MULTI-STAGE OPTIMIZATION FOR MOBILE RADIO NETWORK PLANNING

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Abstract – In this paper, the evolution of mobile radio network is presented. First of all, the network life cycle is considered. A mathematical modeling of these life periods is developed inside an optimization problem: optimal location of base stations. It is a combinatorial optimization problem. A multi-period model is built on a Concentrator Link approach. Finally, three different multi-period techniques are identified, they are based on Genetic Algorithm (GA) to tackle this problem on the design of micro-cellular networks.

I. INTRODUCTION

Considering its different evolution stages, a mobile radio network may be compared to a living organism. Like all living systems, the mobile radio network has a period of gestation before it birth. This period estimates the financial validity and profitability of the mobile radio network deployment. If the gestation period concludes on the decision to deploy the network, the network starts with the deployment of the first base stations (BS). Then, as a second step, it grows at every local or global extension. Each of these extension steps are called new deployments. Regards at economical criteria, a good deployment must involve a minimal number of BS while performing an optimal radio coverage. The evolutions occur frequently in real networks and may be due to traffic consideration, handover margin, service quality, etc. The better those constraints of expansion are satisfied, the better the organism copes with the environment.

In this paper, the multi-period optimization problem is identified. The multi-period optimization problem occurs in the radio network life cycle and GA is used to tackle those problems on the first objective of cellular network deployment: the cover (Chamaret 1997). The strategies of the network to adapt itself to the environments, during is evolutions, are the multi-period techniques expose in this paper.

This paper is organized as follows. Section 2 introduces the evolution problems occurring in mobile radio network life cycle. Section 3 deals with the modeling of the network design based on a concentrator link problem (CLP) and introduces a GA to solve a single period problem. Section 4 deals with the different multi-period techniques and presents comparative results on a micro-cellular network. Then Section 5 presents the future works.

II. NETWORK EVOLUTION

Birth

Before the deployment of the network, there is a period of gestation which is a marketing step including the definition of the commercial objectives of the future network, the macro financial resources needed to claim these objectives and the network profitability with a measurable estimation error. That this is a first optimization problem: the dimensioning. The dimensioning stage is very difficult. At the moment, as for the manufacturing of every complex system, there is a gap between cost estimation and real cost measured at the end of the network deployment. The main objective of the dimensioning stage is the cost estimation. When the decision to built the network is taken, the deployment starts with the first stage of the design. This is the birth of the network. The main objective is to cover the target area with the service thresholds decided by the dimensioning (patterns in Fig.1). The network emerges when the first BS are deployed, and is fully born when the initial objective of cover is fulfilled. Fig.1 shows the third stage of an urban network. The black points are candidate sites used for the deployment in the period 1 (P1), in the period 2 (P2) and in the period 3 (P3). The patterns define the objective of cover in the different periods.

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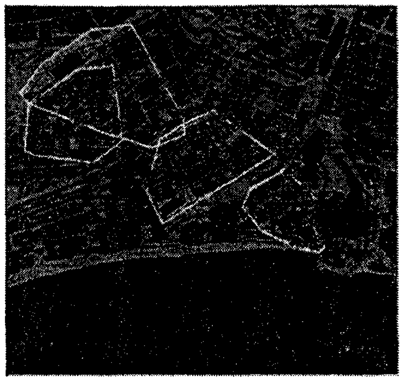

Figure 1: Period 3 of the network life: cover extension.

Growth and Death

When the first operational network is available, that is the end of the birth stage, the designer has two kinds of problems. Firstly it must domesticate the network to improve it quality. It is an optimization step without extension of the network size. The designer must be able to schedule the network expansions during its life cycle. This full stage is the growth of the network: the network must be able to integrate new resources, to tackle new objectives, e.g. a larger traffic demand.

The initial phase of this growth stage is not specifically a growth, but a learning phase. Indeed the aim of this phase is to improve the quality of the existing network without any additional resources (new sites or new BS). The networks have a lot of parameters to tackle the cover holes or to reduce the level of interferences: power control, azimuth and tilt adjustments, addition of TRX, optimization of the frequency plan, etc. When the improvements cannot be addressed with the current resources of the network, the decision is taken to add new sites such as period (P2) and period (P3) Fig.1. In the period 3 of the network life, for example, the sites P3 are now available. Fig.1 also shows an evolution of the previous network with new objectives of service (new patterns).

Then it is the growth of the network, a new period of life, a new deployment. At this step of life, something very different from the initial deployment occurs. The new deployment is done from an existing network. An evolution process is required from the existing network to integrate new sites to deal with new objectives (Fig.2). From an engineering point of view, the new deployments are basically used to increase the network capacity by cell-splitting or to enlarge the cover by adding new sites on the cover border. Evolution means that existing sites must adapt themselves to allow the network the integration of the new individuals (new sites) and BS. Without this integration, the new objectives won't be addressed. For the network, evolution is a question of survival. Some environmental constraints appear in this evolutionary process.

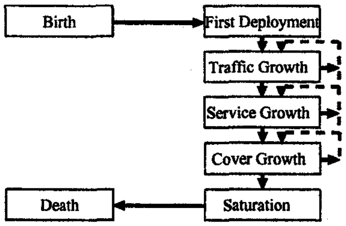

Figure 2: Network evolution.

These two different phases of growth, domestication and evolution, are iterated until the network reaches the saturation point, e.g. the objectives of growth overflow the system ability. Then the network dies. The death may be 'soft' if the existing saturated network supports a progressive migration to a new technology, e.g. the GSM system at 900 Mhz is compatible with the DCS system at 1800 Mhz. Both networks can live together to support the global objectives, the mobile station can use both systems. Or the death may be 'violent' when the system ability does not offer any support to the new environment defined by the new objectives. That might be the case for analogic systems for instance.

III. PROBLEM MODELING

Concentrator Link Model

The following model (Reininger 1998) deals with radio network optimization as a Concentrator Link Problem (CLP) (Sherali 1994). The Reception test points (RTP) have to be concentrated on BS satisfying cover, handover, interference and traffic constraints. CLP approach (Wright 1998, Floriani 1997) is perfectly suited to model the design of mobile radio network if we keep in mind that any mobile station (MS) has to be connected, or concentrated, to at least one BS in order to communicate.

The model deals with the minimization of the number of sites during the periods of network birth, then the minimization of the number of new sites and the number of modification during the stages of cover growth. A network is built on a working area (town, country ...). The working area described by a Digital Map Database is defined by $\mathcal{P}$. Three sets of points are identified on $\mathcal{P}$: a set of candidate sites for the positioning $\mathcal{L} = \{L_i / i \in N\}$. Each site is defined by (x, y, z). A set of Reception Test Points (RTP) in which the signal level will be tested $\mathcal{R} = \{R_i / i \in N\}$. A set of Service Test Points (STP) in which the expected service will be tested $\mathcal{ST} = \{ST_i / i \in N\}$. Each STP is described by S_q a field strength threshold for an expected radio service. A field strength is computed from a BS, on a site, to a MS on each RTP.

A hard constraint is defined on the cover: all STP must be covered considering a service threshold. We do not yet deal with the traffic and interference objectives. The purpose of this paper is not to focus on the multi-objective problem of the network design as it is describe in (Reininger 1998). We focus on the coverage evolution of the network through several periods. The main objective is defined by:

$$\min \sum_{j \in \mathcal{L}} f_j y_j$$

The sites are associated to their installation costs f_j. The site cost is estimated as an average. The installation cost f_j will therefore be the same for all sites seeing the following rules: f_j is set to 1 for initial sites and set 2 to 5 depending on the expansion action on the network ($k \geq 1$) (some sites may be newly installed, some sites may be changed or removed):

$$f_j = \begin{cases} 1, & \text{if } B^0 = \emptyset \\ else, & \begin{cases} 1, & \text{if there is no change on site } L_j^0, \\ & {B_{jk}}^0, k \in [1..3] \\ 2, & \text{if there is any change on site } L_j^0, \\ & ({B_{jk}}^0, {B_{jk}^{Ps}}^0, {B_{jk}^{AT}}^0, \\ & {B_{jk}^{\beta}}^0, {B_{jk}^{\delta}}^0) \\ 5, & \text{if the site } L_j \text{ is newly installed} \\ 7, & \text{if the site } L_j^0 \text{ is removed} \end{cases} \end{cases}$$

Such as:

$$\sum_{j \in \mathcal{L}} \sum_{k \in [1..3]} x_{ijk} = 1, \forall ST_i \in \mathcal{ST}$$

$$x_{ijk} = \begin{cases} 1, & \text{if } ST_i \text{ received the best signal from } B_{jk}, \\ & Cd_{ijk} = \max_{l \in \mathcal{L}} \{Cd_{ilk}\}, Cd_{ijk} \geq S_q \\ 0, & \text{else} \end{cases}$$

$$y_j = \begin{cases} 1, & \text{if } L_j \text{ is used} \\ 0, & \text{else} \end{cases}$$

Where, $x_{ijk} \in \{0,1\}, y_j \in \{0,1\}, \forall ST_i \in \mathcal{ST}, \forall j \in \mathcal{L}$, n is the number of STP $|\mathcal{ST}| = n$, $m (\leq n)$ is the number of sites $|\mathcal{L}| = m$. For each STP ST_i, we sort the field strength received from BS: Cd_{ijk} is the higher field received in ST_i, and we classified all the field strength from every BS, $Cd_{iu_1v_1}, Cd_{iu_2v_2}, \dots, Cd_{iu_hv_h}, Cd_{iu_{h+1}v_{h+1}}, \dots, Cd_{iu_\lambda v_\lambda}, \dots$ If $Cd_{iu_\lambda v_\lambda} < Sm$, the field strength is not considered. Sm is sensitivity of the MS. The following values are the BS parameters: B_{jk}, $k \in [1..3]$, the k BS of site L_j, B_{jk}^{Ps}, the transmitting power of B_{jk}, B_{jk}^{AT}, the antenna type of B_{jk}, omnidirectional or directive, B_{jk}^{β}, the tilt of the antenna of B_{jk} B_{jk}^{δ}, the azimuth of the antenna of B_{jk}, B_{jk}^{δ}, $Cd_{ijk}(Ps, AT, \beta, \alpha)$ the field strength received on the RTP R_i from the BS B_{jk} of site L_j,C_{jk} the cell of the BS B_{jk} of site L_j.

To assure a good quality of service and reduce the interference we also introduced a second objective in this light model. This new objective is to reduce the number of received field strength on each STP. The objectives become minimizing the site number with a good cover for all the STP and minimizing the number of received field strength on each STP. They are antagonistic. We deal with two objectives in the next GA fitness function. The following Section introduces the features of a basic GA we developed for a single-period mobile radio network design problem. The Section 4 will introduce the improvements for a multi-period approach.

GA Problem Representation

For this study on multi-period problem, the GA has not been improved by complex mechanism or heuristic to assure a quick convergence, as in (Dony 1998). We will show in Section 4 that all the multi-period techniques are based on the same basic GA. The basic GA mutes the binary values of the sites and antenna, and selects the power in a table. The crossover is a classic monopoint crossover and the selection is a wheel.

The cost and the complexity of real cellular networks which are currently deployed are strongly depending on the number of BS. The fitness function maximizes the cover of STP and reduces the interferences. Regards at the previous theoretical model we introduce this fitness in the GA: max f_{obj}.

$$f_{obj} = \delta |\{ST\}^1| - u |\{ST\}^n| - v |\{ST\}^0| \quad (1)$$

where, $|\{ST\}^0|$ the number of STP uncovered, $|\{ST\}^1|$ the number of STP covered by only one BS, $|\{ST\}^n|$ the number of STP covered by more than one BS, δ, u and v are constants.

The first term in (1) is the set of good STP, covered by only one BS. The third term, $v.|\{ST\}^0|$, is a classic usage of constraint as penalty function (Surry 1995). All the STP must be covered. The second set of terms is ambiguous. This field is tolerate due to the propagation law, we can not stop this physical effect of the wave on one STP. Therefore we must manage this effect.

On a single period we also add the cost of the network evolution to the fitness function: $\max f_c$. where,

$$f_c = Cost_{\max} - \sum_{j \in \mathcal{L}} f_j y_j \tag{2}$$

$Cost_{\max}$ is the maximum boundary cost of evolution for the period. Then the global fitness for a basic GA on one period is: $\max(\alpha f_c + \beta f_{obj})$, α and β are constants which normalized the fitness.

IV. MULTI-PERIOD GA

In previous Section, a single-period model and algorithm is described. This GA is now improved to a multi-period algorithm without changing its data structure. The interest for multi-period algorithms in the telecommunication planning process is due to the evolution of data flow in the time (Shulman 1993). This problem becomes crucial with the fast growth of mobile radio network. There are two main kind of changes for a multi-period evolution of a cellular radio network : the objectives (coverage, traffic) and the data (number of potential sites, their location). A multi-period problem is an evolution problem characterized by some changes in the environment between two periods. This kind of dynamic adaptation has already been tested in a GA process with success (Surry 95). In the problem of mobile radio network design, the change of objective is assimilated to a change of strategy from a period to the next one The evolution of data (Figure 1) is the addition of new available sites (P0, P1, ...) on different periods. The major interest of processing multi-period is to tackle all periods as a whole instead of ignoring new and objectives from a period to another one.

Multi-period Techniques

Nowadays, three techniques of multi-period optimization based on GA are developed. A single-period algorithm which gives us good results on a mobile radio network design problem is reused. The first technique (A) is the worst technique. The running steps of the algorithms are show in Fig.3. Each period is processed successively but independently. It works from a specific period to the next one. It is a simple repetition of the single-period algorithm, but the initial network of a specific period is the network obtained from the previous period. The initial:

$$F(t) = \alpha f_c(t-1) + \beta f_{obj}(t)$$

with $f_c(0) = 0$, where, T, the total number of periods, t, the period number, $1 \leq t \leq T$, F, the multi-period fitness, f_c, the cost function from one network to another, f_{obj}, the inside period fitness, α and β are constants which normalized the fitness.

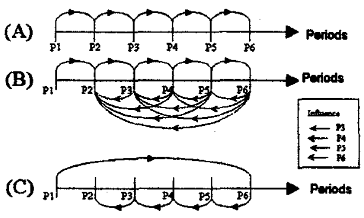

Figure 3: Multi-period techniques.

When the characteristics of all periods are known in advance, the second technique (Fig. 3 (B)) is more interesting because it is based on a kind of influence of the future periods parameters on the current one. It favors the persistence of the main part of the network throughout periods. For this technique, the characteristics of future periods must be known. The influence of each sites in all periods is included the current algorithm. The initial fitness becomes:

$$F(t) = \alpha f_c(t-1) + \beta f_{obj}(t) + \gamma \textstyle\sum_{j=t+1}^{T} f_{inf(j)}$$

with $f_c(0) = 0$, where, j, the number of further period, $f_{inf(j)}$,the influence function. A measure of the sites interest in the future is given by this function. This kind of site might be very interesting in the future, but they are not yet. γ, is a normalized constant.

The last technique (Fig. 3 (C)) is developed in a way of decreasing costs too. The idea is to consider a very long period by using the single-period algorithm to find the best network for the last period. The next step is to search the intermediate networks in the opposite direction (from the last period to the first) by *deteriorating* the last network. It's true that the intermediate solutions may not be the best's ones, but we can make some compromises in a way of having good and more reusable networks. This technique is called a feedback technique. The initial fitness becomes:

$$F(t) = \alpha f_c(t+1) + \beta f_{obj}(t) + \gamma \textstyle\sum_{j=1}^{t-1} f_{inf(j)}$$

Experimentation

These different techniques are tested on a small micro cellular network. In fact, it is hard to define periods on mobile radio network and have good prevision. There are always changes. The tests are based on a random population size of 200, 84 potential sites, 4 potentials antennae by site and the algorithms work 500 generations on each period. The figures 4, 5 and 6 show our usual average result on the multi-period techniques. The evolution of the cost during 5 periods is presented in Fig.4. It's clear that the technique (A) is less interest than the others because of the very high cost of the network at the last period.

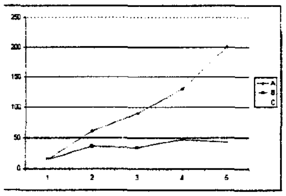

Figure 4: Network cost (f_j) by period.

The evolution of the number of BS used is showed in Fig.5. From this figure, we can extract that all these techniques use approximately the same number of BS. So for the same number of BS, the (A) technique costs more than the others, we can thought that the network of this solution is not very stable.

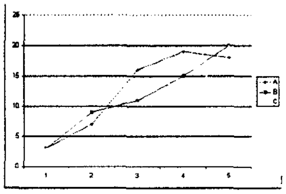

Figure 5: Network BS by period.

The global cost of the network is presented Fig. 6. The observations of this figures can not conclude on the advantage of one multi-period technique between (B) and (C). But they can show that the multi-period is always better that repetition of a single-period algorithm!

V. CONCLUSION

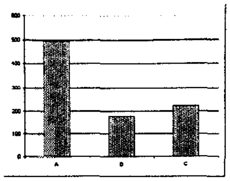

Figure 6: Total cost for all periods.

The life cycle of a mobile radio network as an evolutionary process and three optimization algorithms, based on genetic principle for multi-period optimization, are introduced in this paper. The next step of this work is an integration of the multi-period optimization process in the GA operators. Improving multi-period optimization process inside the GA to tackle with the multi-stage evolution in the life cycle of the mobile radio networks appears as a very attractive problem. From the mobile radio network, the different objectives like the traffic by periods can be introduced.

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