A Novel Grouping Genetic Algorithm for Assigning Resources to Users in WCDMA Networks

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Abstract. In this work we explore the feasibility of applying a novel grouping genetic algorithm (GGA) to the problem of assigning resources to mobile terminals or users in Wideband Code Division Multiple Access (WCDMA) mobile networks. In particular, we propose: (1) A novel cost function (to be minimized) that contains, in addition to the common load factors, other utilization ratios for aggregate capacity, codes, power, and users without service. (2) A novel encoding scheme, and modifications for the crossover and mutation operators, tailored for resource assignment in WCDMA networks. The experimental work points out that our GGA approach exhibits a superior performance than that of the conventional method (which minimizes only the load factors), since all users receive the demanded service along with a minimum use of the assigned resources (aggregate capacity, power, and codes).

Keywords: Grouping genetic algorithm · WCDMA mobile networks · Telecommunication

1 Introduction

Electromagnetic spectrum is an extremely valuable resource for mobile telecommunication companies because of its scarcity and the need for expense licenses to use it. Thus, making an ever increasing more efficient use of the available spectrum has been an ongoing concern since the very beginning of mobile communications. In particular, among other technological advances, great efforts have been made in the field of the so-called multiple access techniques, which aim at enabling a number of devices to transmit over the same medium (the air interface, in this case), sharing its capacity. Key examples in mobile networks are TDMA (Time Division Multiple Access), WCDMA (Wide-band Code Division Multiple Access), and OFDMA (Orthogonal Frequency Division Multiple Access), which, respectively, are used in 2G (Second Generation) networks, 3G (Third Generation) networks, and in the in-deployment 4G mobile networks [1].

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This evolution does not remove previous techniques but, on the contrary, results in forming a mobile access "ecosystem" to provide the best customer service.

Currently, HSPA (High Speed Packet Access), based on WCDMA, is the most widely used deployed mobile *broadband* technology in the world. In fact, HSPA is not an unique technology but a set of technologies that allow mobile operators to easily upgrade their already deployed WCDMA networks to support a very efficient provision of speech services and mobile broadband data services (high speed Internet access, music-on-demand, and TV and video streaming, to name just a few). This illustrates the importance of properly dimensioning WCDMA networks.

With this context in mind, the question arising here is how to optimally assign the limited WCDMA resources to mobile terminals (user equipments (UEs), or simply, users). In WCDMA cellular networks, a number of users are allowed to utilize simultaneously the same frequency. To separate the communications, the network assigns a "code" to each communication so that only the corresponding receiver is able to extract the information that has been sent to it. Then, the remaining communications using the same frequency become an interference signal. This is illustrated in Fig. 1 where the dashed sector S_k of the base station (BS) or node-B (in WCDMA terminology) provides services to a number of users $n_u^{S_k}$. $p_{r,BS}(j)$ is the power received at the base station (BS) emitted by user j. Interferences appear both in the downlink (DL) −signals moving from the BS to the users− and in the uplink (UL) −from the users to the BS−. In this respect, the conventional approach to assigning resources to users is based on minimizing the total interference [1].

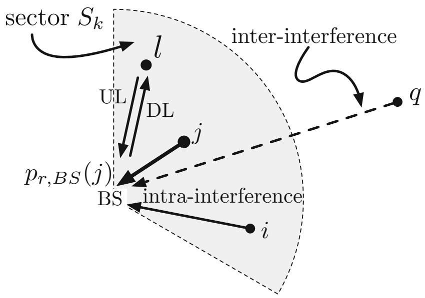

Fig. 1. Simplified representation of the basic concepts involved. i, j and l label users in sector S_k. See the main text for details.

However, the current rising demand of higher speeds reveals that there are other resources that should be taken into account. One of the most evident is based on the fact that the aggregation of higher data rates is leading to a bottleneck in the aggregation interface at the BSs in the sense that the aggregated rates could be higher than the available backhaul capacity for both UL and DL. Another limiting resources are the number of codes and the available power.

In this regard, the purpose of this paper is to explore the feasibility of a novel Grouping Genetic Algorithm (GGA) to assign resources (aggregate capacity, power, codes) to users in WCDMA networks.

The structure of the rest of this paper is as follows. Section 2 reviews the related work, while Sect. 3 focuses on describing the problem within the framework of WCDMA networks, and on modeling the resources to be assigned. Section 4 describes the GGA we propose to tackle the aforementioned problem of assigning resources to users. Finally, Sect. 5 shows the experimental work we have carried out, and Sect. 6 discusses the main findings.

2 Related Work

There is a number of recent works that study the problem of assigning users and base stations, although without using the GGA approach. In this respect, some solutions to optimize both the radio interface and the backhaul capacity have been recently explored [2,3]. There are also some works that focus on the jointly assignment of mobile users to base stations and power [4,5], and to base stations and beamforming schemes [6,7].

As mentioned before, the purpose of this paper is to assign resources (codes, power, capacity) to users by using a GGA-based approach that minimizes not only the interference but also the use of codes, capacity, power, and the number of user without service. The GGA, developed by Falkenauer *et al.* in a series of publications in the last 90's [8–10], was applied thereafter to a number of specific telecommunication applications such as mobile communication network design [11–13], or OFDMA-based multicast wireless systems [14], obtaining subgroups of users within the same multicast group so that OFDMA subcarriers are then assigned to each subgroup to maximize the aggregate data rate. In a more general context, it has been applied to assignment [15] or fuzzy partitioning problems [16], to name just a few. Following the proven good performance of the GGA, alternative meta-heuristic optimization engines for grouping problems have been subsequently developed during the last few years, mainly the Grouping Harmony Search (GHS) [17], the Grouping Particle Swarm Optimization algorithm (GPS) [18], and the Grouping Evolutionary Strategy approach [19].

Despite of the huge application of these techniques, and to the best of our knowledge, the feasibility of the GGA has not been yet explored in WCDMA networks to assign resources to users aiming at minimizing not only the interference but also the use of codes, backhaul capacity, power, and the number of users without service. Next section describes the problem along with the resources that our GGA will assign to users.

3 Problem Statement

The problem consists in optimally assigning N active users to the M sectors of a WCDMA network, by minimizing a novel cost function that will be described in detail in Subsect. 3.4. For the sake of clarity, we use the following notation: S_k

represents the k sector in the network (with $k = 1, \cdots, M$), while $n_u^{S_k}$ stands for the number of users that our GGA will assign to sector S_k in each generation.

Although it will be discussed deeply in Subsect. 4.1, it is worth introducing here the encoding our GGA will use because it will assist us in better describing the mathematical formulation of the problem. In this respect, a chromosome $\mathbf{c}_i$ encoding a trial solution to be explored will be of the form

$$\mathbf{c}_i = [u_1^{S_h}, \ldots, \underline{u_j^{S_k}}, \ldots, u_N^{S_w} \mid n_u^{ws}, n_u^{S_1}, \ldots, \underline{n_u^{S_k}}, \ldots, n_u^{S_M}], \tag{1}$$

where, for the sake of clarity, we have underlined two elements: $u_j^{S_k}$ and $n_u^{S_k}$. $u_j^{S_k}$ encodes that user j is assigned to sector S_k, while $n_u^{S_k}$ quantify the number of users in sector S_k. Note that the example chromosome in Expression (1) contains a "different" element labeled n_u^{ws}. It stands for the number of users *without service* (no sector has been assigned), and its discussion will be postponed to Sect. 4, where it will be better understood, within the context of the novel grouping encoding we propose.

3.1 Background

In a WCDMA network, the users (mobile devices or "user equipments") are allowed to use simultaneously the same electromagnetic carrier. To separate the communications on the same carrier frequency, f_c, the network has a number of (ideally) orthogonal *codes*, and automatically assigns a different code to each communication so that *only* the corresponding receiver is able to extract the information that specifically will be sent to it. This is done by multiplying the user data by a code or sequence of bits (called "chips"), whose rate ("chip rate", W) is much higher than that of the user bit rate.

The problem is that the remaining communications that use the same frequency become an *interference* signal. The effect of interference in the dimensioning of WCDMA celular networks is usually modeled by means of a concept called "load factor" [1]. It is a parameter that allows to quantify to what extent the active users are affecting or "loading" the system with interference.

3.2 Load Factor

Figure 1 will assist us in explain it. For simplicity, it shows only one of the 3 sectors the node-B has. The sector labeled S_k has $n_u^{S_k}$ active users. $p_{r,BS}(j)$ represents the signal power received (subscript "r") *at* the BS, emitted by user j. Note that $p_{r,BS}(j)$ is corrupted by the interference produced by those signal coming from other users with the same frequency. The load factor in all the up-links of sector S_k, defined as the ratio between the interference and the *total* noise (thermal + interference) [1], can be estimated as

$$\eta_{UL}(\mathbf{c}_i) \approx (1 + \xi_{S_k}) \cdot \sum_{j=1}^{n_u^{S_k}} \frac{1}{1 + \frac{1}{(e_b/n_0)_s} \cdot \frac{W}{R_{b,s}^u(j) \cdot \nu_s^u}} \tag{2}$$

where:

- $\mathbf{c}_i = [u_1^{S_h}, \ldots, u_j^{S_k}, \ldots, u_N^{S_w} \mid n_u^{ws}, n_u^{S_1}, \ldots, n_u^{S_k}, \ldots, n_u^{S_M}]$ contains the whole required information: the sector to which any user is assigned ($u_j^{S_k}$), and ($n_u^{S_k}$). We have explicitly written $\eta_{UL} \equiv \eta_{UL}(\mathbf{c}_i)$ in the effort of emphasizing that the encoding chromosome $\mathbf{c}_i$ is related to the parameters that will be used to construct the cost function. This consideration also applies to the other parameters that will be stated below, so that we will not mention this again.
- ξ_{S_k} is the ratio between the inter-interference (coming from users in other sectors, S_l, $l \neq k$) and intra-interference (produced by the $n_u^{S_k}$ users within the same sector S_k).
- $(e_b/n_0)_s$ is the value for the ratio between the mean bit energy and the noise power density (including thermal noise and interference) required to achieve a given quality for service s, for instance, in terms of block error rate (BLER). For the purpose of this paper, $(e_b/n_0)_s$ is an input parameter provided by the service requirements [1].
- $R_{b,s}^u(j)$ is the bit rate of service s in the j uplink within sector S_k. It is an input value stated by the service requirements. Throughout this paper, uppercases "u" and "d" will be used for labeling, respectively, uplink and downlink parameters.
- ν_s^u is an utilization factor, which is 1 for data service, and $0 < \nu_s < 1$ for voice services [1].

In a similar way, the downlink load factor in sector S_k is [1]

$$\eta_{DL}(\mathbf{c}_i) \approx \left[(1 - \overline{\alpha}) + \overline{\xi}\,\right] \sum_{j=1}^{n_u^{S_k}} \frac{(e_b/n_0)_s}{\frac{W}{R_{b,s}^d(j) \cdot \nu_s^d}} \tag{3}$$

where $\overline{\alpha}$ is an average orthogonality factor in the sector, and $\overline{\xi}$ is an average (across the sector) of $\xi_{S_k}(j)$, since in the DL, the ratio of other-sectors to own-sector interference depends on the user location and is thus different for each user j [1].

The conventional method, whose details will be explain in Sect. 6 for comparative purposes, is based on minimizing the total load factor in the network, $\eta = \eta_{UL} + \eta_{DL}$. Furthermore, in addition to the load factor, we consider a novel cost function that contains other five ratios or parameters that are not used in the conventional approach, and that we define in the next section.

3.3 Including More Parameters in the Problem

Each of these parameters aims to quantify the efficiency with which an available resource $\mathcal{R}$ is used, that is: $\Delta_{\mathcal{R}} = \mathcal{R}_{used}/\mathcal{R}_{available}$.

The first telecommunication resource whose use would be optimized is the available capacity for aggregating UL bit rates: C_a^u. In any sector S_k, the UL bit rates of any user u_j for a service s, $R_{b,s}^u(j)$, must be aggregated for ulterior backhauling. The corresponding aggregated capacity ratio in each sector S_k is defined ($\doteq$) as

$$\Delta^u_{C_a}(\mathbf{c}_i) = \Delta^u_{C_a}(n_u^{S_k}) \doteq \frac{1}{C_a^u} \sum_{j=1}^{n_u^{S_k}} R^u_{b,s}(j), \tag{4}$$

where lowercase "a" stands for "aggregated". Note in (5) that we have written explicitly that $\mathbf{c}_i$ contains the necessary information ($n_u^{S_k}$, the number of users to be assigned) to computed the ratio in Sector S_k. In the definitions that follow we will not use yet this notation in an explicit form for the sake of simplicity.

Similarly, its counterpart for DL is defined as

$$\Delta^d_{C_a}(\mathbf{c}_i) \doteq \frac{1}{C_a^d} \sum_{j=1}^{n_u^{S_k}} R^d_{b,s}(j) \tag{5}$$

Another important resource is the maximum power per sector that the BS has in order to serve the active users. We model the efficiency in its use as

$$\Delta^d_{P_{BS}}(\mathbf{c}_i) \doteq \frac{1}{p_{Max,BS}(k)} \sum_{j=1}^{n_u^{S_k}} p^d_{BS}(j) \tag{6}$$

where $p_{Max,BS}(k)$ is the available BS power in sector S_k, and $p^d_{BS}(j)$ is the power for serving user j.

The fraction on channelization codes used for service s in DL in sector S_k is

$$\Delta^d_{\mathcal{C}_s}(\mathbf{c}_i) \doteq \frac{n_u^{S_k}}{N^d_{\mathcal{C}_s}}, \tag{7}$$

$N^d_{\mathcal{C}_s}$ being the total amount of codes for service s.

Finally, the fraction of users *without* service is

$$\Delta^{ws}_{n_u}(\mathbf{c}_i) \doteq \frac{n_u^{ws}}{N} \tag{8}$$

where n_u^{ws}, the number of users without service defined in (1), will be discussed deeply in Sect. 4.1.

These ratios along with the load factors will allow us to propose a novel cost function.

3.4 Novel Cost Function: Complete Mathematical Formulation

Given a WCDMA network with M sectors and N active users, the problem consists in assigning (for each sector S_k, $k = 1, 2, \cdots, M$) the available resources (power, capacity and codes) to its potentially assigned $n_u^{S_k}$ users by minimizing the novel cost function

$$\mathcal{C}(\mathbf{c}_i) = \sum_{k=1}^{M} \sum_{l=1}^{n_u^{S_k}} [\eta_{UL}(\mathbf{c}_i) + \eta_{DL}(\mathbf{c}_i) + \Delta_{C_a}^{u}(\mathbf{c}_i) + \Delta_{C_a}^{d}(\mathbf{c}_i) + \Delta_{P_{BS}}^{d}(\mathbf{c}_i) + \Delta_{C_s}^{d}(\mathbf{c}_i) + \Delta_{n_u}^{ws}(\mathbf{c}_i)], \quad (9)$$

constrained to the conditions that all the ratios (2)–(8) are real numbers ranging from 0 to 1. Note that a further refinement of the cost function (9) could consist in using weighted sums of the ratios (2)–(8), constrained to the mentioned conditions. The values of these weights should depend on the relative importance that each ratio has in a particular design.

4 Proposed Grouping Genetic Algorithm

4.1 Problem Encoding

Our example chromosome in Expression (1) is a variation with respect to the classical grouping encoding proposed initially by Falkenauer [8,9], which is a variable-length encoding scheme. In this classical approach, the encoding is based on separating each chromosome $\mathbf{c}$ into two parts: $\mathbf{c} = [\mathbf{l}|\mathbf{g}]$, the first one being the *element* section, while the second part, the *group* section. Since the number of sectors in our network is constant (M), we have used the following variations of the classical grouping encoding: (1) The group section is an $(M+1)$ length vector, whose elements (labeled $n_u^{S_j}$) represent the number of users in the j-th sector (S_j). Subscript j ranges from -1 to M, $j = -1$ being used to represent those users that are *not* connected to any node, that is, those in an "imaginary" or virtual sector that we have labelled "Sector -1". (2) The element part is an N-length vector whose elements ($u_i^{S_j}$) mean that user u_i has been assigned to sector S_j. As an example, following our notation, in a solution with N elements (users) and M groups (sectors), a candidate individual $\mathbf{c}_i$ could be $[u_1^{S_h}, u_2^{S_p}, \ldots, u_i^{S_j}, \ldots, u_N^{S_w} \mid n_u^{S_{-1}}, n_u^{S_1}, n_u^{S_2}, \ldots, n_u^{S_j}, \ldots, n_u^{S_M}]$, where $n_u^{S_{-1}}$ is the number of users in sector S_{-1}, that is, those without service: $n_u^{S_{-1}} = n_u^{ws}$ in (1), those that have not been assigned to resources and thus do not have service.

Note that $\sum_{k=-1}^{M} n_u^{S_k} = N$, which simply states that the total number of active users in the network are distributed among the M sectors, although $n_u^{S_{-1}} = n_u^{ws}$ have not been received resources.

4.2 Fitness Function

With this in mind, a possible fitness function to describe to what extent candidate chromosome $\mathbf{c}_i$ encodes a trial solution of the problem described in Sect. 3.4 could be

$$f_i = 1 - \mathcal{C}_N(\mathbf{c}_i), \quad (10)$$

where $\mathcal{C}_N$ is the cost function defined by Expression (9) normalized between 0 and 1.

4.3 Selection Operator

Our selection operator is inspired by a rank-based wheel selection mechanism. In a first step, individuals are sorted in a list based on their quality. The position of the individuals in the list is called *rank of the individual*, and labeled R_i, $i = 1, \ldots, \mathcal{P}_{size}$, $\mathcal{P}_{size}$ being the population size. We consider a rank in which the best individual x is assigned $R_x = \mathcal{P}_{size}$, the second best y, $R_y = \mathcal{P}_{size} - 1$, and so on. A *fitness* value associated to each individual is then defined as

$$f_i = \frac{2 \cdot R_i}{\mathcal{P}_{size} \cdot (\mathcal{P}_{size} + 1)} \tag{11}$$

Note that these values are normalized between 0 and 1, depending on the position of the individual in the ranking list. It is worth emphasizing that this rank-based selection mechanism is static, in the sense that probabilities of survival (given by f_i) do not depend on the generation, but on the position of the individual in the list.

The process carried out by our algorithm consists in selecting the parents for crossover using this selection mechanism. This process is performed with replacement, i.e., a given individual can be selected several times as one of the parents, however, individuals in the crossover operator must be different.

4.4 Crossover Operator

It works as follows:

1. Select randomly two individuals (father and mother), and two crossing points in their corresponding group part.
2. Insert the elements belonging to the selected groups of the first individual into the offspring.
3. Insert the elements belonging to the selected groups of the second individual into the offspring, if they have not been assigned by the first individual.
4. Randomly complete the elements not yet assigned with elements from the current groups.
5. Remove empty clusters, if any.
6. Modify the labels of the current groups in the offspring in order to numerate them from 1 to M, including the one labeled "-1" corresponding to users without the required Quality of Service (QoS).

4.5 Mutation Operator

The mutation operator used consists in splitting a randomly selected group into two different ones. The samples belonging to the original group are assigned to the new groups with equal probability. Note that one of the new generated groups will keep its label in the group section of the individual, whereas the other will be assigned a new label.

5 Experiments

They have been carried out with real data (Espoo, Finland) [1]: 19 B-nodes, tree-sector each ($M = 19 \times 3 = 57$ sectors), $\overline{\alpha} = 0.65$, $\overline{\xi} = 0.55$, $W = 3.84$ Mchip/s, $P_{Max,BS} = 12$ W/sector, $C_a^u = C_a^d = 1536$ kbps, and $N = 450$ users with 3 different services, labeled $s_i =$ "1", "2", and "3" in Table 1. The values of the GGA parameters are: crossover probability $\mathcal{P}_c = 0.8$, mutation probability $\mathcal{P}_m = 0.05$, and population size $\mathcal{P}_{size} = 100$ individuals.

Table 1. Values of the services parameters. ARM means adaptive multi-rate.

Service, s_i	$(E_b/N_0)_i$ (dB)	$R_{b,i}^u$ (kbps)	$R_{b,i}^d$ (kbps)	$\nu_i^u = \nu_i^d$	$N_{C_i}^d$ (codes)
"1" (ARM voice)	5	12.2	12.2	0.58	256
"2" (data)	1.5	64	64	1	32
"3" (data)	1	64	384	1	4

In any of the experiments, the N users are distributed randomly (uniform distribution). We have carried out 100 experiments, with 300 generations each. Figure 2 represents the fitness function as a function of the number of generations.

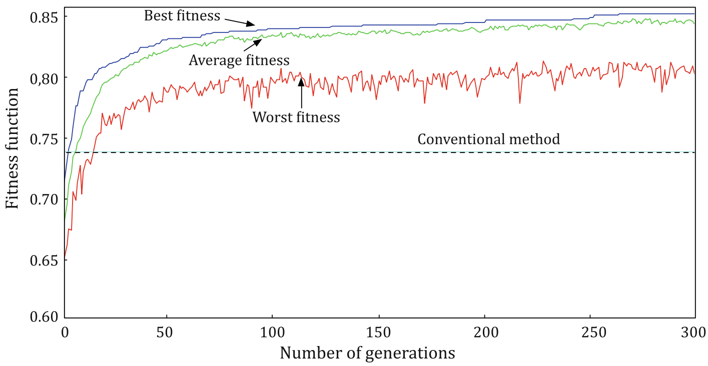

Fig. 2. Fitness values as a function of the number of generations.

The average fitness has been computed over the 100 experiments. The dashed line in Fig. 2 represents the fitness value computed by minimizing the load factor ("conventional method"). Note that the proposed GGA exhibits an average performance ($\bar{f} \approx 0.84$), which is superior to that of the conventional method ($f \approx 0.74$). Figures 3, 4, and 5 will assist us in completing the discussion by representing, respectively, $\eta = \eta_{UL} + \eta_{DL}$, $\Delta_{C_a} = \Delta_{C_a}^u + \Delta_{C_a}^d$, $\Delta_{P_{BS}}^d$, $\Delta_{C_s}^d$, and Δn_u^{ws} as a function of the number of generations.

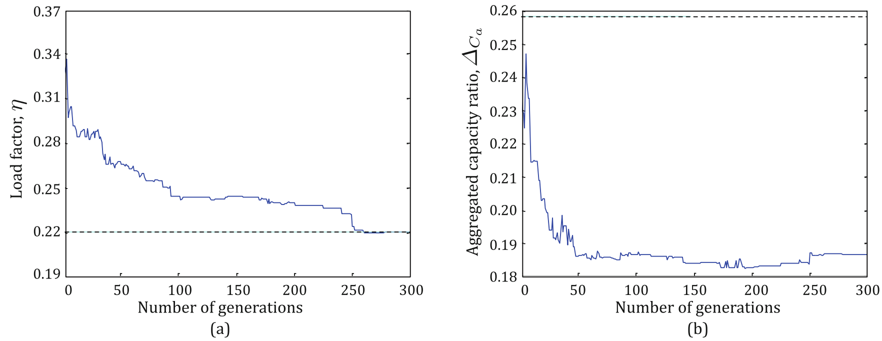

Fig. 3. (a) Load factor as a function of the number of generations. (b) Aggregated capacity ratio Δ_{C_a} as a function of the number of generations.

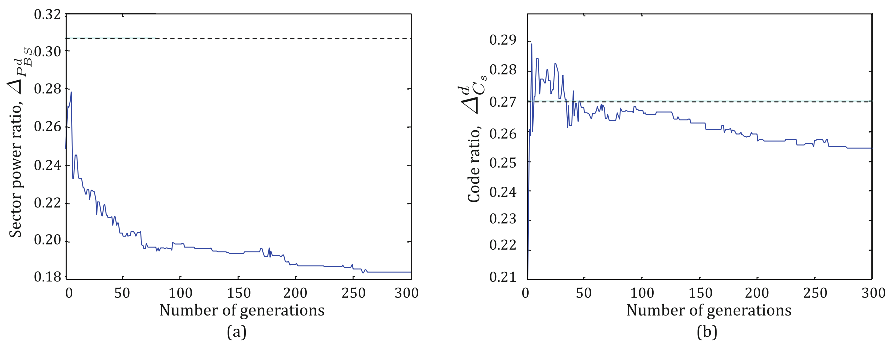

Fig. 4. (a) Sector power ratio $\Delta_{P_{BS}^d}$ as a function of the number of generations. (b) Code ratio $\Delta_{C_s}^d$ as a function of the number of generations.

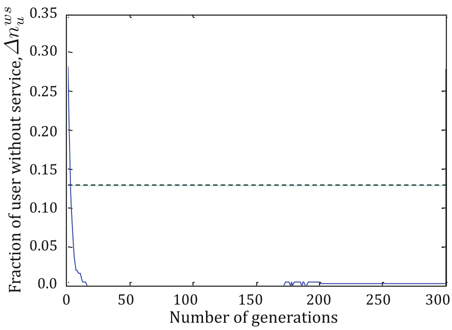

Fig. 5. Fraction of user without service $\Delta_{n_u}^{ws}$ as a function of the number of generations.

Dashed lines in Figs. 2, 3, 4, and 5 represent the defined ratios computed after using the solution found by the *conventional* method. As shown in Fig. 5, the GGA solution is better in the sense that the GGA assigns resources to *all* users −there is *no* user without service ($\Delta_{n_u}^{ws} = 0$), unlike the conventional one, in which about 13 % of users remain without service− along with a *more efficient use* (lower utilization) of Δ_{C_a}, $\Delta_{P_{BS}}^{d}$, $\Delta_{C_s}^{d}$ (Figs. 3 and 4). In particular, Δ_{C_a} and $\Delta_{P_{BS}}^{d}$ are used *much more efficiently*: the fraction of aggregated capacity used Δ_{C_a} reduces from 25.8 % to 18.5 % (Fig. 3(b)), while the power consumption ratio $\Delta_{P_{BS}}^{d}$ decreases from 30.9 % to 18.5 % (Fig. 4(a)).

6 Summary and Conclusions

In this work we have proposed a novel GGA that aims at assigning resources (capacity, codes and power) to users in WCDMA networks. The first contribution is the definition of a novel cost function that contains, in addition to the common load factors, other utilization ratios for capacity, codes, power, and users without service. The second block of contributions is related to the GGA approach in itself: a novel encoding scheme, and modifications for the crossover and mutation operators, suited for assignment in WCDMA networks. The experimental work points out that our GGA approach exhibits a superior performance than that of the conventional method (which minimizes only the load factors). In particular, the proposed GGA assigns resources to *all* users (unlike the conventional one, in which about 13 % of users remain without service), along with a minimization of the used resources. In this respect, a representative results is the one corresponding to the fraction of aggregated capacity used, which reduces from 25.8 % (conventional method) to 18.5 %, while the power consumption ratio decreases from 30.9 % to 18.5 %.

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