Multi-Period Channel Assignment

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Abstract. The well-known fixed channel assignment scheme for cellular networks is not flexible enough to follow the evolution of traffic. This paper introduces a multi-period channel assignment model. In addition to the usual objective of minimizing the interference, the model integrates another requirement to minimize the transition cost from a frequency plan to another one. Several heuristic solution approaches are also proposed. Experimental results on real data are presented to compare the multi-period model and the fixed model, and to assess the effectiveness of the proposed solution algorithms.

Keywords: Multi-period channel assignment, optimization, genetic search, tabu search

1 Introduction

In a GSM network [9], the geographical area is partitioned into cells, each one served by a single base station. To ensure communications occurring on their cells, stations require a certain number of frequencies depending on the expected traffic load. In other words, lightly loaded cells are assigned fewer channels than heavily loaded ones. The mobile network operators dispose of a very limited number of frequencies to cover all the network area. For this reason, frequencies reusing is indispensable to increase the network capacity. Channel assignment consists in assigning the available frequency spectrum to the stations of the network in order to satisfy their demands and to minimize the interference. Interference is caused by the presence of overlapping areas between cells where several signals of good quality are received.

The quality of communications in cellular networks depends closely on how the available frequency spectrum is managed. Because of its implementation simplicity, fixed channel assignment (FCA) is largely used in today's GSM mobile networks. In this case, a subset of nominal frequencies is definitively allocated to each base station. However, the main inconvenient of FCA is that it is not adaptive to traffic variation. In fact, usually frequency plan dimensioning is based on an over-sizing of traffic data [1][6][17] and unused channels in lightly loaded cell are not reassigned to heavily loaded ones. To overcome this handicap, many alternative strategies have been

adopted as dynamic channel assignment [1][3], hybrid channel assignment [15] and channel borrowing [16]. Usually those techniques perform badly in heavy traffic or require additional signaling loads to ensure channel readjustment [8].

This paper presents a channel assignment model noted *MCA* for Multi-period Channel Assignment [12], which associates simplicity and adaptability. In this case, the frequency-planning problem consists in finding a *sequence of frequency plans* following the traffic evolution for a number of time periods. Each frequency plan is conceived to fit the traffic situation at the period in which it is operational. Two reasons make the problem more complicated. First, in addition to the classical criteria dealing with interference, the transition cost caused by frequency plan change must be minimized. Second, the multi-period character of the problem increases its combinatorial complexity. To cope with this complexity, we propose several optimization techniques based on a genetic tabu search algorithm and we compare their performances against the *FCA* scheme in terms of lost traffic.

The paper is organized as follows. In next section we formally describe the *MCA* model and we give a set of definitions used in the remainder of the paper. Section 3 describes in details the basic genetic tabu search algorithm used to solve the *FCA* problem. Section 4 presents how genetic tabu search algorithm is readapted to *MCA* model. Section 5 is dedicated to the experimental tests carried out in order to assess the *MCA* model.

2 Multi-period Channel Assignment Problem

In fixed channel assignment, a single frequency plan is built in order to be permanently operational even if the traffic evolves in time. The key word is then the robustness of the frequency plan over time. To that end, modelers use an aggregation of traffic data, for example traffic at second busy hour to evaluate the quality of frequency plans [10].

In the case of multi-period channel assignment, we assume that traffic evolution follows a cyclical scheme. According to the desired scale level, one cycle is divided into periods of equal duration (hours, days...). We assume also that the traffic load is known on every cell for each period. The objective is then to find a sequence of frequency plans. Each frequency plan is built with the objective to minimize the interference recorded at the associated period. In addition, the frequency plan must meet another requirement to minimize transition costs between frequency plans. Transition cost measures the required effort or damage caused by the frequency plan changes. Several aspects can be taken into account to measure the transition cost between two frequency plans: (a) Minimizing the number of changed frequencies between two frequency plans; (b) minimizing the number of stations affected by the changes or (c) minimizing the traffic load affected by the changes. In this work, the number of changed frequency is taken as the transition criterion.

2.1 Basic Notations

We introduce here the basic notations and definitions, which will be used in the continuation of the paper:

- *N*: The number of stations.
- $\{S_1, ..., S_N\}$: The set of stations composing the network.
- $m_i / i \in [1..N]$: The number of frequencies required by the station S_i .
- F: The number of available frequencies.
- np: The number of studied time periods.
- 2B_i: The period on which the traffic load on the station S_i reaches its second greatest value.

Interference damage between stations depends on several factors such as interchannel separation between used frequencies, signal powers... It is also largely depending on traffic intensity on these stations. The impact of traffic on interference is twofold. As interferer station, traffic load describes the utilization rate of frequencies and hence impacts on the quantity of 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.

Let us note by:

- $I_{i,j,d}$: The interference damage between S_i and S_j caused by a pair of frequencies distanced by d channels.
- $I_{i,j,d}^{2B}$: The interference damage between S_i and S_j measured according to traffic load on station S_i at the period $2B_i$ and on station S_j at the period $2B_j$.
- $I_{i,j,d}^p$: The interference damage between S_i and S_j measured according to traffic situation at the period p.
- Assignment $f_{i,k} \in [1..F]$ corresponds to the k^{th} "permanent" frequency assigned to the station S_i .
- Assignment $f_{i,k}^p \in [1..F]$ corresponds to the k^{th} frequency assigned to the station S_i at the period p.
- A sequence is a vector of temporary frequency plans $\left\langle \left\langle f_{1,1}^1,...,f_{1,m_1}^1,...,f_{N,m_N}^1\right\rangle,...,\left\langle f_{1,1}^{n_p},...,f_{N,m_N}^{n_p}\right\rangle \right\rangle$.

2.2 Problem Formulation

In the fixed channel scheme, a single frequency plan is constructed on the basis of $I_{i,j,d}^{2B}$ values. The objective of the optimization is to find the vector $< f_{1,1}$, ..., f_{1,m_1} , ..., f_{1,m_N} , ..., f_{N,m_N} which minimizes the total interference depicted by the function F_{2B} .

$$F_{2B} = \sum_{i=1}^{N,N} \sum_{j=1}^{m_i, m_j} I_{i,j,|f_{i,k} - f_{j,l}|}^{2B} \tag{1}$$

Where the double sum in the formula 1 measures the total of interference over the network, caused by used frequencies. The frequency plan thus worked out will be permanently operational.

By opposition, in multi-period channel assignment, the objective is to find a sequence of frequency plans corresponding to $f_{i,k}^p$ values, which minimizes the two functions:

$$F_{\Sigma} = \sum_{p=1}^{np} \sum_{i=1,j=1}^{N,N} \sum_{k=1,l=1}^{m_i,m_j} I_{i,j,|f_{i,k}^p - f_{j,l}^p|}^{p}$$
 (2)

$$C_{\Sigma} = \sum_{p=1}^{np-1} \sum_{i=1}^{N} \sum_{k=1}^{m_i} IND(f_{i,k}^p \neq f_{i,k}^{p+1})$$
(3)

$$IND(condition) = \begin{cases} 1 & \text{if condition is true} \\ 0 & \text{otherwise} \end{cases}$$

The function F_{Σ} represents the sum of interference recorded over all the time periods whereas the function C_{Σ} depicts the transition cost between frequency plans composing the sequence.

3 Genetic Tabu Search for Fixed Channel Assignment

The multi-period frequency assignment problem can be seen as an extension of the fixed channel assignment, requiring the generation of a sequence of frequency plans instead of a single frequency plan. For this reason, we describe first the algorithm serving to generate a single frequency plan. This algorithm is also used in Section 5 to compare the fixed channel assignment model and the multi-period frequency assignment model.

Many algorithms based on metaheuristics have been proposed for the fixed channel assignment problem [4][7][11][5]. We present here a hybrid genetic tabu search algorithm that is described in details in [10]. This article doesn't aim to study the performance of such algorithm but tries to show the relevance of MCA scheme and how the FCA algorithms can be readapted to this model.

The FCA algorithm starts from a population of individuals corresponding to frequency plans. The algorithm makes evolve the frequency plans iteratively. At each generation, the algorithm selects two frequency plans from the population and applies a crossover operator to them. The two new generated frequency plans are then improved using a Tabu Search based mutation.

3.1 Crossover Operator

As crossover operator, we adopt the geographical crossover described in [10][13]. The principle is this one: we randomly choose a reference station S_R and we build the set of its neighbors $V(S_R)$ composed of interfering stations S_i (i.e. $\exists d/I_{R,i,d} > 0$). The parts of the frequency plans corresponding to $V(S_R) \cup \{S_R\}$ are then exchanged between the two parents.

Geographic crossover allows the conservation of the building blocs present in the parent chromosomes. This is made by swapping information related to the local resolution of interference between stations. This operator is generalized later to multiperiod assignment (see §4.1.3).

3.2 Tabu Search Based Mutation

After crossover, the two new frequency plans are improved by a tabu search based mutation. The idea is to apply a cycle of local search to the new frequency plans. More concretely, we associate to each assignment $f_{i,k}$ of the individual, a value called *violation score* measuring the contribution of that assignment to the recorded interference. Equation 4 gives the function serving to calculate the violation score of the assignment $f_{i,k}$. At each cycle of the local search operator, one assignment is chosen on the basis of the violation scores and its value is changed. The new frequency value corresponds to the best one which is not tabu. After the change, the new and the old value are considered tabu for this assignment.

$$SCORE_{i,k} = \sum_{j=1}^{N} \sum_{l=1}^{m_j} I_{i,j,|f_{i,k} - f_{j,l}|}^{2B}$$
(4)

Notice that such a tabu management contributes to two different roles. The element (i, k, f_{old}) avoids the recurrence of visited solutions, whereas the element (i, k, f_{new}) prevents the remainder individuals from re-exploring the same search area since the tabu list is shared by all population individuals.

After mutation the new frequency plan are inserted in the population in replacement of another one. The replaced frequency plan is chosen on the basis of its fitness. More precisely, individuals of bad fitness have more chance to be replaced.

The algorithms below describe the main procedure of the genetic tabu search algorithm as well as the tabu based mutation procedure.

```
UpdateScores(fp);
If BetterThan(fp,Best_fp) then Best_fp=fp; End if
End for
End.
```

```
Genetic Tabu Search
Begin

P:=RandomInitPopulation(Pop_size);

For g:=1 to NbGenerations

(p1,p2):=SelectParents(P)

with a Pc probability do (f1,f2):=Crossover(p1,p2)

otherwise f1:=p1; f2:=p2;

f1:=TabuSearchOperator(f1); f2:=TabuSearchOperator(f2);

(v1,v2):=SelectVictims(P);

ReplaceBy(v1,f1); ReplaceBy(v2,f2);

End for
End.
```

4 Genetic Tabu Search for Multi-period Channel Assignment

For the purpose of finding multi-period channel assignment, we have designed and experimented different optimization techniques. Each technique presents a particular manner to readapt FCA algorithms (in our case the Genetic Tabu Search) for the resolution of the MCA problem. These techniques can be roughly classified into two classes: direct optimization and decomposed optimization.

4.1 Direct Optimization

The multi-period character of the problem increases its combinatorial complexity. In direct optimization, the problem is considered in its totality without restriction on search space. In other words, search space will correspond to all the sequences of the form:

$$\left\langle \left\langle f_{1,1}^{1},..,f_{1,m_{1}}^{1},..,f_{N,m_{N}}^{1}\right\rangle ,..,\left\langle f_{1,1}^{np},..,f_{1,m_{1}}^{np},..,f_{N,m_{N}}^{np}\right\rangle \right\rangle$$

The optimization algorithm generates the different frequency plans composing the optimal sequence in a competing way. It is then necessary to readapt search operators of the basic algorithm.

4.1.1 Objective Function

To assess the fitness of a sequence, two criteria are considered: the total of interference recorded over time periods $F_{\scriptscriptstyle \Sigma}$ and the total of transition cost $C_{\scriptscriptstyle \Sigma}$. The quality of each frequency plan in the sequence is calculated regarding to the other

plans. Therefore, choices made on a part of the sequence may lead to other changes in the entire sequence.

The interference and transition criteria (§2.2) are aggregated into a single objective function. A threshold value S_{Σ} is defined as the maximal tolerated number of changes in the sequence. Exceeding this threshold the sequence quality is penalized with a very high value M. The objective function takes then the following form:

$$F = F_{\Sigma} + M \times IND(C_{\Sigma} > S_{\Sigma}) \text{ where } M \text{ is a very high value}$$
 (5)

4.1.2 Initial Population

Generation of the initial population passes through a pre-optimization phase. For each sequence of the initial population, we choose iteratively one period p. An optimization phase is launched to generate a frequency plan, fp, well adapted to that period with the objective function given in equation 6. Then the frequency plan fp is fixed during all periods forming a sequence $\langle fp,...fp \rangle$ which is inserted in the initial population. This process is reiterated for the other individuals of the initial population.

$$F_{p} = \sum_{i=1,j=1}^{N,N} \sum_{k=1,l=1}^{m_{i},m_{j}} I_{i,j,|f_{i,k}-f_{j,l}|}^{p} / p \in [1..np]$$
(6)

4.1.3 Crossover Operator

Considering the effectiveness of the geographical crossover, a multi-period version of this operator should be interesting. The objective is to allow both spatial and temporal configuration exchange between sequences. In other words, the frequency plan evolution in a part of the network is grafted into another sequence. To that end, a reference station is randomly selected and the set of its neighbors is built. Then the corresponding parts in the two parent sequences are exchanged. The crossover working is schematized in the following figure.

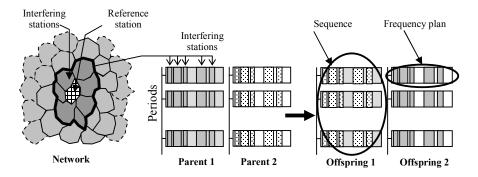


Fig. 1. Crossover operator for multi-period channel assignment

4.1.4 Mutation Operator

Two variants of the previous tabu search based mutation operator are implemented. The first variant (M1) changes the value of a single assignment $f_{i,k}^{p}$. First, a period p is randomly chosen and the violation score of each assignment of the considered period is calculated using the formula 7. Then an assignment $f_{i,k}^{p}$ is selected with a probability proportional to its violation score and the best not tabu value is attributed to it.

$$SCORE_{i,k} = \sum_{p=1}^{np} \sum_{j=1}^{N} \sum_{l=1}^{m_j} I_{i,j,|f_{j,k}^p - f_{j,l}^p|}^{p}$$
(7)

The second variant (M2) resets to the same value all the assignments $f_{i,k}^p$ ($p \in [1..np]$). The working scheme is the same as in mutation (M1) except that the new value is attributed to all assignments of the same position as $f_{i,k}^p$. These two variants are used in a competing way with probabilities Pm_1 , $1-Pm_1$. The algorithm below depicts the Tabu Search based mutation of direct optimization. The main procedure is the same as in fixed assignment except that manipulated individuals are sequences.

```
TabuSearchOperator(Sequence seq)
Begin
    Best_seq:=seq;
    p=Random(np);
    CalculateScores(Seq[period]); {seq(period) corresponds to the frequency
                                              plan of the period p}
    for iter:=1 to TSML {Tabu Search based mutation length}
            (i,k):=SelectAssignment(fp); {on the basis of violation scores}
            f old:= seq[p,i,k];
            f_new := SelectBestFrequency(seq,p, i, k); {which is not tabu}
            with a Pm1 probability, do
                    AddToTabuList(p,i,k,f_old); AddToTabuList(p,i,k,f_new);
                    seq[p,i,k]:=f_new;
            else do
                    AddToTabuList(p,i,k,f old); AddToTabuList(TOUT,i,k,f new);
                    for each per=1..np do seq[per,i,k]:= f_new;
            end with
            UpdateScores(seq);
            If BetterThan(seq, Best fp) then Best seq=seq; End if
    End for
End.
```

4.2 Decomposed Optimization

In decomposed methods, the initial problem is decomposed into several subproblems of lower complexity, leading to reduced search space. On each subproblem, an optimization phase is launched to generate a part of the final sequence of frequency plans. Each optimization phase handles individuals of frequency plan type. Three decomposed algorithms are implemented. Details of their implementation are given here below.

4.2.1 Step by step Optimization

The optimal sequence of frequency plans is built in an iterative manner. At each iteration, one period is considered according to its chronological order. A frequency plan is then generated (by optimization) to fit the traffic situation at this period and to minimize transition cost from previous frequency plan. The final solution corresponds then to the set of those frequency plans. Note that the part of the optimal sequence already built can't be readjusted in further iterations. We give hereafter the different steps followed by the method. The value S designates the maximal tolerated change threshold between two consecutive frequency plans in the sequence. This threshold serves to aggregate the two partial functions F_p (equation 6) and C_p (described in the algorithm).

Find the values
$$f_{i,k}^1$$
, which minimize: F_1

For each period $p \in [2..np]$

Find the values $f_{i,k}^p$, which minimize:

$$F_p + M \times IND(C_p > S), \text{ where } C_p = \sum_{i=1}^N \sum_{k=1}^{m_i} IND(f_{i,k}^p \neq f_{i,k}^{p-1})$$

The final solution will correspond to the sequence $\left\langle \left\langle f_{1,1}^1, \dots, f_{1,m}^1, \dots, f_{N,m_N}^1 \right\rangle, \dots \right\rangle \left\langle f_{1,1}^{np}, \dots, f_{N,m_N}^{np}, \dots, f_{N,m_N}^{np} \right\rangle \right\rangle.$

4.2.2 Sequential Optimization

The idea is to use the robust frequency plan generated by fixed channel assignment method as a starting point for search. More precisely, an initial optimization phase using the function F_{2B} is performed producing a robust frequency plan. The different frequency plans composing the sequence are constructed iteratively in chronological order of periods exactly as in step-by-step optimization. The first frequency plan corresponding to the initial period is generated starting from the robust frequency plan (with respect to the transition cost criterion). We give hereafter the details of sequential optimization algorithm.

```
Find the value f_{i,k}^0, which minimize F_{2B}

For each period p \in [1..np]

Find the values f_{i,k}^p, which minimize: F_p + M \times IND(C_p > S)
```

4.2.3 Parallel (or Simultaneous) Optimization

The iterative aspect of sequential optimization makes it slow. To overcome this inconvenient, a parallel variant of this technique is proposed. In this case, the frequency plans associated with the different periods are constructed starting from the robust plan in parallel. To explain this difference we give the working scheme of this parallel optimization, the parallel algorithm being implemented under PVM (Parallel Virtual Machine) system.

Find the value $f_{i,k}^0$, which minimize F_{2B} For each period $p \in [1..np]$ do simultaneously Find the values $f_{i,k}^p$, which minimize:

$$F_p + M \times IND(C'_p > S)$$
, where $C'_p = \sum_{i=1}^{N} \sum_{k=1}^{m_i} IND(f_{i,k}^p \neq f_{i,k}^0)$

5 Experimental Tests

The objective of this section is twofold. On the one hand, we compare the performance of the implemented multi-period optimization techniques. On the other hand, we compare the quality of solutions generated by the multi-period model with those produced by the FCA model. Results of multi-period and fixed channel assignment are compared from two points of view. The first is based on objective functions (Formulas 1 to 3). The second adopts operator's point of view and compares the solutions according to the lost traffic.

5.1 Benchmark Problems

Tests are carried out on both fictitious ¹ and real data. The first problem, B-63, represents a fictitious problem instance with 63 stations, 30 available frequencies and 6 periods. The second instance, D-639, corresponds to a real world problem. The network is composed of 639 stations with 62 frequencies and traffic data during 13 hours (periods). The third instance, BM-120, is another real world problem with 120 stations and 62 available frequencies. *BM-120* is dedicated to study the performance of *MCA* for large-scale traffic data. Traffic evolution is thus studied over one week, day by day.

5.2 Comparison between Multi-period Channel Assignment Techniques

Four multi-period optimization algorithms, described before, are compared. Those algorithms correspond to direct optimization, step by step optimization, sequential optimization and parallel optimization. Table 1 gives the results obtained by each technique for the two problems B-63 and D-639. We run each algorithm 5 times on every problem. Only the best solution is reported for each algorithm.

Two implementations of the direct optimization technique are presented. The first uses only the mutation operator MI. The second uses in a simultaneous way the two mutation operators MI and M2. For each technique we give the name, the objective and eventually the mutation operator used. Obtained solutions are compared according to interference (F_p) and transition (C_p) cost at each period as well as their sum over time.

¹ By fictitious data, we mean a real network whose traffic data are artificially modified.

From columns (2) and (3) we remark the effectiveness of using the two mutation operators in cooperative way. By using only the MI operator, the transition cost reaches quickly the threshold S_{Σ} and hence slows down the algorithm evolution.

Step-by-step technique gives bad results. This can be explained by the absence of a global vision. In fact, at each phase, step-by-step algorithm optimizes the frequency plan according to the traffic situation at the associated period without taking into account the future evolution of traffic.

However, the main observation is that decomposed approaches, represented in table 1 by columns (4) and (5), give the best results. We notice also that results of sequential and parallel-decomposed optimization are very close.

		(1)		(2)		(3)		(4)		(5)	
Name		Step by s	step	Direct		Direct		Sequential		Parallel	
		decompo	sed					decomposed		decomposed	
Obj	ective	$F_p+IND(C_p>S)$,		$F_{\Sigma}+IND(C_{\Sigma}>S_{\Sigma}),$		$F_{\Sigma}+IND(C_{\Sigma}>S_{\Sigma}),$		$F_p+IND(C_p>S)$,		$F_p+IND(C'_p>S),$	
		S=30, :	50	S=130, 6	00	S=130, 600		S=30, 50		S=30, 5	50
Mu	tation			M1		M1+M2					
	Cost	$\mathbf{F}_{\mathbf{p}}$	$\mathbf{C}_{\mathbf{p}}$	$\mathbf{F}_{\mathbf{p}}$	$\mathbf{C}_{\mathbf{p}}$	$\mathbf{F}_{\mathbf{p}}$	Cp	$\mathbf{F}_{\mathbf{p}}$	Cp	$\mathbf{F}_{\mathbf{p}}$	$\mathbf{C}_{\mathbf{p}}$
	P0	62340	0	68828	0	57110	0	51569	0	51322	0
	P1	59740	29	66587	27	57431	38	49123	25	49012	27
	P2	53525	30	58725	23	47318	37	41837	20	41750	23
53	P3	52350	30	55135	34	43402	15	40922	27	41033	19
B-63	P4	62282	30	61645	15	52139	21	48144	25	48281	28
	P5	63484	30	65181	21	56880	15	51650	6	51584	10
	Total	353721	149	376104	120	314280	126	283245	103	282982	107
	7:00	17289	0	18014	0	16026	0	16663	0	16458	0
	8:00	47376	50	48363	50	45832	50	43268	50	42875	50
	9:00	80311	50	83892	50	75913	50	73962	50	73784	50
	10:00	99960	50	103470	50	89749	50	85750	50	85912	48
	11:00	106898	50	109018	50	98944	50	94713	50	94799	50
D-639	12:00	103367	50	105913	50	95013	49	92103	38	92355	46
	13:00	87468	50	89354	50	82832	49	77725	50	77623	50
	14:00	88088	50	91325	50	83549	48	77904	50	77789	50
	15:00	92669	50	95102	50	90114	50	82921	44	82805	46
	16:00	104715	49	106822	50	99322	50	92023	49	91987	47
	17:00	124727	48	128341	50	119444	48	110814	45	110612	50
	18:00	138748	50	143755	50	136617	44	128595	33	128904	30
	19:00	124642	50	126015	50	125029	41	119212	45	119447	42
	Total	1216258	597	1249384	600	1158387	579	1095653	554	1095350	559

Table 1. Comparison between the different multi-period channel assignment techniques

5.3 Comparison between Fixed and Multi-period Solutions for D-639 Problem

To compare fixed and multi-period channel assignment, we have run the fixed channel assignment algorithm (Section 3) five times on the D-639 problem. In the tables 2 and 3, we compare the best solution found by the *FCA* with the multi-period solution found by the parallel decomposed optimization (column 5 in table 1). This comparison is made on the basis of objective function (table 2) and lost traffic (table

3). In table 3, we give the lost traffic (in Erlang) at each period as well as the total of lost traffic for the two compared solutions. We use for that, the quality evaluator of PARCELL©². Results show a reduction of lost traffic reaching sometime 8% by using the *MCA* model. Notice that in table 2, transition cost for fixed solution is usually zero since there is a single frequency plan.

Na	ıme	Fixed		Paral	lel	
			decomp		osed	
Ot	jective	F_{2B}		$F_p+IND(C'_p>50)$		
Co	ost	Fp	$\mathbf{C}_{\mathbf{p}}$	Fp	$C_{\mathbf{p}}$	
	7:00	17944	0	16458	0	
	8:00	47065	0	42875	50	
	9:00	78944	0	73784	50	
	10:00	92338	0	85912	48	
	11:00	102398	0	94799	50	
63	12:00	96356	0	92355	46	
D-639	13:00	84723	0	77623	50	
Q	14:00	86766	0	77789	50	
	15:00	94820	0	82805	46	
	16:00	104131	0	91987	47	
	17:00	121026	0	110612	50	
	18:00	138218	0	128904	30	
	19:00	125507	0	119447	42	
	Total 1189467 0		1095350	559		

Periods	Traffic	Fixed	Multi-period	Gain
7h-8h	504	1.60	1.47	8.12%
8h-9h	1161	4.90	4.77	2.6%
9h-10h	1746	9.58	9.57	0.1%
10h-11h	2015	10.65	11.27	
11h-12h	2168	12.30	12.19	0.9%
12h-13h	2092	11.42	11.45	
13h-14h	1861	9.84	9.39	4.5%
14h-15h	1944	10.30	9.75	5.3%
15h-16h	1972	11.15	10.30	7.6%
16h-17h	2160	12.77	12.25	4%
17h-18h	2486	15.75	14.40	8.5%
18h-19h	2745	19.01	17.83	6.2%
19h-20h	2696	16.71	15.82	5.3%
Total	25550	145.98	140.46	

Table 3. Comparison between fixed and multiperiod channel assignment in terms of lost traffic for the D-639 problem

Table 2. Comparison between fixed and multi-period channel assignment in terms of objective function

5.4 Comparison between Fixed and Multi-period Solutions for Large-scale Traffic Data (BM-120 Problem)

In tables 4 and 5, we compare two solutions generated for the BM-120 instance. The first solution is generated using the FCA model, and the second using the parallel decomposed algorithm for the multi-period model. As for D-639 problem, we compare these two solutions in terms of objective function (table 4) and lost traffic quantity (table 5). The first observation is that, during the weekend, frequency plan adaptation requires more changes. For both Saturday and Sunday, the change threshold is reached. This can be explained by the great difference between the traffic situation during the weekend and the remainder days. This observation results in table 4, where we note a great quality improvement during the weekend (the gain is of 8% and 11.4%) in the MCA model.

² Engineering tool for design of mobile radio network, ORANGE society all rights reserved.

Days	_	olution 2B	Multi-period solution F _p +IND(C' _p >50)		
	F_{p}	C_{p}	$F_{\mathfrak{p}}$	C_p	
June, Monday 24	39219	0	38708	31	
June, Tuesday 25	40171	0	39647	21	
June, Wednesday 26	40140	0	39866	15	
June, Thursday 27	44537	0	44226	19	
June, Friday 28	42958	0	42504	24	
June, Saturday 29	30543	0	28890	50	
June, Sunday 30	23221	0	21306	50	

Table 4. Comparison between fixed and multi-period channel assignment for BM-120 instance

Days	Traffic	Fixed	Multi-period	Gain
June, Monday 24	183	3.62	3.60	0.55%
June, Tuesday 25	246	3.65	3.35	8%
June, Wednesday 26	340	3.76	3.71	1%
June, Thursday 27	364	4.28	3.97	7%
June, Friday 28	340	4.07	3.98	2%
June, Saturday 29	338	2.66	2.44	8%
June, Sunday 30	322	1.76	1.59	11.4%
Total	2133	23.8	22.64	

Table 5. Lost traffic recorded for fixed and multi-period solution for the BM-120 instance

6 Conclusion

In this paper we have proposed a multi-period channel assignment (MCA) model for GSM mobile networks. In addition to the classical minimization interference criterion, we introduced another optimization criterion based on the transition cost from the frequency plan of a period to the plan of another one. Compared with the fixed channel assignment model, the proposed model has the advantage of being flexible and adaptive to traffic evolution.

Based on the MCA model, we have developed several optimization techniques to find a sequence of frequency plans for a given time periods. These solution techniques are adapted from a hybrid Genetic Tabu Search algorithm for fixed channel assignment. We proposed two ways of generating a solution for the MCA model: direct optimization in which the best sequence of frequency plans is sought directly; and decomposed optimization in which the whole solution is built by finding frequency plans for each individual periods.

Several experiments on three realistic data sets have been carried out. These data sets include both fine grained (hour by hour) and large scale (day by day) time steps. Experimental results have led to the following observations. First, comparing the

different optimization techniques for the MCA model on these data sets shows that the sequential and parallel implementation of the decomposed optimization give frequency plans of better quality in terms of the two optimization criteria (global interference and transition cost between frequency plans). Second, when comparing solutions obtained using the MCA model and the FCA model, one observes that the multi-period model leads to frequency plans of lower interference. Third and most importantly, thanks to the multi-period model, the lost traffic is always reduced, reaching sometimes a gain of communications up to 11.4%. This last point is especially beneficial from an operator's operational point of view.

Finally, let us mention two possible improvements for multi-period frequency assignment. As to the model itself, other optimization objectives may be taken into consideration (as mentioned in Section 2). As to solution techniques, an interesting alternative to the penalty-based aggregation approach used in this study is a true multi-criteria optimization approach that would be certainly worth of investigation.

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