

# Economic Modeling of Radio Resource Management: A Novel Metaheuristic Approach

César L. C. Mattos, Guilherme A. Barreto, Francisco R. P. Cavalcanti

**Abstract**—In this paper we introduce a constrained hybrid PSO algorithm, called Improved Hybrid Particles Swarm Optimization (I-HPSO), in order to find feasible solutions to the problem of resource allocation in the downlink of a multi-cell WCDMA system. An economic model is developed that considers the utility of the provided service, the acceptance probability of the service by the users and the revenue generated for the network operator. The performance of the proposed I-HPSO is compared with those of several other metaheuristics. The obtained results indicate that the proposed approach achieves superior accomplishment.

**Keywords**—Radio Resource Management, Particle Swarm Optimization, Simulated Annealing, Genetic Algorithms.

## I. INTRODUCTION

Radio Resource Management (RRM) is a collection of techniques and methods that assigns to each user in the system a subset of the available radio resources, mainly power and bandwidth, according to a certain optimality criterion on the basis of the experienced link quality (Figure 1).

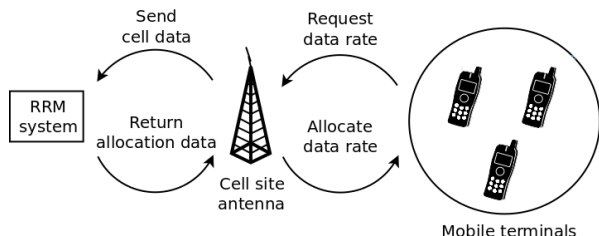


Fig. 1. Illustration of the RRM problem.

RRM is a major issue for the mobile network operators, with great impact on the quality of the service provided. For this reason, the topic has been widely discussed in the recent years. There are several different approaches for RRM-related problems. Some authors, as [5], analyze admission control schemes, which previously select the terminals that will be served and try to guarantee quality of service (QoS) for the accepted users. This strategy analyzes the problem from the user perspective, without evaluating directly the objectives of the service operator. Other work apply concepts from Game Theory to RRM-related problems, such as [14] and [12]. However, in this approach the operator is viewed simply as an arbitrator or a mediator of a non-cooperative game with the presence of several users in the role of players.

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A third approach to RRM-related problems involves power control, given that it is one of the main system limited resources [13]. Such work often consider the use of convex and differentiable cost functions. Finally, a fourth approach include an economic analysis to the solution of the problem of operating communication networks, assessing the sustainability of the model, the charge policy and its capacity of generating revenue. This point of view is adopted, for example, by [1], [4] and partially by [9].

It is worth emphasizing that RRM-related problems often involve several variables, non-differentiable objective functions and sets of strong constraints. Metaheuristic techniques, such as Genetic Algorithms (GA) [8], Tabu Search (TS) [6] and Particles Swarm Optimization (PSO) [10], have been successfully used for solving optimization problems with aforementioned characteristics. In [1], for example, GA is used for the estimation of solutions for RRM-related problems, while in [3] TS is applied for resource allocation purpose. The good results obtained in these work suggest that the study of metaheuristic methods in such a context is therefore relevant.

The remainder of this paper is organized as follows. In Section II we develop an economical model for the RRM-related problem of interest. In Section III we introduce the proposed approach based on metaheuristics. Section IV shows and discusses the obtained results. Final comments and suggestions for further work are given in Section V.

## II. PROBLEM MODELING

This paper utilizes two common functions as quality metrics, namely, the utility function and the acceptance function.

### A. Utility and Acceptance

The utility of a service corresponds to the level of satisfaction of an individual while enjoying that service. Sigmoidal functions are commonly used as the utility of a service [1]:

$$u_i(r_i) \triangleq \frac{(r_i/\beta_i)^{\alpha_i}}{1 + (r_i/\beta_i)^{\alpha_i}}, \quad (1)$$

where  $u_i$  is the utility provided,  $r_i$  is the allocated rate (or another parameter directly related to the quality of the service) and  $\alpha_i$  and  $\beta_i$  are positive parameters which differentiate users from each other.

The provided utility  $u_i$  and the charged price  $p_i$  are used to estimate the probability of acceptance  $A(u_i, p_i)$  for the  $i$ -th user. An acceptance function that is widely used in microeconomics is the one related to the Cobb-Douglas demand curves [4], which is given by

$$A(u_i, p_i) \triangleq 1 - \exp\{-Cu_i^\mu p_i^{-\epsilon}\}, \quad (2)$$

where  $C$ ,  $\mu$  and  $\epsilon$  are positive constants.

### B. Price and Revenue Generation

This paper makes use of the total revenue generated for the service provider as the objective function of the optimization process. Mathematically, for  $N$  users, the total revenue function  $R$  can be defined as [1]:

$$R = \sum_{i=1}^N p_i A(u_i, p_i), \quad (3)$$

where  $p_i$  is the charged price to the user  $i$  and  $u_i$  is the utility of the service provided for this user. It is important to point out that the optimization framework presented in this paper does not restrict the choice of the objective function.

Equations (1) and (3) indicate a strong dependence of  $R$  on the allocated rates  $r_i$  and the price values  $p_i$ ,  $i = 1, \dots, N$ . Thus, both  $r_i$  and  $p_i$  can serve as adjustable parameters for the problem of interest.

### C. Capacity in WCDMA systems

The capacity of interference-limited systems is determined by the current state of the system's users. In the downlink scenario the rate  $r_i$  of the user  $i$ , its power  $w_i$  allocated by the antenna for providing such rate, the service quality and the system interference are related by the following equation [4]:

$$\left[ \frac{E_b}{N_0} \right]_i = \frac{W}{r_i} \frac{g_i w_i}{I_i^{int} + I_i^{ext} + \nu}, \quad (4)$$

where  $[E_b/N_0]_i$  is the Signal to Interference plus Noise Ratio (SINR) of the  $i$ -th user,  $g_i$  is its power gain and  $W$  is the spreading bandwidth. The quantity  $I_i^{ext}$  is related to the cell external interference and  $\nu$  is the power (variance) of the additive white gaussian noise process. The quantity  $I_i^{int}$  is the cell total internal interference, being  $\theta_{ij}$  the cross-correlation coefficient between the spreading codes of the users  $i$  and  $j$ :

$$I_i^{int} = \sum_{j \neq i} \theta_{ij} g_j w_j, \quad (5)$$

where  $w_j$  is the the power allocated to the  $j$ -th user. In this paper, for the sake of simplicity, we apply  $I_i^{ext} = I_i^{int}/2$ .

Considering orthogonal codes such as  $\theta_{ij} = \theta_i$  for all  $j$ , then, following the simpler approach proposed in [11]:

$$\theta_i \approx 1 - \frac{1}{1 + \kappa d_i}, \quad (6)$$

where  $d_i$  is the distance in meters from the  $i$ -th terminal to the cell site and  $\kappa = 0.0029$ , as suggested by [11].

Equation (4) indicates that, for a fixed value of  $[E_b/N_0]_i$ , there is a unique relation between the rate  $r_i$  and the power  $w_i$ :

$$r_i = \frac{W}{\left[ \frac{E_b}{N_0} \right]_i} \frac{g_i w_i}{I_i^{int} + I_i^{ext} + \nu}. \quad (7)$$

From Equation (7) one can note that it is possible to use the power allocated  $w_i$ , instead of the allocated data rate  $r_i$ , as the main adjustable parameter of the problem.

### D. Resource Allocation Constraints

Equation (4) shows that the modification of one user's parameters directly influences the service quality of the other users. Besides, there are physical constraints of the cell site that must be taken into account during the choice of parameters. Thus, some constraints must be followed for each user  $i$  [1]:

$$r_i \leq r_{max}, \quad \sum_{i=1}^N w_i \leq w_{total}, \quad \left[ \frac{E_b}{N_0} \right]_i \geq \frac{E_b}{N_0}, \quad (8)$$

where  $r_{max}$  is the maximum allocatable rate for a single user,  $w_{total}$  is the total available transmission power and  $E_b/N_0$  is the least desirable value for the SINR.

However, if the third inequality constraint in (8) is replaced by an equality (as done in [1]), it is possible to use Equation (7) into the first constraint of (8). The modified constraints then become

$$\frac{W}{\frac{E_b}{N_0}} \frac{g_i w_i}{I_i^{int} + I_i^{ext} + \nu} \leq r_{max}, \quad (9)$$

$$\sum_{i=1}^N w_i \leq w_{total}, \quad \frac{E_b}{N_0} = \frac{E_b}{N_0}. \quad (10)$$

## III. PROPOSED APPROACH

In this paper we develop a novel metaheuristic approach to the constrained optimization problem previously presented and compare its performance with those achieved by other techniques. Metaheuristic methods are mostly stochastic search algorithms comprised by a set of simple rules capable of guiding the solution of optimization problems in general.

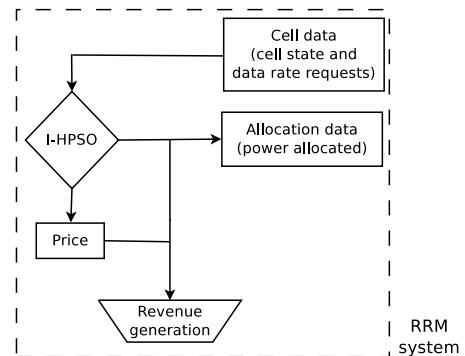


Fig. 2. Role of the metaheuristic algorithms in the RRM problem being tackled in this paper.

In what concerns the problem being tackled, the metaheuristic algorithms act within the RRM block shown in Figure 1, whose inner building blocks are shown in Figure 2.

### A. Solution evaluation

The objective function  $f(\mathbf{x})$  to be minimized is defined as the inverse of the total revenue (see Equation (3)):

$$f(\mathbf{x}) = \frac{1}{\sum_{i=1}^N p_i A(u_i(r_i), p_i)}, \quad (11)$$

with the solution-vector being given, in principle, by  $\mathbf{x} = \{u_i(r_i), p_i\}_{i=1}^N$ , where the adjustable parameters  $r_i$  and

$p_i$  are, respectively, the allocated rate and the charged price for the  $i$ -th user.

However, for the sake of simplicity, we adopt the constant price model, where  $p_i = p$  and  $p$  is a fixed price for all users. It is important to note that the proposed solution model does not impose any constraint to the choice of the charging policy.

Furthermore, as shown in Equation (7), the allocated rate  $r_i$  becomes dependent on the power allocated to each user,  $w_i$ . Thus, in this paper, a possible solution for a scenario with  $N$  users is now given by  $\mathbf{x} = \{w_1, w_2, \dots, w_N, p\}$ .

### B. Improved Hybrid Particle Swarm Optimization (I-HPSO)

The PSO method [10] is inspired by the social behavior and auto-organization of bird flocking and fish schooling. The social behavior, demonstrated by the exchange of information between the elements of the population, generates exploration for better solutions, while the individual learning corresponds to the exploitation component. These features provide a balanced combination of global and local search to the algorithm.

Based on a survey of previous contributions to PSO theory and applications, a standard for the PSO algorithm was defined in [2], being called since then the PSO Standard 2007. This version, applies to the original PSO algorithm a local topology for the swarm and the use of a constriction factor, which will be presented later in the velocity update equation.

In [7] it is proposed an improvement to the original PSO by adding feasibility-based rules for handling constrained problems and a local search step based on Simulated Annealing (SA). This PSO-variant has been called Hybrid Particles Swarm Optimization (HPSO) and has achieved good performance in several optimization problems [7].

We introduce a variant of the PSO Standard 2007, which includes the features of the HPSO algorithm, i.e. the feasibility-based rules and the SA-based local search step. The result is an improved version of the HPSO algorithm, being called henceforth, the Improved HPSO (I-HPSO) algorithm.

The two main changes introduced in the proposed I-HPSO algorithm are the following: (i) the use of a local topology for the swarm, as suggested in PSO Standard 2007. The local topology, where the exchange of information occurs only among a neighborhood of particles, allows the algorithm to escape from a poor local optimum with a slower convergence rate relative to the global topology model of the original HPSO. (ii) the use of a constriction factor, which helps to guarantee the convergence of the algorithm and its stability.

Let  $\mathbf{x}_i \in \mathbb{R}^d$  and  $\mathbf{v}_i \in \mathbb{R}^d$  be, respectively, the position and velocity vectors of the  $i$ -th element in a swarm of  $d$ -dimensional particles, where  $d$  is the number of variables of the problem. Let also  $\mathbf{p}_i \in \mathbb{R}^d$  and  $\mathbf{pl}_k \in \mathbb{R}^d$  be, respectively, the vectors of best historical individual position of the  $i$ -th particle and the best historical position of the neighborhood  $k$ . I-HPSO algorithm updates the swarm during generation  $m$  through Equations (12) and (13):

$$\begin{aligned} \mathbf{v}_i(m+1) &= \chi \{ \mathbf{v}_i(m) + c_1 r_1 [\mathbf{p}_i(m) - \mathbf{x}_i(m)] + \\ &+ c_2 r_2 [\mathbf{pl}_k(m) - \mathbf{x}_i(m)] \}, \end{aligned} \quad (12)$$

$$\mathbf{x}_i(m+1) = \mathbf{x}_i(m) + \mathbf{v}_i(m+1), \quad (13)$$

where  $\chi$  is the constriction factor,  $c_1$  and  $c_2$  are positive constants called acceleration coefficients, while  $r_1$  and  $r_2$  are independent random variables uniformly distributed in  $[0, 1]$ .

After each generation, I-HPSO applies a SA-based local search step over a fraction of randomly chosen neighborhoods. In this paper, 10% of the neighborhoods are chosen.

## IV. SIMULATION AND DISCUSSION

The evaluated algorithms are Hill Climbing (HC), Simulated Annealing (SA), GA, standard PSO, original HPSO and I-HPSO. In this section the obtained results are presented and discussed, as well as the parameters for the simulations developed with the software Scilab, version 5.0.3.

### A. Parameters applied

The model for the RRM problem detailed in Section II is valid for several scenarios of WCDMA networks. However, for the simulations done in this paper, some system parameters have been fixed. The Table I(a) contains cell characteristics and parameters of the utility and acceptance functions.

Some parameters of the evaluated algorithms must be determined empirically, such as the number of iterations, the variation steps applied, the population size for GA, PSO, HPSO and I-HPSO and the mutation/crossover probabilities of the GA. The other parameters of PSO and SA step of HPSO and I-HPSO were chosen accordingly with the values proposed in [2] and [7], respectively. The Table I(b) resumes the parameters for the algorithms.

### B. Simulation Results

A set of tests consists of 20 independent trials. As a remark, it is important to point out that the results to be presented in Subsection IV-B.1 are not directly comparable to those to be presented in Subsection IV-B.2, since there are different users with different usage patterns and localizations in each study.

1) *Variation of Total Revenue with the Number of Users:* In this section the number of terminals to be served is varied, keeping a fixed desirable SINR of 7dB.

Figures 3(a)-3(d) show that the I-HPSO achieved the best average values and the smallest variability for all scenarios. Interestingly, the SA technique produced results only slightly worse than the original HPSO. The HC technique obtained the worst results, presenting large variability for all cases. The GA performed better than the standard PSO in three out of the four scenarios, but presented lower average values than the I-HPSO.

It is worth noting that despite the addition of two new terminals for each scenario, the increase in the total revenue did not remain constant. Figures 3(a)-3(d) show a tendency of stagnation of the revenue. This indicates that the system in some point may be considered overloaded, where the addition of new terminals does not contribute to the total revenue.

2) *Variation of Total Revenue with the Desirable SINR:* In this section the desirable SINR is varied, keeping a fixed set of 10 terminals.

For all cases the I-HPSO achieved the best overall revenues, in terms of average values and variability of the results. Figures

TABLE I  
PARAMETERS APPLIED IN SIMULATIONS.

(a) Parameters of the resource allocation model.

| Parameter                             | Value         |
|---------------------------------------|---------------|
| Cell Radius                           | 500m          |
| Antenna gain                          | 18dBi         |
| Exponent of path loss                 | 3.5           |
| Reference path loss at the cell edge  | 100dB         |
| Standard deviation of shadowing       | 8dB           |
| Total bandwidth available ( $W$ )     | 5MHz          |
| AWGN power ( $\nu$ )                  | -110dB        |
| Maximum rate per user ( $r_{max}$ )   | 600Kbps       |
| Total available power ( $w_{total}$ ) | 43dBm         |
| Parameters $C$ , $\mu$ and $\epsilon$ | 0.05, 2 and 4 |
| Interval of the $\alpha$ parameter    | [2-5]         |
| Interval of the $\beta$ parameter     | [100-300]Kbps |

(b) Parameters for the optimization algorithms.

| Parameter   | HC    | SA    | GA    | PSO           | HPSO          | I-HPSO        |
|---|-------|-------|-------|---------------|---------------|---------------|
| Population size                                     | -     | -     | 100   | 50            | 50            | 50            |
| Number of iterations                                | 10000 | 10000 | 500   | 500           | 500           | 500           |
| Number of iterations of local search                | -     | -     | -     | -             | 20            | 20            |
| Variation step                                      | 0.01  | 0.01  | -     | -             | 0.01          | 0.01          |
| Crossover probability                               | -     | -     | 0.85  | -             | -             | -             |
| Mutation probability                                | -     | -     | 0.001 | -             | -             | -             |
| Constriction factor                                 | -     | -     | -     | 0.72984       | -             | 0.72984       |
| Acceleration coefficients ( $c_1 = c_2$ )           | -     | -     | -     | 2.05          | 2             | 2.05          |
| Maximum velocity ( $\Delta_x = x_{max} - x_{min}$ ) | -     | -     | -     | $0.5\Delta_x$ | $0.5\Delta_x$ | $0.5\Delta_x$ |
| Annealing rate                                      | -     | 1     | -     | -             | 0.94          | 0.94          |

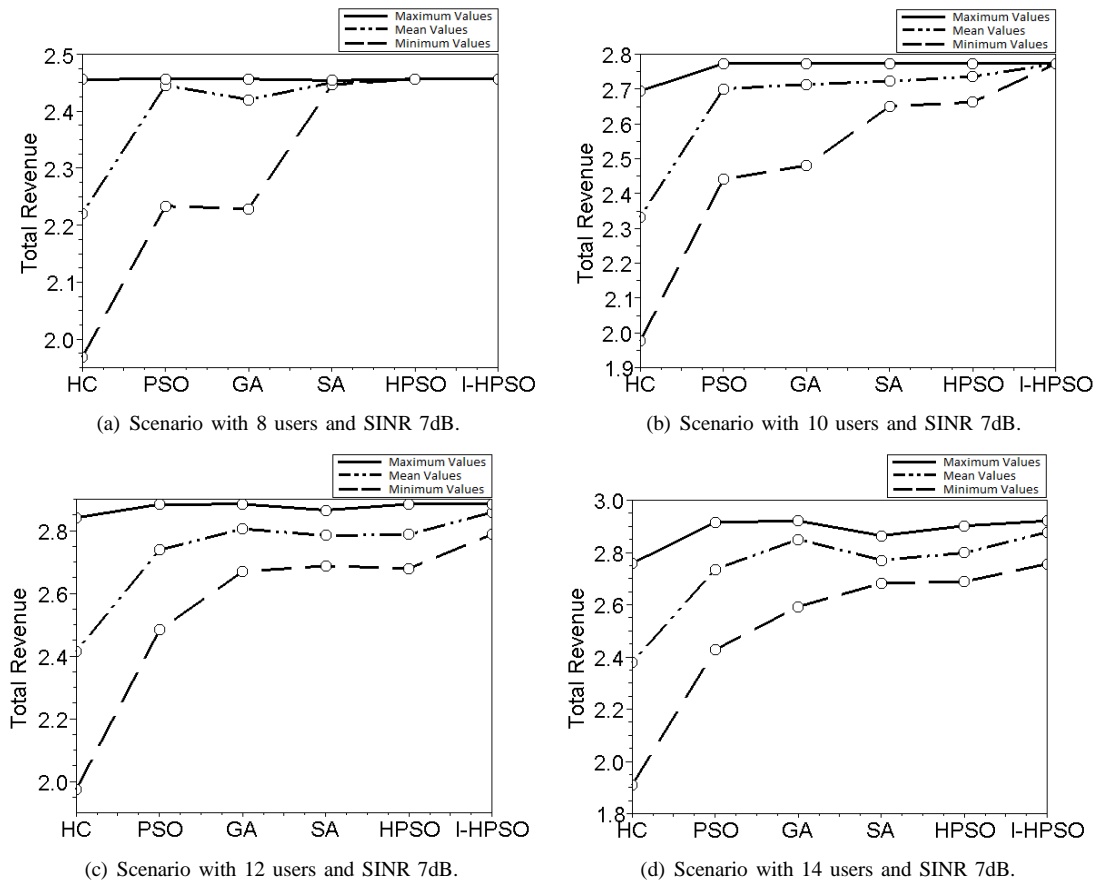


Fig. 3. Variation of total revenue with the number of users.

4(a) and 4(b) indicate that for cases with a more flexible allocation (caused by a lower SINR demand) the GA technique presented much greater variability. The SA and original HPSO methods performed similarly, with SA being better in the scenario of Figure 4(d) and HPSO presenting better average value for the one showed in Figure 4(b). The HC method presented the worst results in three out of four cases.

For all the six algorithms, it can be inferred that greater desirable SINR implies in lower total revenue. This occurs because the requirement of a lower SINR enables the methods to search for solutions where the allocated power has less influence in the intra-cell interference and greater rates can be assigned, directly resulting in better user satisfaction and

greater revenue. This behavior indicates that the development of receiving devices capable of yielding the same QoS while operating with a lower SINR results in more income for the service provider, even without increasing the number of users.

## V. CONCLUSIONS AND FURTHER WORK

In this paper we evaluated the performance of the proposed I-HPSO method and other several metaheuristic algorithms in finding feasible solutions to RRM-related problems. An economic model was considered in order to take into account

<sup>1</sup>Temperature parameter decreases exponentially from  $t = 100$  to  $t = 0.001$  along the iterations of the SA algorithm.

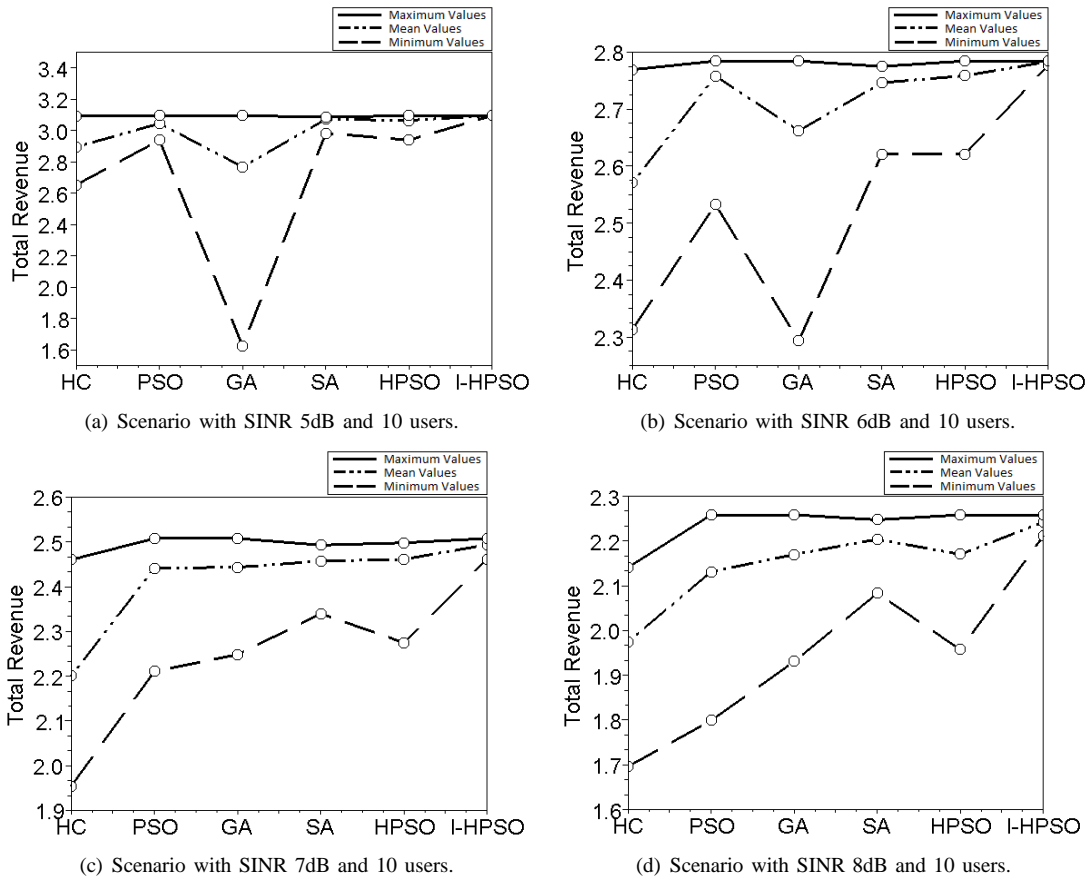


Fig. 4. Variation of total revenue with the desirable SINR.

aspects of QoS, charging and capacity of generating revenue. The proposed approach focused on the WCDMA system, but the model is general enough to be applied to others interference-limited telecommunication systems.

By analyzing the obtained results, it can be concluded that the HC, the standard PSO and the GA provide sub-optimal solutions. The SA and the original HPSO methods were efficient in most cases, but they are more sensitive to changes in the parameters of the economic model than the proposed I-HPSO. As a matter of fact, the I-HPSO achieved the best overall performance among the six evaluated techniques, presenting good solutions with significant stability and uniformity.

Currently, we are extending the studied model by evaluating the addition of criteria of justice to the resource allocation problem and by considering other objective functions which impose different emphasis for the optimization process. Concerning the proposed metaheuristic technique, it could be explored the parallel nature of the I-HPSO method to increase its execution speed through parallel computing.

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