A Dynamic Traffic Model for Frequency Assignment

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Abstract. We are interested in improving the quality of frequency assignment via a more accurate modeling of the traffic over the network. For this purpose, we propose here an original model for FAP, which takes into account both spatial and temporal variation of the traffic. The proposed model is assessed with a hybrid genetic algorithm and compared against a classical model. Experimental results on both artificial and real data show significant improvements of the quality of frequency plan in terms of traffic capacity and robustness of the network.

1 Introduction

In radio mobile networks, the communication is ensured by a radio link. The mobile network operators dispose of a very limited number of frequencies to cover all the network area (limited to 62 frequencies in France). For this reason, the frequency reuse [12] is indispensable to increase the capacity of a network.

A GSM network is composed of a set of sites, each supporting one to three stations [11]. Each station covers an area called cell representing all the points served by this station. According to the quantity of the communications, i.e. the traffic, which may occur in the cell, each station requires a fixed number of frequencies. The frequency assignment problem (FAP) consists in finding an assignment of the available frequency spectrum to the stations of the network, which maximizes the traffic capacity and minimizes interference. Interference is caused by the presence of overlapping areas between cells where several signals of good quality are received. In these areas, traffic satisfaction is highly conditioned by used frequencies. Therefore, traffic modeling constitutes one key aspect of the FAP.

The first works on the FAP are based on a reusing matrix [5, 6, 8, 10] indicating channel separation required between frequencies to completely eliminate the interference. In such a model, interference surface and concerned traffic are ignored. More realistic models were recently proposed, which are based on the quantification of interference risks [3, 4, 9]. This quantification is made on the basis of traffic statistics. More precisely, on each station, traffic intensity recorded at the second busy hour of day (2BH) is considered as traffic reference in interference modeling. We will call this modeling "classical modeling" or "2BH modeling".

In this paper, we discuss about disadvantages of 2BH dimensioning and we propose a dynamic traffic modeling for FAP, which takes into account spatial and temporal variation of traffic, in order to improve the traffic capacity modeling and robustness of the network. The dynamic traffic model is tested on both artificial and realistic data, and compared with the classical modeling. To perform those tests a new heuristic based on a hybridization of genetic algorithms and tabu search is elaborated. Experimental results show significant improvements of frequency plan quality both in terms of robustness and traffic capacity.

2 Traffic modeling in frequency assignment problem

2.1 Traffic engineering

Traffic evolution can be observed in both spatial and temporal scale [1, 2]. Spatial variation of traffic refers to client mobility and concentration. Time variation of traffic is due to behavioral aspects of clients. Hence, traffic evolution analysis can be carried out either by observing time variation of the traffic over each cell, or by observing the traffic distribution over the network at each time point. Fig 1 shows time variation of traffic over two cells where the traffic (expressed in Erlang) is indicated for each hour. Note that the second busy hour is not the same for the two cells.

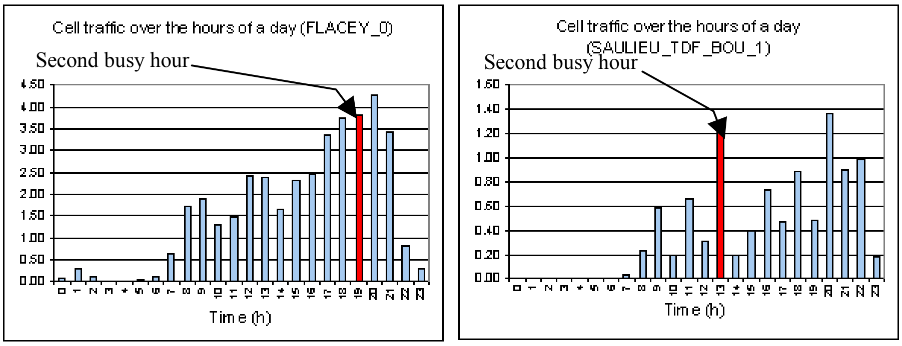

Fig. 1. Time variation of traffic over two cells

2.2 Classical traffic modeling for frequency assignment

A GSM network is composed of a set of sites, each supporting one to three stations [11, 12]. Each station delimits an area called cell representing all the points served by this station. For each station $S_i \in \{S_1, \ldots, S_N\}$, we know the number of frequencies required, MA_i. Frequency assignment to stations is submitted to constraints of different nature and priority. Those constraints are divided into three classes:

- Co-station constraint (call it C1 hereafter): frequencies assigned to the same station must be spaced by at least 3 channels.
- Co-site constraint (call it C2 hereafter): frequencies assigned to stations located on the same site must be spaced by at least 2 channels.
- Inter-site constraint: frequencies assigned to stations belonging to different sites are spaced according to their mutual interference.

The satisfaction of co-station and co-site constraints is indispensable for a frequency plan to be applicable, while satisfying inter-site constraints is generally impossible. The objective of FAP is then to minimize the potential interference generated by the violation of inter-site constraints.

Inter-site constraints may be modeled by an undirected graph (call it interference graph hereafter) whose nodes correspond to stations and edges represent interference risks. Each edge, connecting two stations S_i and S_j, is weighted by a pair of values ($\beta_{i,j,0}$, $\beta_{i,j,1}$). Where $\beta_{i,j,d}$ measures the importance of interference between S_i and S_j, generated by a pair of frequencies spaced by d channels (interference is considered negligible if d>1).

The impact of traffic on interference is twofold. As jamming station, traffic intensity describes the rate of use of frequencies assigned to the station and hence impacts on the quantity of the generated interference. As interfered station, traffic intensity reflects the importance of the area covered by the station and consequently the interest of interference reduction on this area. Therefore, we can roughly consider $\beta_{i,j,d}$ as a returned value of a function, I, having as arguments the traffic intensity on the two stations and considered inter-channel distance as described by equation (1)

$$\beta_{i,j,d} = I(i,j,t_i,t_j,d) \quad \textbf{(1)}$$

where t_i and t_j correspond to traffic intensity on stations S_i and S_j.

In classical traffic modeling, $\beta_{i,j,d}$ values are calculated on the basis of traffic data recorded at the *second busy hour* (2BH) of the day over each cell. Let t_i^{2BH} be the traffic intensity at the second busy hour over the station S_i. The weights of the interference graph are then calculated using the following expression.

$$\beta_{i,j,d}^{2BH} = I(i,j,t_i^{2BH},t_j^{2BH},d) \quad \textbf{(2)}$$

2BH dimensioning suffers from two disadvantages. Firstly, traffic repartition $(t_1^{2BH},...,t_N^{2BH})$ corresponds neither to real traffic cartography nor to a good aggregation of traffic evolution. In others words, 2BH dimensioning causes an alteration in preferential order between interference weights ($\beta_{i,j,d}$) and hence an inaccuracy in traffic capacity measurement. Secondly, 2BH dimensioning ignores time variation of traffic, which is indispensable for elaborating robustness criteria.

3 Dynamic traffic modeling for frequency assignment problem

In order to overcome the difficulties encountered with the classical 2BH modeling, we introduce here the notion of dynamic traffic modeling for FAP. To that end, we dispose of data on traffic evolution during np periods. Let t_i^h be the traffic intensity on station S_i at period h and let $\beta_{i,j,d}^h$ be the weights of the interference graph calculated from traffic data at period h. FAP is then defined by np constraint graphs, one per period, such as:

$$\beta_{i,j,d}^h = I(i,j,t_i^h,t_j^h,d) \quad \textbf{(3)}$$

According to those graphs, the quality of a frequency plan will be measured at both a global and local level. The global quality of the frequency plan refers to the sum over times of interference recorded on the network. The local quality measures the performance stability of the frequency plan over the time period where the quality is the lowest. Two criteria are to be retained then: Total interference, and frequency plan robustness. These criteria can be stated more formally as follows.

- Total interference, or global quality of the frequency plan.

$$F_1 = \sum_{h=1}^{np} \sum_{(S_i, S_j)} \sum_{\substack{(f_{i,k}, f_{j,p}) \\ k \in [1..MA_i] \\ p \in [1..MA_j]}} \beta^h_{i,j,|f_{i,k} - f_{j,p}|} \tag{4}$$

where $f_{i,k}$ represents the k^{th} frequency assigned to station S_i.

- Temporal interference distribution or robustness of the frequency plan through a time period. It aims to minimize the worst performance of the frequency plan over the time.

$$F_2 = \underset{h=1}{\overset{np}{MAX}} \sum_{(S_i, S_j)} \sum_{\substack{(f_{i,k}, f_{j,p}) \\ k \in [1..MA_i] \\ p \in [1..MA_j]}} \beta^h_{i,j,|f_{i,k} - f_{j,p}|} \tag{5}$$

According to this dynamic model, the objective of the frequency assignment problem is to find $f_{i,k}$ values which satisfy co-station and co-site constraints and minimize F_1 and F_2.

We turn now to the presentation of a hybrid algorithm for finding frequency plans. This hybrid algorithm combines genetic search and a tabu algorithm and uses the above quality functions (F_1 and F_2) as part of its evaluation function.

4 A genetic tabu search algorithm for FAP

The following notations will be used in the presentation: nf the number of available frequencies, C1 and C2 two binary functions representing the co-station and co-site constraints:

$$C1(i,k,p) = \begin{cases} 1 & \text{if } |f_{i,k} - f_{i,p}| < 3 \\ 0 & \text{else} \end{cases} \tag{6}$$

$$C2(i,j,k,p) = \begin{cases} 1 & \text{if } |f_{i,k} - f_{j,p}| < 2 \\ 0 & \text{else} \end{cases} \tag{7}$$

4.1 Individual representation and fitness evaluation

A frequency plan is coded by a vector < $f_{1,1}$,…, f_{1,MA_1}, $f_{2,1}$, …, f_{2,MA_2}, … , $f_{N,1}$, …, f_{N,MA_N} >, representing frequencies assigned to each station. The search space of a problem corresponds therefore to all such configurations where $f_{i,k} \in [1..nf]$.

Constraints C1 and C2 are handled using a penalty-based approach. They, together with the criteria F_1 and F_2, are linearly combined in a single *evaluation (fitness)* function. To stress their importance relative to the quality criteria, co-station and co-site constraints are weighted by a large value ω.

$$\text{minimize } F_{DO} = \omega\left(\sum_{i=1}^{N}\sum_{k=1}^{MA_i-1}\sum_{p=k+1}^{MA_i} C1(i,k,p) + \sum_{i=1}^{N-1}\sum_{\substack{j=i+1\\ i,j\in \text{ same site}}}^{N}\sum_{k=1}^{MA_i}\sum_{p=1}^{MA_j} C2(i,j,k,p)\right) + F_1 + F_2 \qquad \textbf{(8)}$$

4.2 Selection and replacement operators

At each iteration, two frequency plans are selected from current population. To favor the selection of good solutions, the population individuals are ordered according to their fitness so that the best solution has the rank 0. Let r_i be the rank of the individual i, the selection probability of i is then calculated following the expression 9.

$$SP_i = \frac{Pop\_size - r_i}{Pop\_size \times (Pop\_size + 1)} \qquad \textbf{(9)}$$

After reproduction, new individuals are directly inserted in the population in place of other solutions. Replacement operator favors the elimination of bad frequency plans. Equation 10 represents the replacement probability of the individual i.

$$RP_i = \frac{r_i}{Pop\_size(Pop\_size - 1)} \qquad \textbf{(10)}$$

Let us notice that the best frequency plan is never replaced.

4.3 Crossover and mutation

The so-called geographic crossover described in [13] is used to generate new frequency plans. This specific crossover operator for the frequency assignment problem works as follow. Given two frequency plans, the first step of the crossover consists in taking randomly a reference station S_i. Let $V(S_i)$ be the set of co-site stations and interfering stations of S_i (S_j interferes with S_i if $\beta_{i,j,\mathrm{d}} \neq 0$). Then the frequencies corresponding to stations $S_i \cup V(S_i)$ are exchanged between the two parents generating two new frequency plans (fig 2).

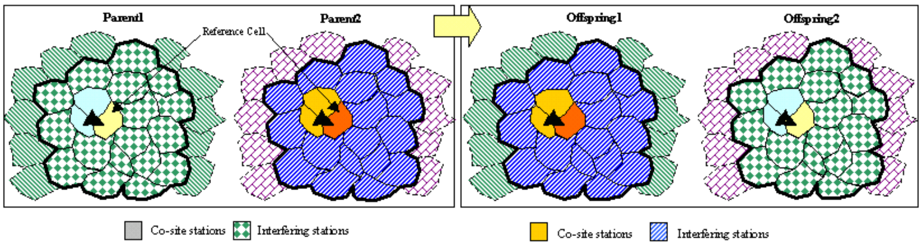

Fig. 2. Crossover operator

For mutation, we use a local search operator based on Tabu search (TS). This operator is basically inspired by the Tabu algorithm described in [7]. The main difference remains at the level of assessing the fitness of frequency assignments.

For a given assignment, a violation score is defined for each frequency of the plan. This score measures the contribution of this frequency to the recorded interference. At each iteration of the TS algorithm, one gene is selected according to its violation score and a new frequency value is affected to it. The pair (gene, old-frequency-value) is then added to the tabu list. Equation 11 and 12 describe respectively the way of calculating the violation scores and gene selection probability of the k^{th} frequency assigned to station S_i.

$$SCORE_{i,k} = \omega \times \left(\sum_{\substack{p=1 \\ p \neq k}}^{MA_j} C1(i,k,p) + \sum_{\substack{j=1 \\ j \neq i \\ i,j \in \text{ same site}}}^{N} \sum_{p=1}^{MA_j} C2(i,j,k,p) \right) + \sum_{h=1}^{np} \sum_{\substack{j=1 \\ j \neq i}}^{N} \sum_{\substack{f_{jp} \\ p \in [1..MA_j]}} \beta^{h}_{i,j,|f_{ik}-f_{jp}|} \quad \textbf{(11)}$$

$$GSP_{i,k} = SCORE_{i,k} \Big/ \sum_{j=1}^{N} \sum_{p=1}^{MA_j} SCORE_{j,p} \quad \textbf{(12)}$$

5. Experimentation and results

This section is dedicated to the presentation of experimental results of the proposed dynamic model using the hybrid genetic tabu algorithm. Tests are carried out on both fictive and real problems. The results of dynamic traffic model are compared with the classical model based on 2BH dimensioning. The hybrid algorithm uses respectively Equation 8 (dynamic modeling) and Equation 13 (2BH modeling) as its fitness function.

$$F_{H2C} = \omega \left(\sum_{i=1}^{N} \sum_{k=1}^{MA_i - 1} \sum_{p=k+1}^{MA_i} C1(i,k,p) + \sum_{i=1}^{N-1} \sum_{\substack{j=i+1 \\ i,j \in \text{ same site}}}^{N} \sum_{k=1}^{MA_i} \sum_{p=1}^{MA_j} C2(i,j,k,p) \right) + \sum_{\substack{(S_i, S_j) \\ i<j \in [1..N]}} \sum_{\substack{(f_{i,k}, f_{j,p}) \\ k \in [1..MA_i] \\ p \in [1..MA_j]}} \beta^{2BH}_{i,j,|f_{i,k} - f_{j,p}|} \tag{13}$$

5.1 Fictive FAP instances

The two fictive FAP instances used in our experimentation represent 63 stations extracted from a real network *B*. The word "fictive" refers only to the data of traffic evolution. The two instances have the following characteristics: 225 frequencies to assign, traffic data over 6 periods and around 1100 inter-site constraints.

Each instance presents a different class of traffic evolution that allows us to study the performance of dynamic traffic modeling on different traffic evolution scenarios. The first network, *B_63_1*, presents synchronous and proportional rises and falls of traffic on the entire network. The second instance, *B_63_2*, stresses the mobility aspect of clients and presents two distinct areas. The rise of traffic on one area is accompanied by a fall of traffic intensity on the other. Table 1 and 2 summarize the traffic evolution for the two instances.

Table 1. Traffic evolution for *B_63_1* instance

Periods	Traffic situation
Period 0	Traffic load on each station S_i corresponds to 20% of t_i^{2BH}
Period 1	Traffic load on each station S_i corresponds to 50% of t_i^{2BH}
Period 2	Traffic load on each station S_i corresponds to t_i^{2BH}
Period 3	Traffic load on each station S_i corresponds to 110% of t_i^{2BH}
Period 4	Traffic load on each station S_i corresponds to 60% of t_i^{2BH}
Period 5	Traffic load on each station S_i corresponds to 20% of t_i^{2BH}

Table 2. Traffic evolution for *B_63_2* instance

Periods	Traffic situation
Period 0	In 1st part, traffic load on S_i corresponds to 110% of t_i^{2BH} and to 20% on the 2nd part
Period 1	In 1st part, traffic load on S_i corresponds to 100% of t_i^{2BH} and to 30% on the 2nd part
Period 2	In 1st part, traffic load on S_i corresponds to 70% of t_i^{2BH} and to 50% on the 2nd part

Period 3	In 1st part, traffic load on S_i corresponds to 50% of t_i^{2BH} and to 70% on the 2nd part
Period 4	In 1st part, traffic load on S_i corresponds to 30% of t_i^{2BH} and to 100% on the 2nd part
Period 5	In 1st part, traffic load on S_i corresponds to 20% of t_i^{2BH} and to 110% on the 2nd part

5.2 Real FAP instance

The proposed traffic model is also tested on a real traffic evolution data (Network D). This network is characterized by: 639 stations, 1411 frequencies to assign, around 30000 inter-site constraints and traffic data over 13 hours (7:00-20:00).

5.3 Performance criteria

Comparison between dynamic traffic modeling and classical modeling for FAP is made on the basis of *lost traffic*, measured in Erlang. One Erlang corresponds to one hour of communication. We use quality evaluator of PARCELL©[1] to measure the lost traffic produced by a given frequency plan. More precisely, given the stations parameters, geographical database, traffic data and a frequency plan, the quality evaluator calculates the lost traffic quantity on each station. Loss in traffic is measured in term of FER (Frame Erasure Rate). The communication is considered bad if this rate exceeds a given threshold. According to required radio quality, we distinguish 3 kinds of thresholds: 2%, 4% and 7%.

5.4 Experimental results

Tables 3-6 below show experimental results of classical and dynamic traffic modeling on the three FAP instances described above. For each instance, we generate two frequency plans. The first is built on the basis of classical traffic modeling (Equation 13). The second is built on the basis of our dynamic traffic modeling (Equation 8). The performance of each frequency plan, in term of lost traffic, is estimated for each period. We present also at the lower part of the tables, the total lost traffic (global quality criteria), maximal lost traffic on the given time period (robustness criteria) and the gain in Erlang between the two models. Information is given for each of the three quality thresholds (2%, 4% and 7%).

Tests were made using the same parameters of the hybrid algorithm: 100000 iterations for a population of 10 solutions.

From those three tables, we notice that the dynamic model gives better frequency plans both in terms of global traffic capacity and robustness. Important gains are observed for different traffic evolution scenarios.

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Table 3. Results of classical and dynamic traffic modeling for *B_63_1*

		Lost traffic at 2% FER (Erl)		Lost traffic at 4% FER (Erl)		Lost traffic at 7% FER (Erl)	
Periods	**Traffic**	**Classical**	**Dynamic**	**Classical**	**Dynamic**	**Classical**	**Dynamic**
Period 0	116.85	1,43	1,36	0,71	0,67	0,39	0,35
Period 1	292.13	5,14	4,46	2,57	2,32	1,36	1,25
Period 2	584.27	17,63	15,36	9,02	8,27	4,87	4,37
Period 3	642.70	20,87	18,43	11,29	9,98	5,84	5,24
Period 4	350.56	6,96	6,16	3,54	3,11	1,81	1,87
Period 5	116.85	1,43	1,36	0,71	0,67	0,39	0,35
Total		**53,46**	**47,13**	**27,84**	**25,02**	**14,66**	**13,43**
Communication gain		**6.33**		**2.82**		**1.23**	
Maximum		**20,87**	**18,43**	**11,29**	**9,98**	**5,84**	**5,24**

Table 4. Results of classical and dynamic traffic modeling for *B_63_2*

		Lost traffic at 2% FER (Erl)		Lost traffic at 4% FER (Erl)		Lost traffic at 7% FER (Erl)	
Periods	**Traffic**	**Classical**	**Dynamic**	**Classical**	**Dynamic**	**Classical**	**Dynamic**
Period 0	329.29	7,69	7,56	4,16	4,4	2,33	2,32
Period 1	340.51	7,63	7,36	4,04	4,25	2,21	2,26
Period 2	339.27	7,03	6,35	3,47	3,45	1,86	1,84
Period 3	361.64	7,50	6,13	3,50	3,24	1,82	1,80
Period 4	418.86	9,39	7,76	4,65	4,13	2,43	2,35
Period 5	430.06	9,99	8,4	5,34	4,21	2,80	2,40
Total		**49,23**	**43,56**	**25,16**	**23,68**	**13,45**	**12,97**
Communication gain		**5.67**		**1.48**		**0.48**	
Maximum		**9,99**	**7,76**	**5,34**	**4,25**	**2,80**	**2,54**

Table 5. Results of classical and dynamic traffic modeling for *D_639_1*

		Lost traffic at 2% FER (Erl)		Lost traffic at 4% FER (Erl)		Lost traffic at 7% FER (Erl)	
Period	**Traffic**	**Classical**	**Dynamic**	**Classical**	**Dynamic**	**Classical**	**Dynamic**
7:00–8:00	504.11	7.41	6.38	4.42	3.92	2.46	2.21
8:00-9:00	1170.02	21.50	19.62	12.98	11.53	7.26	6.43
9:00-10:00	1747.71	37.90	34.79	22.98	20.63	13.22	11.72
10:00-11:00	2017.26	45.09	41.61	26.94	24.12	15.40	13.29
11:00-12:00	2177.03	50.58	45.82	29.96	26.23	17.08	14.48
12:00-13:00	2104.73	46.58	43.50	27.95	25.17	16.54	13.49
13:00-14:00	1863.42	38.66	37.06	23.60	21.14	13.92	11.57
14:00-15:00	1953.59	43.01	38.42	25.82	22.02	15.25	12.10
15:00-16:00	1984.12	45.44	40.66	27.48	23.37	16.03	12.70
16:00-17:00	2174.47	51.24	47.03	30.90	27.25	18.31	14.99
17:00-18:00	2521.20	60.53	57.10	36.20	33.19	20.97	18.08
18:00-19:00	2792.91	69.73	67.55	42.00	39.17	24.24	21.12
19:00-20:00	2743.83	61.65	61.00	36.88	34.77	21.35	18.88
Total		**579.32**	**540.54**	**348.10**	**312.51**	**202.03**	**171.06**
Communication gain		**38.78**		**35.59**		**30.97**	
Maximum		**69.73**	**67.55**	**42.00**	**39.17**	**24.24**	**21.12**

Table 6 shows the fitness of the two frequency plans analyzed in table 5. We notice that even if classical modeling solution is better according to F_{2BH} it stills worst than dynamic modeling solution according to F_1 and F_2. This result confirms that classical traffic modeling doesn't allow the production of well-adapted frequency plan for traffic in evolution.

Table 6. Fitness of the two frequency plans generated for *D_639_1*

Classical solution	Dynamic solution
F_1: 970932,916	F_1: 936139,360
F_2: 115887,751	F_2: 115588,483
F_{H2C}: 128749,617	F_{H2C}: 130377,944

6. Conclusion and future works

We have proposed in this paper a finer and more accurate traffic model for the frequency assignment problem of mobile radio networks. Both spatial and temporal aspects of traffic are taken into account, leading to improvements of the traffic capacity and robustness of the frequency plan. We have also presented a hybrid genetic tabu search algorithm for finding frequency plans. Comparisons between the proposed dynamic traffic model and classical 2BH-based traffic model showed significant improvements of the quality of frequency plans both in terms of global traffic capacity and network robustness.

New criteria of robustness are to be studied in the future especially with regard to spatial distribution of interference. The model might also be enriched to give more importance to certain periods (e.g. to favor professional communications).

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