GENETIC ALGORITHMS FOR OPTIMAL CHANNEL ASSIGNMENT IN MOBILE COMMUNICATIONS

Lipo Wang, Haixiang Shi, S. Arunkumaar, and Wen Gu

School of Electrical and Electronic Engineering
Nanyang Technological University
Block S2, Nanyang Avenue, Singapore 639798

ABSTRACT

Since the usable frequency spectrum is limited, optimal assignment of channels is becoming more and more important. It can greatly enhance the traffic capacity of a cellular system and decrease interference between calls, thereby improving service quality and customer satisfaction. In this paper, we use genetic algorithms (GA) to solve the problem of assigning calls in a cellular mobile network to frequency channels in such a way that interference between calls is minimized, while demands for channels are satisfied. This channel assignment problem is known to be a difficult optimization problem. Simulation results showed that the GA approach is able to further improve on the results obtained by other techniques.

1. INTRODUCTION

In recent years, the rate of increase in the popularity of mobile usage has very much outpaced the availability of the usable frequencies which are necessary for the communication between mobile users and the base stations of cellular radio networks. This restriction constitutes an important bottleneck for the capacity of mobile cellular systems. Careful design of a network is necessary to ensure an acceptable signal-to-interference (S/I) ratio.

There are basically three sources of interference, namely:

- Co-channel Interference: another caller within some range using the same channel;
- Adjacent Channel Interference: another caller within the same region using an adjacent channel in the frequency domain;
- Co-site Interference: Another caller within the same region using another channel within some range.

The dependence of interference on regions and channels is determined by the radio frequency (RF) propagation (obtained from the regional topography and morphostructure) and the spatial density of the expected traffic, which are also used to predict the demand for channels.

One aim of the channel assignment problem (CAP) is to assign the required number of channels to each region in such a way that interference is precluded and the frequency spectrum is used efficiently. This problem (called CAP1 in [1]) can be shown to be equivalent to a graph coloring problem and is thus NP-hard.

In most practical situations, there may not be sufficient channels available to assure interference-free channel assignments. In these cases, we can attempt to minimize the interference for a given set of channels, while the demand is met (call ed CAP2 in [1]).

Over recent years, several modern heuristic approaches [2]-[4] have been used to solve various channel assignment problems. Neural networks and simulated annealing have been considered for the channel assignment problems. These approaches have suffered from the infeasibility of the final solutions, due to their limitations of the technique [8] or the appropriateness of the chosen representation of a solution and its manipulation.

Genetic Algorithms are adaptive search techniques that can find the global optimal solution by manipulating and generating recursively a new population of solutions from an initial population of sample solutions. GAs are generally good at finding acceptably good solution to any problem very quickly. GAs are an interesting approach for combinatorial optimization problems, since they search from one population of points in search space to another, and tend to focus increasingly on areas with deeper minima. This is in contrast to other heuristic approaches such as simulated annealing which only examines one point at a time and is one-dimensional in their search.

There have been a number of attempts in using GA to solve CAPs. For example, [12],[19]-[22] used GA for CAP1. [23] and [24] formulated CAP2; however, they were interested only in interference-free situations. [16] gives a unique formulation of CAP2 in terms of GA.

The objective of the paper is to solve CAP2 using genetic algorithms (GA), following the formulations given in [16] and treating the non-interference constraints as soft constraints in the objective function and the demand satisfaction as a hard constraint. Ten benchmark problems are used in our simulations and the results are compared with those obtained with other methods.

2. CHANNEL ASSIGNMENT PROBLEM

Lets consider a network of N cells and M channels. The channel requirements (expected traffic) for cell i are given by D_i. Assuming that the RF propagation and the spatial density of the expected traffic have already been calculated, the noninterference constraints can be determined. The electromagnetic compatibility (EMC) constraints specify the minimum distance in the frequency domain by which two channels must be separated in order that an acceptably low S/I ratio can be guaranteed within the regions to which the channels have been assigned. These minimum distances are stored in a symmetric compatibility matrix C which has a dimension N×N.

The mathematical formulation of CAP2 given by Smith and Palaniswami [8] is reviewed below. Let

$X_{j,k}$ = 1, if cell j is assigned to channel k
0, otherwise

For j=1, …N and k=1…M. Suppose $X_{j,k} = X_{j,l}$ =1; that is, calls in j and i have been assigned channels k and l, respectively. One way to measure the degree of interference caused by such assignments is to weight each assignment by an element in a cost tensor $P_{j,i,m+1}$ where $m = |k-l|$ is the distance (in the channel domain) between channels k and l. If $k = l$, then the interference cost should be at its maximum, with the cost decreasing until the two channels are far enough apart that no interference exists.

The problem can thus be formulated to minimize the total cost of all the assignments in the network.

Minimize

$$F(X) = \sum_{j=1}^{N}\sum_{k=1}^{M} X_{j,k} \sum_{i=1}^{N}\sum_{l=1}^{M} P_{j,i,(|k-l|+1)} X_{i,l} \qquad (1)$$

Subject to

$$\sum_{k=1}^{M} X_{j,k} = D_j \qquad \text{j=1,…N} \qquad (2)$$

$$X_{j,k} \in \{0,1\} \quad \forall j=1, \ldots, N \quad \text{and } \forall k=1, \ldots, M$$

$$\textit{for } j=1, \ldots N \textit{ and } k=1\ldots M \qquad (3)$$

The cost (or proximity factor) tensor **P** described above can be generated according to recursive relation

$$P_{j,i,m+1} = \max(0, P_{j,i,m} - 1) \quad \text{for m=1, … , M} \qquad (4)$$

$$P_{j,i,l} = C_{ji} \quad \text{for all } j,\ i \neq j \qquad (5)$$

$$P_{j,j,l} = 0 \quad \text{for all j} \qquad (6)$$

Proimity factor tensor **P** is a three dimensional matrix. The front square of the cuboid is simply the matrix **C** with the diagonal terms overwritten to zero. This is because if $j=i$ and $k=l$, there should be no penalty incurred (there is effectively only a single call and no interference is possible). The third dimension of the tensor decreases the penalty linearly until the penalty becomes equal to zero. Thus the effective depth of the tensor is equivalent to the value of the maximum diagonal of **C**. This linear decrease in cost is a means of encouraging less severe violations of the non-interference constraints. If the network demands are such that violation is inevitable, it is preferred that the strength of the resulting signal to still be as strong as possible

The above cost function is the fitness function for the genetic algorithm to be minimized. The demand matrix is the constraint to be satisfied by each solution the genetic algorithm produces.

3. SIMULATION RESULTS

We adopt the GA implementation proposed in [16] as follows. A population of solution matrices is first randomly generated to satisfy the demand in each cell. Crossovers are carried out by swapping a number of rows of two individuals in the population. The rows themselves are unchanged during crossovers. A mutation represents a swap of a randomly selected 1 with a randomly selected 0 in a given row. Thus both crossover and mutation operators maintain the validity of the solutions in the population. The interference value given in eq.(1) is used to evaluate the fitness of an individual and tournament selection is used to select the individuals for the next generation.

Problem	Population Size	Crossover Probabi-lity	Mutation Probabi-lity
EX1	50	0.6	0.25
EX2	50	0.6	0.25
HEX1	120	0.8	0.85
HEX2	140	0.8	0.85
HEX3	140	0.8	0.85
HEX4	140	0.8	0.85
KUNZ1	120	0.6	0.7
KUNZ2	140	0.7	0.7
KUNZ3	140	0.8	0.85
KUNZ4	140	0.8	0.85

Table 1. Parameters used in the GA simulations.

We use the same data sets in our simulations as in [8]. The data sets can be divided into three classes. The first class consists of the problems EX1 and EX2 which are very small with N=4 and N=5, respectively. The second class of test problems (HEX1-HEX4) is based upon the 21-cell regular hexagonal network used by Sivarajan *et al.* [5]. Two sets of demands are used for this 21-cell hexagonal network. The final set of problems (KUNZ1-KUNZ4) is derived from the topographical data of an actual 24 x 21 km area around Helsinki, Finland, as used by Kunz [18]. Table 2 compares the interference values obtained by different methods given used in [8] with those obtained here using GA.

Tables 3 and 4 present two solutions with the lowest interference values generated GA.

4. CONCLUSIONS AND DISCUSSIONS

The results for EX1, EX2 and Kunz4 show that interference-free assignments can be found, as evidenced by a zero objective value. We can see that for HEX3 and KUNZ2 we get better values then the hill-climbing Hopfield neural network (HCHN) [8].

	GA	GAMS	SD		SA		HN		HCNN		SONN	
Problem	Min	Min	Av.	Min	Av.	Min	Av.	Min	Av.	MIN	Av.	Min
EX1	0	2	0.6	0	0.0	0	0.2	0	0.0	0	0.4	0
EX2	0	3	1.1	0	0.1	0	1.8	0	0.8	0	2.4	0
HEX1	48	54	56.8	55	50.7	49	49.0	48	48.7	48	53.0	52
HEX2	19	27	28.9	25	20.4	19	21.2	19	19.8	19	28.5	24
HEX3	***76***	89	88.6	84	82.9	79	81.6	79	80.3	78	87.2	84
HEX4	17	31	28.2	26	21.0	17	21.6	20	18.9	17	29.1	22
KUNZ1	20	28	24.4	22	21.6	21	22.1	21	21.1	20	22.0	21
KUNZ2	***29***	39	38.1	36	33.2	32	32.8	32	31.5	30	33.4	33
KUNZ3	13	13	17.9	15	13.9	13	13.2	13	13.0	13	14.4	14
KUNZ4	0	7	5.5	3	1.8	1	0.4	0	0.1	0	2.2	1

Table 2. Comparison of results obtained using GA with those obtained with other methods [8]: GAMS/MINOS-5 (labeled GAMS), the traditional heuristics of steepest descent (SD), stochastic simulated annealing (SSA), the original Hopfield network (HN) (with no hill-climbing), the hill-climbing Hopfield network (HCHN), and the self-organizing neural network (SONN).

Cell	Demand	Assigned Channels
1	1	21
2	1	2
3	1	20
4	2	8,12
5	3	9,11,14
6	6	3,7,10,16,18,20
7	7	1,3,9,13,15,17,19
8	6	2,4,6,8,12,14
9	10	1,3,5,7,9,11,14,16,18,20
10	10	1,3,5,7,10,13,15,17,19,21
11	11	2,4,6,8,10,12,13,15,17,19,21
12	5	1,11,16,18,20
13	7	2,4,6,8,12,14,21
14	6	1,5,9,11,16,20
15	4	13,15,17,19
16	4	6,8,12,18
17	7	1,3,5,9,11,16,18
18	5	2,4,7,19,21
19	5	2,4,7,10,21
20	5	8,11,13,15,20
21	6	6,9,12,14,17,20

Table 3. Channel Assignment for HEX3. Minimum Interference = 76. The number generations required to obtain this minimum value is 9423.

Cell	Demand	Assigned Channels
1	10	3,9,21,26,28,30,33,35,37,40
2	11	3,12,16,19,21,26,28,33,35,37,44
3	9	1,5,7,15,20,24,27,34,42
4	5	9,16,19,28,33
5	9	2,6,11,17,19,22,29,31,41
6	4	16,19,21,28
7	5	4,6,17,22,32
8	7	2,11,13,25,29,38,41
9	4	12,14,23,31
10	8	5,8,10,18,20,36,39,43
11	8	3,21,26,30,35,37,40,44
12	9	1,7,15,24,27,30,34,40,42
13	10	8,10,12,14,18,23,31,36,39,43
14	7	4,6,13,17,25,32,38
15	7	1,7,15,24,27,34,42

Table 4. Channel Assignment for KUNZ2. Minimum interference is 29. The number generations required to obtain this minimum value is 43190.

During the simulations, several parameters, such as the crossover probability, mutation probability and population size, need to be set. These values were set by trial and error. For any GA applications, the settings of these parameters are generally ad hoc. But for problems of higher complexity we can see that the mutation rate is higher.

In this paper, we have considered the problem of assigning channels to calls in a cellular mobile communication network. While many researchers have studied the problem of finding the minimum number of channels required to obtain an interference-free assignment, it is more useful in practical situations, where the number of available channels is substantially fewer than the minimum number for interference-free assignments, to find the assignment which minimizes the severity of any interferences given the number of available channels. Genetic Algorithms are an interesting approach for combinatorial optimization problems, since they search from one population of points in search space to another, and tend to focus increasingly on areas with deeper minima.

The simulations done on the benchmark problems showed that this approach could achieve desirable results, satisfying the demand constraint and solutions with lower (or equally low) interference when compared to other heuristic approaches.

More advanced genetic algorithms like parallel GA and micro-GA can be used to solve the CAP2 to give better results in a short span of time. GA is particularly well suited to implementation on parallel computers. Evaluation of the objective function and constraints can be done simultaneously for a whole population, as can the production of the new population by mutation and crossover. Thus, on a highly parallel machine, a GA can be expected to run nearly K times as fast for many problems, where K is the population size. This can be used effectively to obtain the optimum solution in a minimum time though one has to parallelism the evaluation of individual problem functions effectively.

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