Swarm Power-Rate Optimization in Multi-Class Services DS/CDMA Networks

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Abstract. *This paper discusses the rate resource allocation with power constraint in multiple access multi-class networks under heuristic optimization perspective. Multirate users associated with different types of traffic are aggregated to distinct user' classes, with the assurance of minimum target rate allocation per user and QoS. Therein, single-objective optimization (SOO) methodology under swarm intelligence approach was carried out aiming to achieve promising performance-complexity tradeoffs. The results are promising in terms of sum rate maximization while simultaneously minimizing the total power allocated to the multirate mobile terminals is minimized.*

1. Introduction

The code division multiple access (CDMA) networks increasingly gain prominence in the scenario of multiple access networks, due to its flexible resource allocation, high spectrum efficiency and soft capacity [Al-Hezmi et al. 2007]. In the current telecommunications scenario, companies must deal with spectrum scarcity, power consumption issues and quality of service (QoS) requirements, associated with minimum rates, maximum allowed delay, and so on. In order to satisfy consumers necessities, while keeping companies' profits the resource allocation issues, mainly the spectrum and power[1] allocation, in these networks must be optimized. Thus, many researchers have been seeking resource allocation algorithms that could be easily applied to CDMA systems with high performance guarantee, i.e. low complexity combined with high solution quality.

In this paper, optimization approach based on particle swarm intelligence is investigated in order to efficiently solve the rate allocation problem (throughput maximization) with power constraint in multiclass DS/CDMA wireless networks, which show different quality of service requirements (QoS), related to different user classes, making the resource allocation optimization procedure a more challenging problem. Furthermore, a rigorous and extensive analysis for the input parameters of proposed heuristic algorithm solution were carried out. It is important to note that swarm intelligence was chose due

[1]Power allocation procedures imply in battery autonomy improvement.

to its low computational complexity and less input parameters when compared to other evolutionary algorithms, e.g. genetic algorithms, and its high capacity to scape from local optima.

This paper is organized as follows. In Section 2 an overview of the classical solution for the power control problem, how it is adapted to multirate scenarios, as well as an explanation of the throughput maximization multirate problem is given. In Section 3 the rate allocation based on swarm optimization approach is discussed. Single-objective optimization (SOO) criteria for throughput maximization using PSO algorithm are analyzed. Numerical results with corresponding simulation parameters setup are treated in Section 4. Finally, the conclusions are offered in Section 5.

1.1. Related Work

In the current telecommunications scenario, a lot of efforts in terms of research and new algorithms has been spent in order to satisfy the new telecommunication services requirements, such as growing capacity, availability, mobility, and multiclass services (i.e., multirate users) with different quality of service (QoS). Hence, inspired by this scenario, a different optimization approach based on heuristic procedures has been investigated. The application of heuristic optimization to the power allocation in CDMA systems was discussed in [Moustafa et al. 2000, Elkamchouchi et al. 2007]. In [Moustafa et al. 2001, Moustafa et al. 2000], a genetic approach, named genetic algorithm for mobiles equilibrium (GAME), was considered in order to control two main resources in a wireless network: bit rate and corresponding transmitting power level from mobile terminals. The basic idea is that all the mobile terminals have to harmonize their rate and power according to their location, QoS, and density. However, due to the centralized nature of the power-rate allocation problem and the complexity aspects, the GAME algorithm is suitable to be implemented in the base station only, which forwards the controlling signals to the mobile terminals.

Another heuristic solution that solve efficiently the power allocation problem, while resulting in lower computational complexity than genetic schemes, involves the swarm intelligence principle. In [Elkamchouchi et al. 2007], particle swarm optimization (PSO) algorithm was used to solve the power allocation problem, while in [Zielinski et al. 2009] the power control scheme with PSO was associated with parallel interference cancelation multiuser detector.

From another perspective, the classical power allocation problem in wireless networks, posed two decades ago, has been analyzed and investigated over the years and many algorithms were proposed to solve this specific problem. One of these algorithms was proposed by Foschini and Miljanic [Foschini and Miljanic 1993], and can be considered foundation of many well-known distributed power control algorithms (DPCA).

More recently, many researchers have proposed new algorithms to solve the resource allocation problem in wireless networks. A distributed power control algorithm for the downlink of multiclass wireless networks was proposed in [Lee et al. 2005]. Also, under specific scenario of interference-limited networks, a power allocation algorithm to achieve global optimality in weighted throughput maximization based on multiplicative linear fractional programming (MLFP) was proposed in [Li Ping Qian 2009]. Moreover, in [Dai et al. 2009] the goal is to maximize the fairness between users in the uplink of

CDMA systems, satisfying different QoS requirements.

In [Gross et al. 2006] the Verhulst mathematical model, initially designed to describe population growth of biological species with food and physical space restriction, was adapted to a single rate DS/CDMA system DPCA. The work was the first to propose a Verhulst equilibrium equation adaptation to resource allocation problems in DS/CDMA networks.

2. Power-Rate Allocation Problem

In a multiple access system, such as DS/CDMA, the power control problem is of great importance in order to achieve relevant system capacity[2] and throughput. The power allocation issue can be solved by finding the best vector that contains the minimum power to be assigned in the next time slot to each active user, in order to achieve the minimum quality of service (QoS) through the minimum carrier to interference ratio (CIR).

In multirate multiple access wireless communications networks, the bit error rate (BER) is often used as a QoS measure and, since the BER is directly linked to the signal to interference plus noise ratio (SNIR), we are able to use the SNIR parameter as the QoS measurement. Hence, associating the SNIR to the CIR at time slot n results:

$$\delta_i[n] = \frac{R_c}{R_i[n]} \times \Gamma_i[n], \qquad n = 0, 1, \dots N \tag{1}$$

where $\delta_i[n]$ is the SNIR of user i at the nth iteration, R_c is the chip rate and approximately equal to the system's spreading bandwidth; $R_i[n]$ is the data rate for user i, $\Gamma_i[n]$ is the CIR for user i at iteration n, and N is the maximal number of iterations.

In multirate DS/CDMA systems with multiple processing gains (MPG), where each user class has a different processing gain $\mathtt{G} > 1$, defined as a function of the chip rate by:

$$\mathtt{G}_i^\ell = \frac{R_c}{R_i^\ell}, \qquad \ell = 1, 2, \dots, L, \tag{2}$$

where L is the number of total user's classes defined in the system (voice, data, video). Hence, in MPG-DS/CDMA multiple access systems, the SNIR and CIR for the ℓth user's class are related to the processing gain of that service class: $\delta_i^\ell = \mathtt{G}_i^\ell \times \Gamma_i$.

From (1) we are able to calculate the data rate for user i at iteration n:

$$R_i[n] = \frac{R_c}{\delta_i[n]} \times \Gamma_i[n], \qquad n = 0, 1, \dots, N \tag{3}$$

The CIR for the ith user can be calculated as [Gross et al. 2006, Elmusrati and Koivo 2003]:

$$\Gamma_i[n] = \frac{p_i[n] g_{ii}[n]}{\sum_{\substack{j=1 \\ j \neq i}}^{K} p_j[n] g_{ij}[n] + \sigma^2}, i = 1, \dots, K \tag{4}$$

[2] In this paper the term capacity is employed to express the total number of active users in the system.

where $p_i[n]$ is the power allocated to the ith user at iteration n and is bounded by $P_{\max}$, the channel gain (including path loss, fading and shadowing effects) between user j and user (or base station) i is identified by g_{ij}, K is the number of active users in the system (considering all user's classes), and $\sigma_i^2 = \sigma_j^2 = \sigma^2$ is the average power of the additive white Gaussian noise (AWGN) at the input of ith receiver, admitted identical for all users. Therefore, in DS/CDMA multirate systems the CIR relation to achieve the target rate can be calculated to each user class as follows [Elmusrati et al. 2008]:

$$\Gamma_{\min}^{\ell} = \frac{R_{\min}^{\ell}\delta^*}{R_c}, \qquad \ell = 1 \cdots L \tag{5}$$

where $\Gamma_{\min}^{\ell}$ and $R_{\min}^{\ell}$ is the minimum CIR and minimum user rate[3] associated to the ℓth user class, respectively, δ^* is the minimum (or target) signal to noise ratio (SNR) to achieve minimum acceptable BER (or QoS). Besides, the power allocated to the kth user belonging to the ℓth class at nth iteration is:

$$p_k^{\ell}[n], \quad k = 1 \cdots K_{\ell}; \quad \ell = 1 \cdots L. \tag{6}$$

Hence, the total number of active users in the system is given by $K = K_1 \cup \ldots \cup K_{\ell} \cup \ldots \cup K_L$. Note that indexes associated to the K users are obtained by concatenation of ascending rates from different user's classes. Thus, K_1 identifies the lowest user's rate class, and K_L the highest.

The $K \times K$ channel gain matrix, considering path loss, shadowing and fading effects, between user j and user i (or base station) is given by:

$$\mathbf{G} = \begin{bmatrix} g_{11} & g_{12} & \cdots & g_{1K} \\ g_{21} & g_{22} & \cdots & g_{2K} \\ \vdots & \vdots & \ddots & \vdots \\ g_{K1} & g_{K2} & \cdots & g_{KK} \end{bmatrix}, \tag{7}$$

which could be assumed static or even dynamically changing over the optimization window (T time slots).

Assuming multirate user classes, we are able to adapt the classical power control problem to achieve the target rates for each user, simply using the Shannon capacity relation between minimum CIR and target rate in each user class, resulting:

$$\Gamma_{k,\min}^{\ell} = 2^{\frac{R_{k,\min}^{\ell}}{R_c}} - 1 = 2^{r_{k,\min}^{\ell}} - 1 \tag{8}$$

where $r_{i,\min}^{\ell}$ is the normalized minimum capacity for the kth user from ℓth user class, expressed by bits/sec/Hz. This equation can be obtained directly from the Shannon capacity equation:

$$r_{i,\min}(\mathbf{p}) = \log_2\left[1 + \Gamma_{i,\min}(\mathbf{p})\right] \tag{9}$$

Now, considering a $K \times K$ interference matrix $\mathbf{B}$, with

$$B_{ij} = \begin{cases} 0, & i = j; \\ \dfrac{\Gamma_{i,\min}\, g_{ji}}{g_{ii}}, & i \neq j; \end{cases} \tag{10}$$

[3]Or target rate, for single (fixed) rate systems.

where $\Gamma_{i,\min}$ can be obtained from (5), taking into account each rate class requirement and the column vector $\mathbf{u} = [u_1, u_2, \ldots, u_K]^T$, with elements:

$$u_i = \frac{\Gamma_{i,\min}\sigma_i^2}{g_{ii}}, \tag{11}$$

we can obtain the analytical optimal power vector allocation $\mathbf{p}* = [p_1, p_2, \ldots, p_K]^T$ simply by matrix inversion as:

$$\mathbf{p}^* = (\mathbf{I} - \mathbf{B})^{-1}\,\mathbf{u} \tag{12}$$

if and only if the maximum eigenvalue of $\mathbf{B}$ is smaller than 1 [Seneta 1981]; $\mathbf{I}$ is the $K \times K$ identity matrix. In this situation, the power control problem shows a feasible solution.

2.1. Throughput Maximization for Multirate Systems under Power Constraint

The aiming herein is to incorporate multirate criterion with throughput maximization for users with different QoS, while the power consumption constraint at mobile terminals is bounded by a specific value at each user. As a result, the optimization problem can be formulated as a special case of generalized linear fractional programming (GLFP) [Phuong and Tuy 2003]. So, the following optimization problem can be posed:

$$\begin{aligned} \max \quad & \prod_{i=1}^{K} \left[\frac{f_i(\mathbf{p})}{g_i(\mathbf{p})}\right]^{w_i} \\ \text{s.t.} \quad & 0 < p_i^\ell \leq P_{\max}; \\ & \frac{f_i(\mathbf{p})}{g_i(\mathbf{p})} \geq 2^{r_{i,\min}^\ell}, \qquad \forall i \in K_\ell, \text{ and } \forall\, \ell = 1, 2, \cdots L \end{aligned} \tag{13}$$

where $r_{i,\min}^\ell \geq 0$ is the minimum normalized (by CDMA system bandwidth, R_c) data rate requirement of ith link, including the zero-rate constraint case; and $w_i > 0$ is the priory weight for the ith user to transmit with minimum data rate and QoS guarantees, assumed normalized, so that $\sum_{i=1}^{K} w_i = 1$. Moreover, note that the second constraint in (13) is obtained directly from (8), (4), and (1), where the minimum data rate constraints was transformed into minimum SNIR constraints through Shannon capacity equation:

$$R_i \;=\; R_c \log_2 \left[1 + \theta^{\mathrm{BER}_i} \mathrm{G}_i^\ell \times p_i g_{ii} \times \left(\sum_{j\neq i}^{K} p_j g_{ij} + \sigma^2\right)^{-1}\right], \tag{14}$$

for $i = 1, \ldots, K$, with $\theta^{\mathrm{BER}_i} = -\frac{1.5}{\log(5\,\mathrm{BER}_i)}$, BER_i is the maximal allowed bit error rate for user i,

$$f_i(\mathbf{p}) = \theta^{\mathrm{BER}_i} \mathrm{G}_i^\ell \times p_i g_{ii} + \sum_{\substack{j=1 \\ j\neq i}}^{K} p_j g_{ij} + \sigma^2, \text{ and } \quad g_i(\mathbf{p}) = \sum_{\substack{j=1 \\ j\neq i}}^{K} p_j g_{ij} + \sigma^2 \tag{15}$$

for $i = 1, \ldots, K$. The objective function in (13) is a product of exponentiated linear fractional functions, and the function $\Pi_{i=1}^{K}(z_i)^{w_i}$ is an increasing function on K-dimensional nonnegative real domain [Li Ping Qian 2009]. Furthermore, the optimization problem (13) can be rewritten using the basic property of the logarithmic function, resulting:

$$\begin{aligned} J(\mathbf{p}) = \max\sum_{i=1}^{K} w_i \left[\log_2 f_i(\mathbf{p}) - \log_2 g_i(\mathbf{p})\right] \;&=\; \max\sum_{i=1}^{K} w_i \left[\widetilde{f}_i(\mathbf{p}) - \widetilde{g}_i(\mathbf{p})\right] \\ \text{s.t. } \; 0 < p_i^\ell \leq P_{\max}; & \\ \widetilde{f}_i(\mathbf{p}) - \widetilde{g}_i(\mathbf{p}) \geq r_{i,\min}^\ell, \qquad & \forall i \in K_\ell, \; \ell = 1, 2, \cdots L \end{aligned} \tag{16}$$

2.2. Quality of Solution × Convergence Speed

The quality of solution achieved by any iterative resource allocation procedure could be measured by how close to the optimum solution is the found solution, and can be quantified by means of the normalized squared error (NSE) when equilibrium is reached. For power allocation problem, the NSE definition is given by:

$$NSE[n] = \mathbb{E}\left[\frac{\|\mathbf{p}[n] - \mathbf{p}^*\|^2}{\|\mathbf{p}^*\|^2}\right], \tag{17}$$

where $\|\cdot\|^2$ denotes the squared Euclidean distance to the origin, and $\mathbb{E}[\cdot]$ the expectation operator.

3. Particle Swarm Optimization Approach

In this section, a different approach for throughput maximization under power constraint problems, described by (16) will be considered using swarm intelligence optimization method [Kennedy and Eberhart 2001]. Single-objective optimization (SOO) approach was adopted. The convexation of the original multi-class throughput maximization problem, obtained in (16), is employed hereafter as cost function for the PSO.

3.1. PSO Algorithm

Particle swarm optimization (PSO) was developed after some researchers have analyzed birds behavior and discern that the advantage obtained through their group life could be explored as a tool for a heuristic search. Considering this new concept of interaction among individuals, in 1995 J. Kennedy and R. Eberhart developed a new heuristic search based on a particle swarm [Kennedy and Eberhart 1995].

The PSO principle is the movement of a group of particles, randomly distributed in the search space, each one with its own position and velocity. The position of each particle is modified by the application of velocity in order to reach a better performance [Kennedy and Eberhart 1995]. The interaction among particles is inserted in the calculation of particle velocity. The problem described in (16) indicated an optimization developed in the $\mathbb{R}$ set. Hence, in the PSO strategy, each power candidate-vector defined as $\mathbf{p}_i[n]$, of size[4] K, is used for the velocity calculation of next iteration:

$$\mathbf{v}_i[n+1] = \omega[n]\cdot\mathbf{v}_i[n] + \phi_1\cdot\mathbf{U}_{i_1}[n](\mathbf{p}_i^{\text{best}}[n] - \mathbf{p}_i[n]) + \phi_2\cdot\mathbf{U}_{i_2}[n](\mathbf{p}_g^{\text{best}}[n] - \mathbf{p}_i[n]) \tag{18}$$

[4]Remember, as defined previously, for multirate power optimization problem: $K = K_1 \cup \ldots \cup K_\ell \cup \ldots \cup K_L$.

where $\omega[n]$ is the inertia weight of the previous velocity in the present speed calculation; $\mathbf{U}_{i_1}[n]$ and $\mathbf{U}_{i_2}[n]$ are diagonal matrices with dimension K, and elements are random variables with uniform distribution $\sim \mathcal{U} \in [0,1]$, generated for the ith particle at iteration $n = 1, 2, \ldots, N$; $\mathbf{p}_g^{\text{best}}[n]$ and $\mathbf{p}_i^{\text{best}}[n]$ are the best global position and the best local positions found until the nth iteration, respectively; ϕ_1 and ϕ_2 are acceleration coefficients regarding the best particles and the best global positions influences in the velocity update, respectively.

The particle(s) selection for evolving under power-multirate adaptation strategy is based on the lowest fitness values satisfying the constraints in (16). The ith particle's position at iteration n is a power candidate-vector $\mathbf{p}_i[n]$ of size $K \times 1$. The position of each particle is updated using the new velocity vector (18) for that particle:

$$\mathbf{p}_i[n+1] = \mathbf{p}_i[n] + \mathbf{v}_i[n+1], \qquad i = 1, \ldots, M \tag{19}$$

The PSO algorithm consists of repeated application of the update velocity and position update equations. A pseudo-code for the single-objective PSO power-multirate allocation problem is presented in Algorithm 1.

Algorithm 1 SOO PSO Power-Multirate Allocation

Input: $\mathbf{p}$, M, N, ω, ϕ_1, ϕ_2, V_{m}; **Output:** $\mathbf{p}^*$
begin
1. initialize first population: $n = 0$;
   $\mathbf{P}[0] \sim \mathcal{U}[P_{\min}; P_{\max}]$
   $\mathbf{p}_i^{\text{best}}[0] = \mathbf{p}_i[0]$ and $\mathbf{p}_{\text{g}}^{\text{best}}[0] = \mathbf{p}_{\max}$;
   $\mathbf{v}_i[0] = \mathbf{0}$: null initial velocity;
2. while $n \leq N$
   a. calculate $J(\mathbf{p}_i[n]), \forall \mathbf{p}_i[n] \in \mathbf{P}[n]$ using (16);
   b. update velocity $\mathbf{v}_i[n],\ i = 1, \ldots, F$, through (18);
   c. update best positions:
      for $i = 1, \ldots, M$
         if $J(\mathbf{p}_i[n]) < J(\mathbf{p}_i^{\text{best}}[n]) \wedge R_i[n] \geq r_{i,\min}$,
            $\mathbf{p}_i^{\text{best}}[n+1] \leftarrow \mathbf{p}_i[n]$
         else $\mathbf{p}_i^{\text{best}}[n+1] \leftarrow \mathbf{p}_i^{\text{best}}[n]$
      end
      if $\exists\ \mathbf{p}_i[n]$ such that $\left[J(\mathbf{p}_i[n]) < J(\mathbf{p}_{\text{g}}^{\text{best}}[n])\right] \wedge R_i[n] \geq r_{i,\min}$
         $\wedge\, [J(\mathbf{p}_i[n]) \leq J(\mathbf{p}_j[n]),\ \ \forall\, j \neq i]$,
         $\mathbf{p}_{\text{g}}^{\text{best}}[n+1] \leftarrow \mathbf{p}_i[n]$
      else $\mathbf{p}_{\text{g}}^{\text{best}}[n+1] \leftarrow \mathbf{p}_{\text{g}}^{\text{best}}[n]$
   d. Evolve to a new swarm population $\mathbf{P}[n+1]$, using (16);
   e. set $n = n + 1$.
   end
3. $\mathbf{p}^* = \mathbf{p}_{\text{g}}^{\text{best}}[N]$.
end

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$\mathbf{p}$: power input vector, $K \times 1$ dimension, uniformly distributed in $\sim \mathcal{U}[P_{\min}; P_{\max}]$.
M: population size.
$\mathbf{P} = [\mathbf{p}_1, \ldots, \mathbf{p}_i, \ldots, \mathbf{p}_M]$ particle population matrix, dimension $K \times M$.
N: maximum number of swarm iterations.
$\mathbf{p}_{\max}$: maximum power vector considering each mobile terminal rate class.

In order to reduce the likelihood that the particle might leave the search universe, maximum velocity V_{m} factor is added to the PSO model (18), which will be responsible for limiting the velocity in the range $[\pm V_{\mathrm{m}}]$. The adjustment of velocity allows the particle to move in a continuous but constrained subspace, been simply accomplished by:

$$v_i[n] = \min\{V_{\mathrm{m}};\, \max\{-V_{\mathrm{m}};\, v_i[n]\}\} \tag{20}$$

From (20) it's clear that if $|v_i[n]|$ exceeds a positive constant value V_{m} specified by the user, the ith particle' velocity is assigned to be $\mathrm{sign}(v_i[n])V_{\mathrm{m}}$, i.e. particles velocity on each of $K-$dimension is clamped to a maximum magnitude V_{m}. If we could define the search space by the bounds $[P_{\min};\, P_{\max}]$, then the value of V_{m} will be typically set so that $V_{\mathrm{m}} = \tau(P_{\max} - P_{\min})$, where $0.1 \leq \tau \leq 1.0$, please refer to Chapter 1 within the definition of reference [Nedjah and Mourelle 2006].

To elaborate further about the inertia weight we note that a relatively larger value of w is helpful for global optimum, and lesser influenced by the best global and local positions[5], while a relatively smaller value for w is helpful for convergence, i.e., smaller inertial weight encourages the local exploration as the particles are more attracted towards $\mathbf{p}_i^{\mathrm{best}}$ and $\mathbf{p}_{\mathrm{g}}^{\mathrm{best}}$ [Eberhart and Shi 2001, Shi and Eberhart 1998].

Hence, in order to achieve a balance between global and local search abilities, a linear inertia weight decreasing with the algorithm evolving, having good global search capability at beginning and good local search capability latter, was adopted herein:

$$w[n] = (w_{\mathrm{initial}} - w_{\mathrm{final}}) \cdot \left(\frac{N-n}{N}\right)^m + w_{\mathrm{final}} \tag{21}$$

where w_{initial} and w_{final} is the initial and final weight inertia, respectively, $w_{\mathrm{initial}} > w_{\mathrm{final}}$, N is the maximum number of iterations, and $m \in [0.6; 1.4]$ is the nonlinear modulation index [Chatterjee and Siarry 2006].

3.2. PSO Parameters Optimization

Simulation experiments were carried out in order to determine the suitable values for the PSO input parameters, such as acceleration coefficients, ϕ_1 and ϕ_2, maximal velocity factor, V_m, weight inertia, ω, and population size, M, regarding the throughput multirate optimization problem.

Under discrete optimization problems, such as DS/CDMA multiuser detection, it is known that fast PSO convergence without losing certain exploration and exploitation capabilities could be obtained increasing the parameter ϕ_2 [de Oliveira et al. 2006] while holding ϕ_1 into the low range values. However, for the continuous optimization problem investigated herein, numerical results presented in Section 4.1 indicate that after an enough number of iterations (N) for convergence, the maximization of cost function were obtained within low values for both acceleration coefficients.

The V_{m} factor is then optimized. The diversity increases as the particle velocity crosses the limits established by $[\pm V_{\mathrm{m}}]$. The range of V_{m} determines the maximum change one particle can take during iteration. Without inertial weight ($w = 1$), Eberhart and Shi

[5]Analogous to the idea of the phenomenon that it is difficult to diverge heavier objects in their flight trajectory than the lighter ones.

[Eberhart and Shi 2001] found that the maximum allowed velocity $V_{\rm m}$ is best set around 10 to 20% of the dynamic range of each particle dimension. The appropriate choose of $V_{\rm m}$ avoids particles flying out of meaningful solution space. Herein, for multirate DS/CDMA rate allocation problem, a non exhaustive search has indicated that the better performance$\times$complexity trade-off was obtained setting the maximal velocity factor value to $V_{\rm m} = 0.2 \times (P_{\max} - P_{\min})$.

For the inertial weight, ω, simulation results has confirmed that high values imply in fast convergence, but this means a lack of search diversity, and the algorithm can easily be trapped in some local optimum, whereas a small value for ω results in a slow convergence due to excessive changes around a very small search space. In this work, it was adopted a variable ω, as described in (21), but with $m = 1$, and initial and final weight inertia setting up to $w_{\rm initial} = 1$ and $w_{\rm final} = 0.01$. Hence, the initial and final maximal velocity excursion values were bounded through the initial and final linear inertia weight multiplied by $V_{\rm m}$, adopted as a percentage of the maximal and minimal power difference values:

$$w_{\rm initial} \times V_{\rm m} = 0.2\,(P_{\max} - P_{\min}), \qquad \text{and} \qquad w_{\rm final} \times V_{\rm m} = 0.002\,(P_{\max} - P_{\min}) \tag{22}$$

Finally, stopping criterion can be the maximum number of iterations (velocity changes allowed for each particle) or reaching the minimum error threshold, e.g.:

$$\left| \frac{J[n] - J[n-1]}{J[n]} \right| < \epsilon_{\rm stop} \tag{23}$$

where typically $\epsilon_{\rm stop} \in [0.001; 0.01]$. Alternately, if we want to evaluate the average percent of success[6], taken over T runs to arrive at the global optimum, and considering a fixed number of iterations N, we can evaluate a convergence test. A test is considered to be 100% successful if the following relation holds:

$$|J[N] - J[\mathbf{p}^*]| < \epsilon_1 J[\mathbf{p}^*] + \epsilon_2 \tag{24}$$

where, $J[\mathbf{p}^*]$ is the global optimum of the objective function under consideration, $J[N]$ is the optimum of the objective function obtained by the algorithm after N iterations, and ϵ_1, ϵ_2 are accuracy coefficients, usually in the range $[10^{-6}; 10^{-2}]$. In this study we have set $T = 100$ trials and $\epsilon_1 = \epsilon_2 = 10^{-2}$.

4. Numerical Results

In order to validate the proposed swarm optimization approach in solving resource allocation problems on multiple access CDMA wireless networks, simulations were carried out through MatLab ver.7.3 platform, with system parameters indicated in Table 1. In all simulation results discussed in this section, it was assumed a retangular multicell geometry with a number of base station (BS) equal to 4 and mobile terminals (mt) uniformly distributed over $25Km^2$ area. Besides, the initial rate assignment for all multirate users was admitted discretely and uniformly distributed over three chip rate submultiple, $R_{\min} = [\frac{1}{128}; \frac{1}{32}; \frac{1}{16}]R_c$ [bps].

[6]In terms of the PSO algorithm achieves full convergence.

Table 1. Multirate DS/CDMA system parameters

Parameters	Adopted Values
DS/CDMA Power-Rate Allocation System	
Noise Power	$P_n = -63$ [dBm]
Chip rate	$R_c = 3.84 \times 10^6$
Min. Signal-noise ratio	$SNR_{\min} = 4$ dB
Max. power per user	$P_{\max} \in [30, 35]$ [dBm]
Min. Power per user	$P_{\min} = SNR_{\min} + P_n$ [dBm]
Time slot duration	$T_{\text{slot}} = 666.7\mu$s or $R_{\text{slot}} = 1500$ slots/s
# mobile terminals	$K \in [5, 250]$
# base station	BS $= 4$
Cell geometry	rectangular, with $x_{\text{cell}} = y_{\text{cell}} = 5$ Km
Mobile term. distrib.	$\sim \mathcal{U}[x_{\text{cell}}, y_{\text{cell}}]$
Fading Channel Type	
Path loss	$\propto d^{-2}$
Shadowing	uncorrelated log-normal, $\sigma^2 = 6$ dB
Fading	Rice: $[0.6; 0.4]$
Max. Doppler freq.	$f_{D\max} = 11.1$ Hz
Time selectivity	slow
User Types	
# user classes	$L = 3$ (voice, video, data)
User classes Rates	$R_{\min} = [\frac{1}{128}; \frac{1}{32}; \frac{1}{16}]R_c$ [bps]
User classes BER	$\theta^{\text{BER}} = [5 \times 10^{-3}; 5 \times 10^{-5}; 5 \times 10^{-8}]$
Swarm Power-Rate Algorithm	
Accel. Coefs.	$\phi_1 = 1$ $\phi_2 = 2$
Max. veloc. factor	$V_{\text{m}} = 0.2 \times (P_{\max} - P_{\min})$
Weight inertia (linear decay)	$w_{\text{initial}} = 1$; $w_{\text{final}} = 0.01$
Population Size	$M = K + 2$
Max. # iterations	$N \in [500, 2000]$
Simulation Parameter	
Trials number	$T = 1000$ samples

A number of mobile terminals ranging from $K = 5$ to 250 was considered, which experiment slow fading channels, i.e., the following relation is always satisfied:

$$T_{\text{slot}} < (\Delta t)_c \tag{25}$$

where $T_{\text{slot}} = R_{\text{slot}}^{-1}$ is the time slot duration, R_{slot} is the transmitted power vector update rate, and $(\Delta t)_c$ is the coherence time of the channel[7]. This condition is part of the SINR estimation process, and it implies that each power updating accomplished by the DPCA happens with rate of R_{slot}, assumed here equal to 1500 updates per second.

The optimization process $J(\mathbf{p})$ in (16) should converge to the optimum point before each channel gain g_{ij} experiments significant changing. Note that satisfying (25) the gain matrices remain approximately static during one convergence process interval, i.e., 666.7μs.

In all of the simulations the entries values for the QoS targets were fixed in $\delta^* = 4$ dB, the adopted receiver noise power for all users is $P_n = -63$ dBm, and the gain matrix G have intermediate values between those used in [Uykan and Koivo 2004] and [Elmusrati et al. 2008].

[7]Corresponds to the time interval in which the channel characteristics do not suffer expressive variations.

Finally, the PSO resource allocation performance analysis was characterized considering static channels condition. In this scenario, the channel coefficients remain constant during all the convergence process (N iterations), i.e., for a time interval equal or bigger than T_{slot}. However, the extension of the presented numerical results to dynamic channels is straightforward.

4.1. Numerical Results for the Multirate SOO Throughput Maximization

A parameters analysis was done in order to determine the best combination of ϕ_1 and ϕ_2 parameters under multirate SOO throughput maximization problem. Simulations were carried out using the same configuration, i.e., channel conditions, number of users in the system, users QoS requirements and users services classes.

Table 2 and Figure 1 illustrate the different solution qualities in terms of cost function value, when different values for ϕ_1 and ϕ_2 are combined in a system with $K = 5$ users. The average cost function values where taken as the average over 1000 trials. Furthermore, the cost function values showed in Table 2 were obtained at the 1000th iteration. User's rates were assigned following just one class rate: $R_{\min} = \frac{1}{128} R_c$ [bps].

Table 2. Acceleration coefficients choice for $K = 5$ users, single-rate problem.

(ϕ_1, ϕ_2)	$(1, 2)$	$(2, 1)$	$(2, 2)$	$(4, 2)$	$(2, 8)$	$(8, 2)$
$J[N]$	4.2866	4.3131	4.2833	4.3063	4.2532	4.3091

$N = 1000$ Its, average value taken over 1000 trials.

From Table 2 and Figure 1 it is clear that for $K = 5$ users the parameters $\phi_1 = 2$ and $\phi_2 = 1$ result in an average cost function value higher than other configurations at the 1000th iteration. Thus, the use of this parameters for a small system loading is the best in terms of rate-power allocation optimization problem. It is worth to note that the differences between the results shown in Table 2 are equivalent to a sum rate difference raging from $\Delta\Sigma_R = 60$ kbps to $\Delta\Sigma_R = 670$ kbps, Figure 1.

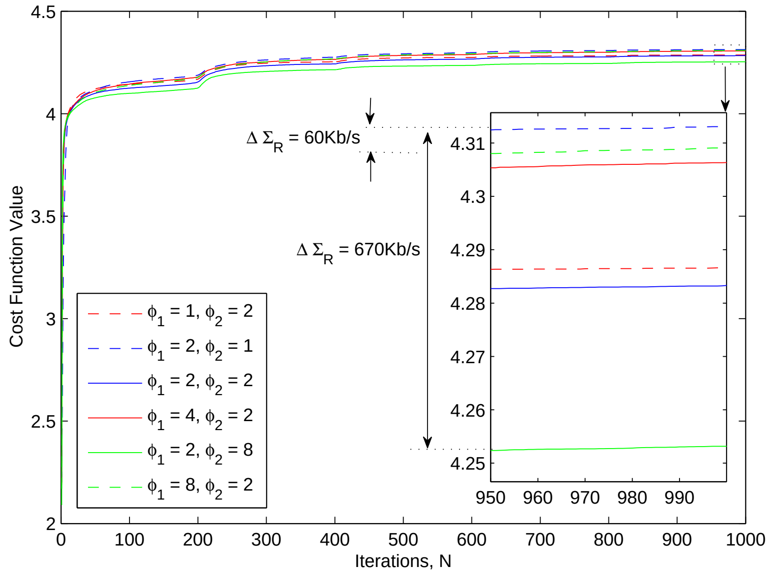

Figure 1. Cost function evolution through 1000 iterations, averaged over 1000 realizations. $K = 5$ users under the same channel conditions for different ϕ_1 and ϕ_2 parameters.

Figure 2.a shows typical sum rate and sum power allocation evolution through iterations with $K = 20$ users, $\phi_1 = 2$ and $\phi_2 = 1$ and population size $M = K + 2$. Observe that the power allocation updates after ≈ 385th iteration are almost insignificant in terms of sum rate values. This happens due to the small increments on each user rate, ranging from 1 to 10 kbps, when compared to the system throughput.

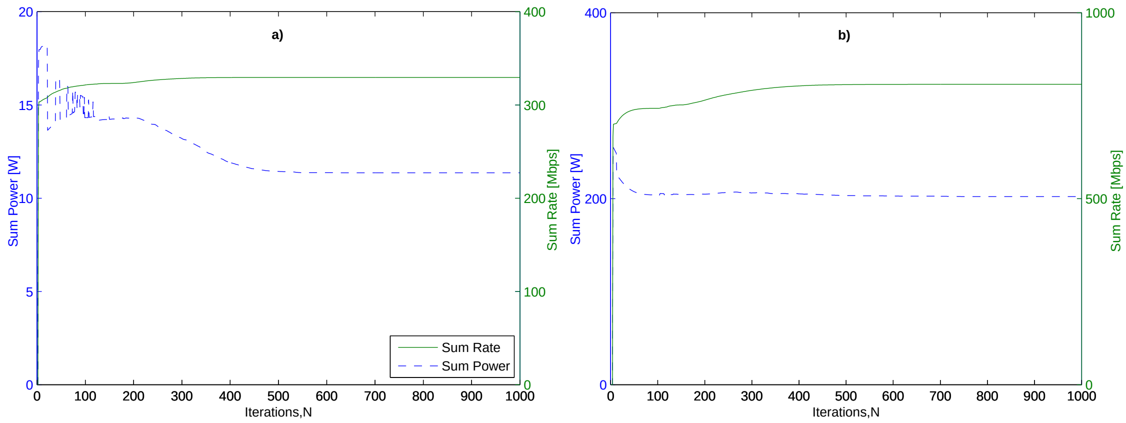

Figure 2. Typical sum rate and sum power evolution with $\phi_1 = 1, \phi_2 = 2$. a) $K = 20$ users; b) $K = 100$ users

The proposed algorithm has been found robust under a high number of multirate active users in the system. Figure 2.b shows typical sum rate and sum power allocation evolution through iterations for $K = 100$ users. As expected, the algorithm needs more iterations to achieve convergence (around 500 iterations), regarding to $K = 20$ users case, but the gain in terms of throughput increasing combined to power reduction after optimization is significant.

Additionally, a small increase in the maximum power per user, i.e. from 30dBm to 35dBm, allows the algorithm to easily find a solution to the throughput optimization problem for a huge system loading, i.e 250 multirate users in a $25Km^2$ rectangular cell geometry. Figure 3 shows a typical sum power and sum rate evolution through iterations for $K = 250$ users. Observe that the algorithm achieves convergence around 750 iterations, which implies that convergence speed, in terms of iterations, grows with the number of active users in the system.

5. Conclusions

Numerical results showed that searching for the global optimum over a high dimensional resource allocation problem is a hard task. The search universe is denoted as $\mathbb{R}^K$ and constrained by power, rate and SNR ranges. Since the search space is continuous we can conclude that there is an infinite number of solutions, even if all these solutions are constrained.

The simulations results revealed that the proposed PSO approach can be easily applied to the throughput maximization problem under power consumption constraint in a large multirate system loading and realistic fading channel conditions. The algorithm has been found robust under a high number of active users in the systems, e.g. $K \geq 200$, while held the efficient searching feature and quality solutions. Those features make the PSO resource allocation algorithm a strong candidate to be implemented in real multiple access networks.

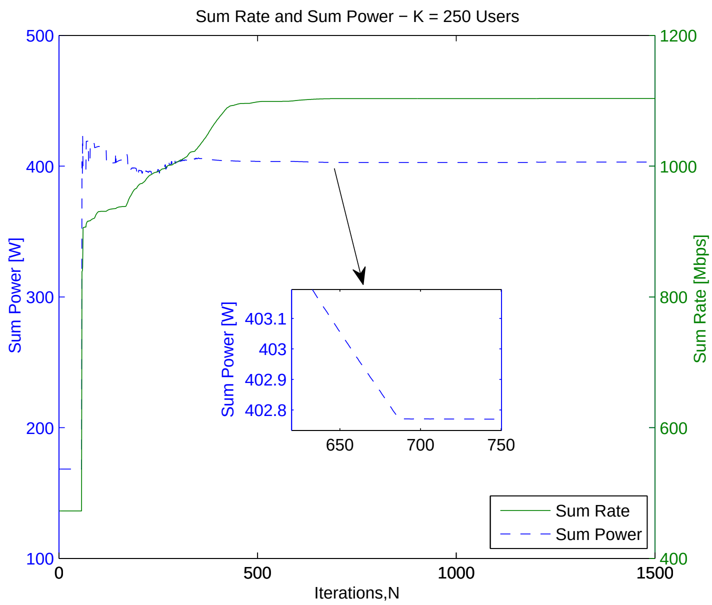

Figure 3. Typical sum rate and sum power evolution with $K = 250$ users, $P_{\max} = 35$dBm per user.

Further work and directions include a) the discretization of the search space, in order to reduce the problem dimension, and as a consequence. the complexity order; b) the application of the heuristic optimization techniques to solve resource allocation problems under the multi-objective optimization perspective; and c) the analysis of power and rate allocation problems under dynamic channels condition.

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