Evolutionary Methods for the Antenna Parameter Setting Problem

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Abstract

This paper presents an evolutionary approach to the Antenna Parameter Setting Problem. It investigates the amenability of evolutionary techniques to the field of Radiomobile Networks, giving a formal modeling of the APSP and the corresponding genetic modeling. It eventually carries out some tests in order to tune the genetic algorithm for further large-size problems.

1. Introduction.

The increasing importance of the field of mobile computing and particularly the growing size of Radiomobile Networks give rise to ever more demanding issues [7, 16]. Radiomobile networks [7, 4] are composed of two kinds of transmitters/receivers : the mobile phones and the stationary antennae. The goal of such networks is to ensure the communication between the antennae and the phones moving through the area to be covered. The intensity of the radio waves establishing the link between one antenna and one phone is predicted thanks to a propagation model which takes into account the power and orientation of the antenna, as well as the relief and nature of obstacles (i.e. woods, buildings...). This enables to define for each antenna the area it covers, that is where communications with phones can occur with a given quality, and so, looking at the network, which antenna effectively covers each portion of land.

The Antenna Parameter Setting Problem (APSP) fits into the global process of radiomobile network design [3, 10, 11]. This process is composed of the three following main stages, namely, positioning, parameter setting and frequency assignment. These three stages successively consist in the positioning (locating) of antennae onto the available sites, the setting of their parameters and eventually frequency allocation. The issues related to the whole process deal with both quantitative aspects : optimization of the network coverage and minimization of the interference between antennae ; and qualitative ones, as detailed later on.

The APSP, which deals with the determination of the optimum setting for antenna parameters to ensure the best overall network coverage, may be seen as a constrained optimization problem [5, 8]. The importance of such problems have led to the development of numerous methods, whether exact such as linear programming, branch-and-bound and backtrack algorithms, or approximated, and particularly metaheuristics, such as simulated annealing, taboo search or evolutionary algorithms (EA). These metaheuristics, based upon general principles and adaptable to a broad range of problems, are characterized by their effectiveness in producing good quality solutions at a reasonable computational cost. Among these latter methods, EA [1, 6], which are techniques based upon an analogy with natural evolution of biological organisms, constitute an effective and widely used approach to optimization problems [5, 8, 9]. Furthermore, they have already been applied successfully on similar problems from the field of radiomobile networks [2, 3, 4, 15].

This paper addresses various goals : giving a formal modeling of the APSP and investigating an evolutionary approach, as well as laying the basis for further work regarding real large-size problems. It is organized as follows : section 2 presents an overview of the APSP as well as goals and constraints defined and used throughout our approach. Section 3 then details the genetic approach, its modeling and the results. Section 4 eventually concludes about our genetic approach to the APSP.

2. Antenna parameter setting problem

We describe here the context of antenna parameter setting and propose a model. We then define the framework of our optimization problem, defining constraints and stating our goals.

2.1. Problem Statement.

The problem of parameter setting which concerns us here, deals with the following issues : maximizing the area covered by antennae as well as restricting the interference and allowing a given service quality.

The global problem is to determine the optimum setting of the parameters associated with the antennae in charge of the radiomobile coverage of a given area. The antennae are distributed upon the surface to cover, which is modeled as meshes whose size may vary from 25 to 100 meters, depending on the type of land.

For each mesh m, a propagation model enables to predict the local variation $Fade_m^{a_i}$ of the radioelectric field emitted by every antenna a_i. The main parameters of an antenna are $Power^{a_i}$, $Tilt^{a_i}$, $Azim^{a_i}$, its emission power, tilt and azimuth. However, we just consider here omnidirectional antennae, which are characterized by their power parameter only. This parameter defines the radioelectric field $F_m^{a_i} = f\,(Fade_m^{a_i}\ Power^{a_i})$ that each mesh receives from every surrounding antenna a_i. The goal of antenna parameter setting is to determine the parameter values in order to obtain the best service quality on the considered area. Given three antennae, figure 1 illustrates the handover, interference and coverage notions, showing the corresponding areas for a given network.

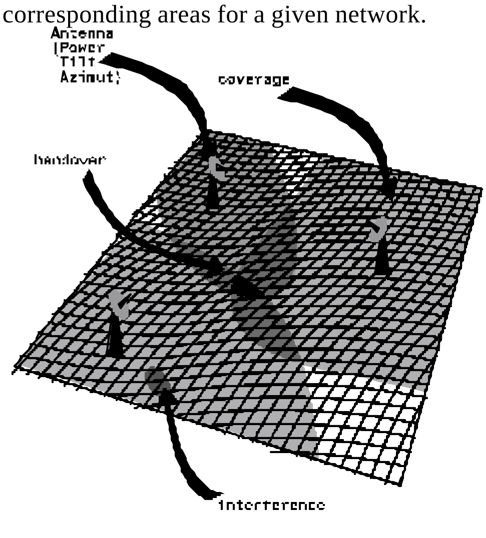

Figure 1 : the antenna parameter setting problem.

2.2. Formal modeling

In fact, the term service quality includes several aspects : coverage, interference and handover. Indeed, we want every mesh m to be covered, that is to receive a field greater than a given quality gate $G_{quality}$ from an antenna a_i, enabling the communication with a mobile phone in the mesh. This is specified by the following formula :

$$Cov_m^{a_i} = \begin{cases} \text{if } \left(F_m^{a_i} \geq G_{quality}\right) \text{ then } 1 \\ \text{else } 0 \end{cases}.$$

We also consider that an antenna a_i is interfered by another one a_j if the field received from the latter is greater than a sensibility gate $G_{sensibility}$ $\left(G_{sensibility} << G_{quality}\right)$, that is

$$I_m^{a_i,a_j} = \begin{cases} \text{if } \left(Cov_m^{a_i} \text{ and } G_{quality} \geq F_m^{a_j} \geq G_{sensibility}\right) \text{ then } 1 \\ \text{else } 0 \end{cases}.$$

The notion of handover is used to enable a mobile phone to go from an area covered by one antenna to an area covered by another one. A handover area is covered by two antennae and has to be neither too small, hindering the effective transition between antennae, nor too large, which would be useless. So, a mesh m establishes a handover relationship between two antennae if covered by both and if the difference between the received fields is under the handover gate $G_{handover}$:

$$H_m^{a_i,a_j} = \begin{cases} \text{if } \left(Cov_m^{a_i} \text{ and } Cov_m^{a_j} \text{ and } \left|F_m^{a_i} - F_m^{a_j}\right| \leq G_{handover}\right) \text{ then } 1 \\ \text{else } 0 \end{cases}$$

We consider the coverage optimization as our unique goal, whereas handover and interference are viewed as constraints. They are defined as follows :

- coverage goal : maximize $\sum_i NC^{a_i}$ the number of meshes covered by an antenna a_i.
- Handover constraint :

$$CH^{a_i} = \begin{cases} \text{if } NH_{\min} \leq NH^{a_i,a_j} \leq NH_{\max} \text{ then } 1 \\ \text{else } 0 \end{cases} \quad (\forall a_j \in A,\ j \neq i)$$

the proportion NH^{a_i,a_j} of meshes covered by an antenna a_i and in handover with any other a_j must be limited.

- interference constraint :

$$CI^{a_i} = \begin{cases} \text{if } NI^{a_i,a_j} \leq NI_{\max} \text{ then } 1 \\ \text{else } 0 \end{cases} \quad (\forall a_j \in A,\ j \neq i)$$

the proportion NI^{a_i,a_j} of meshes covered by an antenna a_i and interfered by any other a_j has to be limited.

3. Evolutionary Algorithm approach.

Several methods have been applied to problems from the field of radiomobile networks. EA, which include genetic algorithms (GA) [1, 7] and evolution strategies,

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have shown to offer good performances on such cases [2, 3, 4, 15].

As other metaheuristic methods, GA are domain independent methods, characterized by their relative easiness of implementation and robustness for a large scale of applications, which require no or few specific domain knowledge [8, 6, 1]. The development time of evolutionary applications can even be shortened and facilitated through the use of efficient reuse and prototyping tools such as genetic libraries [12]. This enables fast validation and tests on an entire approach to a given problem, that is in our case, validation of both the APSP modeling and its evolutionary solution.

3.1. Genetic modeling.

The design of a GA depends on the following points : genetic coding, definition of an objective function, and definition of the crossover, mutation and selection genetic operators. However, we only focus on the coding and on the objective function, as standard genetic operators can be used for crossover, mutation and selection. The definition of the genetic coding draws from the previous model. A solution to the problem is defined by the state of all the antennae, i.e. their respective parameters of power, tilt and azimuth. As we rather stand from an evolutionary point of view, we don't make any difference between phenotype and genotype, and define the chromosome manipulated by the algorithm as the aggregation of the antennae parameters. We define a phenotype constituted from the three parameters of each antenna, as in figure 2.

antenna 1	antenna 2	...	antenna n
pwr | tilt | azim	pwr | tilt | azim	...	pwr | tilt | azim

Figure 2 : genotype and phenotype.

In the same manner, the objective function is defined from the criteria characterizing the problem. The goal is to maximize the coverage of every antenna and to satisfy the constraints of interference and handover, given the relationships between antennae. The quality of a solution (representing the configuration of the network as a whole) is logically defined as the sum of the quality of each antenna :

$$quality_{global} = \sum quality^{a_i} \quad (\forall a_i \in A)$$

The objective score for an antenna has to avoid the definition of a multi-criteria score bearing on coverage, interference and handover as well. Therefore, it represents both the quality of the antenna coverage and the discrimination of the violation of constraints, through a penalty function, as in [2][7]. It is thus given by the following equation :

$$quality^{a_i} = NC^{a_i} - K_i \sum \Delta_{interf}^{a_i a_j} - K_h \sum \Delta_{hand}^{a_i a_j} \quad (\forall a_j \in A, j \neq i)$$

$$with\ \Delta_{interf}^{a_i a_j} = NI^{a_i a_j} - NI_{max} \text{ if } \left(NI^{a_i a_j} > NI_{max} \right)$$

$$with\ \Delta_{hand}^{a_i a_j} = \left| NH^{a_i a_j} - NH_{max} \right| \text{ if } \left(NH^{a_i a_j} > NH_{max} \right) \text{ or } \left| NH^{a_i a_j} - NH_{min} \right| \text{ if } \left(NH^{a_i a_j} < NH_{min} \right)$$

$$with\ K_i, K_h \ / \ \left(K_i \sum \Delta_{interf}^{a_i a_j} - K_h \sum \Delta_{hand}^{a_i a_j} \right) \gg NC^{a_i}$$

This defines a strictly monocriterion objective function which gets rid of solutions violating constraints.

From the genotype, that is from the antennae parameters, and given the corresponding fading matrix, we compute for each antenna the resulting field matrix. We can then deduce the coverage, interference and handover constraints, and compute the antenna score and thus the final score of an individual.

3.2. Result analysis

This section presents the results from a series of simulations implemented using GA Lib [12] and carried out in order to validate our approach and determine what set of values was best for genetic parameters. The tests were done upon a network of small size (6 antennae), not in the perspective of processing the kind of network presented in this paper, but rather to tune the GA for further processing of large-size networks. They were however carried out on a real sample network from Belfort city in France.

Our choices are thus oriented toward obtaining a global population fitness decrease and toward robustness rather than toward obtaining a fast convergence to earlier minima solutions, which could actually be achieved trivially due to the low complexity of the test network. The following tests concern the population size, mutation rate, as well as best crossover operator and rate.

The tests regarding the population size were carried out with a mutation rate set at a typical value (1%) as well as the crossover rate (100%), using a typical Gaussian mutation operator and uniform crossover, with roulette-wheel selection. We determined the best population size of 40 by compromising between computational cost (i. e. amount of evaluations) and global decrease of population fitness, that is robustness. However this size has only been determined in order to carry out the subsequent tests and does not allow to conclude definitively about the best population size to use. Indeed, as the population size closely depends on the combinatorial aspect, that is on the problem size, some other tests would have to be conducted regarding the relative population and problem size. Figure 4a and 4b illustrates the evolution of the population best fitness, relatively to the number of generations and to the number of evaluations for our problem.

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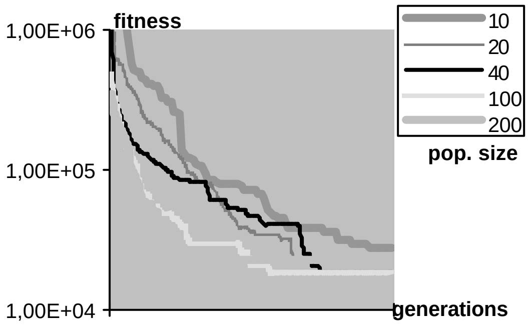

Figure 4a: best population fitness versus generations.

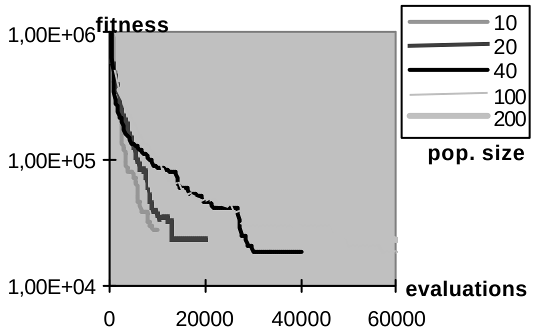

Figure 4b: best population fitness versus evaluations.

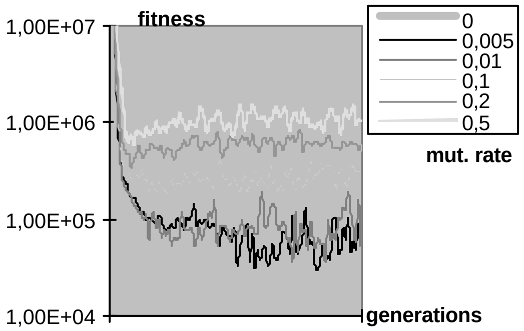

Figure 5a: mean population fitness.

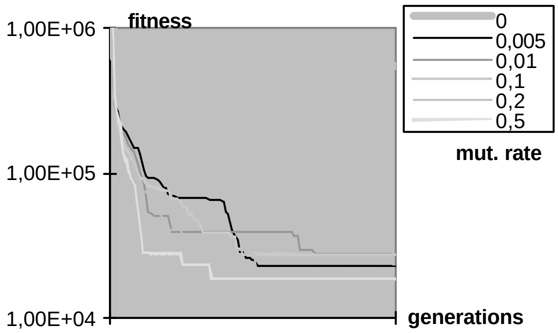

Figure 5b: best population fitness

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The tests for mutation were thus performed with 40 individuals and with the same crossover operator and rate as before. Population mean fitness and best fitness are shown in figure 5a and 5b. The great variations which can be observed in the mean population fitness are due to the apparition -either trough mutation or crossover- of individuals whose score reflects a violation of constraints. A rather small mutation rate of 5‰ seems best for overall efficiency and robustness, even if higher values lead to earlier and better solutions in the short term.

However, although several types of crossover operator (uniform, 1-point and 2-point) were tried at different rates, no conclusions could be drawn regarding the best one to use, even if they both seem to work best at rates in the range 70-80%. This is why results are not presented here. Thus, in the lack of any definitive clue, uniform crossover will be used at a 80% rate.

The settings obtained trough these tests (uniform crossover at 80% rate with 5‰ mutation) should in the long run prove to be effective on large size networks, as they were chosen from a robustness standpoint. As stated above, the population size remains to be set according to the size of the networks at hand.

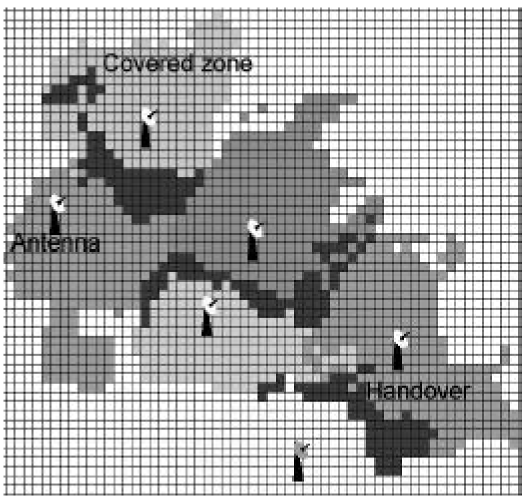

Figure 6 : typical solution found by our GA.

Figure 6 shows an example solution found by the GA on the test network. It presents the overall view of a typical result network, depicting for each antenna its coverage zone in soft gray, as well as handover areas between them as dark regions, whereas interference meshes are not depicted for obvious graphical reasons.

4. Conclusion.

This paper has addressed an evolutionary approach to the Antenna Parameter Setting Problem, investigating the amenability of evolutionary techniques to the field of Radiomobile Networks. It described the context of the APSP and associated a formal modeling to this constrained optimization problem through the definition of goals and constraints. It then presented our evolutionary approach and the corresponding genetic modeling. It eventually depicted some preliminary test results on small networks, focusing on tuning the GA parameters for overall robustness.

Consequently, the application of our generic modeling will have to be extended to the case of real large-size network. In this perspective, future work will have to investigate the efficiency of the genetic algorithm on such cases as well as possible improvements. Work is currently being done on a cooperative coevolutionary [13] application of the APSP modeling. Its comparison with the non coevolutionary GA presented here have yet to be carried out. Work should also be conducted toward the adjunction of azimuth and tilt parameters, and their consequences on the GA behavior.

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