# Genetic Algorithms with Stochastic Ranking for Optimal Channel Assignment in Mobile Communications

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**Abstract.** Optimal channel assignment can enhance traffic capacity of a cellular mobile network and decrease interference between calls, thereby improving service quality and customer satisfaction. We combine genetic algorithms with stochastic ranking, 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. Simulation results showed that this approach is able to further improve on the results obtained by some other techniques.

## 1 Introduction

There is a continuously growing number of mobile users. However, the number of usable channels (frequencies), which are necessary for the communication between mobile users and the base stations of cellular radio networks, is very limited.

The purpose of channel assignment problems is to assign channels efficiently in order that interference is minimized while the demand of each cell is satisfied. Our research is focused on static channel assignment problems since static assignment is the basis of dynamic assignment to a large extent.

One kind of SCA is to minimize the number of channels used while interference is precluded and the demand of each cell is satisfied. This kind of problem is defined by Gamst and Rave [16] and denoted as CAP1 in [12]. In most practical situations, the number of available channels may be not enough for an interference-free assignment. In such cases, we have to try to minimize the interference for a given set of channels while the demand is met, which can be called CAP2 [12]. Over recent years, many heuristic techniques have been applied to solve channel assignment problem [1-2]. In [12], demand satisfaction is treated as hard constraints and non-interference is treated as soft constraints. However, how to balance the constraints becomes a difficult problem.

In this paper, we apply a new constraint balance technique proposed by Runarsson and Yao [4], i.e., stochastic ranking, together with genetic algorithms, to balance the constraints in CAP2.

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## 2 Channel Assignment Problem

Let us consider a network of $N$ cells and $M$ channels. The channel required (expected traffic) for cell $i$ is given by $D_i$ . The electromagnetic compatibility (EMC) constraints specify the minimum distance in the frequency domain by which two channels must be separated so that no interference exists. These minimum distances are stored in a symmetric compatibility matrix $C$ which has a dimension of $N \times N$ .

The mathematical formulation of CAP2 given by Smith and Palaniswami [12] is reviewed below.

$$X_{j,k} = \begin{cases} 1, & \text{if cell } j \text{ is assigned to channel } k \ , \\ 0, & \text{otherwise} \ , \end{cases} \tag{1}$$

for $j = 1, \cdots, N$ and $k = 1, \cdots, M$ . 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 $l$ [12]. Now, the problem becomes how to minimize the total cost of all the assignments in the network.

Minimize

$$F(X) = \sum_{j=1}^{N} \sum_{k=1}^{M} X_{j,k} \sum_{i=1}^{N} \sum_{l=1}^{M} X_{i,l} P_{j,i,(|k-1|+1)} \ , \tag{2}$$

Subject to

$$\sum_{k=1}^{M} X_{j,k} = D_j \ , \qquad \forall j = 1, \cdots, N \ , \tag{3}$$

The proximity factor tensor $P$ described above can be generated according to the recursive relation

$$P_{j,i,m+1} = \max\{0, P_{j,i,m} - 1\} \ , \text{ for } m = 1, \cdots, M-1 \ , \tag{4}$$

$$P_{j,i,1} = C_{ji} \ , \qquad \text{for all } j, i \neq j \ , \tag{5}$$

$$P_{j,j,1} = 0 \ , \qquad \text{for all } j \ . \tag{6}$$

The cost function given by eqn. (2) is the objective function to be minimized and the demand vector $D$ is the constraint that can be transformed to penalty function as shown below

$$p(x) = \sum_{j=1}^{N} \left[ \left( \sum_{k=1}^{M} X_{j,k} \right) - D_j \right]^2 \ . \tag{7}$$

# 3 Brief Review of Stochastic Ranking

## 3.1 Constrained Optimization

The general nonlinear programming problem can be formulated as: Find $x$ to

$$\text{minimize } y(x), \quad x = (x_1, \cdots, x_n) \in R^n \ . \tag{8}$$

In eqn. (8), $x$ is an $n$-dimensional vector and $x \in S \cap F$, where $S$ defines the s*earch space* and $F$ defines the feasible region. S is an $n$-dimensional space whose boundary is:

$$x_{\min} \le x_i \le x_{\max,} \quad i \in (1, \cdots, n) \ , \tag{9}$$

where $x_{min}$ is the lower bound of $x_i$ and $x_{max}$ is the upper bound of $x_i$. The *feasible region F* is given by

$$F = \{x \in R^n \mid c_j(x) \le 0 \ \ \forall j \in \{1, \cdots, m\}\} \ , \tag{10}$$

where $c_j(x),\ j \in \{1, \cdots, m\}$ are constraints.

One way often used to deal with constrained optimization problems is to introduce a penalty term into the objective function to penalize constraint violations [4].

$$f(x) = y(x) + w_g \, p(c_j(x);\ j = 1, \cdots, m) \ . \tag{11}$$

In this equation, $p \ge 0$ is a real-valued function and it represents a "penalty". The "strength" of the penalty is controlled by a sequence of penalty coefficients. There are some forms of penalty functions. One often used is the following quadratic loss function [3]:

$$p(c_j(x);\ j = 1, \cdots, m) = \sum_{j=1}^{m} \max\{0,\ c_j(x)\}^2 \ . \tag{12}$$

Although for many problems, the penalty function approach may work quite well, another difficult optimization problem, i.e., how to determine the penalty coefficients arises.

## 3.2 Stochastic Ranking

In order to avoid setting penalty coefficients, Runarsson and Yao [4] proposed a novel constraint-handling technique for evolutionary algorithms. Using this new technique, the right balance between objective and penalty functions can be achieved stochastically.

In stochastic ranking [4], firstly we initialize $n$ individuals randomly, $X_1, X_2, \cdots, X_n$. Each individual represents a potential solution and has an objective value $y(X_i)$ and a penalty value $p(X_i),\ i = 1, 2, \cdots n$. Then, we rank the individuals according to either their objective function values eqn. (2) or penalty function values eqn. (7) in order to select $m$ individuals to be parents. $m<n$. $m/n$ is called truncation level. In order to balance the dominace of objective function and penalty function without setting $w_g$, a probability $P_f$ is used. $P_f$ decides whether we use objective function or penalty function to compare adjacent individuals. That is, given any pair of two

adjacent individuals (in order to determine which one is fitter) if both of them are feasible, the comparison is determined by the objective function; otherwise, the probability of comparing them according to the objective function is $P_f$ . The one with lower values (in the case of minimizing fitness function) has higher position than those with larger values in the ranking list. Ranking can be achieved by a bubble-sort-like procedure [4]. After ranking, *m* individuals are chosen as parents to generate next generation. Then the new generation is ranked and parents are chosen. This procedure will go on until stop criteria are satisfied.

## 4 Experimental Studies

The evolutionary optimization algorithm described in this section is based on genetic algorithms (GA) and stochastic ranking. There have been several attempts in using GA to solve CAPs. For example, [5-9] used GA for CAP1. [10-11] and [13] used GA for CAP2.

The data set can be divided into three classes. The first class consists of the problems EX1 and EX2 [15]. The second class of test problems (Kunz1-Kunz4) was used by Kunz [14]. The third class of test problems (HEX1-HEX4) is based on the 21-cell regular hexagonal network used by Sivarajan *et al.* [15].

During simulations, several parameters, such as $P_f$ , the crossover probability, mutation probability, and population size need to be set. These values were set by trial and error. Table 1 shows the parameters for various CAP2s**.** Table 2 compares the interference values obtained by different methods used in [12-13] and [18] with those obtained here using stochastic ranking. The minimum values and average values obtained by other algorithms listed in that table are calculated from 10 runs' results. In order to compare with them, we also run the program 10 times and calculate the average values. We note that standard deviations are not available in most methods shown in Table 2; however, we list the standard deviation for our method for comparisons with further work. “Min” represents the minimum objective function. “Ave” is the average objective value and “Sd” is the standard deviation.

**Table 1.** Parameters used in the simulations. (*Ps* is the population size; *Pc* is the crossover probability; *Pm* is the mutation probability)

| Problem | $P_s$ | $P_c$ | $P_m$ | $P_f$ |
|---|---|---|---|---|
| EX1 | 40 | 0.75 | 0.3 | 0.45 |
| EX2 | 60 | 0.85 | 0.2 | 0.46 |
| HEX1 | 100 | 0.7 | 0.4 | 0.46 |
| HEX2 | 120 | 0.65 | 0.35 | 0.465 |
| HEX3 | 140 | 0.8 | 0.4 | 0.455 |
| HEX4 | 140 | 0.85 | 0.35 | 0.46 |
| KUNZ1 | 80 | 0.75 | 0.25 | 0.45 |
| KUNZ2 | 80 | 0.7 | 0.2 | 0.445 |
| KUNZ3 | 120 | 0.8 | 0.3 | 0.455 |
| KUNZ4 | 140 | 0.75 | 0.4 | 0.46 |

**Table 2.** Comparison of the total interference obtained by different methods: Genetic algorithm with stochastic ranking (GASR), genetic algorithm without stochastic ranking (GA) [13], the self-organizing neural network (SONN) [12] and stochastic chaotic simulated annealing [18] . The values in bold indicate improved solutions over all other algorithms

| | GA-SR | | GA | | SONN | | SCSA | |
|---|---|---|---|---|---|---|---|---|
| Problem | Min | Ave±Sd. | Min | Ave | Min | Ave | Min | Ave±Sd. |
| EX1 | 0 | 0±0.0 | 0 | 0 | 0 | 0.4 | 0 | 0.0±0.0 |
| EX2 | 0 | 0±0.0 | 0 | 0 | 0 | 2.4 | 0 | 0.0±0.0 |
| HEX1 | 46 | 47.7±0.4 | 48 | 48.1 | 52 | 53.0 | 47 | 47.7±0.3 |
| HEX2 | 17 | 18.4±0.2 | 19 | 19.3 | 24 | 28.5 | 18 | 18.5±0.2 |
| HEX3 | 76 | 76.5±0.5 | 76 | 76.4 | 84 | 87.2 | 76 | 77.3±0.3 |
| HEX4 | 16 | 17.5±0.6 | 17 | 17.2 | 22 | 29.1 | 16 | 17.2±0.4 |
| KUNZ1 | 19 | 19.8±1.0 | 20 | 20.1 | 21 | 22.0 | 19 | 20.0±2.1 |
| KUNZ2 | 29 | 29.4±0.3 | 29 | 29.4 | 33 | 33.4 | 30 | 30.3±0.2 |
| KUNZ3 | 13 | 13.00 | 13 | 13.0 | 14 | 14.4 | 13 | 13.0±0.0 |
| KUNZ4 | 0 | 0±0.0 | 0 | 0 | 1 | 2.2 | 0 | 0.0±0.0 |

We can see that for HEX1 and HEX2 we obtained lower interference values than other methods including genetic algorithm [13] without stochastic ranking. In [14], the search space is limited to feasible regions.

## 5 Conclusions and Discussions

In this paper, we have considered the problem of assigning channels to calls in a cellular mobile communication network. We have combined stochastic ranking proposed by Runarsson and Yao with GA and applied to CAP2. The simulations done on the benchmark problems showed that genetic algorithm using stochastic ranking can achieve desirable results compared to other heuristic approaches. For several problems, GA with stochastic ranking can obtain better results than using GA only.

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