Radio Network Planning with Combinatorial Optimization Algorithms

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Group: Software tools

Abstract: *Future UMTS radio planning engineers will face difficult problems due to the complexity of the system and the size of these networks. In the STORMS project, a software for the optimisation of the radio network is under development. Two mathematical models of the radio planning problem are proposed. Two software prototypes based on these models are described with the first experimental and comparative results.*

1. Introduction

The radio planning of a mobile network is a task that is currently being accomplished by second generation operators with the aid of commercial planning tools. These tools provide propagation models that allow computing the coverage supplied by a given configuration of the BTS network. Even if they are very useful for operators, second generation tools suffer from several limitations. The tougher one, as far as radio planning is concerned, is the limited range of propagation environments they may analyse (microcells are already being installed in second generation networks).

Furthermore, the deployment and planning of UMTS will bring in additional requirements. The list of propagation environments is enlarged to include not only macro and microcells but also indoor cells. A mixed service environment must be considered, where advanced data services will coexist together with the traditional voice or low rate data services. This has to be taken into account in the definition of the radio level requirements to be imposed in the radio planning of the network in order to achieve the QoS and GoS requirements. Finally, being the specification of UMTS still open, different radio access techniques must be considered by any third generation planning tool designed today.

This is the framework for STORMS, that aims at the design and implementation of the first third generation planning tool, as far as the radio aspects are concerned.

2. The radio coverage optimization problem

The STORMS radio planning tool is being designed as to extend the applicability of second generation systems in terms of environments (including micro and pico cells) and the features of UMTS (radio access techniques, services). But also, it will bring in the capability of performing radio planning in an automatic way. This will be done taking as an input a large set of candidate BS sites (either introduced by a skilled operator or by an automatic engine). From this large set, a minimum set is selected that guarranties the required coverage while keeping cost at a minimum. Then, optimisation of the radio configuration of the selected set of BS is performed.

The development of the software prototype is being done following an incremental approach. As of today, the first stage of the problem that is being tackled consists in the extraction of the final set of BS locations. For solving this optimisation problem, two different algorithms are being implemented into software prototypes.

3. Hypothesis and data

In order to be able to tackle this difficult problem we used a first simplified approach by assuming the following hypothesis:

- Uniform Traffic: We will focus on the coverage problem by assuming that the traffic is uniform all over the area to be served.
- Constant Cost for the BSs: The total cost of the network is therefore equivalent to the number of BSs.
- We focus on rural areas.

With the evolution and the validation of the methodologies developed in the STORMS project, these restrictive hypothesis will be gradually released.

In the remaining of this paper, we assume that a user-defined set of potential BSs locations is provided as an input to our computation, and that each BS location is associated a cost. We also assume that the area served by a given BS, called *a cell*, can be computed by a function ad hoc. The computation that is actually performed by this function may be based on sophisticated wave propagation models, or it may be the result of a draft estimation. Our only requirement is that a cell be discretized, that is, a cell should be described as a finite collection of geographical locations.

4. Models

Our goal is to select a satisfactory subset out of the user-provided set of BS location, while ensuring that at least a given percentage of the considered area is served by the selected BS. For that problem, we propose two graph theory based models.

In both approaches we start from a very large list L of possible locations for BS in the area of interest.

4.1 Maximum Independent Set Model

The first model consists in building a graph that models the mutual redundancy of BS sites. Then selecting a network of BS sites will consist in searching for a set of not redundant sites that maximise the coverage of the area of interest.

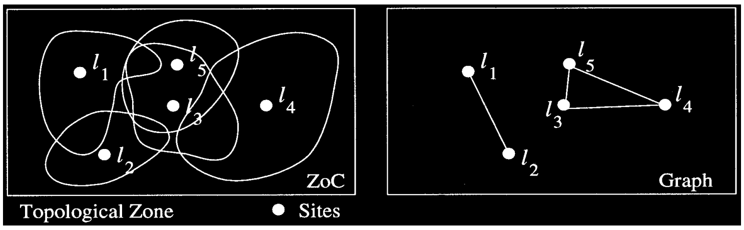

Figure 1. Initial graph construction

The graph is built (see Figure 1) according to an « interdiction » function: there exists an edge between two BSs if these two must not be found together in a final solution (i.e., their overlap is too large for technical or economical reasons). The interdiction function creates an edge if the size of the overlap of the two cells divided by the size of the smallest cell is greater than or equal to K. K is a constant that must be set according to the characteristics of the cellular network that is being built.

With this assumption, each solution corresponds to a set of BS in which each pair of locations (i.e., vertices of the graph) does not break the interdiction rule. Translated in terms of graph theory, this means finding an independent set.

4.2 Dominating Set Model

The second approach we consider is based on the notion of *dominating set*, also called *vertex-cover* [1].

4.2.1 Definition:

- Given a graph G=(V,E) where V is a set of vertices and E is a set of edges, **a dominating set** for G is a subset V' of V such that for all u in V-V' there is a v in V' for which (u,v) is in E.
- A dominating set V' is said to be **minimum** if no other dominating set has a smallest cardinality (number of vertices).

In the case we consider, V is the union of two sets A and B, where A is the set of all possible BSs locations, and B is the set of all potentially covered locations. There exists an edge (u,v) in E when u is in A (i.e., u is a BS location), v is in B (i.e., v is a covered location), and the BS located in u covers the location v.

Finding a set of BSs locations which covers the region considered satisfactorily is equivalent to finding a subset of A which is a minimum dominating set of G. In the case we consider, we know that such a set of G exists because A is itself a dominating set of G (although it is likely not to be the minimum one).

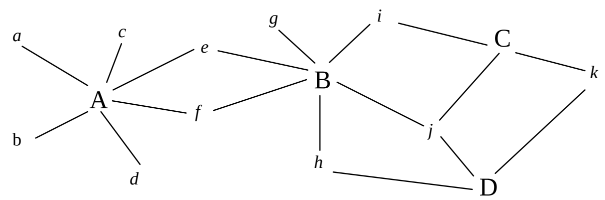

Figure 2. Graph-based modelisation of the BS selection problem.

5. Software and Algorithms

So far, both mathematical models and associated algorithms have been implemented in two software prototypes. For experimental and future integration purposes, they have been designed to use the same geographical data, the same sets of potential BS sites[1] and the same radio propagation[2] algorithms.

For the Maximum Independent Set (MIS) model, we implemented a greedy algorithm with seven different heuristic variants. For Dominating Set model, we implemented a genetic algorithm.

5.1 The Greedy Algorithm for MIS extraction

We use a classical scheme for MIS extraction [2], described in a pseudo code way as follows:

[1] For experimental purposes these sites are most of time generated automatically but can also be user-defined

[2] This model is a classical multiple diffraction model provided by TDF

```
Input: G(V,E) a graph
Output: I ⊂ V a MIS
I←∅
while V≠∅ do
        v ← a vertex from V
        I ← I ∪ {v}
        delete {{v} ∪ Neighbour(v)} from V
endwhile
```

The heuristics consists in different schemes that can be used to select the vertex v.

5.2 Genetic algorithm

The problem of finding an exact minimum dominating set in a graph is a NP-complete problem and therefore requires non-polynomial execution time. Due to the amount of possible BS locations we must consider (typically, 1000 potential BS locations for a 150 km x 150 km area), it is not achievable to look for an exact solution. Consequently, we must go round this problem and look for satisfactory -- yet sub-optimal -- solutions.

To achieve this goal, we are investigating several approaches, which are said to be bio-inspired because they are based on implementations of "heuristics from nature", that is, heuristics that have some analogies with natural or social systems [3]. To date, we most especially focus on the so-called genetic approach.

A genetic algorithm is a population-based model inspired by evolution that uses selection and recombination operators to generate new sample points in a search space [4]. Each individual in a population represents a possible subset of chosen BSs and is encoded as a chromosome-like bit string.

The first step in the execution of a genetic algorithm consists in the generation of an initial population. In our implementation, the individuals of the initial population are determined randomly and so, are not dominating sets.

Each iteration step during the execution of a genetic algorithm can be thought of as a two stage process. First selection is applied to the current population to create an intermediate population. Crossover and mutation are then applied to the intermediate population to create the next population.

The selection is achieved based on the fitness value associated with each individual: the higher the fitness value of an individual, the higher it is likely to be selected. In our implementation, the function returning the fitness value is: $Fitness = (Coverage^{\alpha} / NbBSs)$, where *Coverage* is the coverage achieved by the subset of BSs associated to an individual, *NbBSs* is the number these BSs, and α is a parameter greater than 1 in order to favour the coverage.

Crossover is a combination of two selected individuals. It produces new individuals that are likely to own characteristics of their parents. Mutation introduces random modifications on individuals to avoid premature convergence of the population to non-optimal solutions. As, thank to the fitness function, selection favours individuals that cover many locations with few BSs, population converges to individuals which have properties close to minimum dominating sets.

The execution terminates when a satisfactory individual has been produced or when a predefined number of iteration steps has been run through.

6. Experimental results

The experiments with both software aimed at:

1. assessing and tuning each software parameters and heuristics
2. comparing performances of the two pieces of software.

The experiment was conducted in an area of 73×76 km² in the north-east of France (see Figure 4). For practical reasons 150 potential sites were generated automatically[3]. At each potential site a BS with an antenna height of 30 m is located and a cell according to a maximum pathloss of 110 dB at 900 MHz is computed with a multiple diffraction propagation model.

For the Maximum Independent Set model, the first experiments that were conducted aimed at finding the best heuristic. The experiment consisted in comparing the coverage achieved for different maximum overlap between cells and seven different heuristics. The results showed that the heuristic that consists in selecting the vertex that performs the best coverage and that has the smallest degree in the graph is the best one. The computations were performed with a SUN SPARC 10 and took about 2 hours[4].

From this experiment we decided to conduct some more measurements with this heuristic, in order to determine the algorithm behaviour of the regarding the maximum allowed overlap between cells.

For different maximum overlap between cells, we ran the optimisation and measured:

1. the relative coverage, i.e. the achieved coverage compared to the total coverage obtained by adding the coverage of all the potential sites
2. the number of selected BS

For the dominating set prototype, the same kind of measurements were carried out in order to determine the best internal parameters of the genetic algorithms. In both cases, measurements (Figure 3) show that the algorithm has the expected behaviour:

- the more coverage to be achieved, the more BS are necessary
- the last coverage holes are very expensive to cover (curve slope gets steeper for large coverage)

From these measurements we computed the mean coverage per BS which is the relative coverage of the selected network divided by the number of selected BS. This figure gives an idea of the efficiency of the obtained radio network.

To compare both models and algorithms, we measured that value for the dominating set and the maximum independent set models.

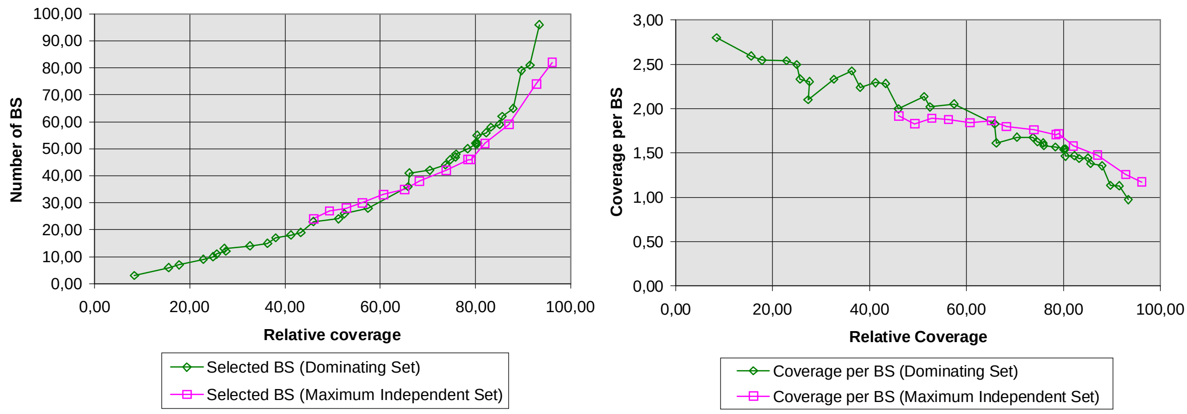

Figure 3. Compared performances of of the two pieces of software

Although the mathematical models are completely different, both prototypes show the same performances in terms of radio network planning: they achieve the same coverage with similar amounts

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3 The (p×q) potential sites were generated automatically with the following algorithm:
- divide the area of interest in p×q rectangles of equal size (here 7×5 km²)
- find the local maximum for terrain elevation in each square and generate a potential BS location
The resulting set of locations L is uniformly distributed on the area of interest

4 We observed that 99% of computing time was devoted to the radio propagation computations and that the statble search was always a matter of seconds.

of BS and the distribution (Figure 3, Figure 5, Figure 6). The main difference lies in computing times: the genetic algorithm involves many computation of a time consuming fitness function whereas the greedy algorithm for MIS extraction is very fast.

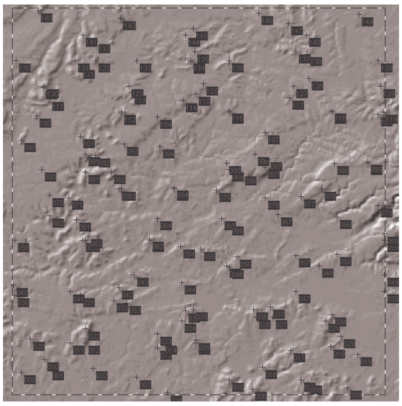

Figure 4. Initial set of 150 locations on a 73 × 76 km² area

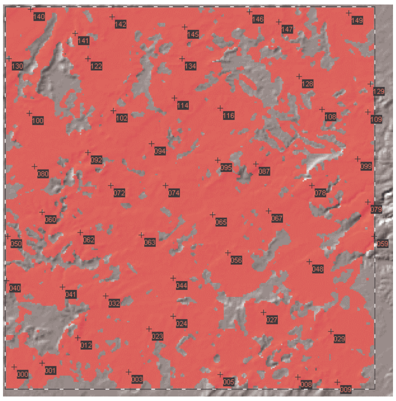

Figure 5. MIS prototype BS selection with 28% max. overlap 52 BS were selected

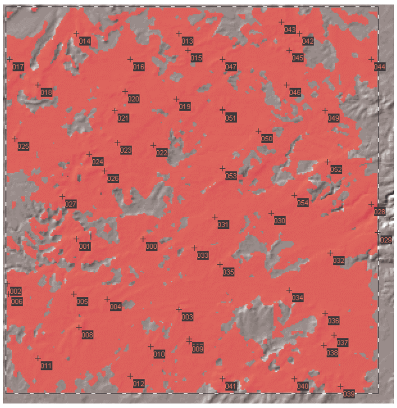

Figure 6. Dominating Set prototype BS selection and coverage 55 BS were selected

7. Conclusion

Automatic location of BS has not been broadly studied yet. The prototypes we have developed show that graph theory provides good models for that problem. With different models of the problem and different algorithms, promising and similar results have been obtained in both cases. These approaches were designed to cope with large problems (up to a few thousand potential sites) and are independent from proagation. They will be integrated in a single software and upgraded with the following features:

- new cellular network parameters, and multiple BS characteristics i.e.: antenna diagrams, antenna height, orientation, sectorisation
- mobile traffic demand forecasts taken into account for the BS selection and configuration
- urban propagation model and mobile network structure (small cells and microcells);

1. References

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