

# A Genetic simulated annealing algorithm for solving the Channel Assignment problem

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**Abstract** — A novel algorithm to solve the problem of channel assignment (CAP) in cellular radio networks is presented. The algorithm proposed here is a metaheuristic approach, which uses a simulated annealing and genetic algorithm for solving the problem. The selection method based on Boltzmann annealing method, crossover and intelligent move in the mutation operator are used to keep the population diversity. The performance of our algorithm is evaluated using for the results eight well-known benchmark problems.

**Index Terms:** channel assignment problem; simulated annealing; genetic algorithm; metaheuristic.

## I. INTRODUCTION

Due to the insufficiency of available bandwidth resources and the increasing demand for cellular communication services, the channel assignment problem becomes increasingly important. The main objective of this problem is to be able to achieve an efficient use of the available radio spectrum on the network. The available channel band is assigned to the transceivers installed in each base station of the network.

Channel assignment is generalization of the graph coloring problem, which belongs to the class of NP-complete problems [1]. For this category of problem, there is no known algorithm that can generate a guaranteed optimal solution in an execution time that may be expressed as a finite polynomial of the problem dimension. As this reason many heuristic methods have been proposed to deal with CAP. This large production has been analyzed and organized in several surveys [2-4]. Different approaches have been proposed, including simulated annealing [5], genetic algorithms [6], neural networks [7], dynamic programming [8], Tabu search [9] and Cultural algorithm [10]. From the experiments made by most researchers on a variety of standard benchmark problems, simulated annealing (SA) and genetic algorithm GA have been two of the most effective heuristic algorithms for the CAP. Traditional GA often explore the candidate solution encoded in chromosomes and exploit those with better fitness iteratively until the solution is reached. Simulated annealing is an effective algorithm to solve large scale combinatorial

optimization problem. Kirkpatrick et al [11] were the first to introduce simulated annealing to optimization problems in 1983. Our approach proposed here uses the simulated annealing and genetic algorithm as method for solving the CAP with a new mechanisms and operators. The key idea of the GSA is to use traditional GA to explore in the same time several regions of the search space and simultaneously incorporates a good mechanism like SA to intensify the search around some selected regions. The move in the proposed approach is based on the intelligent search which embrace more efficient the direction of the space to search.

We consider a general cellular radio network subjected to all three kinds of constraints [12] :

1. the cochannel constraint (CCC): the same frequency cannot be assigned to certain pairs of radio cells simultaneously;
2. the adjacent channel constraint (ACC): frequencies adjacent in the frequency domain cannot be assigned to adjacent radio cells simultaneously;
3. the co-site constraint (CSC): any pair of frequencies assigned to a radio cell must have certain distance in the frequency domain.

The rest of the paper is organized as follows. In Section 2, we formulate the frequency assignment problem. In Section 3, we present the proposed algorithm. In Section 4, experimental results are presented. Future work and perspectives are discussed in the last section.

## II. PROBLEM DESCRIPTION

Radio channels are represented by the positive integers. Let  $M = \{1, 2, \dots, m\}$  be a set of available channels where  $m$  is the Number of available channels in the mobile network. The basic model of the channel assignment problem can be represented as follows:

1.  $N$ : The number of cells in the mobile network.
2.  $d_i$  : represents the number of frequencies that must be assigned to cell  $i$  ( $1 \leq i \leq N$ )
3.  $C$ : Compatibility matrix,  $C = (c_{ij})_{N \times N}$  represents the Minimal channel separation between channels in cells  $i$  and  $j$ ,  $1 \leq i, j \leq N$ .
4.  $Call_{ik}$  : Cell  $i$  with call  $k$  where  $1 \leq i \leq N$ ,  $1 \leq k \leq d_i$ .

5.  $f_{ik}$  : A radio channel is assigned to  $\text{Call}_{ik}$ , where  $f_{ik} \in$  a set of radio channel  $F$ .
6. *Frequency separation constraint* :  
 $|f_{ik} - f_{jm}| \geq c_{ij}$ , for all  $i, j, k, m$  ( $i \neq j, k \neq m$ ),  $c_{ij}$  is defined in Compatibility Matrix,  $C$ . If  $i=j$ , it become co-site constraint.

Therefore, the objective is to find an assignment that minimizes the total number of violations in an assignment, Subject to[13]:

$$\min \sum_{i=1}^n \sum_{k=1}^m \sum_{j=1}^n \sum_{l=1}^m f_{ik} \text{viol}(i,j,k,l) f_{jl}$$

where:  $\text{viol}(i,j,k,l) = \begin{cases} 0 & |k-l| \geq C_{ij} \\ 1 & \text{otherwise} \end{cases}$

and

$$f_{ik} = \begin{cases} 0 & \text{if channel } k \text{ is not assigned to cell } i \\ 1 & \text{otherwise} \end{cases}$$

for  $1 \leq k, l \leq m$  and  $1 \leq i, j \leq N$ .

### III. THE PROPOSED ALGORITHM

In this paper, a genetic simulated annealing (GSA) is proposed for CAP. The mechanisms and operators of the GSA are given below.

#### A. Solution representation

We represent a solution by a binary matrix  $N \times m$ .  $N$  is the number of cells and  $m$  is the number of channels. If a gene  $f_{ik} = 1$ , then the  $k^{\text{th}}$  channel is assigned to the  $i^{\text{th}}$  cell (see fig 1.).

$f_{1,1}$	$f_{1,2}$	$f_{1,3}$	$f_{1,4}$	.....	$f_{1,m-1}$	$f_{1,m}$
$f_{2,1}$	$f_{2,2}$	$f_{2,3}$	$f_{2,4}$	.....	$f_{2,m-1}$	$f_{2,m}$
$\cdot$	$\cdot$	$\cdot$	$\cdot$	.....	$\cdot$	$\cdot$
$\cdot$	$\cdot$	$\cdot$	$\cdot$	.....	$\cdot$	$\cdot$
$\cdot$	$\cdot$	$\cdot$	$\cdot$	.....	$\cdot$	$\cdot$
$f_{n-1,1}$	$f_{n-1,2}$	$f_{n-1,3}$	$f_{n-1,4}$	.....	$f_{1,m-1}$	$f_{1,m}$
$f_{n,1}$	$f_{n,2}$	$f_{n,3}$	$f_{n,4}$	.....	$f_{1,m-1}$	$f_{1,m}$

Figure 1. solution representation

#### B. Initial solution generation

The co-site constraint (CSC) may cause more interference in the real-world situation [13], we have generate the initial solution with the method from [14] (see fig.2). In order to get an initial solution in which the search efficiency is improved, Any pair of channel assigned to the same cell (line) must have the distance defined in the compatibility matrix.

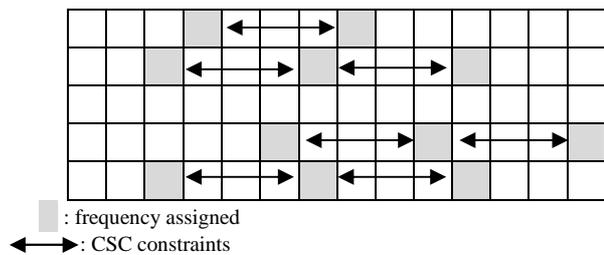


Figure 2. Initial solution generation

#### C. Crossover operator

The mechanism of crossover is shown in Fig 3. Two parents (P1,P2) are selected from the population randomly and crossed with The following technique:

- 1- Generate a sequence of binary number (SQB) equal to the number of cell (rows in our case) i.e SQB=1010 if the number of cell =4.
- 2- exchange the row "I" of the two parents if SQB(I)=1 .  $\forall I \in [1..N]$ . Two kids are generated K1 and K2.
- 3- The survivor step: the survivor step is the method of selection. It is an important process in the population evolution. The familiar method such as roulette selection, while just based on the fitness of individual, usually out come to local optimum. In this paper, Boltzmann simulated annealing operator is used to select new solutions. Its gain is that some inferior solutions can also be selected to join into evolution, and diversity of population is kepted preferably. The crucial points of simulated annealing method are initial temperature and annealing operation. According to reference [15], initial temperature can be confirmed by the relative performance between fitness function and original population. The initial temperature can be calculated as follows:

$$t_0 = \frac{|f_{\min} - f_{\max}|}{\ln(f_{\min} / f_{\max})} \quad (1)$$

Where  $f_{\min}$   $f_{\max}$  represents the minimal and maximal fitness in initial population respectively. The initial temperature considers relative performance of population and bad infection of evolution is avoided promptly. Annealing temperature can be showed by (2):

$$t_{k+1} = \alpha t_k \quad (2)$$

where  $\alpha$  is a proportion factor, and a large  $\alpha$  means that temperature descends much slowly.

- 4- If  $\text{fitness}(K1) < \text{fitness}(P1)$  then accept the result of the crossover operator else accept with the probability PB where PB is random variable such us:

$$\text{PB} < \exp(-|\text{fitness}(K1) - \text{fitness}(P1)| / t) \quad (3)$$

And the same work is done for K2 and P2

#### D. Mutation operator

The mission of the mutation operator is to perform some move to improve the fitness. Our basic move is then moving a 1 to a 0 entry of the same row, thus changing the assigned channel of one cell, maintaining the number of assigned channels unchanged and keeping the result of the initial solution (co-site interference). The power of our mutation operator is the covering the whole feasible space in the same line (cell). The computations needed for each movement is O (1).

#### E. Stopping criteria

In traditional stopping criteria, the number of iteration and solution improved is selected as termination criterion. In this

paper, all of them are considered. The algorithm stops when any of the conditions is true.

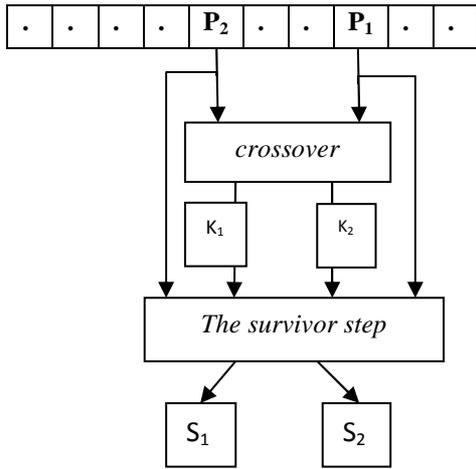


Figure 3. Crossover operator

#### F. GSA description

Figure 4 shows the framework of the proposed genetic Simulated annealing algorithm for minimizing the objective function. The first step is creating and selecting an initial solution, setting that initial solution as the best seen and calculating the initial temperature. The proper algorithm starts searching for an optimal solution until a stopping condition is met. A Pair of parent is selected for the above methods of crossover and mutation. The selection method is performed on these solutions. This process continues until stopping criteria is met, at which point, the best solution seen during the search process is returned.

#### Algorithm :GSA

- 1) Initialization.
- 2) Set the size of population  $N$  and evolution generation  $Ne=10000$ .
- 3) Generate the initial population, calculate initial temperature  $t_k$ .
- 4) select tow parents
- 5) Do the crossover operation.
- 6) Set the annealing temperature,  $t_{k+1}=at_k$ , get a new population  $C'$  through the selection method.
- 7) Do the mutation operation in population  $C'$  ( results of selection method) , get population  $C''$  .
- 8) Refresh the optimal individual .
- 9) Check the stopping criterion. If the stopping criterion is satisfied then go to next step, otherwise, go to the step (4) and continue the procedure.
- 10) Finish the evolution and output the reconfiguration results.

Figure 4. GSA framework

### IV. EXPERIMENTAL RESULTS

In these experiments we used the Philadelphia instances [14]. These instances are widely known within problem CAP, and they are characterized by a number of hexagonal cells (habitually 21), that represent a cellular phone network of the Philadelphia city (see Figure 5). The main differences among

the instances correspond with the use of different interference matrices and demand vectors (see table 1). Figure 7 shows the different interference matrices (C) and the demand vectors (D) used.

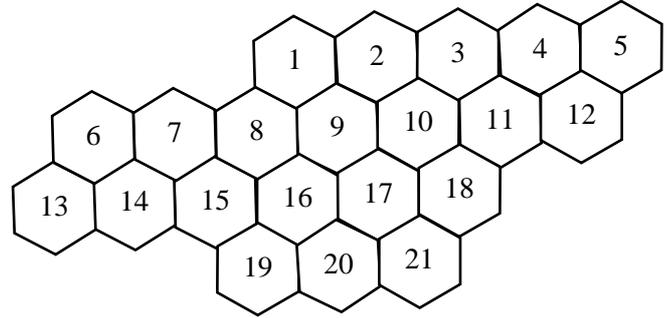


Figure 5. Cellular geometry of test problems

TABLE 1. PROBLEM SPECIFICATION

Instance	# of Cell	Lower Bound (lb)	Compatibility matrix (C)	Demand vector (D)
P1	4	11	$C_1$	$D_1$
P2	25	73	$C_2$	$D_2$
P3	21	381	$C_3$	$D_3$
P4	21	533	$C_4$	$D_3$
P5	21	533	$C_5$	$D_3$
P6	21	221	$C_3$	$D_4$
P7	21	309	$C_4$	$D_4$
P8	21	309	$C_5$	$D_4$

The result of simulation of problem # 1, 4 is presented in table 2 and 3.problem #1 is simple to solve . Figure 6 shows the required generation to converge to the solution in the problems # 4. The x-axis represents the number of generations whilst the y-axis represents the fitness. In problem # 4, our GSA found the solution within 5000 generation.

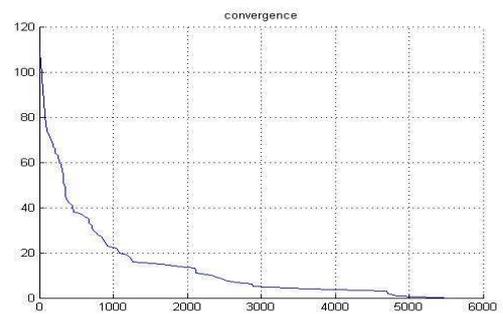


Figure5. problem # 4 convergence

TABLE2. FREQUENCY PLAN FOR PROBLEM #1

Cells	Frequency assigned
1	6
2	2
3	3
4	1      6      11

TABLE3. FREQUENCY PLAN FOR PROBLEM #4

Cells	Frequency assigned
1	24,139,151,200,275,433,455,532
2	10,28,51,70,77,90,125,142,161,175,189,210,235,251,263 272,289,307,322,350, 359,371,396,417,431
3	23,105,160,179,205,286,462,501
4	14,40,103,154,188,213,291,382
5	67,109,186,194,206,245,290,405
6	31,41,78,99,156,177, 212,223,256,287,322, 331,363,415,424
7	14,48,59,93,104,119,132,163,198,277,296, 326,335,343 403,420,521,528
8	159,166,173,180,187, 194,201,208,215,222, 229,236,243 ,250,257,264,271,278,285,292,299,306,313 ,320 327,334,341,348,355, 362,369,376,383,390, 397 404,411,418,425,432, 439,446,453,460,467, 474 481,488,495,502,509, 516
9	1,8,15,22,29,36,43,50,57,64,71,78,85,92,99,106,113,120 127,134,141,148,155, 162,169,176,183,190, 197 204,211,218,225,232, 239,246,253,260,267, 274 281,288,295,302,309, 316,323,330,337,344, 351 358,365,372,379,386, 393,400,407,414,421, 428 435,442,449,456,463,470,477,484,491,498, 505 512,519,526,533
10	12,31,39,61,79,97,117,130,158,167,181,191,209,230, 240 256,275,287,294,314, 321,329,345,363,385, 406 424,483
11	32,44,73,80,102,140, 182,210,279,296,440, 460,471
12	28,58,69,89,145,162, 177,212,233,265,298, 322,340,356,436
13	13,24,40,53,63,74,84, 94,111,127,137,161,174,185,195, 204,224,235,252,274, 282,291,307,320,328, 345 358,371,446,486,514
14	10,23,33,60,72,86,97, 117,152,211,238,267, 284,294,312
15	11,30,42,55,67,79,100,110,135,146,154,170,181,191, 205 226,245,254,266,273, 280,293,308,317,329, 340 382,394,422,450,459, 469,480,493,506,515
16	80,87,94,101,108,115,122,129,136,143,150,157,164,171 178,185,192,199,206, 213,220,227,234,241, 248 255,262,269,276,283, 290,297,304,311,318, 325 332,339,346,353,360, 367,374,381,388,395, 402 409,416,423,430,437, 444,451,458,465,472
17	9,17,25,52,68,75,84,95,104,131, 145,152,186,200,219, 231 244,252,270,301,315, 364,377,399,436,473, 499 530
18	35,55,126, 139,175,196,259,503
19	38,69,121,128,153,167,237,417, 494,520
20	27,48,77,109,140,195,223,272,289,305,352,392,485
21	42,74,83,133,278,443,468,531

V. CONCLUSIONS

A genetic simulated annealing algorithm for solving the channel assignment problem in cellular radio networks is presented. Due the importance of CSC constraints, we have considered this in the solution initialization. However, due to the limitation of the number of problems presented here, it could not conclude that the metaheuristic approach here would outperform all the algorithms. Further work should be carried out. The hybridization between this algorithm and tabu approach is good perspectives in our work to accelerate the discovery of good solutions. The crossover and mutaion operator must be compared with others crossover to see its efficiency.

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C2	D2	C3	D3
21101011110111100000000000	10	511001111000011100000	8
12101010101111000000000000	11	151100111100001110000	25
11211111111111000000000000	9	115110011110000111000	8
00120011111110000000000111	5	011510001111000011000	8
11102000011111100000000000	9	001150000111000001000	8
00100211110000000000000000	4	100005110000111000000	15
11110121111100000000000000	5	110001511000111100100	18
11110112111100000000000010	7	111001151100011110110	52
10110111211100000000000011	4	111100115110001111111	77
111111112111110000001010	8	011110011511000111011	28
001110111201111011111111	8	001110001151000011001	13
11110111102110000000000000	9	000110000115000001000	15
11111011011121111111000000	10	000001100000511000000	31
1110100001112111111000000	7	100001110000151100100	15
11001000011011211111110000	7	110001111000115110110	36
00001000011011121111000000	6	110001111000115111111	57
0000000000001112110000000	4	011100011110001151111	28
00000000001011111211000000	5	001110001111000115011	8
00000000001011111211110000	5	000000111000011110511	10
00000000010111011211110000	7	000000111000011111511	13
00000000010001000112111000	6	000000001110000111115	8
0000000001100010001121111	4		
00010000001000000011112111	5		
0001000111100000000011211	7		
000100001010000000001112	5		
C4	D4	C5	D1
711001111000011100000	5	721001221000011100000	5400 1
171100111100001110000	5	272100122100001110000	4501 1
117110011110000111000	5	127210012210000111000	0052 1
011710001111000011000	8	012720001221000011000	0125 3
001170000111000010000	12	001270000122000001000	
100007110000111000000	25	100007210000221000000	
110001711000111100100	30	210002721000122100100	
111001171100011101110	25	221001272100012210110	
111100117110001111111	30	122100127210001221111	
011110011711000111011	40	012210012721000122011	
001110001171000011001	40	001220001272000012001	
000110000117000001000	45	000120000127000001000	
000001100000711000000	20	000002100000721000000	
100001110000171100100	30	100002210000272100100	
11000111000117110110	25	110001221000127210210	
111000111000117111111	15	0111000122100012721221	
011100011100011711111	15	011100012210001272122	
00111000111000117011	30	001110001221000127012	
00000011000011110711	20	000000111000012210721	
0000001100001111171	20	00000011100001221272	
0000000111000111117	25	0000000111000122127	

Figure 7. Interference matrix (C) and demand vector (D) for the tested instances