A Multiobjective Genetic Algorithm for Radio Network Optimization

Hervé MEUNIER, El-ghazali TALBI
LIFL / University of Lille
59655 Villeneuve d'Ascq CEDEX, France
{meunier,talbi}@lifl.fr

Philippe REININGER
CNET / France Telecom
BP 382 - F90000 Belfort - France
philippe.reininger@cnet.francetelecom.fr

Abstract- Engineering of mobile telecommunication networks endures two major problems: the design of the network, and the frequency assignment. We address the first problem in this paper, which has been formulated as a multiobjective constrained combinatorial optimisation problem. We propose a genetic algorithm that aims to approximate the Pareto frontier of the problem. Advanced techniques have been used such as Pareto ranking, sharing and elitism. The GA has been implemented in parallel on a network of workstations to speed up the search.

To evaluate the performances of the GA, we have introduced two new quantitative indicators: the entropy and the contribution. Encouraging results are obtained on real life problems.

1 Introduction

Engineering of mobile telecommunication networks evolves two major problems, the design of the network, and the frequency planning. The design consists in positioning base stations (BS) on potential sites, in order to fulfil some objectives and constraints [GZBS86]. The frequency planning sets up frequencies used by BS with criterias of reusing. In this paper, we address the first problem. Network design is a hard and complex combinatorial problem. The BS positioning problem deals with finding a set of sites for antennas from a set of pre-defined candidates sites, determining the type and the number of antennas, and the configuration of different parameters of the antennas (tilt, azimuth, power, ...). A definition of the problem of BS positioning is given in a multiobjective optimization context. The model deals with specific constraints due to the engineering of cellular radio network.

Many search algorithms have been used to solve multiobjective combinatorial optimization problems [Tal00][Ste86]. Exact algorithms such as branch and bound [SK99] and dynamic programming [CMM90] have been used to solve small instances of bi-objective problems. The design problem is a complex multiobjective combinatorial problem, where a heuristic approach is required. Some metaheuristics have been suggested to deal with this problem [VH99][BHMZ99]. They transform the multiobjective problem into a single objective one by combining the objectives in a linear agregation method. These approaches generate a single supported solution. In this paper, we propose a population based metaheuristic, a genetic algorithm (GA), to approximate the Pareto frontier of the problem, by generating a set of non dominated solutions.

GAs are well suited to multiobjective optimization problems [Coe99][FF95b][Deb99]. In order to represent an interesting set of solutions, solutions produced by the GA need to satisfy two conditions. First, they have to be good approximations of Pareto optimal solutions. Second, they must be uniformly distributed on the Pareto front. Solutions tend to be good enough, and well scattered. Pareto ranking, sharing and elitism have been used to satisfy those conditions. Due to the large computation required, a parallel implementation of the algorithm has been used.

The paper is organised as follows. In section 2, the network design problem is formulated as a multiobjective constrained combinatorial optimization problem. In section 3, the multiobjective GA is described. Finally, in sections 4 and 5, we present the performance evaluation protocol and the experimental results obtained.

2 The network design problem

The network design problem may be reduced to the placement and the configuration of base stations (BS) on candidate sites. In this section, we give a simple formulation of the problem. An extensive analytical formulation may be found in [RC98].

2.1 Working area

The working area $\mathcal{P}$ is a geographical area, discretized in testing points. It is a set of geographical information required for the design. A working area is described by a Digital Map Database. Four sets of points are identified in $\mathcal{P}$:

- A set of sites which are candidate for the positioning of BS, $\mathcal{L} = \{L_i / i \in \mathbb{N}\}$. Each site is defined by its coordinates (x, y) and the height above the sea level z.
- A set of Reception Test Points (RTP) in which the radio signal will be tested, $\mathcal{R} = \{R_i / i \in \mathbb{N}\}$. Every RTP may be used as a signal test point to compute the cover of the network [FMB96].
- A set of Service Test Points (STP) in which the expected service is tested, $\mathcal{ST} = \{ST_i / i \in \mathbb{N}\}$. $\mathcal{ST}$ defines the set of STP where the network must overcome a signal quality threshold to ensure a given Quality of Service (QoS). This threshold, S_q, depends on the mobile type. STP are used to define the cell notion. The

set of STP covered by a BS is the cell associated to this BS.

- A set of Traffic Test Points (TTP) in which the expected amount of traffic will be tested, $\mathcal{T} = \{T_i / i \in \mathbb{N}\}$. Each TTP is associated with the amount of traffic on this point e_i, given in Erlang (unit of traffic measure). Depending on the global amount of traffic on its TTP, each BS will support a given number of Transmitters (TRX).

To ensure a good quality of signal in the area where the traffic is located, each T_i is associated to a ST_i on the same coordinates. Moreover, it is necessary to know the radio signal on each ST_i, that the reason why each ST_i is associated to a R_i. This inclusion is always satisfied.

Proposition 1 $\mathcal{T} \subseteq \mathcal{ST} \subseteq \mathcal{R}$

Fig. 1 shows a real working area and Fig. 2 shows the associated discrete working area.

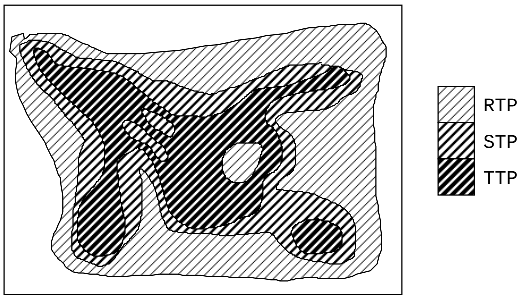

Figure 1: Relationships on $\mathcal{P}$ between TTP, STP and RTP.

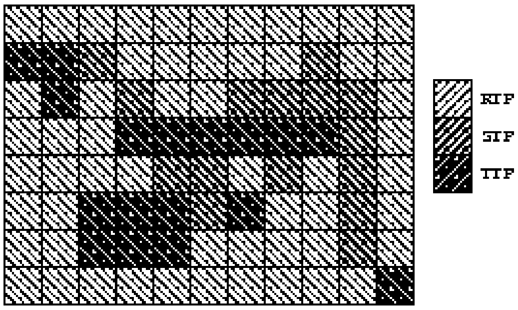

Figure 2: Grid view of relationships between TTP, STP and RTP.

2.2 Decision space

The main decision variable of the problem deals with the mapping of the BS on the potential sites. BS are of three types: omnidirectional, small directive, or large directive. Each site may be equipped with either one BS with a single omnidirectional antenna or with one to three BS, each having a directive antenna.

In addition to the mapping decision variable and the type of antenna, each BS is configured by some engineering parameters (Table 1): the azimuth, that is the direction the BS is pointing to, the transmitter power and the vertical tilt.

Table 1: Engineering parameters.

Azimuth	[0,360], step 10°
Power	[26,55], 2 dBm
Tilt	[0,-15], step 3°

Hence, the huge number of combinations in the design of a network. In the real-life network used in our experiments, the search space has $2^{3689160}$ possible solutions.

2.3 Objectives

We define three main objectives for the problem:

- Minimize the number of sites used: reducing the number of sites reduces the cost of the design.
- Maximize the amount of traffic held by the network: considering a set of traffic test points TTP, $\mathcal{T}$, located on $\mathcal{P}$. Each TTP is defined by a given amount of expected communications. This amount of traffic must be handled by a BS. At the network level, the traffic problem is to adapt the capacity of the network to the traffic demand.
- Minimize the interferences: the management of interferences due to overlapping cells is the main problem to deal with. The more cells are overlapping, the more interference will be important, and the frequency assignment will be more difficult. The problem is to adapt the number and the amount of signals received by each STP. Theoretically, each STP does not required more than 2 BS considered as potential servers: the current BS and the handover BS.

2.4 Constraints

Now we introduce the two main constraints which have to be satisfied to design a cellular network:

- Cover of the area: all STP must be covered with a minimal radio field value, that must be greater than the receiver sensibility threshold of the mobile.
- Handover: by definition, a mobile moves at any time. The cellular network must be able to ensure the communication continuity from the starting cell to the target cell, when a mobile is moving toward a new cell. The handover is a mechanism which supplies this continuity. When the mobile is moving from one cell to another one, the starting cell drops out its communications with the mobile as soon as the target cell is able to ensure the communication with the incoming mobile. This mechanism requires to manage overlap areas between cells. Every cell need a handover area.

In addition to the huge number of potential solutions, the other difficulty of the network design problem is the high computational cost required to evaluate the objective functions and to test the constraints. We need also a high requirement of memory. To tackle this complexity and to reduce the search time, we have proposed a parallel implementation of the algorithm.

3 A multiobjective genetic algorithm

Genetic algorithms have been widely used to solve multiobjective problems (MOP), as they are working on a population of solutions [Coe98]. Two objectives have to be taken into account while solving MOP:

- Converge toward the Pareto frontier: most of research about application of genetic algorithms to MOP concentrates on the selection stage. At this stage, ranking methods are applied, in order to assign a fitness to individuals. This fitness depends on the dominance notion, and thus, directly depends on the Pareto optimality.

  Definition 1 *A solution $u^* \in C$ is Pareto optimal if a solution $v \in C$ such as $F(v)$ dominates $F(u^*)$ does not exist. In maximizing n objectives f_i, solution u is said to be dominated by v iff $\forall i \in [1,..,n], f_i(u) \leq f_i(v)$ and $\exists j \in [1,..,n]$ such that $f_i(u) < f_i(v)$.*

- Find diversified solutions on the Pareto frontier: some sharing methods able to maintain the diversity, using ecological niche induction, may be used to stabilize multiple subpopulations along the Pareto frontier.

The population of a multiobjective GA is composed of dominated and non dominated individuals. The basic line of the algorithm is derived from a steady state genetic algorithm, where only one replacement occurs per generation.

The first modification we have brought in the GA lies in the selection step. The selection phase implements a roulette wheel selection. The crossover and mutation operators are then applied. The crossover is applied on both selected individuals, generating one child. The mutation is applied on the best individual. The best resulting individual is integrated into the population, replacing the worst ranked individual in the population. The figure 3 presents the model of the algorithm.

Initial solutions are randomly generated using an uniform random number of sites. As a result, the initial population is spread along the search space in terms of the number of sites..

3.1 Encoding

We need to encode a solution of the network design problem, that is a network and its parameters, into an individual. An individual encodes all potential informations of the network. We use a multilevel encoding: level 1 decides the activation of sites, level 2 decides the number and the type of antennas,

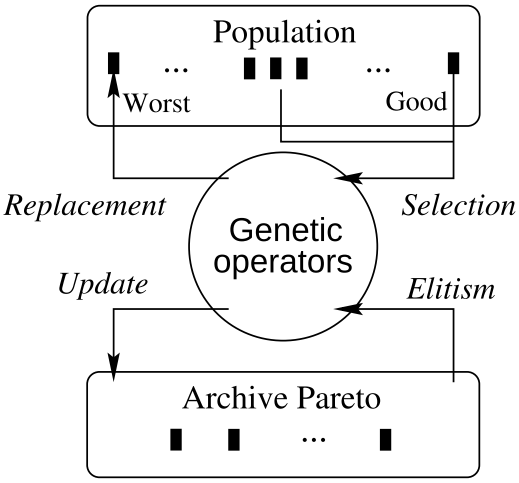

Figure 3: The steady state GA model.

and level 3 handles the parameters of the BS. When a site is used, one or more antennas are activated. When an omnidirectional antenna is chosen, we settle the power and the tilt parameters. Moreover, when a directive antenna is used, the azimuth parameter is initialized. The engineering constraint of 1 omnidirectional antenna or 1 to 3 directive antennas is ensured. The Fig. 4 shows the hierarchical encoding of an individual.

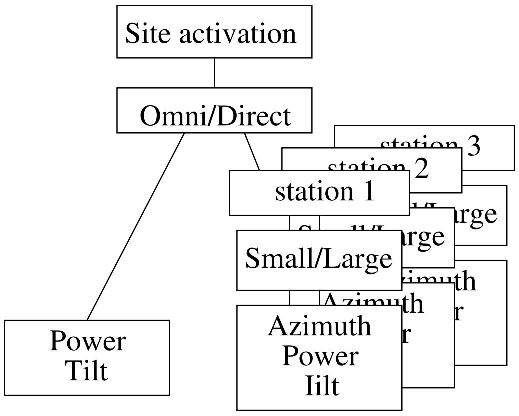

Figure 4: The hierarchical encoding of a network.

3.2 Genetic operators

The genetic operators (crossover and mutation) are used, but modified to suit with the problem. Indeed, the classical crossover dont't take into account the geographical data, and the mutation must be handled at different levels of the encoding. So, we have introduced two problem-oriented operators : a geographical crossover and a multilevel mutation.

The geographical crossover works at level 1 of the encoding hierarchy. It exchanges sites that are located within a given radius around a randomly chosen site. In this context, the crossover operator is non destructive: the offspring inherit good properties of the parents.

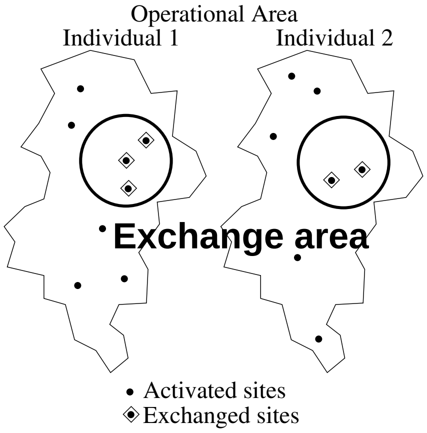

Figure 5: Geographical crossover in the operational space. Sites located in the circular area are exchanged.

The mutation operator acts at all levels of the gene hierarchy. When the mutation occurs, it may act at one level at a time. The mutation type is chosen between station activation toggling, transmitter power tuning, BS tilt tuning, BS azimuth tuning and BS diagram tuning. This is a blind mutation. To ensure a non destructive mutation, we apply it with a low rate. We modify only one site per mutation.

3.3 Ranking, sharing, and elitism

Standard GA mechanisms need a revision in order to take into account several objectives. The multiobjective evaluation function becomes mono-objective, using ranking methods to sort the population according to the definition of Pareto dominance. The GA handle diversity using sharing, and elitism is used to speedup the search.

We use the ranking function that is proposed by Fonseca and Fleming in [FF95a]. An individual i of the population, dominated by k individuals, obtains the rank $k+1$. The ranking is based on the three following objective functions: minimize the number of sites, minimize the overall interference, and minimize the traffic loss.

To maintain diversity along the Pareto frontier, we use a sharing technique, that aims to spread the population of individuals along this Pareto frontier by penalizing individuals that are strongly represented into the population. Sharing can be used in genotypic or phenotypic space. It is usually applied at phenotypic level, to enforce a diversity in the objective space. As the Pareto frontier is defined in phenotypic space, we use a sharing in the phenotypic space.

We use the following sharing. The fitness f of each individual is divided by the niche count:

$$f^{'}(u) = \frac{f(u)}{m(u)}$$

The niche count $m(u)$ of each individual is calculated using the formula:

$$m(u) = \sum_{v \in pop} sh(d(u,v))$$

Where sh is defined the sharing function:

$$sh(d(u,v)) = \begin{cases} 1 - (\frac{dist(u,v)}{\gamma_{sh}})^{\alpha} & \text{If } dist(u,v) < \gamma_{sh} \\ 0 & \text{Else} \end{cases}$$

where γ_{sh} is the size of the niche. We use the following formula [Deb99] : $\frac{0.5}{\sqrt[n]{q}}$ where n is the number of objectives and q is the desired number of distinct Pareto-optimal solutions. With q equal to 10.0 and n equal to 3, we have γ_{sh}=0.23.

The distance between individuals $d(u,v)$ is defined as:

$$d(u,v) = \sqrt{\sum_{i=1}^{n} \frac{f_i(u) - f_i(v)}{fmax_i - fmin_i}}$$

$d(u,v)$ gives the euclidian distance between individuals u and v in the objective space, normalized with fitness ranges, $fmax$ and $fmin$. The ranges are dynamically calculated at each iteration of the algorithm. The α parameter modifies the relative strength (Fig. 6) of the sharing function (α=0.4 for our experiments).

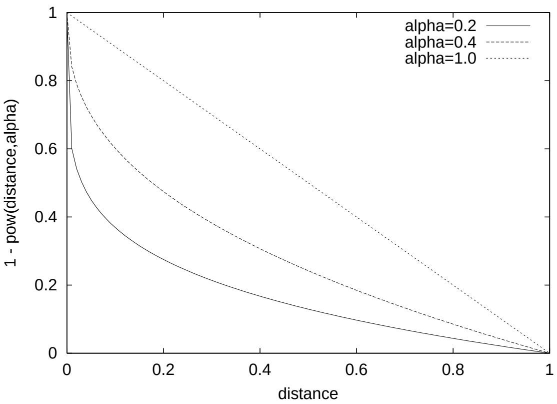

Figure 6: Influence of the parameter α on the sharing function.

The constraints are handled using a linear penalty in the objective function :

$$f^{'}(u) = penalty(u) * f(u)$$

For the cover constraint, the penalty is :

$$penalty_c(u) = \begin{cases} 5 * (\frac{cover}{100}) - 4 & \text{If cover > } 80\% \\ 0 & \text{Else} \end{cases}$$

For the handover constraint, we have :

$$penalty_h(u) = \begin{cases} 2 * (\frac{handover}{100}) - 1 & \text{If handover > } 50\% \\ 0 & \text{Else} \end{cases}$$

Then, the ranking is applied on the objective functions obtained after sharing and the constraint handling :

$$f^{''}(u) = f(u)\frac{penalty_h(u) * penalty_c(u)}{m(u)}$$

The elitism method used consists in maintaining an archive population that will contain the Pareto solutions encountered during all the search (Fig. 3). This population will participate to the selection phase. With a certain period of the number of generations, an individual is randomly selected from the archive to intensify the search in the Pareto frontier. For our experiments, the period is equal to 4.

3.4 Parallel implementation

In order to run the algorithm in tractable time, we have made a synchronous parallel implementation of the evaluation function. The evaluation function is basically parsing the working area, calculating radio wave fields at each point, updating network global fitness like cover or interferences, and updating handover and handled traffic for each cell.

The implementation is based on a master / workers model. Each worker is given a part of the geographical working area to work on. Each worker computes cover and interferences of points that it is in charge with. Handover and traffic are cell-based notions so they have to be handled differently. Each worker stores cells effectively received by treated RTPs. These informations are returned to the master and merged.

The hardware platform used is a network of 24 modern homogeneous workstations using LINUX operating system. The programming environment used is C/PVM (Parallel Virtual Machine) [GBDa94].

4 Performance evaluation

Two complementary types of new indicators are proposed to evaluate the results: the entropy indicator and the contribution indicator. The proposed metrics compare the relative performance of a Pareto front PO_1 obtained by a given algorithm against another Pareto front PO_2. The entropy indicator gives an idea about the diversity of the solutions found. The contribution indicator evaluates two populations of solutions in terms of dominance. We use also a graphical analysis which helps to understand the behaviour of algorithms by comparing the resulting Pareto frontiers.

4.1 Numerical indicators

We introduce the relative entropy $E(PO_1, PO_2)$ of a set of non dominated solutions PO_1 regarding to the Pareto frontier PO defined by the non-dominated solutions of PO_1 and PO_2 ($PO = ND(PO_1 \bigcup PO_2)$, where ND represents the non dominated set).

The N-dimension space, where N is the number of objectives to optimize, is clustered. For each space unit with at least one element of PO, the number of present solutions of PO_1 is calculated. Then the following formula is applied to evaluate the entropy E of PO_1 relatively to the space occupied by PO:

$$E(PO_1, PO_2 = \frac{-1}{C\log(C)}\sum_{i=1}^{C}\left(\frac{n_i}{C}\log\frac{n_i}{C}\right)$$

Where C is the cardinality of the non-empty space units of PO, and n_i is the number of solutions of set PO_1 inside the corresponding space unit.

The indicator behaves such as the more the solution set PO_1 is well diversified on the frontier, the higher is the entropy value $(1 \geq E \geq 0)$.

We introduce another numerical indicator, the contribution, that quantifies the domination between two sets of non-dominated solutions.

The contribution of algorithm PO_1 relatively to PO_2 is roughly the ratio of non dominated solutions produced by PO_1.

Let C be the set of solutions in $PO_1 \bigcap PO_2$. Let W_1 (resp. W_2) be the set of solutions in PO_1 that dominate some solutions of PO_2 (resp. in PO_1). Similarly, let L_1 (resp. L_2) be the set of solutions in PO_1 (resp. PO_2) that are dominated by some solutions of PO_2 (resp. PO_1). The set of solutions in PO_1 (resp. PO_2) that are not comparable to solutions in PO_2 (resp. PO_1) is $N_1 = PO_1 \backslash (C \cup W_1 \cup L_1)$ (resp. $N_2 = PO_2 \backslash (C \cup W_2 \cup L_2)$.

The contribution $CONT(PO_1/PO_2)$ is stated as:

$$CONT(PO_1/PO_2) = \frac{\frac{|C|}{2}+|W_1|+|N_1|}{|C|+|W_1|+|N_1|+|W_2|+|N_2|}$$

The contribution of the algorithm PO_2 relatively to PO_1 is defined in a similar way. Notice that if both algorithms produce the same solutions then:

$$CONT(PO_1/PO_2) = CONT((PO_2/PO_1) = \frac{1}{2}$$

On the other hand, if all the solutions produced by PO_2 are dominated by solutions produced by PO_1 then

$$CONT(PO_2/PO_1) = 0$$

5 Results

The algorithm has been evaluated on a large and realistic highway area (Fig. 9) generated by the France Telecom's research laboratory (CNET) with the parameters defined in table 2.

The multiobjective evaluation of a network engages the use of a propagation model. We are using the so-called Free Space model [LGT99]. Although this propagation model is simple, it is not trivial to compute and requires the use of computational intensive mathematical functions, such as arctangent and square root. For example, a single evaluation

Table 2: Parameters of the network used for our experiments.

Width	Length	Total Traffic
39 km	168.8 km	3210.94 Er

RTP	STP	TTP	Service	Sites
164580	29954	4967	8 Watt outdoor	250

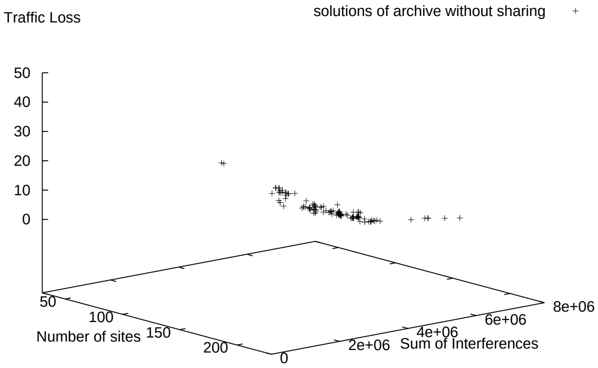

Figure 7: Site Number vs. Total Interference vs. Traffic Loss of archive without sharing.

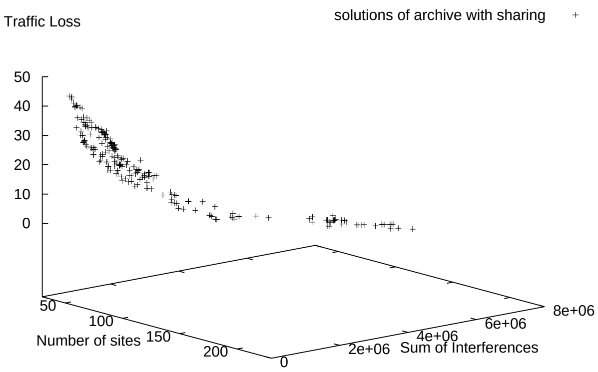

Figure 8: Site Number vs. Total Interference vs. Traffic Loss of archive with sharing.

takes about 10-20 seconds on a network with all base stations activated, using a single workstation.

We compare the behaviour of the GA when using or not the sharing feature (see Fig. 7 and Fig.8). The Pareto frontier represents the feasible solutions of the archive produced by the GA. Comparison results are made on the three objectives: number of sites, interferences and traffic loss. The size of the GA's population is 100, and the number of generations is initialized to 10000. Each run typically takes 10 hours on average.

The resulting Pareto front of the GA without using the sharing mechanism shows concentrated solutions into a limited area of search space 7. However, the Pareto front found by the GA using the sharing mechanism shows a wide frontier comparing to the first one 8. Entropy values of Table 3 enforce these visual assumptions. A large entropy value is given to the Pareto front using the sharing mechanism.

In addition, contribution values show that the GA with sharing brings more Pareto solutions than the GA without sharing, but the difference is not very important (see Tab. 4). An explanation of this result is that the GA without sharing makes a local intensive search into a small part of the front, so these solutions are locally better than solutions of the GA with sharing in this part of the Pareto frontier.

Table 3: Entropy of the set of non-dominated solutions computed by the GA with and without the use of sharing.

solution sets	entropy
no sharing	0.42
sharing	0.95

Table 4: Contribution of non-dominated solution sets resulting of the GA with and without the use of sharing.

solution sets	CONT	W	L	N
no sharing	0.36	0	9	85
sharing	0.63	110	42	111

To illustrate the difference between Pareto solutions found, we sample two solutions from the Pareto front (see Fig. 9 and Fig. 10). They represent two solutions with different number of sites. The first one features a few number of sites, few interferences, and a lot of traffic loss while the second one features a large number of used sites, large interferences, but a low traffic loss (see Table 5).

Table 5: Sample of solutions of the Pareto frontier.

solutions	Sites	Interf	TLoss (%)
Fig. 9	54	1285235	25.1
-	79	2114415	11.2
-	105	3218750	3.0
Fig. 10	167	5607464	0.2

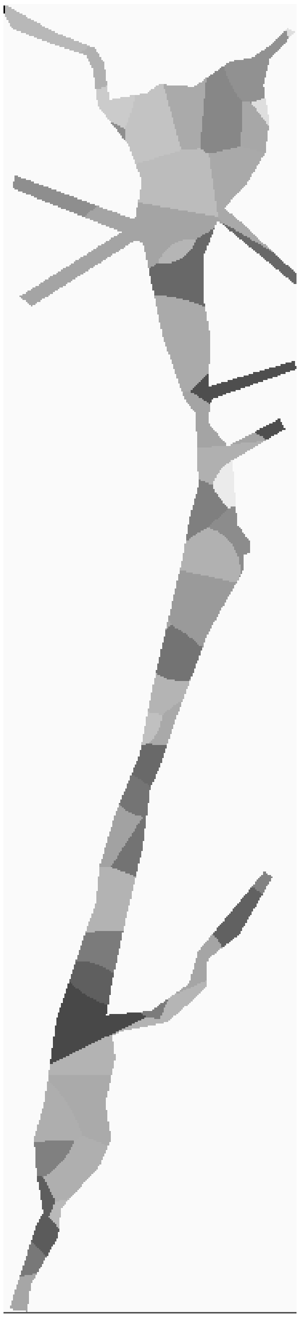

Figure 9: A solution with few used sites (54).

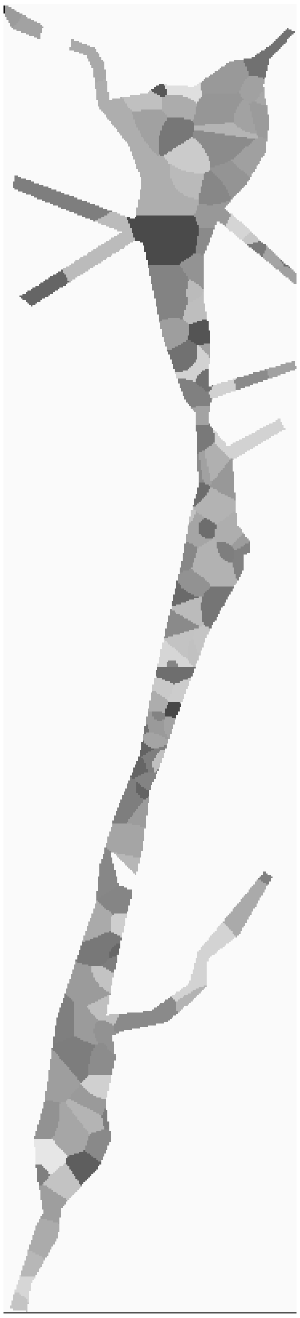

Figure 10: A solution with a lot of used sites (167).

6 Conclusions

In this paper, we have presented a multiobjective model of a problem involved by the radio network design. This problem is actually handled manually. Our aim is to treat this problem automatically. We have investigated the use a multiobjective genetic algorithm in order to obtain a population of Pareto solutions spread on the Pareto frontier. We have shown that the proposed GA is able to handle multiple objectives and constraints, to create and maintain a set of solutions widely spread on the Pareto frontier. The complexity of the problem (number of solutions, evaluation cost, memory requirement) has lead to a parallel implementation of the algorithm which is based on domain decomposition.

Two performance indicators were suggested: the contribution indicator to evaluate the convergence of the algorithm, and the entropy indicator to measure the diversity of the solutions obtained. The results obtained on real life problems show the importance of the sharing mechanism.

This study opens many directions for future works. First, it would be interesting to study the hybridization of GAs with local search algorithms to intensify the search in the Pareto frontier. Finally, we investigate the design of an interactive decision making algorithm. The final decision maker may exploits the Pareto frontier to guide the algorithm towards the final solution.

References

[BHMZ99] J. Bendisch, R. Höns, H. Mühlenbein, and J. Zimmermann. Algorithms for radio network optimisation. In *ARNO-Workshop at EPMCC'99*, Paris, March 1999. GMD.

[CMM90] R.L. Carraway, T.L. Morin, and H. Moskowitz. Generalized dynamic programming for multicriteria optimization. *European Journal of Operational Research*, 44:95–104, 1990.

[Coe98] C.A.C. Coello. An updated survey of ga-based multiobjective optimization techniques. Technical Report RD-98-08, Laboratorio Nacional de Informática Avanzada (LANIA), Xalapa, Veracruz, México, December 1998.

[Coe99] C. A. C. Coello. A comprehensive survey of evolutionary-based multiobjective optimization techniques. *Knowledge and Information Systems. An International Journal*, 1(3):269–308, 1999.

[Deb99] K. Deb. Evolutionary algorithms for multicriterion optimization in engineering design. In *Proc. of Evolutionary Algorithms in Engineering and Computer Science, EUROGEN'99*, 1999.

[FF95a] C.M. Fonseca and P.J. Fleming. Multiobjective genetic algorithms made easy: selection, sharing and mating restrictions. In *IEEE Int. Conf. on Genetic Algorithms in Engineering Systems: Innovations and Applications*, pages 45–52, Sheffield, UK, 1995.

[FF95b] C.M. Fonseca and P.J. Fleming. An overview of evolutionary algorithms in multiobjective optimization. *Evolutionary Computation*, 3(1):1–16, 1995.

[FMB96] T. Fruhwirth, JR. Molwitz, and P. Brisset. Planning cordless business communication systems. *IEEE Expert Magasine*, pages 662–673, 1996.

[GBDa94] A. Geist, A. Beguelin, J. Dongarra, and al., editors. *PVM: Parallel Virtual Machine, A User's guide and tutorial for Networked Parallel Computing*. MIT Press, 1994.

[GZBS86] A. Gamst, E.G. Zinn, R. Beck, and R. Simon. Cellular radio network planning. *IEEE AES Magasine*, pages 8–11, February 1986.

[LGT99] X. Lagrange, P. Godlewski, and S. Tabbane. *Réseaux GSM-DCS*. Hermes Science, 4e édition revue et augmentée edition, 1999.

[RC98] P. Reininger and A. Caminada. Model for gsm radio network optimisation. *2nd International Workshop on Discrete Algorithms and Methods for Mobile Computing and Communications, In conjuction with ACM/IEEE Mobicom'98*, 1998.

[SK99] S. Sayin and S. Karabati. A bicriteria approach to the two-machine flow shop scheduling problem. *European Journal of Operational Research*, 113:435–449, 1999.

[Ste86] R. Steuer. *Multiple criteria optimization: Theory, computation and application*. Wiley, New York, 1986.

[Tal00] E-G. Talbi. Metaheuristics for multiobjective combinatorial optimization: state of the art. Technical report, LIFL, Lille, France, 2000.

[VH99] M. Vasquez and J-K. Hao. A heuristic approach for antenna positioning in cellular networks. In *Journal of Heuristics*, June 1999. submitted.