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Mid-Term frequency domain scheduler for resource allocation in wireless mobile communications systems

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ABSTRACT

This article approaches the dynamic resource allocation problem for the downlink of a wireless mobile communication system (WMCS). The article defines the architecture and functions of the global resource scheduler, as well as the quality index for scheduling, the signal to interference-plus-noise ratio (SINR). The proposed approach divides the scheduling task into two components: a distributed one, with local, short-term scope; and a centralized one, with global, medium-term scope. The optimization model considers a set of slack variables for guaranteeing feasibility. This allows the service provider to fully satisfy the users' service demands. The model type is mixed, non-linear, which demands large computational power for an exact solution. So an approximate strategy is used, in order to decouple the search space. The time limit imposed to reach a solution forces to define a reduced neighborhood structure. Thus, the obtained results are the best solution obtained in the allotted time interval, evaluating a suitable set of neighbors, and using an objective, effective criterion for searching. The solution offers high levels of full service satisfaction (greater than 97%), low levels of service denial (less than 2%), and efficient power usage (30% in average).

1. Introduction

A WMCS consists of a set of cells covering a geographical area, with defined topographical features that determine the signal propagation environment. Each cell has a base station (BS), in charge of managing resources (power and frequency) allowing offering services to users, that interact with the system using terminal equipment (TE). Communication channels are characterized by the signal to interference-plus-noise ratio (SINR), a quality index allowing to establish service satisfaction levels (relevant to users) and resource utilization levels (relevant to service providers). A WMCS incorporates several technologies, LTE (Long Term Evolution) among them. LTE is a standard proposed by 3GPP [1] to develop and consolidate 3 G/4 G networks. The most salient feature of LTE, with respect to this article, is OFDMA (Orthogonal Frequency Division Multiple Access), the multiple access technique for the radio interface (physical level), which has become a *de facto* standard for the current generation of WMCS.

The article structure is as follows: First section introduces the problem and its context; second section formulates the problem; third section describes the resource scheduling task, its background, and proposed solution strategies. Fourth section formulates the optimization model; fifth section presents the model's solution; sixth section presents the resource scheduler design in its structural, operative, spatial and temporal dimensions. Seventh section presents the proposed scenarios and experiments to evaluate the goodness of the model; finally, eighth section presents conclusions and future work.

2. Problem formulation

The problem solved by this article is the dynamic resource allocation to a user population demanding a set of services, on a WMCS using OFDMA at its physical level. The context for solution is the downlink of a multi-user, multi-cell, multi-service WMCS, with either a homogeneous or heterogeneous architecture. This task is executed by the base station resource scheduler, which accounts for channel variations in the time and frequency domains, and for changes in user number, position and service requests. In order to optimally allocate resources, the scheduler faces a key constraint: a limited time interval for task execution, as a

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consequence of the system's dynamics. The scheduler must identify all required resources for offering the different services and harmonize their coexistence in such time interval.

3. Resource scheduling task

Resource scheduling is a complex task, facing multiple hurdles: efficient resource usage, time limit (see previous section), and satisfying users with different service requirements [2]. The BS scheduler must consider the services, characterized by the quality of service class identifier (QCI); and the channel condition, characterized by the channel quality indicator (CQI). These indicators must be reported by every TE to the BS. This process has several challenges: overhead (both in processing and communications), accuracy and timeliness of reports, and the length of the time interval for guaranteeing an accurate report of the system status [3,4]. There is another difficulty, arising from frequency reuse: inter-cell interference, the most important of OFDMA's shortcomings [5]. Power allocation to a certain frequency block in one cell becomes interference to the neighboring cells. In order to minimize its impact, inter-cell interference coordination (ICIC) strategies [6], including constraints for resource usage, are employed.

3.1. Problem formulations

The treatment of this problem has evolved over time. After reviewing related work from over the last fifteen years, authors classified their evolution into five phases: Orientation to performance, quality of service, interference management, heterogeneous networks (HetNets) and energy efficiency (EE) management (details of some of these phases can be found in [7]).

Oriented-performance proposals are centered in the WMCS and the satisfaction of some system performance indicator (maximize data rate or minimize power use), ignoring users and fair resource distribution. Later, researchers recognize the importance of giving service to all users, without regard to their condition. In order to achieve this, the models incorporate a set of constraints guaranteeing proportional fairness at the service levels, hence recognizing the existing compromise between fairness and performance. Then, WMCS faced the challenge of providing and satisfying several services to their users. In order to do so, researchers resort to Economical Sciences theory, and formulate the problem using the utility concept [8]. The optimization problem aims to maximize profit for best-effort traffic users, subject to full satisfaction of guaranteed user traffic requirements. Several utility functions have been proposed [9,10]. Popularization of offered services caused an exponential increase in the number of users. Thus, the operator was forced to intensively reuse available spectrum, taking interference to critical levels. Interference management became necessary and SINR was proposed as a quality metric for such purpose. Cicalo et al. [11] suggest that adequate interference management is a key factor in the Long-Term Evolution (LTE) context. Kim et al. [12] suggest using an intelligent strategy for resource allocation, which reduces interference in order to improve SINR and increase the data rate.

The need of covering large geographical areas prompted deployment of multiple cells, to increase the system coverage area. Distributed solutions for resource allocation, featuring cooperation and coordination mechanisms, are proposed for this scenario. Fehske et al [13] consider resource allocation under a distributed, cooperative approach, by using the historical rate in place of the system's global vision; Bolla et al [14] simultaneously allocate modulation type, coding rate and resources (power and frequency) by using a coordination-based self-organized approach that aims to keep a stable frequency reuse pattern; Mokari et al. [15] formulate a proposal for dynamic spectrum sharing by using cognitive radio. In this proposal, the secondary infers the primary's behavior and nature of its environment. This knowledge keeps the secondary from generating excessive interference on the primary's transmissions. Bai et al. [16] proposal allocates resources in an environment with different quality of service demands (streams with different sizes and latencies); Keerthana & Vinoth [17] propose to allocate resources in two phases: in the first one, they use the geographical location of users to build a graph to mitigate interference, and in the second one, they allocate frequency resources by using said graph. With respect to formulating the optimization model: Feshke et al. [13], propose optimizing spectral efficiency by using a profit function; Keertana & Vinoth [17], Rajamannar & Vijaya [18], and Karthik & Kumaran [19], formulate a model to maximize throughput for users at the edge of the cell, subject to throughput fulfillment of users close to the base station. This formulation punishes users at the edge of the cell, because they are not offered full service guarantees, thus its fairness is questionable. Swapna et al. [20] formulate a proposal for resource allocation if OFDMA using cooperation and aiming for energy efficiency; Abdelhadi & Clancy [21] define a context, time and location-aware architecture for resource allocation in next-generation WMCS.

Increase in the number of users and demand for rich multimedia services impact the system architecture, motivating the inclusion of small cells (cells with less capacity and coverage area). WMCS are evolving towards a heterogeneous architecture, which features cells with different coverage and capacity, yielding a multi-level hierarchical structure (HetNet). Inclusion of small cells allows to: Improve the spectral efficiency (SE) by taking advantage of the spatial diversity; increase the offered data rates and reduce the amount of radiated power [22]. However, this approach also poses challenges, i.e. interference increase [23] and the backhaul's capacity for allowing exchange of coordination information for resource allocation [24]. López-Pérez et al [25] formulate a proposal for resource allocation, based upon minimizing power in OFDMA networks, by arbitrarily deploying femtocells in homes or businesses. Femtocells constitute a distributed system, and make decisions in an independent, self-organized fashion; Fan et al. [23], analyze the strategies for resource allocation in HetNets, and propose an algorithm for resource allocation in a cluster featuring a macrocell (in the center) and a set of small cells (randomly distributed in the macrocell's coverage area). The proposed model maximizes the transmission rate, subject to power constraints, and setting priorities for accessing and using frequency resources, favoring the macrocell.

Increase of computing power requirements in next-generation WMCS also increases the energy consumption of its components. CO_2 emissions lead to consider energy efficiency as an important design parameter for WMCS [26]. Initially, EE considered only the power used for transmission by the base station; however Li et al. [27] and Zappone et al. [28], among others, extend the concept, and present a more general expression including power consumed by the components' circuits. With respect to proposals for better EE in the WMCS, Miao et al. [29] maximize it through adaptive transmission, considering the channel state, and aiming to balance power used for transmission with power used by the components' circuits; Abdulkafi et al. [24] analyze energy-aware proposals in the HetNet context, establishing compromise relationships between architecture, base station design, and quantity/location of deployed sites in the macrocell-microcell scenario, which is the object of study of the present article; Devarajan et al. [30] and Gurupandi & Vadivel [31], formulate a proposal for guaranteeing EE in the cluster formed by the base station and the set of associated relays in a HetNet; Yu et al. [26] use a different strategy, by minimizing the energy consumption of the user terminal, subject to meeting the per-user rate requirements and the availability of power; Ren et al. [32] include the equity criterion and consider EE in their resource allocation model; Xiong [33] considers EE mandatory for designing a WMCS, and thus resorts to Green Radio concepts and the ratio between SE and EE metrics, which impacts channel gain and circuit power; Aligrudic & Pejanovic-Djurisic [34], solve the problem in a scenario similar to the one presented in this article (downlink of an OFDMA system with SISO antennas); Saeed et al. [35] analyze several proposals that mitigate interference effects in the heterogeneous architecture of 5G networks, also offering the possibility of enabling and disabling small cells, depending on the traffic load of the system; Zappone et al. [36] develop power control algorithms to maximize EE in the WMCS. In order to do so, they set constraints on the minimum achieved data rare, and propose a general expression for the SINR, for usage in the most promising technologies for 5G networks. Looking into the future, 5G WMCS will be characterized by massive deployment of heterogeneous networks, hence the need for mechanisms enabling EE self-management, aiming for reducing the operation costs [37]. It will be a universal communication environment where “all is a service” [38]. The system will feature a multi-level, hierarchical architecture according to Hasan et al. [39], and traffic flows will be exposed to high interference levels as they traverse all levels in the architecture, thus coordination and cooperation mechanisms among said levels in accordance with Hossain et al. [40]. The arrival of 5G poses challenges related to the subject of this article: interference management [39] and improvement of the compromise ratio between spectral efficiency and energy efficiency [41].

3.2. Solution strategies

Resource scheduling can be treated as a combinatory optimization problem, which can be solved via exact methods. However, Huang et al. [42] and Necker [43] have demonstrated that resource scheduling in a WMCS behaves as a NP-hard problem, and consequently, cannot be solved in polynomial time, and requires plenty of time and computing resources. Approximate strategies have been devised as an alternative. Such strategies abandon reaching the global optimal value, and yield sub-optimal solutions. Bohge et al. [44] have classified them into three categories: relaxation strategies [45], heuristic-based strategies [46] and problem breakdown strategies [8,47–49].

According to Martí [50], usage of heuristics is justified when the solution requires a huge amount of resources, when it is not necessary to find the optimal global solution, when the available information is not exact, and when there is a time limit for reaching a solution (all these aspects are applicable to the problem described in this article). Algorithms implementing this solution approach can be classified into two categories: Construction algorithms and improvement algorithms. Local search algorithms [51] are a particular type of improvement algorithms, which can be applied in problems where it is not required to track the path to the solution. They only keep the best solution reached so far, and try to improve it through an iterative process, using an evaluation function allowing check the goodness of the proposed solution.

3.3. Problem validity

Considering the huge amount of research in the last decade for formulating and solving the problem, one could ask if the problem is still valid. The authors identify the following challenges that keep the problem as valid:

a. The need of using power efficiently, for economic and environmental reasons.
b. An increase in the density of base stations, derived from deployment of cells with different coverage and capacities, leading to the emergence of heterogeneous architecture WMCS. As more base stations are deployed, interference increases, producing undesirable technical problems. There are also financial consequences, derived from the need of deploying more infrastructure in the system’s coverage area [52–54].
c. Utilization of software-based radio technologies, affecting the system’s structure and functionality [55].
d. Migration of infrastructure and services to the cloud, favoring coordinated, centralized resource allocation [56].

Table 1
Throughput required by the services offered in the WMCS, by user type.

Service	Required throughput for Type 1 users (Kbps)	Required throughput for Type 2 users (Kbps)
File transfer	468.1143	468.1143
Web browsing	376.5564	753.1128
Video	62.5000	81.2500
VoIP	12.2000	12.2000
Video games	17.3295	51.9886

In this work, the authors tackle challenges a and b, formulating a coordinated, centralized strategy for resource allocation (Challenge d).

4. Formulation of the optimization model

This section formulates the optimization model for efficient resource allocation. In order to do so, we characterize the scenario for this task, identifying relevant aspects of the WMCS, the users, the demanded services, and the resources required to offer them.

4.1. Characterization of the scenario for model formulation

In order to formulate the optimization model, we need to characterize the following:

(a) The *mobile communication system*. The WMCS is LTE-based, uses OFDMA at the physical level, its architecture can be either homogeneous (all cells have the same coverage and capacity) or heterogeneous (cells have different coverage and capacities, i.e. macrocells and picocells), and is deployed in an urban environment.
(b) *WMCS users* are pedestrian users, enjoying two types of services: normal and superior.
(c) The *number of deployed users in* each macrocell sector, or in each picocell, is an input parameter for the model.
(d) *Services offered by the WMCS* have five categories: Interactive, real-time, real-time interactive, multicast and best effort. In this work, we selected a service for each category: File transfer, web browsing, video, Voice over IP (VoIP), video games. Each service category is associated to a set of performance parameters, which determine the required quality of service. Table 1 shows the quality requirements for each category and user type, in terms of the required throughput (Kbps).

The number of users deployed per service, in each one of the sectors in the WMCS, is generated according to the probability distribution on Table 2, built upon [57,58].

(e) *Resources*. In the LTE environment, users are allocated frequency blocks for service. The number of available frequency blocks depends on the channel’s bandwidth. We also need to know the available amount of power in each base station, and the minimum power level required at the user terminal for successful reception, i.e. the receiver sensitivity. Table 3 specifies those parameters.

There is a direct relationship between the SINR and the minimum required throughput to offer the service (noted as γ and

Table 2
Percent distribution of users, by service type and user type.

Service	Type 1 user	Type 2 user	Total
File transfer	6%	4%	**10%**
Web browsing	12%	8%	**20%**
Video	12%	8%	**20%**
VoIP	18%	12%	**30%**
Video games	12%	8%	**20%**
Total	**60%**	**40%**	**100%**

Table 3
WMCS available resources and configuration parameters.

Parameter	Value
Available power at macrocell (W)	40
Available power at microcell (mW)	250
Receiver sensitivity (dBm)	−106.4
Number of frequency blocks (10 MHz channel)	50
Number of frequency blocks (5 MHz channel)	25
Sectors per cell (tri-sectored cell)	3
Antenna configuration	SISO

Table 4
CQI-SINR-Throughput relationship.

CQI	SINR	Throughput γ (Kbps)
1	0.1128	21.42
2	0.2159	32.96
3	0.3892	53.02
4	0.6610	84.52
5	1.0962	123.33
6	1.7474	165.35
7	2.8113	207.65
8	4.3321	269.17
9	7.0081	338.39
10	10.6316	383.98
11	16.6648	467.20
12	25.8345	548.76
13	38.4503	636.10
14	60.0620	719.32
15	95.6974	781.13

measured in Kbps). Table 4 shows the relationship between the CQI, the SINR and the minimum required throughput for offering the service.

4.2. Obtained SINR

When a user obtains resources (power and frequency) from the system, his SINR is given by:

$$SINR_{j,k,r} = \frac{g_{j,j,k}.P_{j,r}}{N_{j,r} + \sum_{x \neq j}^{1 \leq x \leq j} g_{x,j,r}.P_{x,r}} \tag{1}$$

where the x and j indexes correspond to the interfering and interfered sectors in the WMCS, k notes the user, and r notes the frequency block.

The obtained SINR determines the users' condition with respect to service. Three different states are considered:

(a) *User with full satisfaction*. In this state, the obtained SINR is greater than the minimum required value for offering the service ($SINR_{j,k,r} \geq \gamma_{j,k}$). The model's proposed objective is for all WMCS users to reach full satisfaction.
(b) *User with degraded service*. In this state, the obtained SINR is less than the minimum required value for offering the service, but greater than the minimum required value for data transmission ($\gamma_{\min} \leq SINR_{j,k,r} < \gamma_{j,k}$). Our proposal takes advantage of the elastic nature of some services, and considers this condition as a possible state for the system. Some proposals ([59]) have considered this state as non-feasible, ignoring elasticity of some services. By doing this, they degrade the resource usage efficiency, and lose the possibility of using resources to give degraded service to some users in the WMCS.
(c) *User with denied service*. In this state, the obtained SINR is less than the minimum required value for data transmission ($SINR_{j,k,r} < \gamma_{\min}$).

4.3. Model formulation

Formulation of the optimization model considers several facts. First, it is not possible to obtain the global optimum value, because there is a time limit for obtaining the solution; thus, it is necessary to use an approximate strategy for solving the model. Second, it is not possible to have precise instantaneous information about the channel state, as a consequence of the processing and communications overhead this would cause. Our proposal recognizes these facts, and instead of asking for channel state reports, it estimates the obtained SINR using 3GPP's standard channel models [60]. These models consider physical phenomena associated with propagation, path loss (PL) and fading (X_σ), and calculate losses in the macrocell (2) and picocell (3) channels. In the equations, R is the distance between the base station and the user, in Kilometers.

$$Channel\_Loss_{MACRO} = 128.1 + 37.6 Log_{10}(R) + X_{\sigma_{MACRO}} \tag{2}$$

$$Channel\_Loss_{pico} = 140.7 + 36.7 Log_{10}(R) + X_{\sigma_{pico}} \tag{3}$$

The received signal power at the user position is expressed as follows:

$$PotRx_{mW} = \frac{GainTx_{mW}}{Channel\_Loss_{mW}}.PotTx_{mW} = g.PotTx_{mW} \tag{4}$$

Notation and definitions used for formulating the optimization model are as follows:

(a) $\mathbf{J} = \{1,2,3,\ldots,J\}$, is the set of sectors.
(b) $\mathbf{M_j} = \{1,2,3,\ldots,M_j\}$, is the set of users in sector j. Distribution of users in sectors is known, and corresponds to a random pattern.
(c) $\mathbf{R} = \{1,2,3\ldots..,R\}$, is the set of frequency resource blocks.
(d) $g_{x,j,k}$ is the gain from base station in xth sector to the location of mth user in jth sector.
(e) $P_{x,r}$ is the power allocated by the base station in sector x to frequency block r.

Model constraints include:

(a) Constraint over SINR:

$$u_{j,k,r}.[SINR_{j,k,r} - \gamma_{j,k}] = u_{j,k,r}.\left[\frac{g_{j,j,k}.P_{j,r}}{N_{j,r} + \sum_{x \neq j}^{1 \leq x \leq 1} g_{x,j,k}.P_{x,r}} - \gamma_{j,k}\right] \geq 0;$$
$$\forall (j \in \boldsymbol{J}, k \in \boldsymbol{M}(j), r \in \boldsymbol{R}(j)) \tag{5}$$

The value of $\gamma_{\text{j,k}}$ is associated to the minimum throughput value required for offering the service.

(b) Boolean variables:

$$u_{j,k,r} = \{0, 1\} \quad \forall (j \in \boldsymbol{J}, k \in \boldsymbol{M}(j), r \in \boldsymbol{R}(j)) \tag{6}$$

(c) Service is guaranteed to all users:

Guarantees every user is allocated at least one frequency resource block.

(d) Block orthogonality:

$$\sum_{k=1}^{M_j} u_{j,k,r} \quad \leq \quad 1 \quad \forall (j \in J, r \in \boldsymbol{R}(j)) \tag{8}$$

Ensures each frequency resource block is allocated to a user at most.

(e) Power cannot be negative:

$$P_{j,r} \quad \geq \quad 0 \quad \forall (j \in \boldsymbol{J}, r \in \boldsymbol{R}(j)) \tag{9}$$

(f) Power limit:

$$\sum_{r \in R(j)} P_{j,r} \quad \leq \quad P_j \quad \forall (j \in \boldsymbol{J}) \tag{10}$$

Where $\mathbf{P_j}$ is the total power available for the jth sector. This is a known parameter.

(g) Receiver sensitivity:

$$u_{j,k,r}.(g_{j,j,k}.P_{j,r} - p_{\min}) \quad \geq \quad 0 \\ \forall (j \in \boldsymbol{J}, k \in \boldsymbol{M}(j), r \in \boldsymbol{R}(j)) \tag{11}$$

States that, when power is allocated to the rth frequency resource block assigned to kth user *in* jth sector, the received power will be greater than a minimum value (p_{min}), corresponding to the receiver sensitivity.

In general, it is not possible to satisfy all constraints at the same time, hence, we waive the SINR (5) constraint, and introduce a slack variable (Δ) that guarantees feasibility of the model. Thus, we rewrite constraint (5) and reformulate the optimization model.

4.3.1. Model 1

Objective function 1 (OF-01):

$$\min_{u,P,\Delta} \Delta \\ subject\ to: (6) - (11) \tag{12}$$

Feasibility (5) is forced through the artificial variable Δ:

$$u_{j,k,r}.\left[g_{j,j,k}.(P_{j,r} + \Delta) - \gamma_{j,k}.(N_{j,r} + \sum_{x \neq j}^{1 \leq x \leq J} g_{x,j,k}.P_{x,r}) \right] \geq \quad 0 \\ \forall (j \in \boldsymbol{J}, k \in \boldsymbol{M}(j), r \in \boldsymbol{R}(j)) \tag{13}$$

The slack variable Δ may be interpreted as an index giving information about the amount of improvement (when $\Delta > 0$) or deterioration (when $\Delta < 0$) the user experiments in the best/worst system state. Model 1 (12), was proposed by Pachón et al. [61,62].

4.3.2. Model 2

Model 1 has a great weakness: It focuses into improving the condition of a single user, ignoring the possibilities offered by the remaining users. In order to overcome this weakness, we introduce a set of slack variables, one for each frequency block ($\Delta_{j,r} \geq 0$). These variables represent the amount of improvement each user requires to reach full service satisfaction. Thus, we reformulate the model and the SINR (13) constraint:

Objective function 2 (OF-02):

$$\min \sum_{j=1}^{J} \sum_{r=1}^{R} \Delta_{j,r} \\ \text{subject to}: (6) - (11) \tag{14}$$

Constraints: Feasibility is forced through artificial variables $\Delta_{j,r}$:

$$u_{j,k,r}.\left[g_{j,j,k}.(P_{j,r} + \Delta_{j,r}) - \gamma_{j,k}.(N_{j,r} + \sum_{x \neq j}^{1 \leq x \leq J} g_{x,j,k}.P_{x,r}) \right] \geq \quad 0 \\ \forall (j \in \boldsymbol{J}, k \in \boldsymbol{M}(j), r \in \boldsymbol{R}(j)) \tag{15}$$

Slack variables guarantee model feasibility, and approach the problem in a different way, since the model assumes compliance with the required SINR, and then finds the system configuration that reaches this goal. Consequently, Model 2 is always feasible, but does not always reach the proposed objective (full satisfaction of service requests for all users). In addition, some constraints of the model ((11) and (15)) are quadratic, so the optimization model is non-linear, mixed.

The value of the objective function may be used to determine whether the proposed goal is met or not. When the objective function yields zero, the proposed goal is met (all slack variables are zero, and it is possible to satisfy all user requirements with the available resources). When the objective function yields a value greater than zero, the proposed goal is not met (at least one of the slack variables is greater than zero).

5. Optimization model solution

The optimization model solution involves four aspects: Specifying the model's solution, characterizing the solution (including specification of the approach to solve the problem, the problem solution strategy, the solution algorithm, the search space exploration strategy and the local search method), analyzing the model and the problem solution approach, and analyzing fairness in transmission capacity allocation by the WMCS.

5.1. Model solution specification

Given the model characteristics (MINLP, NP-Hard), it is impossible to obtain an exact solution in the allotted time interval. Thus, we give up obtaining the global optimum value, and use an approximate strategy which decouples the search space into Boolean and continuous variables. This implies beginning by assigning values to the Boolean variables, using a frequency block allocation strategy. This allocation is represented by a permutation defining the system state ($\boldsymbol{U}$), defined as follows:

Definition 1. ***System State, U:*** *The permutation representing the frequency block allocation to users, in all the system's sectors.*

Given $\boldsymbol{U}$, the model presented in (14) becomes a linear programming model in the variables $P_{j,r}$ and $\Delta_{j,r}$, which is much easier to solve. Since que also require to evaluate the goodness of a system state $\boldsymbol{U}$ against achieving the proposed goal, we define the functional value of $\boldsymbol{U}$, f($\boldsymbol{U}$), as follows:

$$f(U) = \min \sum_{j=1}^{J} \sum_{r=1}^{R} \Delta_{j,r} \\ \text{subjecto to}: (6) - (11), (14) \tag{16}$$

The value for f($\boldsymbol{U}$) can be greater than or equal to zero. It can be interpreted as an index for evaluating the goodness of a system state. If f($\boldsymbol{U}$) is zero, the proposed goal is met, and in addition, it is possible to perform an optimal power allocation, by solving the next optimization model:

$$\forall (j \in J, k \in \boldsymbol{M}(j), r \in \boldsymbol{R}(j))$$
$$\min \sum P_{j,r}$$
$$\text{Subject to:} \quad P_{j,r} \geq 0$$
$$\bar{u}_{j,k,r}\cdot\left[g_{j,j,k}\cdot(P_{j,r}+\bar{\Delta}_{j,r})-\gamma_{j,k}\cdot(N_{j,r}+\sum_{\substack{x\neq j}}^{1\leq x\leq J} g_{x,j,k}\cdot P_{x,r})\right] \geq 0 \tag{17}$$

5.2. Model solution algorithm

The model solution algorithm proposes an initial system state ***(U₀***) and evaluates its goodness by calculating $f(\boldsymbol{U_0})$. Then, through an iterative strategy, it tries to reduce the functional value, knowing that this action leads to larger levels of full service satisfaction. The key aspect is to generate the next system state. This is accomplished through two heuristics:

a. Heuristic that ignores the current system state, and makes a random change on the current system state ($\mathbf{U_i}$) yielding the next state ($\mathbf{U_{i+1}}$). To implement it, we propose two approaches: the intensification-oriented approach, which performs a random, partial change over some sectors in the system, aiming to take advantage of the accumulated search experience; and the diversification-oriented approach, which performs random changes in all the system's sectors, aiming to explore diverse regions of the search space.
b. Heuristic that considers the current system state ($\mathbf{U_i}$) and changes it partially, generating the next state ($\mathbf{U_{i+1}}$). It is based upon a local search method that considers a practical fact: The next system state is close to the current one; thus, it is not necessary to make significant changes with respect to the system's current state.

5.2.1. Aspects involved in algorithm formulation

Three aspects must be determined, in order to formulate the problem solution algorithm:

a. The strategy for allocating frequency blocks to users.
b. The strategy for exploring the search space, which allows determine the system's next feasible state.
c. The system administrator point of view on what he considers an acceptable solution. This determines the time interval between system state updates, and imposes a time limit to the iterative improvement strategy.

5.2.2. Local search heuristic formulation

To formulate the local search heuristic, we need to:

(a) Define distance between feasible allocations:

Definition 3. Distance (d) between feasible allocations U and U'. Number of differences between their underlying permutations.

For example, if $\boldsymbol{U}=\{2,3,4,1\}$ and $\boldsymbol{U'}=\{2,1,3,4\}$ are feasible allocations, then the distance d(***U,U'***) equals 3.

(b) Define neighborhood structure:

Definition 4. Neighborhood structure for U, V(U).

$$V(\boldsymbol{U}) = \{U' : d(U', \boldsymbol{U}) \leq dist\} \qquad dist \in \mathbb{Z}^+ \tag{18}$$

(c) Define the mechanism allowing generate a new system state, considering the neighborhood structure. In this work, we consider the neighborhood structure with the smallest possible distance ($dist = 2$). Hence, the number of neighbors to evaluate before declaring the existence of a local minimum is:

$$NeighborsEvaluated = NumerOfSectors \times \frac{BlocksBySector \times (BlocksBySector - 1)}{2} \tag{19}$$

This yields a huge amount of neighboring states to evaluate in the considered time interval (25,724 states in a 7 macrocell scenario, and 69,824 states for a 19 macrocell scenario), so the algorithm will not be able to evaluate all of them, and it will be impossible to declare the existence of the local minimum. Thus, we require to reduce the number of evaluated neighboring states, preserving the improvement goal (reduce the functional value of f(***U***)). In order to achieve this, we always reallocate the frequency block associated with the slack variable that contributes the most to f(***U***). This block, named *critical interference block,* is noted as r^*. This is an objective, effective criterion to generate the next system state. In consequence, we define a reduced neighborhood structure, which involves always reallocating the critical interference block for generating the next system state.

Definition 5. Reduced neighborhood structure for *U*, $V^a(U)$. *If* $u_{j^*,k^*,r^*} = 1$*, the reduced neighborhood structure for **U** is defined as*:

$$V^a(\boldsymbol{U}) = \{v \in \boldsymbol{U} : u_{j*,k*,r*} = 0\} \tag{20}$$

5.2.3. Problem solution algorithm, using the local search heuristic

The solution algorithm integrates:

(a) An iterative improvement strategy.
(b) A frequency block allocation strategy.
(c) A search space exploration strategy.
(d) Means for controlling the duration of iterative improvement.

Fig. 1 shows the flowchart of the problem solution algorithm, using the local search heuristic.

5.2.4. Model and solution approach analysis

a. *Regarding power usage*. SINR allows efficient power allocation, because each frequency block receives enough power to guarantee service provision (constraint (15)) and successful information reception (constraint (11)). At the same time, it limits allocated power for avoiding excessive interference to neighboring cells. This allows better results, when compared to proposals that require full power utilization [63,64], or equally distribute power among all blocks [12,65], or perform coordinated power allocation [66,67].
b. *Regarding interference*. The model minimizes interference to fair values, even though it was not designed to minimize interference. The model considers all interferers, allowing compute the aggregated effect of interference in an accurate and realistic way. Other proposals consider only the effects of the largest interferer [68,69].
c. *Regarding the optimization model*. The model is always feasible. Although it does not always reach the proposed goal, it does not deliberately punish any service or user category, as other proposals do [59]. Instead, the model lets the system condition (as a consequence of resource allocation) determine the users getting full service satisfaction, degraded service or denied service. In this sense, the model is completely fair.

6. Resource allocation scheduler design

6.1. Design considerations

According to Section 3, resource allocation in a next generation WMCS must have the following features: a) must be distributed

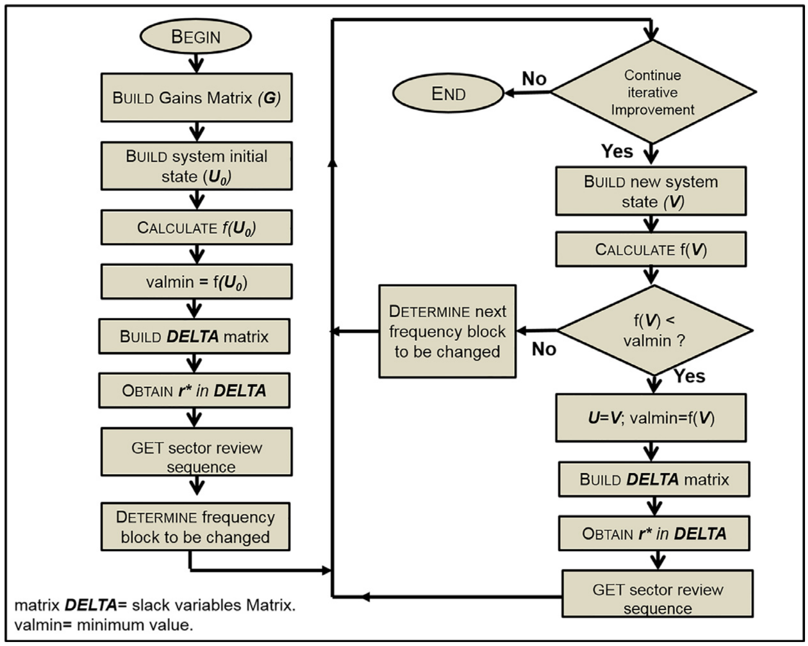

Fig. 1. Flowchart for the model solution algorithm.

and cooperative, because the task is complex and demands high computational power in order to process the huge volumes of information that must be exchanged to perform resource allocation; b) must take advantage of the different operation perspectives (time, frequency and space) to improve system performance, because there is a relationship among the time-frequency variations experimented by channels and the resource scheduler performance [70]; c) must operate in a heterogeneous architecture environment, typical in current WMCS and in 5G systems [39,40]. Hence the scheduler must take into account:

(a) The *OFDMA context*, corresponding to the time-frequency space for resource allocation. OFDMA is the *de facto* technology [71,72] used in current WMCS. Thus, the problem and its solution are formulated within this context.
(b) The *time perspective*, corresponding to the time scale for resource allocation.
(c) The *architecture perspective*, which includes structure and interrelations between the components allocating resources.
(d) The *operational perspective*, which recognizes component interaction in time, frequency and space.
(e) The *spatial perspective*, which considers the spatial distribution of the components executing the task.

6.2. OFDMA context

OFDMA accommodates resources in a two-dimension (time and frequency) grid. In this space, the minimal unit is known as a resource element. A set of resource elements in the time dimension constitute an OFDM symbol. In LTE, a frequency block (the resource allocated by the base station scheduler for delivering services) is made by an OFDM symbol in the time dimension, and 12 resource elements in the frequency dimension. Using frequency blocks (chunks) allows to reduce the amount of reported information, because the contiguous subcarrier subset may be characterized using an average value [27,73,74].

6.3. Spatial perspective

The problem is solved through a cooperative, distributed approach which splits the task into two components: a distributed one, and a centralized one. In this sense, it agrees with the solution proposed by Álvarez [75] that lightens the computational load on the central scheduler, by distributing the solution.

(a) Our approach is *distributed,* because the task is split among a central coordinator and a local component.
   (1) The *central coordinator* (CC) uses a global perspective for resource allocation, and is housed in one of the WMCS components (Mobility Management Entity (MME), Radio Network Controller (RNC) or Base Station (BS)). This component performs centralized resource allocation in the medium-term time scale (to reduce interference).
   (2) The *local component,* housed in the base stations, uses a local perspective to allocate resources in a short-term time scale.
(b) Our approach is *cooperative*, because both components (central coordinator and local components) interact to solve the problem.

6.4. Time perspective

Fodor et al. [76] consider three different time scales for resource allocation, each one with a different purpose: *short-term time scale*: Corresponds to milliseconds, aims to allocate resources in order to satisfy user demands; *medium-term time scale*: Considers from tenths of a millisecond to a second, and it aims to mitigate interference. This perspective matches the time scale we chose for solving the problem, since in this time frame the average traffic in the WMCS is relatively stable [77]. Thus, the system state may be considered as quasi-static; and l*ong-term time scale*: Considers from days to weeks. It aims to modify the configuration of the WMCS operational parameters. Usage of these time scales allow to decompose and distribute the resource allocation task into two perspectives: a) the *short-term perspective*, which is distributed and autonomous. In this perspective, each base station allocates resources using the local environment point of view; b) the *medium-term perspective*, which is centralized. In it, the scheduler adjusts the global resource allocation, aiming to satisfy users' service requirements, through the improvement of the SINR. Operation of the global resource scheduler considers three different time intervals: *Interval* Δt_1, in which base stations report user position and demanded services to the CC. Using this information, the CC builds the current system state. This interval poses a processing and communication overhead to the problem solution; *interval* Δt_2, in which the CC solves the optimization model, performing global resource allocation. This interval poses a processing overhead to the problem solution; *interval* Δt_3, in which the CC reports the global resource allocation to base stations. This interval poses a communication overhead to the problem solution. The sum of these three intervals is the scheduler operation time frame, in which the system is considered in quasi-static state. This leads to the following constraint:

$$\Delta t = \Delta t_1 + \Delta t_2 + \Delta t_3 \leq \quad 5sec \tag{21}$$

6.5. Operational perspective

We now establish the following features for operation of the resource scheduler, as a consequence of the proposed architecture and the defined time perspective:

(a) The scheduler executes its task in the medium-time perspective, assuming the system as quasi-static. In it, the time-dependent parameters are considered as constant. This assumption is valid within a short time frame, which depends upon the system dynamics, and has been formally considered as an operational constraint in (21).

(b) The scheduler builds a global vision of the system, by estimating the gain between each base station and each user, using the reported position information. Instead of reporting the channel quality index (CQI) for each one of the frequency blocks, users notify their position and the service they demand. Consequently, the volume of reported information is significantly smaller, and the communications/processing overhead is reduced. This work agrees with the statements of Stiogannakkis et al. [78] and Bittencourt et al. [79], which question the possibility of having perfect, instantaneous information about the channel, as a consequence of the increase of the amount of generated information (proportional to the system's size and dynamics) and the short time interval allowed to execute the scheduling (in the millisecond order). Some of the reviewed proposals assume the scheduler has this information at hand, ignoring these practical considerations [15,29]. The generated system global vision allows determine the impact produced by frequency resource allocation over the services offered to users, in the form of interference. Interference limits the SINR, and thus the level of service offered to users.

(c) The scheduler periodically readjusts the system state, by reallocating available resources, aiming to reduce the average level of interference and to improve the SINR and benefits for each user, in the medium-time perspective.

6.6. Analysis of resource allocation scheduler

a. *With respect to the used metric and the model's objective*: The proposed model aims to satisfy user requirements, by globally allocating system resources. By using SINR, the model allocates sufficient power to satisfy the service requirements for users, trying to impact ongoing transmissions using the same frequency blocks in neighboring cells as little as possible. Optimization of the summation rate proposals, as formulated by Kim et al. [80], consider only the operator's interests, denying service to those users keeping it from reaching the objective, and although it is valid to impose a constraint for guaranteeing a minimum rate for each user, the users having a requirement greater than the value imposed by the constraint are punished. In this sense, the approach is unfair, because in some cases, depending in the system status (user position and power allocation in neighboring cells), it is possible to fully satisfy the requirements of some of these users, without needing to relax the requirement. Our approach takes this argument into account, and concentrates in user satisfaction, aiming to guarantee the required data rate, and without privileging any particular type of service.

b. *With respect to energy efficiency*: The formulated model does not explicitly consider the energy consumption of the WMCS circuits. However, it makes an important consideration on efficient allocation of transmission power in the base station, mitigating interference and using a coordinated strategy for global allocation of frequency resources. Experimental results presented in Section 7 evidence the efficiency of our proposal: When the global allocation of frequency blocks does not allow reach full service satisfaction, the average power utilization is about 30% of available power, and when the frequency block allocation allows reach full user satisfaction, power is allocated optimally. Some authors consider proposals offering the best possible data rate for a given energy value as efficient (Miao et al. [29]). However, we consider these proposals questionable, because technical and financial resources may be wasted by allowing users to have greater data rates than required. Energy efficiency is achieved by allocating each user the required data rate, by using the least possible power resources. This reasoning has been incorporated in our work.

c. *With respect to some analyzed significant proposals*: We identify and analyze some significant recent proposals, in order to evaluate the goodness of their models and their solution strategies. Miao et al. [29] propose an energy-efficient scheduler in the uplink of a WMCS using OFDMA, in a scenario featuring a cell with N users and K subcarriers. However, they omit the complexity of the multi-cell heterogeneous scenario, ignoring interference and assuming a perfect, instantaneous knowledge of the channel's state. Venturino et al. [81] propose an energy-efficient scheduler, and power allocation in a scenario pretty similar to the one proposed by us: Downlink of an OFDMA system, cluster of M base stations, one receive and one transmit antenna, channel stability in the resource allocation interval, presence of a central controller, use of the SINR as a source for energy efficiency optimization, consideration of transmission power and power consumption on the WMCS circuits (amplifier and RF transmit circuits, specifically). This proposal assumes a perfect, instantaneous knowledge of the channel, which is not achievable in practice. In addition, it proposes a centralized controller which has instantaneous, perfect information about the subcarriers' status. This aspect is also questionable, because of the volume of generated information (one channel status per subcarrier in each base station) and the limited time interval for solving the problem. In practice, the scheduler has a very narrow time frame for achieving resource allocation, and the amount, availability and precision of the obtained information become hurdles to an expedited resource allocation matching the system status. Sung et al. [82] propose a coordinated scheduling mechanism in a heterogeneous environment, aiming to mitigate interference in a cluster featuring one macrocell and a set of picocells inside it. In their reported results, they do not mention scalability of the solution in a heterogeneous, multi-cell environment (several macrocells, with picocells inside them), as we do in this article. Li et al. [83] formulate a proposal for a coordinated scheduler in a multi-cell environment, using MIMO in a LTE network, aiming to minimize interference, and taking advantage of diversity gain and spatial multiplexing. They assume availability of channel state information, and establish a direct relationship between system performance and the in-

Table 5
Implementation variants for the solution algorithm.

ObjectiveFunction	System architecture	Frequency reuse factor (K)	Search space exploration strategy	Implementation ID
Model-01	Homogeneous	1	Intensification	IMPL1
Model-01	Homogeneous	1	Diversification	IMPL2
Model-01	Homogeneous	1/3	Intensification	IMPL3
Model-01	Homogeneous	1/3	Diversification	IMPL4
Model-01	Heterogeneous	1	Intensification	IMPL5
Model-01	Heterogeneous	1/3	Diversification	IMPL6
Model-01	Heterogeneous	1/3	Intensification	IMPL7
Model-01	Heterogeneous	1/3	Diversification	IMPL8
Model-02	Homogeneous	1	Intensification	IMPL9
Model-02	Homogeneous	1	Diversification	IMPL10
Model-02	Homogeneous	1	Local Search	IMPL11

stantaneous, precise availability of such information. Although we recognize the goodness of using MIMO in LTE environments, the perfect materialization of this proposal (in terms of performance), is questionable from the practical point of view.

7. Results and analysis

The software was developed in Java 1.7, with Eclipse as the choice IDE (integrated Development Environment). The software interacted with IBM's Ilog Cplex Optimization Studio v12.2 [84] for solving the formulated model. This chapter establishes the indicators allowing assess efficacy and efficiency of the model and the proposed solution; the scenarios for evaluating the model; and the experiments for each scenario. The proposed algorithm allows integrate:

(a) The *objective function*. This work considers two objective functions: Model 1 (12) and Model 2 (14).
(b) The *WMCS architecture*, either homogeneous or heterogeneous.
(c) The *frequency reuse factor*. This work considers two such factors: fixed ($K = 1$), which allows allocate all available frequency blocks, and variable ($K = 1/3$), which limits usage and allocation of frequency blocks, in order to mitigate interference.
(d) The *search space exploration strategy*, which considers three heuristics: intensification, diversification and local search in a reduced neighborhood structure.

Multiple combinations among these factors allowed 11 different implementations (not necessarily comparable) which evidence the versatility of our approach. Table 5 shows the implementations and their parameters.

7.1. Indicators

The indicators that will be used belong to one of these categories:

(a) *Efficacy-oriented*, to assess the model behavior with respect to reaching the goals and heeding the imposed constraints. This aspect is interesting to the system users. The defined indicators are: Percentage of users with full service satisfaction, with degraded service and with denied service; and percentage of compliance with the required data throughput.
(b) *Efficiency-oriented*, to assess the model behavior with respect to utilization of available resources. This aspect is interesting to the service provider. The defined indicators are: Value of the objective function, and available power utilization percentage.

7.2. Scenarios for model validation

The defined scenarios consider three evaluation aspects:

a. *Model behavior assessment*. Aims to compare results obtained by the model to the results obtained by exhaustive enumeration in a small scenario including two base stations, 3 frequency blocks and 3 users per sector. In this experiment (experiment 1), the model was executed 10 times, and the results matched the exhaustive enumeration values in all cases. In the first case, the result was obtained in 0.2812 s (in average), while in the second case, it took 737.42 s to sweep through all the search space (a total of 46,656 system states).
b. *WMCS parameter configuration assessment.* Aims to validate system configurations, by assessing the impact of changes in the WMCS configuration on the defined indicators. In particular, we varied the number of base stations (experiment 2), the number of users in each system sector (experiment 3) and the number of deployed picocells in each system sector (experiment 4).
c. *Assessment of the model and algorithm goodness.* This set of experiments compares the objective functions for models 1 and 2 (experiment 5), the improvement effect of the iterative strategy on the defined metrics (experiments 6 and 7), the search space exploration strategy (experiments 8 and 9) and the model fairness with respect to the data throughput obtained by every service offered in the system (experiment 10).

7.3. Experiment definition

Tables 6 and 7 describe the performed experiments for scenarios 2 and 3. Experiments in Table 6 evaluate scalability of the proposed model. In order to do so, we increment the configuration parameters in the experiment scenario, by varying the number of base stations (from 2, the simplest case; up to 19, the most complex case, with two levels of interferers with respect to the central cell); the number of users per sector (30 and 40); and the number of picocells per sector (0 for homogeneous architecture; 1, 2 and 4 picocells per sector, for a heterogeneous architecture with macrocells/picocells). In all cases, and according with the obtained results, the proposed model was able to satisfy the defined metrics with high performance levels, and without experimenting significant degradation.

Table 7 shows the assessment of aspects unique to the model: a) We compare the proposed objective function to versions previously formulated by us, and to the min-max model by Schubert & Boche [59] as a baseline; b) we also assess the goodness of the iterative improvement; and c) the fairness of the scheduler for resource allocation, an aspect with the highest importance. In the evaluation, model (14) performed better than the previously proposed objective functions and the baseline. In addition, and as a result of the results of experiment 10, we conclude that the sched-

Table 6
Experiments for scenario 2.

Expe-riment	Parameters and values used for model assessment		Configuration				
	Assessed parameter	Values	Number of macrocells	Picocells per sector	Users per sector	Distance between BS (m)	Used implementation
2	Number of base stations	2,4,7,12,19	–	0	25	750	IMPL1
3	Users per sector	30,40	7	0	–	500	IMPL1-IMPL4
4	Picocells per sector	0,1,2,4	7	–	40	500	IMPL1-IMPL8

Table 7
Experiments for scenario 3.

Experiment	Evaluated aspect	Configuration				
		Number of macrocells	Picocells per sector	Users per sector	Distance between BS (m)	Used implementation
5	Objective function	7	0	50	500	IMPL9
6	Iterative improvement	7	0	50	500	IMPL11
7	Iterative improvement	19	0	50	500	IMPL11
8	Search space exploration strategy	7	3	50	500	IMPL9-IMPL11
9	Search space exploration strategy	19	3	50	500	IMPL9-IMPL11
10	Fairness in transmission capacity allocation	19	0	50	500	IMPL9-IMPL11

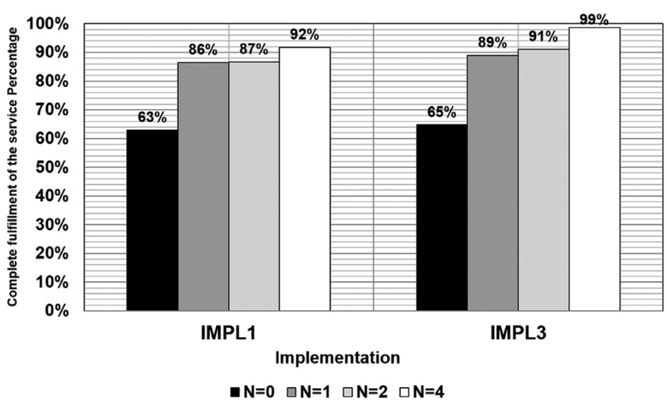

Fig. 2. Complete fulfillment of the service percentage in Experiment 4.

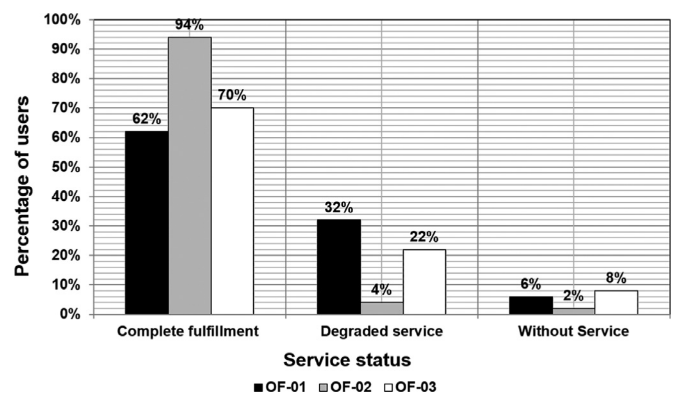

Fig. 3. Service status statistics for Experiment 5.

uler does not privilege a particular type of service *a priori*, allowing that the characteristics of the experiment scenario determine which users will receive service, and which ones will be denied service.

For extension reasons, we present the results of the more representative experiments, evidencing model behavior and the efficacy / efficiency for solving the problem.

7.3.1. Experiment 4: behavior in heterogeneous architecture environments

This experiment deploys 7 macrocells, 0/1/2/4 picocells, 40 users per sector and 2 users per picocell, using implementations IMPL1 and IMPL3. The experiment evaluates the model's ability to mitigate interference due to an increase in the number of deployed base stations in the WMCS geographical area.

Fig. 2 shows the percentage of users achieving full service satisfaction in different system configurations (0, 1, 2 and 4 deployed picocells per sector). Results show the goodness of our approach, because the percentage of fully satisfied users increases when the number of deployed picocells is increased. The rationale for this behavior is: a) users are closer to the base stations, which demands lower power levels; and b) the centralized, coordinated approach allows to globally mitigate interference.

7.3.2. Experiment 5: objective function for the optimization model

This experiment considers the objective function for Model 1 (12), named OF-01; the objective function for Model 2 (14), named OF-02; and the objective function of the min-max model (proposed by Schubert and Boche [59]), named OF-03. The test scenario features 7 macrocells, homogeneous architecture (zero picocells), 50 users per sector, and implementation IMPL9. Obtained results (shown in Fig. 3) evidence better results for function OF-02 (14): a significant difference in users with full service satisfaction (93% for OF-02, 70% for OF-03 and 62% for OF-01), and less users are left without service (2% for OF-02, 8% for OF-03 and 6% for OF-01). We also demonstrate the aforementioned weakness of FO-01, which tries to improve conditions for a single user; OF-01 (12) presents the highest level of users with degraded service, a condition that OF-02 improves upon. Model 2 (14), with its function OF-02, improves significantly upon previous results presented by the authors in [61], reaching higher levels of full satisfaction, lower percentages of users with degraded or denied service, and higher fulfillment levels with respect to the achieved throughput.

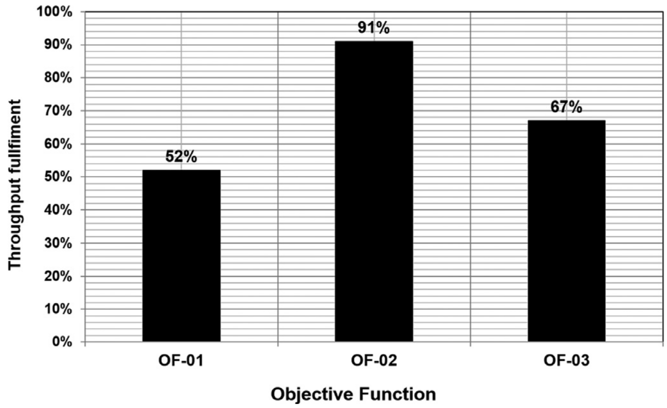

Fig. 4. Throughput fulfillment with different Objective Functions in Experiment 5.

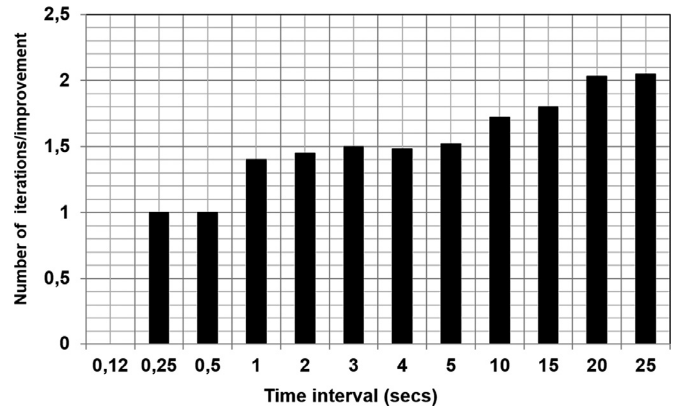

Fig. 6. Effectiveness index for experiment 6.

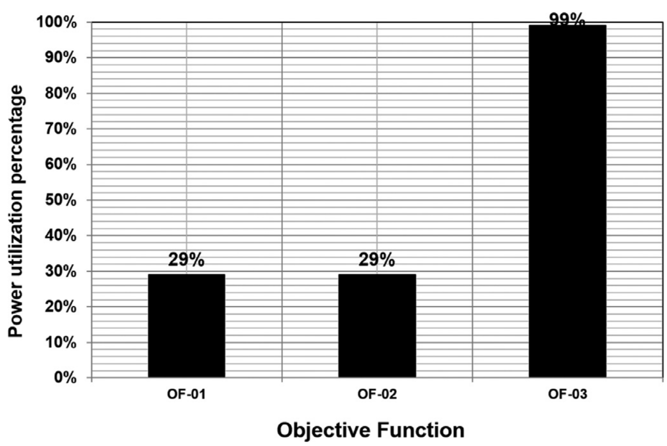

Fig. 5. Power utilization percentage in Experiment 5.

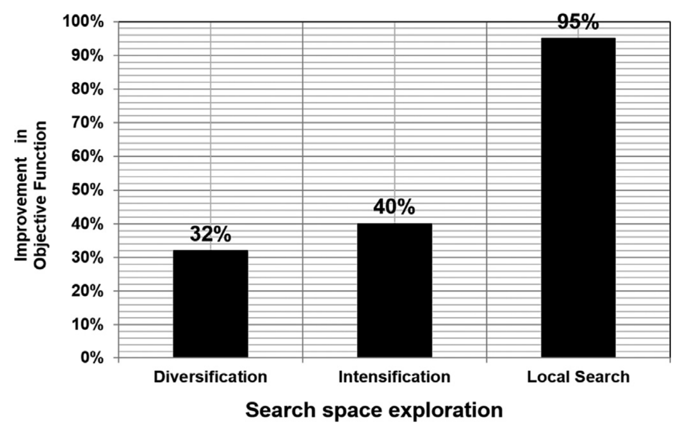

Fig. 7. Search space exploration strategies in Experiment 8.

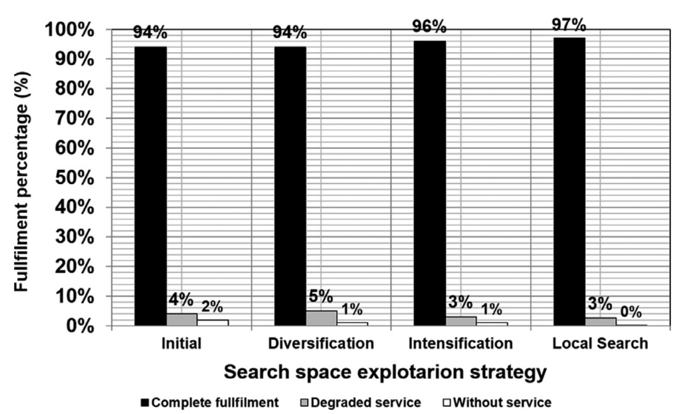

Fig. 8. Search space exploration strategy in Experiment 8.

Fig. 4 shows the throughput results (91% fulfillment for OF-02, 53% for OF-01 and 67% for OF-03).

Fig. 5 shows power utilization. Functions OF-01 and OF-02 feature smaller power usage (less than 30%) when compared to OF-03 (99%). Efficient power usage is one of the key aspects keeping the problem as valid.

7.3.3. Experiment 6: effectiveness of iterative improvement

This experiment considers function OF-02 (14). The test scenario features 7 macrocells, homogeneous architecture (zero picocells), 50 users per sector, implementation IMPL11 (using the local search / reduced neighborhood heuristic), and the time interval to reach a solution is varied from 0.12 to 25 s. We increase the time interval in order to discard this factor as a cause for ending the iterative improvement. In addition, we define the effectiveness index (22), as the average number of iterations required to achieve a better system state.

$$\text{Effectiveness Index} = \frac{\#\, iterations\, in\, \Delta\, t}{\#\, improvements\, in\, \Delta\, t} \tag{22}$$

Fig. 6 shows the effectiveness index for several time intervals. The reported value is less than 2.1 in all cases, evidencing the effectiveness of the proposed heuristic. In average, it takes only two iterations to reach a better system state.

7.3.4. Experiment 8: search space exploration strategy effectiveness

This experiment considers function OF-02 (14). The test scenario features 19 macrocells, homogeneous architecture (zero picocells), 50 users per sector, implementation IMPL11, and the three heuristics for search space exploration (intensification, diversification, and local search in the reduced neighborhood). The procedure is to start with the same initial state, calculate the performance indicators, and calculate them again at the end of the iterative improvement (with a 5 s time limit). Fig. 7 shows the obtained results. The local search heuristic reports a significant improvement (around 95%) when compared to the intensification (40%) and diversification (32%) heuristics.

After solving the model, about 94% of users achieve full service satisfaction, and only 2% of users do not obtain service. Thus, the iterative improvement impact in this experiment is not significant, with an increase of only 3% with the local search heuristic, 2% with the intensification heuristic, and even less with the diversification heuristic. This is shown in Fig. 8. The results evidence the goodness of Model 2 (14), which achieves high fulfillment levels, even without iterative improvement (it could be omitted in an extreme case).

7.3.5. Experiment 10: fairness in resource allocation

According to Einhaus et al. [85], fairness in resource allocation to users does not necessarily translate into fairness in capacity distribution in the WMCS. In our model, constraint (7) guarantees fair allocation of resources to users; however, we require to evaluate fairness from the transmission capacity point of view. For this, we use Jain's index [86], an indicator to evaluate the fairness of a resource allocation strategy. Advantages of this index include: It has no dependency on the population size, it is independent from the evaluated metric, and its value always lies within the [0, 1] interval. A value of 0 means a totally unfair allocation scheme, while a value of 1 indicates a totally fair allocation scheme. In our case, the index evaluates the fairness of our proposed frequency block allocation strategy, considering the data throughput of the different services as a performance metric. Expression (23) presents Jain's index.

$$Fairness \quad Index = \frac{\left[\sum_{i=1}^{n} X_i\right]^2}{n\left[\sum_{i=1}^{n} X_i^2\right]} \tag{23}$$

where X_i represents the ratio between obtained and required throughput. Experiment 10 aims to evaluate fairness in resource allocation, considering function OF-02 (14). The test scenario features 19 macrocells, homogeneous architecture (zero picocells), 50 users per sector, implementations IMPL9 and IMPL10, and both the intensification and diversification heuristics. Results show a Jain's index of 0.8784 for the intensification heuristic, and 0.8760 for the diversification heuristic. This allows us to deem the formulated approach as fair for transmission capacity allocation.

8. Conclusions and future work

8.1. Conclusions

The article boards the problem of dynamically allocating resources to a population of pedestrian users demanding a diverse set of services, from a WMCS deployed in an urban environment. This task is dynamic, due to the changes the system experiments, and faces multiple challenges. As a performance metric, SINR allows to determine the user satisfaction level (important to users) and resource utilization (important to service operators).

We consider two factors to solve the problem: the engineering factor, in charge of the resource scheduler architecture and functionality; and the optimization factor, in charge of formulating and solving the optimization model for resource allocation.

The resource scheduler, in charge of global resource allocation, performs its task in a medium-term time scale, assuming a quasi-static system state, using a centralized approach, and periodically readjusting the system state, in order to improve service offered to all users.

The article states three important facts: (1) The values for the input parameters are constant during the time interval used for resource allocation, allowing to examine the system in a quasi-static state; (2) It is not possible to have perfect, instantaneous knowledge about the frequency block condition; thus, the central component estimates it; (3) Instead of finding the system configuration yielding the best SINR, this is taken for granted, and the system finds the resource allocation satisfying the service demands for each user. Since this is not possible in all cases, one or more slack variables are used, so the model is always viable, enabling to obtain high performance.

The optimization model is non-linear, mixed. Its characteristics limit obtaining an exact solution in the available time interval, and prevent obtaining a global optimum value. Thus, we adopt an approximate strategy that decouples the search space.

The article formulates a flexible framework for the model solution algorithm. The framework allows integrate: an iterative improvement strategy, that aims to improve a quality index associated with fulfillment of the defined performance metrics; a strategy for frequency block allocation to users; and a strategy for search space exploration.

Power usage is a key aspect to the solution algorithm for technical reasons, related to interference; for economic reasons, related to operational costs; and environmental concerns, related to radiated power levels. For all executions, and all experiments involving the formulated optimization models ((12) and (14)), full power utilization was not required.

To overcome the difficulty arising from exploring a pretty large search space, we define a reduced neighborhood structure, which preserves the goal (generate smaller functional values), and we formulate a heuristic for generating the new system state, involving the critical interference block, an objective and effective criterion to conduct the exploration required to mitigate interference and improve the objective function value. Applying this criterion allows to consistently explore the search space, using less computing effort. We corroborated this through using a search effectiveness index that yielded good results: in average, 2.1 iterations are required to reach a better system state.

The obtained solution corresponds to the best achievable solution in the allotted time interval, by evaluating a promising set of neighbors in the defined neighborhood structure. This solution is acceptable to the system administrator.

8.2. Future work

The problem can be reformulated, in order to simultaneously optimize more than an objective. Full user satisfaction (a service-oriented metric) can be maximized by minimizing generated interference in the system (a performance-oriented metric). In order to do so, a compromise must be reached between the two objectives. Contrary to optimization problems with a single objective, the "optimum" concept is relative, and it is necessary to establish the best solution from the points of view of all involved parties. In addition, the SINR ratio may be reformulated to incorporate the energy consumption of the circuits, and thus fully consider the energy efficiency (EE) of the proposed solution.

The formulated model can be enriched by incorporating additional features in the base station transmission component. Specifically, we consider using MIMO (*Multiple Input Multiple Output*) in the transmitter antennas, to increase the system's spectral efficiency, increasing its transmission rate and decreasing its error rate. We also consider changing the radiation pattern of the transmitter antennas in each cell, by modifying its height, tilt and azimuth.

The proposed experiments were performed using only one computer, and the software did not exploit multiprocessing. There is an interesting option to improve the value of the objective function without incurring into an execution time penalty: use multiprocessing. If only one computer is available, a shared memory approach can be used, so the algorithm can be run on several threads. A variable in shared memory will allow every thread to report the best value they have found, so the best value can be chosen. If several computers are available, grid computing can also be considered. Values found in each computer must be reported to the other computers, using asynchronous messaging. In this case, it is very important to consider the communications overhead, so the solution time is not affected.

As it is possible to select the modulation and coding scheme as a function of the channel and the demanded service, one could also consider the estimated channel state, the user load level and the system architecture, in order to adaptively select the resource allocation strategy and the system architecture, allowing to selectively enable picocells when the system capacity has to be increased due to a growing number of users. Transmission parameters could also be dynamically adjusted, by changing the base station antenna's tilt and azimuth. All these elements may be integrated into a framework, incorporating all described functionality in the scheduler, so the system may operate in an auto-optimized mode. Finally, migration of the communication system infrastructure to the cloud offers an important chance to evaluate application of the model and the solution algorithm described in this work.

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