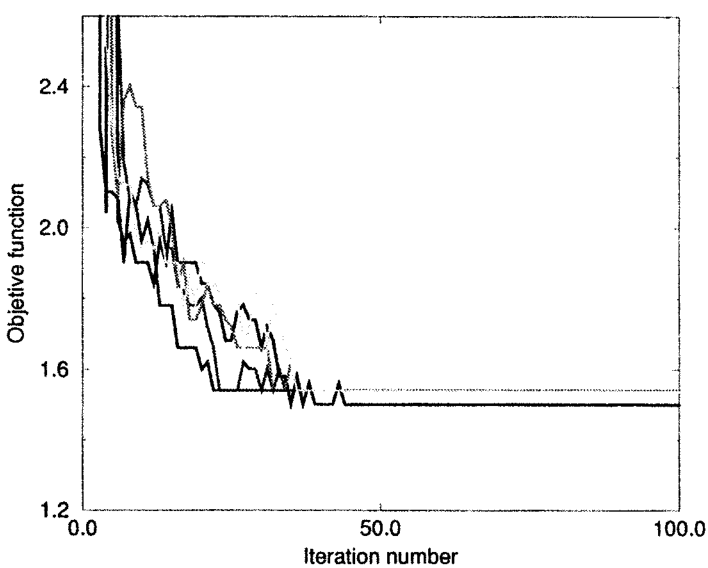

Figure 11. ES1: Cost of the grid against generations.

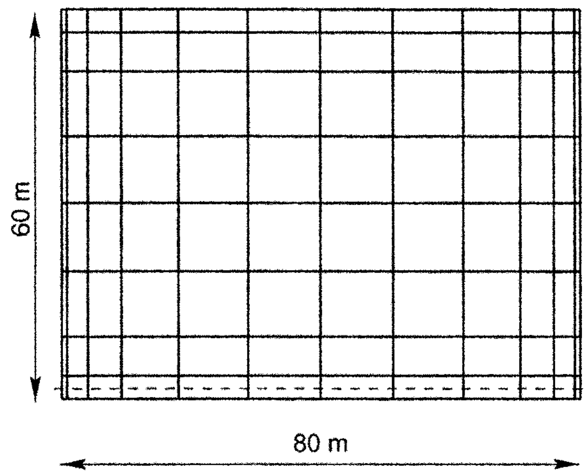

Figure 12. ES1: Grid obtained.

Compared with the equally spaced grid of the same cost, the obtained solution has a maximum touch potential of 780 V, against 1220 V for the regular grid. In Figure 13, potentials on the surface along the dashed line in both grids are shown.

Case 2. The grid obtained with the ES is shown in Figure 14. As can be observed, this system is practically identical to the GA2 grid. The evolution of the cost function can be seen in Figure 15.

The algorithms were applied in a large number of different cases (only two are presented in this paper), and satisfactory results were obtained in all of them. Obviously, the computation time depends on the problem size, as can be seen in the above two cases.

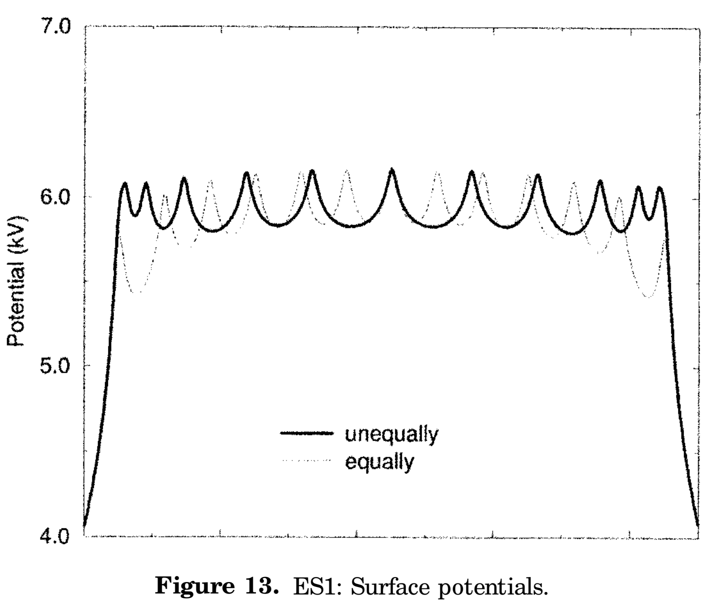

Figure 13. ES1: Surface potentials.

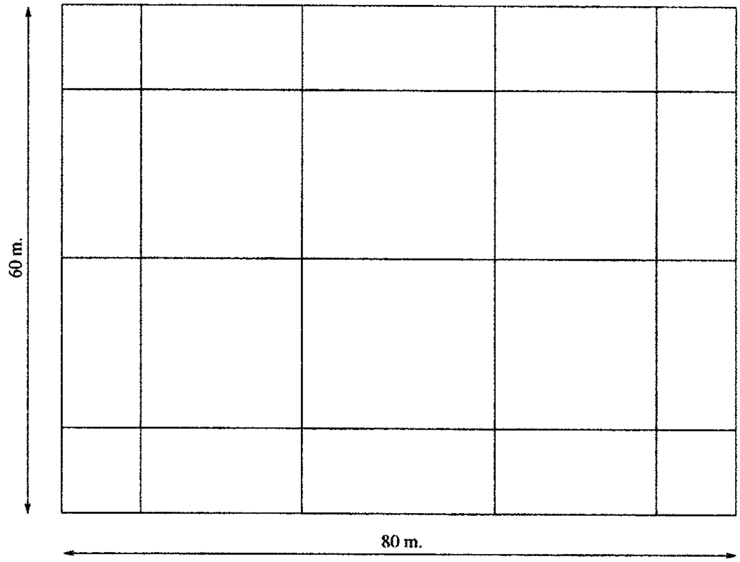

Figure 14. ES2: Grid obtained.

The GA needs a higher number of iterations than the ES to achieve the final result; however, this is partially compensated by the higher time per iteration in the ES.

6. Conclusions

In this paper we have proposed a new methodology for carrying out the design of a grounding grid using evolutionary computation techniques. The objective being

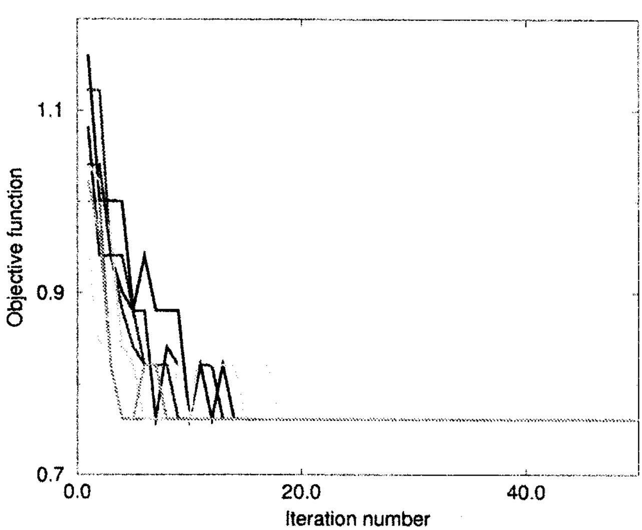

Figure 15. ES2: Cost of the grid against generations.

pursued is to obtain a grounding network at minimum cost and which meets the technical conditions for safety that have been established in this field.

This evolutionary computation-based focus allows the optimum design for ground networks of any shape. The possibility of including vertical rods will be investigated in future papers. Satisfactory results have been generated by the application of the method to solve distinct practical cases.

Acknowledgment

The financial support received from the *Ministerio de Educación* under the contract PB94-0487 is gratefully acknowledged by the authors.

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