Resource Allocation for Energy Efficiency and QoS Provisioning

Weskley V. F. Maurício, F. Rafael M. Lima, Taufik Abrão
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***Abstract*—In this paper, we formulate and solve two Energy Efficiency (EE) problems, namely the Power Minimization Problem (PMP) and the Maximization of Energy Efficiency Problem (MEEP), for a wireless system using power and frequency resource allocation considering Quality of Service (QoS) requirements and multiple services. Despite those problems are nonlinear, they can be converted into Integer Linear Problems (ILPs). Therefore, the optimal solution for both PMP and MEEP can be obtained by well-known methods. Additionally, we propose two fast suboptimal algorithms as to avoid the high computational complexity of obtaining optimal solution for MEEP. Our results show that the MEEP has a better trade-off between transmitted data rate and power saving than the PMP solution. Moreover, the suboptimal algorithms present good performance compared to the optimal solution for moderated loads but with a much lower computational complexity, thus achieving a remarkable trade-off between performance and computational complexity.**

***Index Terms*—Radio Resource Allocation, Energy Efficiency, Quality of Service, Multiple Services.**

I. Introduction

Mobile communications have been experiencing an incredible development from the analog First Generation (1G) until the commercial deployment of Fourth Generation (4G) systems. Currently, industry and academia have been focusing its research on the Fifth Generation (5G) of mobile communications [1]. With the advent of 5G and its stringent requirements, we expect networks with higher data rates and Energy Efficiency (EE), improved Quality of Service (QoS) and more powerful devices boosted by the evolution/massification of the digital technology [2] Nowadays, industry forecasts [3] point out an exponential increase in data traffic and for the number of devices connected to the mobile networks daily, thus providing a challenging scenario for the 5G (r)evolution.

It is shown in [4] that there will be a great increase in the devices connected to mobile communications at the end of this year, mainly due to the advent of Internet of Things (IoT), where several kinds of equipment (e.g., cars, drones, portable devices and clothes) will be connected to a cellular network [5]. Therefore, network capacity will need a boost in order to satisfactorily serve all these devices. However, the increase in the network capacity does not come for free: it will be necessary the use of more and more energy resources and this could lead to unacceptable operation costs. Therefore, it will be necessary to use the energy wisely, *i.e.*, EE will be one of the pillars of the future networks [6]. Besides that, since technology and information systems account for about 5% of the global carbon dioxide emission [5], [7], increasing EE is crucial for environmental sustainability. Indeed, energy costs and contributions to global carbon dioxide emissions are emerging major concerns in several areas, including 5G [8].

Technological advances in architecture and radio access technologies able to meet the network requirements are needed to cope with this challenging scenario, among which we highlight Radio Resource Allocation (RRA) as a relevant network functionality. RRA has been successfully used to *optimize* mobile networks in terms of spectral efficiency, fairness, QoS satisfaction, etc. [9], [10] Herein, we employ RRA algorithms to manage the scarce radio resources (power and frequency spectrum) in order to improve the system EE while guaranteeing QoS. Therefore, we deal with the challenge of improving the Spectral Efficiency (SE)-EE trade-off [9].

A. Literature Review

EE can be improved using different strategies such as network planning and development, energy harvesting and RRA [5]. With network planning and development, infrastructure changes are done to maximize the covered area per consumed energy instead of just maximizing the coverage. As an example, power consumption can be reduced through switch-on/switch-off algorithms, where during low traffic periods the system can turn off underutilized Base Stations (BSs) and transfer their loads to neighboring BSs [11]. With energy harvesting, transceivers collect (harvest) energy from the environment, including radio signals, wind and solar energy, and use it for information processing and transmission [7]. Thus, energy harvesting can contribute to EE since it adds new extra source of energy instead of optimizing its use. Finally, RRA is capable of managing the use of radio resources so as to save energy or optimize its use while respecting other system constraints. In this article we focus on RRA solutions for EE optimization.

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In [12], RRA is analyzed from the perspective of data rate maximization considering QoS requirements and satisfaction guarantees. Therein, a percentage of the terminals from each service should be satisfied in terms of data rate requirements. However, only frequency resource assignment is optimized while the transmit power is equally divided among frequency resources. In [13], the RRA problem of [12] is extended to a more challenging setting with the simultaneous optimization of transmit power and frequency resource assignment. Nonetheless, the proposed transmit power optimization in [13] aims at maximizing the spectral efficiency and not EE.

One of earliest efforts towards more efficient use of energy in wireless systems consisted in the power minimization problem subject to QoS constraints, presented in the seminal work of Wong et al. [14]. More recent studies on EE have considered other metrics depending on the system and its characteristics [8]. In urban scenarios, where the data traffic is considerably high, the most appropriate metric of EE is the ratio between transmit data rate and the average transmit power. Regardless of the EE metrics, QoS constraints that ensures an adequate provision of multimedia services should be considered. Depending on the considered metrics and radio resources to be optimized, RRA problems have different degrees of complexity. For example, transmit power optimization considering a link adaptation based on continuous Signal to Noise Ratio (SNR) applied over the Shannon's capacity formula can be solved efficiently and optimally via convex optimization for which many polynomial-time algorithms can be found. The Water Filling power allocation is a representative approach where basically more transmit power is allocated to the channels with better conditions [15]. However, assuming discrete transmission levels or Modulation and Coding Schemes (MCSs), as in practical systems, we may have nonlinear combinatorial optimization problems that are mostly NP-Hard [16]. An exception to this context is the transmit power allocation problem of a point-to-point connection with discrete MCSs, which can be almost optimally solved with Hughes-Hartogs (HH) algorithm [17].

In [18], the EE maximization of a multi-relay Orthogonal Frequency Division Multiple Access (OFDMA) network is studied and a low-complex solution based on Dinkelbach (DKB) and Lagrange Dual Decomposition (LDD) algorithms is provided. The main limitations of [18] are the dependence of the proposed solution on the initial values of the dual variables and step size of the LDD algorithm to provide a fast convergence. In [19], the same problem is studied in an uplink scenario and a procedure to calculate those initial values is provided. In [20], three different metrics of EE maximization are studied in a multi-cell scenario: the ratio between the sum rate and the total power consumption, the weighted sum of the energy efficiencies achieved on each Resource Block (RB) and the exponentially-weighted product of the energy efficiencies achieved on each RB. In [21], it is proposed an RRA scheme to optimize the EE in a millimeter-wave multi-user massive Multiple Input Multiple Output (MIMO) scenario, and their system model considers a Cloud - Radio Access Network (C-RAN)-based scheduling and a hybrid beamforming architecture. In [22], the authors formulate a problem of EE considering the strategy of energy harvesting in a device-to-device communication heterogeneous network. The original formulate problem is not convex, and it is transformed into a convex problem. The proposed solution to solve the convex problem is based on DKB and LDD algorithms. However, the works [18], [19], [20], [21], [22] do not model QoS constraints and multiservice scenario. In [23], the EE maximization problem considering QoS requirements in a multi-cell OFDMA scenario is studied. It is formulated as a probabilistic nonconvex optimization problem and an iterative algorithm is proposed. In [24], the proportional-fair energy efficient RRA problem for uplink in a small cell scenario is studied and a low-complexity heuristic is proposed. In [25], a scheme using online learning to maximize the EE while maintaining QoS requirements in a heterogeneous C-RAN is proposed. The proposed scheme is implemented in centralized and decentralized scenarios. Although the works [23], [24], [25] directly model QoS constraints, neither multi-service scenarios nor discrete link adaptation are considered. In [26] the authors propose a Dinkelbach-based iterative resource allocation algorithm in a mult-icell OFDMA scenario, which finds a solution to the main problem by solving a sequence of subproblems. However, their subproblems are mixed combinatorial and non-convex optimizaton problems to which is necessary an exhaustive search to find the optimal solution. Therefore, they propose a suboptimal solution by splitting the subproblem into three steps: frequency allocation, precoder design and power allocation. However, the authors do not consider MCSs or multiples services. In [27], the EE maximization problem subject to QoS constraints with discrete transmit power allocation and RB assignment is studied. However, although discrete power levels are assumed, the SNR-to-data rate mapping is performed by a continuous function. Additionally, multiservice scenarios are not modeled in [27].

B. Contributions

In summary, none of the presented works in this literature review has jointly considered the EE maximization subject to QoS and satisfaction guarantees in a multiservice scenario with RB assignment and transmit power allocation with discrete MCS levels. This problem will be studied in this article. The considered EE metric is the ratio between the offered data rate and the total consumed transmit power. Moreover, we formulate the total power minimization problem subject to the same constraints. The main contributions of this work are threefold:

(i) Proposal of the optimal solution to the Maximization of Energy Efficiency Problem (MEEP) and the Power Minimization Problem (PMP) considering the joint frequency resource and discrete power allocation, and considering QoS in a multiservice scenario. The solution to the total PMP is obtained after reformulating the original problem, that is nonlinear and integer, as an Integer Linear Problem (ILP). The optimal solution of the MEEP, which is fractional, nonlinear and integer, is obtained by solving a sequence of ILP subproblems;

(ii) Proposal of two efficient low-complexity solutions for the MEEP;

(iii) Performance-complexity tradeoff analyses of the involved solutions for both problems in order to assess the efficiency of the suboptimal solutions.

II. System Modeling and Formulations

Considering the downlink of a Single Input Single Output (SISO) system based on a combination of OFDMA and Time Division Multiple Access (TDMA), the system is composed of sectored cells connected to a BS serving a group of terminals. The available radio resources are organized in a time-frequency grid and an RB is the minimum unity of resource that can be allocated to a terminal. As the system utilizes OFDMA, the BS can serve different terminals by the assignment of distinct RBs without causing interference among them, i.e., there is no intra-cell interference within a sector. Figure 1 illustrates the considered system model and RRA, where we have a BS employing RRA assigning frequency, and power to terminals as to satisfy the QoS requirements of different types of services. Furthermore, "T." refers to terminals and f(frequency and power allocation) is a generic function that maps the channel gain in a given frequency and the power allocated to it on data rate.

We consider the simplifying assumption that the thermal noise term in the SNR expression already takes into consideration the inter-cell interference. We emphasize that this simplifying consideration becomes increasingly valid as the number of BS per square meters increases [28]. In 3rd Generation Partnership Project (3GPP) distributed networks, there are schemes to mitigate the interference, such as Intercell Interference Coordination (ICIC) [29] and Enhanced ICIC (eICIC) [30], [31]. On basic approach is to avoid the simultaneous reuse of some RBs by neighbor cells. Therefore, our single-cell consideration is also a valid model for a multi-cell scenario [7].

The RRA problems considered in this work are ILP and this class of problems has exponential worst-case computational complexity [32]. Hence, the optimal solution, that is utilized as an upper bound in performance to the proposed low-complexity algorithms, can only be obtained for a reduced number of terminals, RBs and MCS levels. Thus, as the time to find a solution grows exponentially with the problem size and due to computational limitation, it is impracticable to obtain the optimal solution considering a multi-cell scenario.

For RRA be implemented in practice, it is necessary an entity with processing power to execute algorithms such as those proposed in this article. This entity is typically located at the BS where decisions are made, such as users scheduling, RB assignment, power allocation, and others. These decisions are executed and impact on different system layers. In practical scenarios, the data link layer has a sublayer called medium access control that is responsible for the RRA. Information of different types and layers are required to serve as input to these algorithms. As an example, we can cite Channel State Information (CSI) measurements, amount of data in the transmission buffers, average QoS and satisfaction level, among others. The physical layer is responsible for the transmission and reception, managing the circuits power consumption associated to it. The main power consumption entities in a BS are the digital baseband, radio frequency chain, power amplifier, and overhead (power systems and cooling) [33]. Furthermore, according to [33], in a macro BS, the power amplifiers are responsible for the power consumption of more than 50% of its power. Therefore, the energy spent on RRA processing and decision making is an insignificant fraction of the total energy spent on a BS.

We assume that in a given Transmission Time Interval (TTI) there are J terminals competing to get RBs out of the N available ones. Furthermore, we define the sets of available RBs and terminals as $\mathcal{N}$ and $\mathcal{J}$, respectively. We consider that the set of all services provided by the system operator is $|\mathcal{S}| = S$, where $|\cdot|$ denotes the cardinality of a set. Moreover, the set of terminals belonging to service s is $\mathcal{J}_s$ and $|\mathcal{J}_s| = J_s$. Note that $\bigcup_{s\in\mathcal{S}} \mathcal{J}_s = \mathcal{J}$ and $\sum_{s\in\mathcal{S}} J_s = J$. Moreover, also notice that for scalar values $|x|$ denotes the absolute value.

The received SNR $\gamma_{j,n}$ of terminal j on its assigned RB n is

$$\gamma_{j,n} = \frac{\alpha_j \; p_n \; |h_{j,n}|^2}{\sigma_j^2}, \tag{1}$$

where α_j represents the combined effect of shadowing and path gain between the BS and terminal j, $h_{j,n}$ is the short-term fading channel response of terminal j on RB n, σ_j^2 is the noise power at terminal j and finally p_n is the transmit power allocated to the RB n.

The channel state information is collected by Channel Quality Indicator (CQI) reporting, where each terminal observes its Signal to Interference-plus-Noise Ratio (SINR) and send a CQI to the BS. This quality information is a 4-bit integer and is used to indicates a suitable MCS value (transmission data rate). Therefore, the reported CQI is used by the BS to calculate the MCS, which is used by the RRA (scheduler) [34]. We assume that the system has a link adaptation feature that chooses the highest MCS level that assures an estimated BLock Error Rate (BLER) lower than a given fixed BLER target. Therefore, different transmit data rates can be achieved depending on the SNR interval. Table I contains the modulation, CQI index, Effective Coding Rate (ECR) and number of transmitted bits per TTI for the 15 MCS schemes employed in Long Term Evolution (LTE) system.

TABLE I
MCS TABLE [35].

CQI Index	Modulation	ECR	Transmitted number of bits
1	QPSK	0.0762	25
2	QPSK	0.1172	39
3	QPSK	0.1885	63
4	QPSK	0.3008	101
5	QPSK	0.4385	147
6	QPSK	0.5879	197
7	16QAM	0.3691	248
8	16QAM	0.4785	321
9	16QAM	0.6016	404
10	64QAM	0.4551	458
11	64QAM	0.5537	558
12	64QAM	0.6504	655
13	64QAM	0.7539	759
14	64QAM	0.8525	859
15	64QAM	0.9258	933

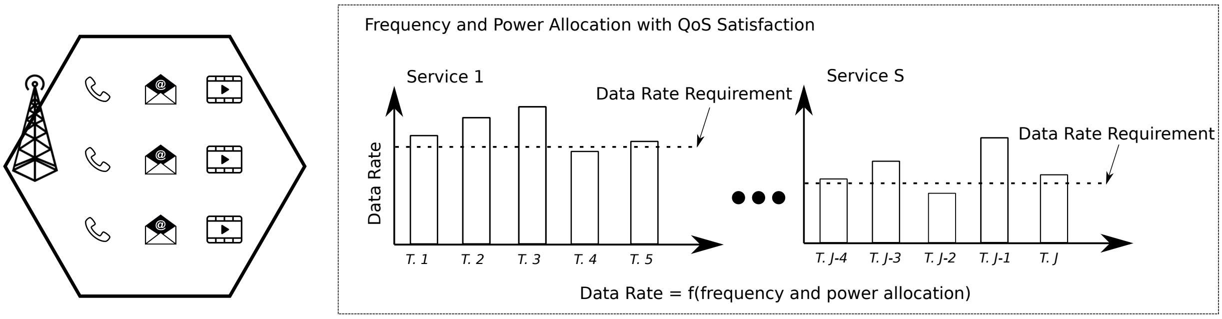


Fig. 1. System Model and RRA

Consider in this study that there are M MCS levels and, consequently, M transmit data rates different of zero. $\mathcal{M} = \{1, 2, \cdots, M\}$ is the set of all MCS. According to our model, the m^{th} MCS level is used when the estimated SNR is between γ_m and γ_{m+1} with $\gamma_m < \gamma_{m+1}$.

Note that, as the MCSs belongs to a discrete set, we can also model the transmit power as a discrete variable. As previously commented, the link adaptation feature with a target BLER can select the MCS based on SNR regions. Due to this fact, it is acceptable that the transmit power to achieve a given MCS is the lowest value capable of produce a SNR that satisfy the BLER requirement. Therefore, the minimum transmit power $\lambda_{j,n,m}$ allocated to terminal j on RB n so as to employ the MCS m can be defined as

$$\lambda_{j,n,m} = \frac{\gamma^m \, \sigma_j^2}{\alpha_j \, |h_{j,n}|^2}. \tag{2}$$

In this context, we can introduce $\mathbf{Y}$ as a $J \times N \times M$ assignment tensor with elements $y_{j,n,m}$ that has the value 1 if terminal j gets assigned RB n and the MCS m is employed. The assignment tensor $\mathbf{Y}$ is the optimization variable of both PMP and MEEP. Moreover, the total available power at the BS is defined as P^{tot}.

A. Problem Formulation

Two optimization problems are developed in this subsection. The first one is the PMP, whose objective is to minimize the total transmit power. The second one is the MEEP, which aims at maximizing the ratio of total transmit data rate and the total utilized power. Both of these problems are subject to a minimum number of satisfied terminals per service, provided by a system operator in a given TTI.

In this paper, we assume an adaptive power and RB allocation. Let us define t_j as the data rate requirement of terminal j at a given TTI. Although we assume instantaneous data rate requirements, the authors in [36] show that time-averaged data rate requirements can be converted to instantaneous data rate requirements. Let us define the minimum number of terminals from service s that should be satisfied as k_s. Moreover, the index of terminals are sequentially disposed according to the service.

Using the definitions above, the PMP can be mathematically formulated as

$$\min_{y_{j,n,m}} \sum_{j\in\mathcal{J}} \sum_{n\in\mathcal{N}} \sum_{m\in\mathcal{M}} \lambda_{j,n,m} \, y_{j,n,m}, \tag{3a}$$

$$\text{s. t.} \sum_{j\in\mathcal{J}} \sum_{n\in\mathcal{N}} \sum_{m\in\mathcal{M}} y_{j,n,m} \, \lambda_{j,n,m} \leq P^{\text{tot}}, \tag{3b}$$

$$\sum_{j\in\mathcal{J}} \sum_{m\in\mathcal{M}} y_{j,n,m} \leq 1, \; \forall n \in \mathcal{N}, \tag{3c}$$

$$\sum_{j\in\mathcal{J}_s} u\left(\sum_{n\in\mathcal{N}} \sum_{m\in\mathcal{M}} \nu_m \, y_{j,n,m}, \; t_j\right) \geq k_s, \; \forall s \in \mathcal{S}, \tag{3d}$$

$$y_{j,n,m} \in \{0,1\}, \; \forall j \in \mathcal{J}, \forall n \in \mathcal{N}, \forall m \in \mathcal{M}, \tag{3e}$$

where $u(x,b)$ is a Heaviside function at b that assumes the value 1 if $x \geqslant b$ and 0 otherwise, and ν_m is the transmitted number of bits considering the MCS m. In (3a), we minimize the total transmit power from the BS. Constraints (3b) and (3c) guarantee that the total transmit power limit is obeyed and that each RB should be associated to only one terminal and MCS level. Constraints (3d) and (3e) guarantee for each service, a minimum number of terminals satisfied in terms of their QoS constraints and that the optimizations variables are binary, respectively.

The second problem studied in this article, the MEEP, has the same set of constraints as problem (3). However, the main objective is to minimize the ratio of the total transmit power from the BS and the total transmit data rate in the downlink, that is equivalent to maximize the total EE. Therefore, the MEEP problem can be stated as

$$\min_{y_{j,n,m}} \frac{\sum\limits_{j\in\mathcal{J}} \sum\limits_{n\in\mathcal{N}} \sum\limits_{m\in\mathcal{M}} \lambda_{j,n,m} \, y_{j,n,m}}{\sum\limits_{j\in\mathcal{J}} \sum\limits_{n\in\mathcal{N}} \sum\limits_{m\in\mathcal{M}} \nu_m \, y_{j,n,m}}, \tag{4a}$$

$$\text{s. t. (3b), (3c), (3d) and (3e).} \tag{4b}$$

Problems (3) and (4) are optimization problems with integer (binary) variables $y_{j,n,m}$, thus belonging to the category of combinatorial optimization problems. Generally, optimization problems of this class are known to be very hard to solve optimally. Practically, exhaustive search over all possible RB assignments and MCS allocations (power allocation) can be used to obtain the optimal solution. The complexity of the problems (3) and (4) are increased because of the nonlinear and nonconvex constraint (3d). Problem (4) has an additional difficulty because of the fractional objective function (4a). The methods to obtain the optimal solution are presented in the next section.

B. PMP Optimal Solution

The non linearity of constraint (3d) increases the computational complexity to obtain the optimal solution. Therefore, we introduce a new optimization variable to linearize this constraint and reduce its complexity. Assume $\boldsymbol{\rho} = \begin{bmatrix}\rho_1 & \cdots & \rho_J\end{bmatrix}^T$, where ρ_j is a binary selection variable that assumes the value 1 if terminal j is selected to be satisfied and 0 otherwise. In this way, the PMP can be reformulated by substituting the constraint (3d) by the following three new constraints

$$\sum_{n\in\mathcal{N}}\sum_{m\in\mathcal{M}} \nu_m\, y_{j,n,m} \geq \rho_j\, t_j,\ \forall j \in \mathcal{J}, \tag{5a}$$

$$\sum_{j\in\mathcal{J}_s} \rho_j \geq k_s, \quad \forall s \in \mathcal{S}, \tag{5b}$$

$$\rho_j \in \{0,1\}, \quad \forall j \in \mathcal{J}. \tag{5c}$$

With the linearization of (3d), the PMP becomes an ILP that can be solved optimally by standard solvers mainly based on Branch and Bound (BB) [37]. This method has a much lower average computational complexity than the full enumeration or brute force method. Appendix A contains the computational complexity analysis to obtain the PMP optimal solution.

C. MEEP Optimal Solution

We used the method proposed by Anzai et al. in [38] to linearize the fractional objective function and find the optimal solution to the MEEP. Therefrom, the fractional objective function can be replaced by the difference between the numerator and denominator multiplied by a weight. Thus, the MEEP can be reformulated as

$$\min_{y_{j,n,m},\rho_j} \ P - \beta\, V, \tag{6a}$$

$$\text{s. t.} \sum_{j\in\mathcal{J}}\sum_{n\in\mathcal{N}}\sum_{m\in\mathcal{M}} y_{j,n,m}\,\lambda_{j,n,m} \leq P^{\text{tot}}, \tag{6b}$$

$$\sum_{j\in\mathcal{J}}\sum_{m\in\mathcal{M}} y_{j,n,m} \leq 1,\ \forall n \in \mathcal{N}, \tag{6c}$$

$$\sum_{n\in\mathcal{N}}\sum_{m\in\mathcal{M}} \nu_m\, y_{j,n,m} \geq \rho_j\, t_j,\ \forall j \in \mathcal{J}, \tag{6d}$$

$$\sum_{j\in\mathcal{J}_s} \rho_j \geq k_s, \quad \forall s \in \mathcal{S}, \tag{6e}$$

$$\rho_j \in \{0,1\}, \quad \forall j \in \mathcal{J}, \tag{6f}$$

$$y_{j,n,m} \in \{0,1\},\ \forall j \in \mathcal{J}, \forall n \in \mathcal{N}, \forall m \in \mathcal{M}. \tag{6g}$$

where β is a weight, $P = \sum\limits_{j\in\mathcal{J}}\sum\limits_{n\in\mathcal{N}}\sum\limits_{m\in\mathcal{M}} \lambda_{j,n,m}\, y_{j,n,m}$ and $V = \sum\limits_{j\in\mathcal{J}}\sum\limits_{n\in\mathcal{N}}\sum\limits_{m\in\mathcal{M}} \nu_m\, y_{j,n,m}$.

According to [38], for a specific value of β, the optimal solution of problems (4) and (6) are the same. Solving (6) instead of (4) is much simpler, since problem (6) is an ILP. In order to find the weight β and optimally solve the MEEP, the following steps should be performed:

(a) In the first iteration β is a large enough number.
(b) Find the optimal solution $y^{\star}_{j,n,m}$ of (6). If the objective function (6a) is positive, stop the algorithm and $y^{\star}_{j,n,m}$ is the optimal solution of (4). Otherwise, go to step (c).
(c) Update P and V with the new solution $y^{\star}_{j,n,m}$, update β as $\frac{P}{V}$ and go back to step (b).

Note that, according to [38], the convergence to obtain the optimal solution through this method is guaranteed if the solution space of optimization problem is limited. As the search space of MEEP is limited due to the power and QoS constraints, the convergence of our proposed optimal solution is guaranteed. Thus, the method proposed by [38] is able to solve integer fractional problems by solving a sequence of ILP subproblems. Appendix B contains the computational complexity analysis to obtain the MEEP optimal solution.

III. Proposed Low-Complexity Solutions

Although the optimal solution to the MEEP obtained according to Section II is less complex than the one achieved with brute force method, its complexity is still exponential in terms of the input variables.

Motivated by this, in this section, two new low-complexity quasi-optimal heuristics are proposed for solving the MEEP. However, before that, we show a strategy to decrease the complexity to obtain a solution to MEEP without significant loss of optimality.

A. Pre-Selection of Terminals for Complexity Reduction

In a similar way to [39] and using the main aspects presented in Section II, we observed the behavior of the optimal solution by performing numerical simulations. We assume $J = 8$ terminals using the same service type $(S = 1)$ inside a cell sector with $N = 15$ available RBs. It is important to emphasize that this simplifying approach is considered only to this analysis, i.e., the performance evaluation in Section IV considers multiple services. It is analyzed 3000 independent snapshots with terminals uniformly distributed inside a cell. The results considered here are the outage rate and the total EE. The outage rate is the percentage of the independent snapshots where the algorithms are not able to satisfy the constraints of the problem (4). The total EE is the ratio of the total downlink transmit data rate and the total transmit power at the BS in a given snapshot. The system load is emulated by increasing the terminals' required data rate, which is assumed to be equal to all terminals.

This analysis aims at evaluating the system performance in terms of outage rate and EE when we discard some of the terminals of the set $\mathcal{J}$. Discarding a terminal j means that it will not be considered for RRA. However, the constraints of (4) should not be violated with this procedure. Consider that "MEEP OPT" and "MEEP Selec." are the optimal solutions obtained according to Section II-C assuming all terminals in the problem and assuming that only k terminals (the minimum number of terminals that should be satisfied per service) were chosen to solve the problem, respectively. The pre-selection method is done by picking the k out of J terminals with

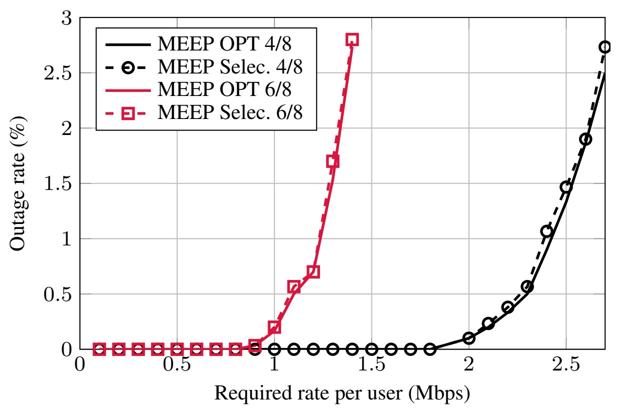


Fig. 2. MEEP Behavior: analysis of outage rate percentage *vs* data rate requirements per terminal for the optimal MEEP solution and the optimal MEEP after the pre-selection of the best k_s terminals.

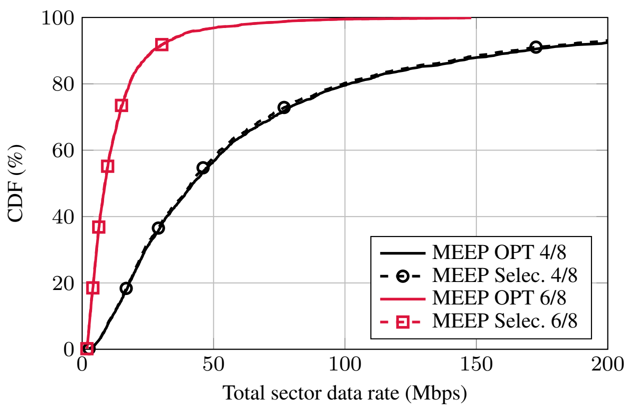


Fig. 3. MEEP Behavior: CDF total EE *vs* data rate requirements per terminal for the optimal MEEP solution and the optimal MEEP after the pre-selection of the best k_s terminals to a required data rate of 1.5 Mbps.

highest ratio between the average SNR $\overline{\gamma}_j$ and the data rate requirement t_j. The average SNR is given by

$$\overline{\gamma}_j = \frac{1}{N} \sum_{n \in \mathcal{N}} \frac{\alpha_j \, |h_{j,n}|^2}{\sigma_j^2}. \quad (7)$$

Our objective with the terminal discard method is to remove from the allocation process the terminals that are most difficult to get the QoS requirements fulfilled. In Fig. 2 we evaluate the outage performance varying the data rate requirements per terminal for “MEEP OPT” and “MEEP Selec.” assuming $J = 8$ and $k = 4$, identified as “4/8” in the figure, and $J = 8$ and $k = 6$, identified as “6/8”. Here, the performance of the “MEEP Selec.” is approximately optimal in both scenarios. Note that the scenario “4/8” has a large degree of freedom to perform the allocation process than the scenario “6/8”, which leads to a performance degradation of “MEEP Selec.” as it can be seen in Fig. 2. Nevertheless, in practical scenarios, the system operators generally require a satisfaction ratio higher than 80%, which is considerably greater than the satisfaction ratio of 50% demanded in scenario “4/8” [40].

In Fig. 3, we evaluate the Cumulative Distribution Function (CDF) of the total EE with a varying data rate requirement per terminal for “MEEP OPT” and “MEEP Selec.” in the same scenario. Fig. 3 shows that the “MEEP Selec.” has approximately the same performance in both scenarios. Therefore, there is no substantial performance loss between the original MEEP and the MEEP after selection of k_s terminals.

It is noteworthy that this *quasi*-optimal pre-selection method also be applied in a scenario with multiple services by choosing the best k_s terminals of each service $s \in \mathcal{S}$. Consider that $\tilde{\mathcal{J}}_s$ is the new terminal set with size $\tilde{J}_s$ after selecting the k_s best terminals from $\mathcal{J}_s$, and that $\tilde{\mathcal{J}} = \bigcup_{s\in\mathcal{S}} \tilde{\mathcal{J}}_s$ and $\tilde{J} = \sum_{s\in\mathcal{S}} \tilde{J}_s$. The benefit of this pre-selection method is that the optimization problem to be solved has its dimension and complexity reduced. With this method, besides reducing the number of optimization variables, we can also remove the slack variables $\boldsymbol{\rho}$ and constraints (6e) and (6f) from the optimization problem. In the next section, our proposed low-complexity solution incorporates this strategy.

B. Low-Complexity Algorithms to MEEP

The proposed low-complexity solutions to MEEP are composed of three parts. In part 1, depicted in Fig. 4, we adopt an initial RB allocation considering that each terminal should receive a minimum number of RBs to obtain a data rate equal to its requirement based on the assumption that it is able to transmit on the RBs at the highest MCS level. In part 2, presented in Fig. 5, we assign some or all the remaining RBs while applying an adaptive transmit power allocation among RBs in order to satisfy minimally the system QoS requirements, i.e., using the lowest possible transmit power to meet them. Note that, parts 1 and 2 are also present as part of the suboptimal solution for the Joint RB Assignment and Power Allocation Problem (JRAPAP) for Rate Maximization with QoS constraints in our previous work [13]. Part 3 branches into two different algorithms, as it will be explained in Sections III-B1 and III-B2.

We start with the description of the first part of the proposed algorithm, where in step 1 it is applied the pre-selection of terminals according to Section III-A, i.e., the k_s terminals with highest $\overline{\gamma}_j/t_j$ ratio for each service $s \in \mathcal{S}$ are selected. Then, we define the auxiliary set $\mathcal{A}$ that is composed of the pre-selected terminals. In step 2, we define a set $\mathcal{B}$ with all available RBs in the system. After that, the algorithm in step 3 estimates the minimum number of RBs needed by each terminal to satisfy its data rate requirements considering the hypothesis that they are able of using the highest MCS, i.e., it implies that the minimum number of RBs needed to satisfy the data rate requirement t_j for terminal j is equal to t_j/ν_M. Therefore, this step has as objective to know the minimum number of RBs that are necessary to satisfy each terminal. In step 4 it is tested if set $\mathcal{A}$ is empty while the same test is performed for set $\mathcal{B}$ in step 5. In steps 6 and 7 we assign the terminal whose data rate requirement is more difficult to fulfill, i.e., the one with lowest $\overline{\gamma}_j/t_j$, to its RB with highest channel gain. Basically, terminals with low values for $\overline{\gamma}_j/t_j$ have poor channel conditions and thus, few RBs in good conditions, and also require more RBs to become satisfied. In step 8, we check if the chosen terminal in step 6 has the minimum number of RBs, according to step 3. If so, this terminal is removed from

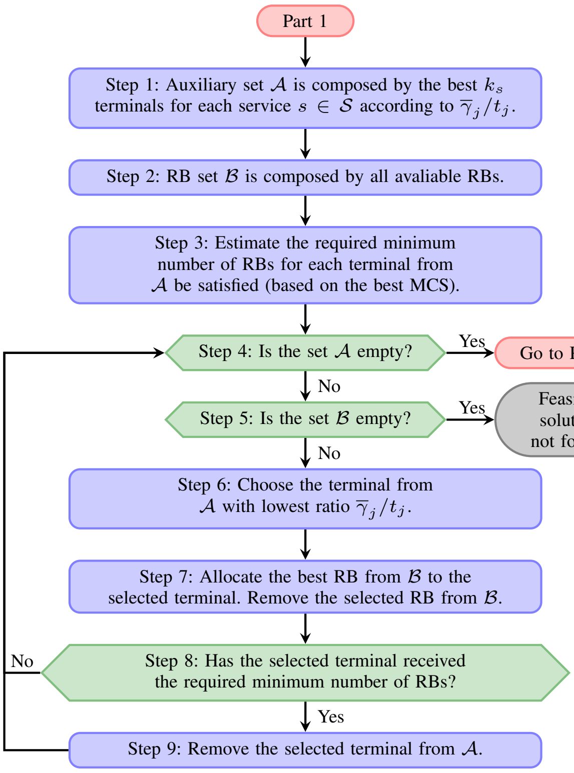


Fig. 4. Part 1 of the suboptimal algorithm for MEEP.

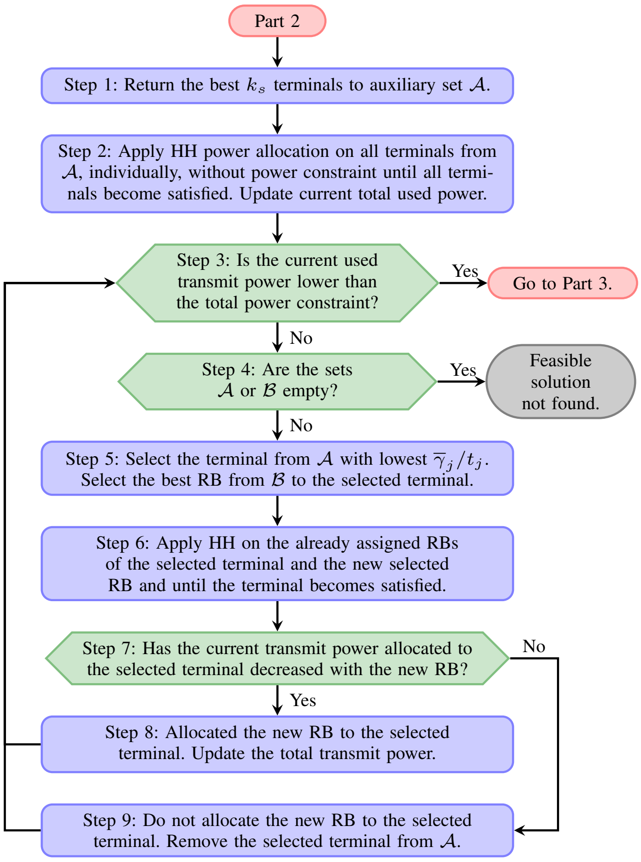


Fig. 5. Part 2 of the suboptimal algorithm for MEEP.

$\mathcal{A}$ in step 9. Otherwise, this terminal still needs to receive more RBs. Note that, an outage event happens when the set $\mathcal{B}$ is empty, and there are still terminals in set $\mathcal{A}$. I the end of this section we provide a discussion on how the proposed algorithm can act in such cases.

Once part 1 is finished, the terminals have got assigned their required minimum number of RBs and, it is possible that there are still available RBs. In steps 1 and 2 of part 2, shown in Figure 5, the best k_s terminals are re-added to the auxiliary set $\mathcal{A}$ and we allocate the transmit power to the RBs of each one of them according to HH algorithm [17], neglecting the total available power constraint and assuming that transmit power is allocated until the required data rate of each terminal is met. In step 3 we check if there was a violation of the total available power P^{tot} of the BS. If so, in step 4, we evaluate if $\mathcal{A}$ and $\mathcal{B}$ are empty. If so, an outage event happens. In the end of this section we provide a discussion on how the proposed algorithm can act in such cases. Step 5 uses the previous idea presented in steps 6 and 7 of part 1 to select a terminal, i.e., it chooses the terminal with lowest $\overline{\gamma}_j/t_j$, and associate it to the RB from $\mathcal{B}$ with best channel quality. In step 6 the HH algorithm is applied for the chosen terminal considering the already assigned RBs and the new RB (selected in step 4). The HH solution is executed until the terminal achieves its data rate requirement. If the newly selected RB is in good channel conditions, it is likely that the total transmit power allocated to the terminal will decrease. Therefore, step 7 checks if this new allocation (RB and power) was capable of decreasing the total allocated power. If so, step 8 assigns this new RB to the chosen terminal and update the total BS power P^{tot}. Otherwise, in step 9, as no more power saving can be obtained by assigning new RBs to the chosen terminal, this terminals is taken out of $\mathcal{A}$, and the RB is not assigned to it. The algorithm keeps testing if the addition of new RBs is capable of decreasing the total used power. Finally, we proceed to part 3 if the total used power is lower than the total available one.

Therefore, if part 3 is reached, we have an initial solution to the MEEP that satisfies the constraint (3d) and uses a low transmit power. Based on this assumption, we can reformulate the MEEP without QoS and satisfaction constraints. In Sections III-B1 and III-B2, we present the branches (part 3) of the two suboptimal solutions to the MEEP.

In some problem instances, the proposed solution may not be able to satisfy all constraints of MEEP, i.e., not able to find a feasible solution. In these situations, we propose to decrease the data rate requirements of all terminals. In this case the new data rate requirement would be the original data rate requirement multiplied by a factor Ψ, where $0 < \Psi < 1$. Then, our proposed solution can be executed again to evaluate if the new required data rates can be satisfied. Depending on τ, we expect to satisfy the system QoS requirements with the limited RBs and available transmit power. Appendix C contains its computational complexity analysis.

1) MEEP heuristic 1: The third part of the first MEEP heuristic has the steps shown in Fig. 6. In the step 1, we allocate the remaining RBs (that were not associated to any terminal yet) to their terminals with best channel quality.

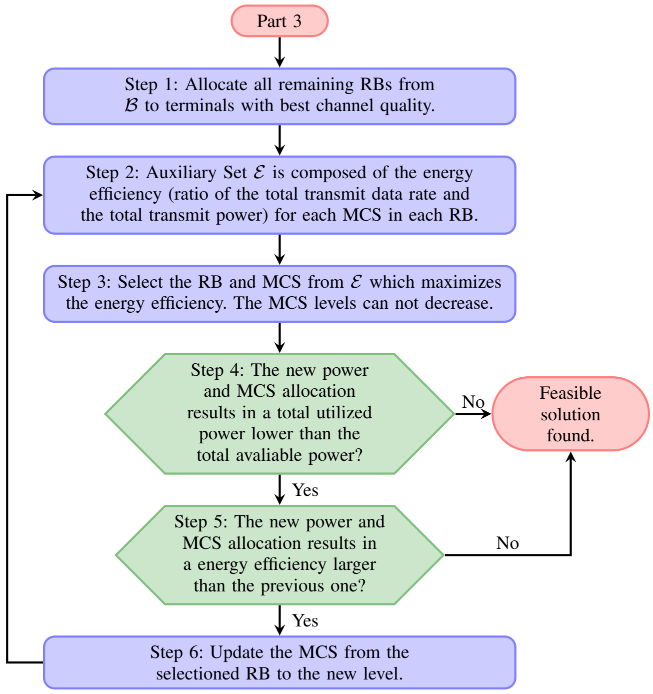


Fig. 6. Part 3 of heuristic solution 1 to MEEP.

Assuming that the RB n was configured with MCS level m_n in the solution of part 2, in step 2 of part 3, for each RB, we estimate the total EE when the MCS level of the RB is increased by one until it reaches the maximum MCS M. Meanwhile, the MCS levels of the other RBs are maintained. The EE estimations of all possible combinations are stored in the set $\mathcal{E}$. In step 3, we select the MCS from the RB which provides the highest increase in terms of EE, based on $\mathcal{E}$. It is important to mention that in this step, the terminals' data rate cannot be decreased as that would leave them unsatisfied. This is the reason for estimating the EE when the MCS level of an RB n varies from n_m to M (not lower than n_m). Step 4 is responsible for testing whether the new power allocation violates the total available power constraint (3b). If so, the algorithm ends with a feasible solution, without updating the MCS level. Otherwise, in step 5, we test whether this new power allocation and MCS are capable of increasing the total system EE, i.e., we test whether the total system power is more efficiently allocated than in the previous iteration. If so, in step 6, we assign the new selected MCS to the chosen RB and the algorithm keeps testing if it is possible to increase the EE through power and MCSs allocations. Otherwise, the algorithm ends and a feasible solution is found. Appendix E contains its computational complexity analysis.

2) MEEP heuristic 2: Part 2 of low-complexity algorithm in Section III-B gives us a feasible solution which minimizes the consumed power. Therefore, we propose to use this solution as the initial solution of the Anzai's method and solve the optimization problem (6). As the solution of part 2 already satisfies the terminals' QoS requirements, we can omit the constraints (6d), (6e) and (6f). Furthermore, as the RB assignment is already defined, we recast the problem to a power allocation problem solved by HH algorithm with the additional constraint that the initial MCS levels in each RB could not decrease, as this would reduce the transmit data rate and violate the QoS requirements of some terminals. Appendix D contains its computational complexity analysis.

Therefore, we can adapt and use the algorithm of [38] to obtain the third part of the second MEEP heuristic, following the steps below

(a) Initially assume that β is a large enough number.
(b) Compute the current value of objective function $P - \beta\, V$, where P and V are defined as in Section II-C using the current solution.
(c) Find the suboptimal solution to the problem, $y^{\diamond}_{j,n,m}$, using HH algorithm, with the additional stop criterion that the current allocated power needs to be lower than the previous one.
(d) Test whether the new objective function, $y^{\diamond}_{j,n,m}$ is positive, i.e., a suboptimal solution to the problem and stop the algorithm if so. Otherwise, go to step (e).
(e) Update P, V and β according to $\beta = \frac{P}{V}$ and go back to step (b).

C. Convergence of Low-Complexity Algorithms

The proposed low-complexity solutions to MEEP are composed of three iterative parts. In part 1 there are two sets, $\mathcal{A}$ and $\mathcal{B}$, with a finite number of elements. At each iteration one element is removed from both sets. If the set $\mathcal{A}$ becomes empty, the algorithm moves to part 2. On the other hand, if the set $\mathcal{B}$ becomes empty, no feasible solution is found and the proposed heuristic ends.

In part 2, there are two auxiliary sets, $\mathcal{A}$ and $\mathcal{B}$, with a finite number of elements. At each iteration of part 2, one element of $\mathcal{A}$ or $\mathcal{B}$ is removed. In this part, if $\mathcal{A}$ or $\mathcal{B}$ becomes empty, no feasible solution is found and the algorithm ends. On the other hand, if the power constraint is achieved, then the algorithm goes to part 3.

Note that, parts 1 and 2 of the proposed solutions iterate a finite number of steps until no feasible solution is found or the algorithm flow moves to part 3. These parts are common to both proposed MEEP heuristics, which differs only in their last part. In the first MEEP heuristic, the part 3 reaches the end of the algorithm when the algorithm tries to allocate more power to a given RB and the EE is not improved. Thus, as the search space is finite, the algorithm improves his EE until convergence. In its turn, in the second MEEP heuristic, the part 3 is based on the method proposed by [38] and the search space is limited due to the power constraint. Therefore, both proposed heuristics cannot decrease their EE, then their EE is always improved until reach the convergence.

IV. Performance Evaluation

In this section we evaluate the performance of the optimal solution to PMP, and optimal and low-complex suboptimal solutions to MEEP. Our main focus is on the existing trade-offs of optimizing the total used transmit power and the EE, as well as evaluating the performance of the low-complexity solutions to the MEEP. In Section IV-A we show the main simulation assumptions whereas in Section IV-B we show and discuss the simulation results.

TABLE II
MAIN SIMULATION PARAMETERS.

Parameter	Value	Unit
Cell radius	334	m
Total transmit power	$0.35\ N$	W
Number of subcarriers per RB	12	-
Number of MCS levels	15	-
Shadowing standard deviation	8	dB
Path loss	$35.3 + 37.6\ \log_{10}(d)$	dB
Noise spectral density	$3.16 \cdot 10^{-20}$	W/Hz
Number of snapshots	3000	-

A. Simulation description

The simulation scenario is the downlink of one sector deployed in a tri-sectorized cell of a cellular system. We performed several snapshots with the terminals evenly distributed inside a cell sector with its BS placed at the corner. We consider the specifications in [41], where each RB is composed of a group of consecutive Orthogonal Frequency Division Multiplexing (OFDM) symbols and 12 adjacent subcarriers.

Channel manifestations such as distance-dependent path loss model, a log-normal shadowing component and a Rayleigh-distributed fast fading component are considered in a propagation model. We consider that the system has a link adaptation feature based on the report of 15 discrete CQIs used by the LTE [35], shown in Table I. We also assume that the SNRs threshold to switch from one MCS to another can be obtained in [42]. The most relevant parameters utilized in the simulation are summarized in Table II.

The suboptimal solutions presented in Sections III-B1 and III-B2 are identified in the plots by PROP1 and PROP2, respectively. The optimal solution of the PMP is identified in the plots by PMP OPT. In order to perform a fair comparison among different solutions, we utilized the same channel realizations for all algorithms. The IBM ILOG CPLEX Optimizer [37] is used to solve the ILPs. The computational complexity to obtain the optimal solutions is a limitation factor for the choice of the number of RBs, terminals and services.

Four performance metrics are evaluated: the percentage of unused power, the total data rate, the outage rate and the total EE. The percentage of unused power is the ratio between the saved transmit power (non-used transmit power) and the total available transmit power at the BS. The total data rate is the sum of the transmit data rate of all terminals. The outage rate and total EE were defined previously in Section III-A. Finally, by increasing the data rate requirements of the terminals we are able to simulate high loads where the demand for RBs and transmit power is augmented.

Our proposed solutions are evaluated over different conditions, therefore, in Table III we present some scenarios where the main parameters of our model are changed.

B. Results and Discussion

In Fig. 7, we show the CDFs of total data rate for all algorithms in scenario 5 with required data rate of 100 kbps and 600 kbps. One observation that is valid for all scenarios is that, PMP OPT provides the lowest data rate. This is expected,

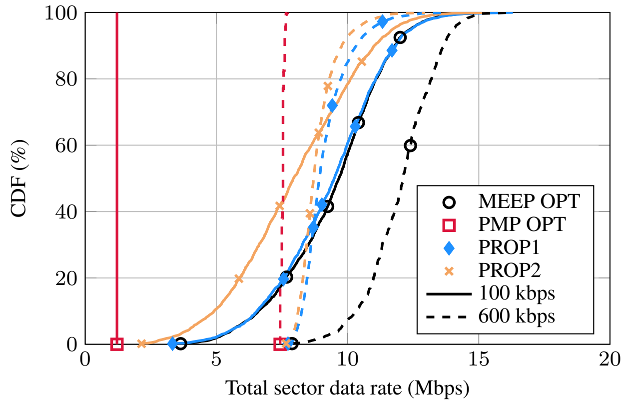


Fig. 7. CDF of total data rate to a required data rate equal to 100 and 600 kbps in scenario 5 to the algorithms MEEP OPT, PMP OPT, PROP1 and PROP2 with four services ($S = 4$).

since this solution aims at delivering only the minimum required data rate to the terminals to save transmit power. This is not the case for the MEEP solutions, since not necessarily saving power leads to maximum EE. The performance gain at the 50th percentile of the total data rate of MEEP OPT, PROP1 and PROP2 solutions relative to the PMP OPT solution are 697%, 683% and 555% for the required data rate of 100 kbps and 61%, 18% and 15% for the required data rate of 600 kbps, respectively. From the analysis of the results in Fig. 7, we can see that our proposed solutions PROP1 and PROP2 perform near optimally (compared to MEEP OPT) for low rate requirements and suffers a performance degradation for high loads.

In Fig. 8, we present the percentage of unused power *versus* the data rate required by each terminal for all solutions in scenario 5. One general observation is that PMP OPT provides the best performance when we consider the unused power, since power economy is directly modeled in the objective function of the PMP, as shown in (4a). Moreover, we can see that the percentage of unused power decreases with the data rate requirements of the terminals. The reason is that, as the QoS demands of the terminals increase, the task of satisfying the problem constraints becomes more difficult and, consequently, more transmit power is used. However, this optimized transmit power usage in PMP OPT leads to low total transmit data rates, as observed in Fig. 7. As we will show next, this behavior impacts on the EE performance. Considering the required data rate by the terminals of 400 kbps in scenario 5, we see that the solution PMP OPT is capable of saving 82.2% of the total available power while the solutions MEEP OPT, PROP1 and PROP2 save 77%, 76.89% and 75.66%, respectively.

Fig. 9 shows the total EE CDFs for all algorithms in scenario 1 for a required data rate per terminal of 100 kbps and 1 Mbps. A general observation is that, for all remaining figures, the MEEP OPT algorithm provides the best performance in EE terms. Basically, the total EE is the objective function (4a) of the MEEP. The performance gains of MEEP OPT in the 50th percentile of EE relative to solutions PMP OPT, PROP1 and PROP2 are 300%, 8% and 14.5%, for a required data of 100

TABLE III
SIMULATED SCENARIOS.

Scenario	S	J_1	J_2	J_3	J_4	k_1	k_2	k_3	k_4	N	**Required data rate**
1	2	4	4	-	-	3	3	-	-	15	All terminals demand the same data rate
2	3	3	3	3	-	3	3	2	-	15	All terminals demand the same data rate
3	3	3	3	3	-	3	3	2	-	15	Terminals from service 3 demand a data rate 250 kbps higher than those from services 1 & 2
4	4	3	3	3	3	3	3	2	2	20	All terminals demand the same data rate
5	4	3	3	3	3	3	3	3	3	20	All terminals demand the same data rate

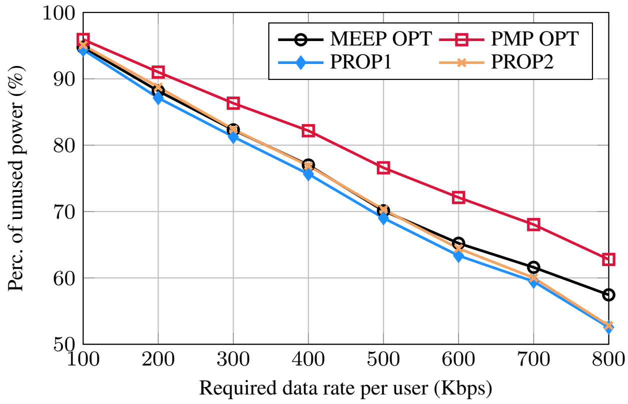


Fig. 8. Non-used transmit power versus required data rate in scenario 5 for MEEP OPT, PMP OPT, PROP1 and PROP2 algorithms with four services ($S = 4$).

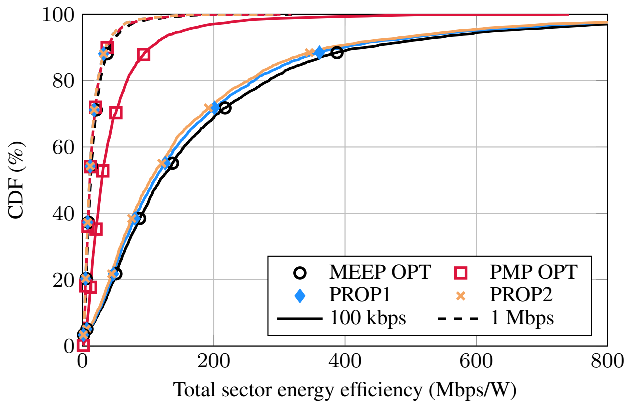


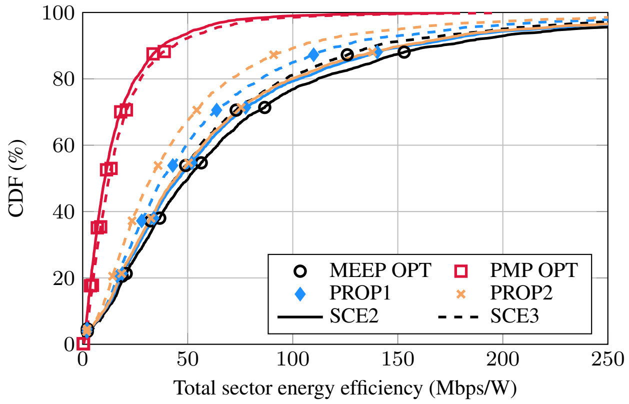
Fig. 9. CDF of EE for a required data equal to 100 kbps and 1 Mbps in scenario 1 to MEEP OPT, PMP OPT, PROP1 and PROP2 algorithms with two services ($S = 2$).

kbps, and 15,6%, 16,2% and 16,2% for a required data of 1 Mbps. Note that, PROP1 and PROP2 solutions are capable of maintaining a low performance loss compared to MEEP OPT solution especially for low QoS demands. Another important observation is that the MEEP OPT solution tends to become the PMP OPT solution with the increasing rate requirement. The reason for this is that for high data rate requirements per terminal, the MEEP and PMP solution space become smaller and, therefore, there is a lower optimization margin to increase the EE. Thus, the two problems converge to similar solutions.

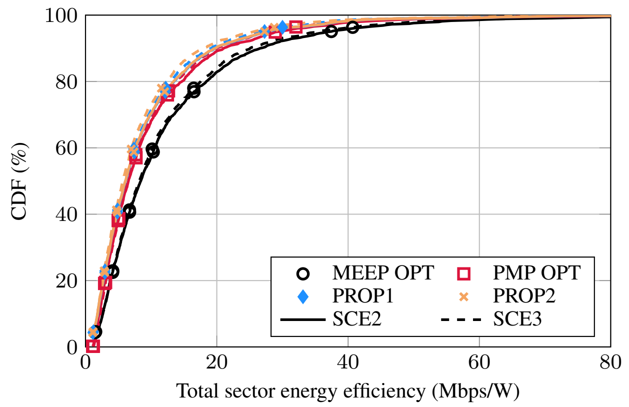
Fig. 10 shows the total EE CDFs for all algorithms in scenarios 2 and 3 for a data rate requirement of 100 kbps and 600 kbps, respectively. It is important to mention that the required data rates in the x-axis in Figs. 10(a) and 10(b) are for services 1, 2 and 3 in scenario 2, and for services 1 and 2 in scenario 3. The terminals from service 3 in scenario 3 demand a data rate 250 kbps higher than the terminals from services 1 and 2, as indicated in Table III. The objective is to show the impact of the terminals' data rate requirements, t_j, on the performance of the proposed algorithms. Basically, with low QoS demands, the variation of t_j between terminals from different services shows a significant impact on the EE, except for the PMP algorithm, as depicted in Fig. 10(a). With high QoS demands, all algorithms seem to be insensitive to the variation of the required data rate of service 3 in scenario 3. As the QoS demands are increased to 1 Mbps, the fixed difference in the required data rate of 250 kbps between service 3 and the other services in scenario 3 becomes negligible and this justifies the small performance difference in 10(b).

Fig. 11 shows the total EE CDFs for all algorithms in scenarios 4 and 5 for a data rate requirement of 100 kbps and 600 kbps, respectively. The objective is to show the impact of the minimum number of satisfied terminals per service, k_s. All solutions show a considerable EE loss with the variation of k_s. Basically, the EE loss when k_s is increased is more preeminent in high QoS demands. In high QoS conditions, satisfying or not one terminal has an important impact in the resource usage as a single terminal demands more RBs and transmit power to become satisfied. The performance gains in the 50$^{\text{th}}$ percentile of EE of the MEEP OPT solution compared to the PMP OPT, PROP1 and PROP2 solutions in scenario 4 are 508%, 10% and 20%, and 45.8%, 45.2% and 58.15% in Figs. 11(a) and 11(b), respectively. The PROP1 solution shows a good performance performance in Fig. 11(a), however, it presents a performance loss in Fig. 11(b).

In Fig. 12, we show the outage rate versus the required data rate per terminal for the algorithms MEEP OPT and PROP1 in scenario 5. Note that, the MEEP OPT and PMP OPT have the same set of constraints and, therefore, they present the same outage performance. This is also the case of PROP1 and PROP2 that share common steps related to QoS and service satisfaction. As expected, the outage rate increases with the required data rate per terminal. Focusing on the relative performance among algorithms, the proposed heuristic solutions present a small performance degradation compared to the MEEP OPT solution for low and moderated loads. When the MEEP OPT solution reaches an outage rate of 10%, the difference in outage rate between our solution and MEEP OPT is 5.2%.

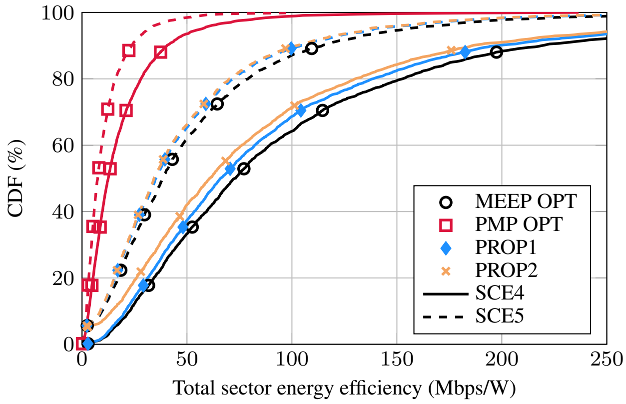


(a) Required data rate of 100 kbps.

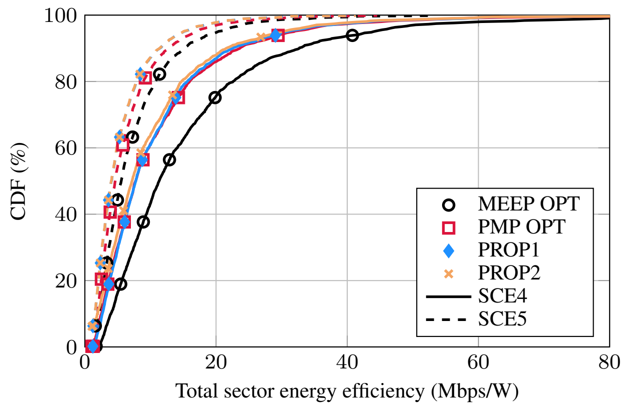


(b) Required data rate of 600 kbps.

Fig. 10. CDF of EE for a specific required data to MEEP OPT, PMP OPT, PROP1 and PROP2 algorithms with three services ($S = 3$). Assuming the scenarios 2 and 3, and evaluation the impact of variable t_j.



(a) Required data rate of 100 kbps.



(b) Required data rate of 600 kbps.

Fig. 11. CDF of EE for a specific required data to MEEP OPT, PMP OPT, PROP1 and PROP2 algorithms with four services ($S = 4$). Assuming the scenarios 4 and 5, and evaluation the impact of variable k_s.

In summary, from the analysis of the results of Figs. 7 to 12, the PROP1 and PROP2 solutions achieve a good performance compared to the optimal solution considering the problem objective and constraints for lower and medium loads.

Table IV shows the Complexity/EE trade-off of each solution for a given scenario and required data rate. The complexity is calculated by substituting the variables in the worst-case computational complexity calculated in the appendixes. Thus, the Complexity/EE metric is determined by dividing the calculated complexity by the EE obtained in the 50$^{\text{th}}$ percentile. The objective is to show how promising are the algorithms in terms of the obtained EE and the computational cost associated to achieve it. As we can see the EE trade-off for the MEEP OPT have extremely higher values even for the least challenging scenario. Furthermore, for the other scenarios, the trade-off metric is above the maximum representable value in the software used for simulation that is 1E+308. Therefore, besides the MEEP OPT having the best EE, its complexity is prohibitive. Considering the analyzed scenarios, we can see that the PROP1 algorithm results in the best trade-off between complexity and EE.

As we are dealing with algorithms, it is also important to present a computational complexity analysis for them. The worst-case computational complexities of solving

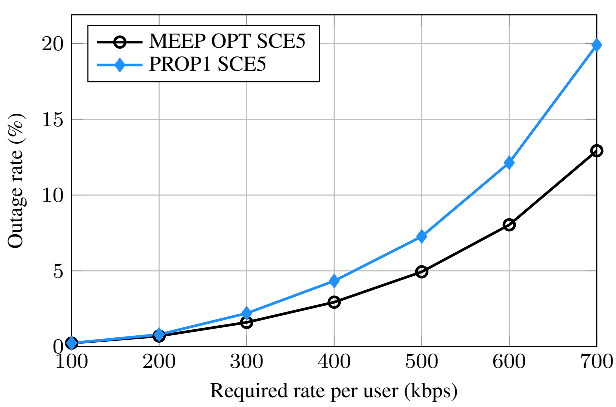


Fig. 12. Outage rate versus required data rate in scenario 5 for MEEP OPT and PROP1 algorithms with four services ($S = 4$).

MEEP and PMP using BB are $O\left(JN\sqrt{2}^{(JNM+J)}\right)$ and $O\left(\sqrt{2}^{(JNM+J)}\right)$, respectively, as explained in Appendices A and B. The worst-case computational complexity for the PROP1 and PROP2 solutions, detailed in Appendices C to D, are $\mathcal{O}\left(JM^2N\,\log_2 N\right)$ and $\mathcal{O}\left(qJMN\,\log_2 N\right)$, respectively, where q is the number of iterations. As we can observe, the computational complexity of the suboptimal solutions are polynomial and much lower than those of the optimal

TABLE IV
TRADE-OFF BETWEEN COMPUTATIONAL COMPLEXITY AND EE.

Scenario - -	Required data rate - (kbps)	MEEP OPT Complexity/EE Trade-off Nº of operations per Joule	PROP1 Complexity/EE Trade-off Nº operations per Joule	PROP2 Complexity/EE Trade-off Nº operations per Joule
1	100	1.35e+266	0.0010	0.0099
1	1000	1.29e+267	0.0097	0.0946
2	100	-	0.0026	0.0292
2	600	-	0.0194	0.2119
4	100	-	0.0035	0.0706
4	600	-	0.0300	0.5972

solutions. Thus, we can identify an excellent performance-complexity trade-off for them, when compared to the MEEP OPT and PMP OPT strategies.

V. CONCLUSIONS AND PERSPECTIVES

In this work, we studied RRA problems involving energy and power optimization with QoS and satisfaction constraints in multiservice scenarios. Two problems were formulated: MEEP and PMP. PMP is an ILP problem and can be optimally solved by BB-based algorithms, while MEEP is a fractional integer optimization problem. To solve the latter, we employed an iterative method proposed in [38]. Motivated by the high computational burden to obtain the optimal solutions, we also proposed two suboptimal algorithms to the MEEP.

According to the performance results, we could show the relevance of optimizing energy resources, especially under the MEEP point of view that is able to obtain high data rates with an acceptable transmit power. Moreover, we could show that the proposed suboptimal solutions presented a good performance especially in low and moderated system loads. The computational complexity of the involved algorithms were presented and we could show that the suboptimal solutions are able to offer good performance-complexity trade-offs.

Regarding the possible extensions, in MIMO scenarios, besides the time-frequency dimension, the RRA needs to manage also the space resources, introducing the concept of Space-Division Multiple Access (SDMA). However, one of the major problems in SDMA solutions is the possible number of group compositions that grows up with the number of terminals and antennas [43]. Therefore, one possible extension of the current framework is to perform a pre-selection of the most promising groups before starting the framework. Note that, the steps of the framework should be adapted for a MIMO scenario. Furthermore, this extension also can be valid for massive MIMO scenarios.

In power-domain Non-Orthogonal Multiple Access (NOMA), terminals with different channel conditions are multiplexed at the same frequency with different power coefficients. After that, in downlink, each terminal applies successive interference cancellation to obtain the desired signal [44]. However, as the application of NOMA in all terminals may be unpractical, an alternative approach is to combine NOMA and Orthogonal Multiple Access (OMA)[3] leading to a hybrid multiple access system [7]. Furthermore, the number of compositions of NOMA terminals grows combinatorially with the number of terminals and RBs. Thus, one of the challenges is to find the best composition of terminals NOMA that maximizes the EE satisfying the QoS requirements. Therefore, one possible extension of the current framework is to adapt the frequency assignment functionality to handle with the hybrid NOMA/OMA approach.

[3]OFDMA is an example of OMA.

APPENDIX A
COMPLEXITY ANALYSIS OF THE PMP OPTIMAL SOLUTION

As in [45] and [46], we consider summations, multiplications, and comparisons as the most relevant and time-consuming operations. The computational complexity considered here is the worst-case one that gives an upper bound on the computational resources required by an algorithm and is represented by the asymptotic notation $\mathcal{O}$. To obtain the optimal solution, we used the BB algorithm. Firstly, remember that the optimal solution of MEEP is obtained by iteratively solving ILPs. Therefore, we firstly calculate the computational complexity of solving an ILP with BB algorithm. Assuming that the optimization problem has l integer variables, there are at least $(\sqrt{2})^l$ linear subproblems to be solved [32]. For each linear subproblem with m constraints and l variables, it is needed $2(m+l)$ iterations, and each iteration in its turn requires $(lm-m)$ multiplications, $(lm-m)$ summations, and $(l-m)$ comparisons [45], [32]. Moreover, the optimal solution of PMP problem (3) can be obtained by BB algorithm. Therefore, the problem has $JNM+J$ optimization variables and $JN+J+N+S+1$ constraints. By retaining only the high order operations, its worst-case computational complexity is given by $\mathcal{O}\left((\sqrt{2}^{(JNM+J)}\right)$.

APPENDIX B
COMPLEXITY ANALYSIS OF THE MEEP OPTIMAL SOLUTION

We assume the same hypothesis of Appendix A. As in problem (6) there are $JNM+J$ integer variables and $JN+J+N+S+1$ constraints. By retaining only the high order operations, the worst-case computational complexity is $\mathcal{O}\left(\sqrt{2}^{(JNM+J)}\right)$ for problem (6). However, the algorithm proposed in [38] obtains the optimal solution with a maximum of $3\times I$ iterations, where I is the number of constraints. As our problem has $JN+J+N+S+1$ constraints, then the worst-case complexity is $\mathcal{O}\left(JN\ \sqrt{2}^{(JNM+J)}\right)$.

APPENDIX C
COMPLEXITY ANALYSIS OF PARTS 1 AND 2 OF THE MEEP SUBOPTIMAL SOLUTION

According to the description of parts 1 and 2, we can see that the most computationally intensive operations are present in the HH algorithm. The worst-case computational complexity of HH algorithm for N RBs and M MCSs is given by $\mathcal{O}(MN \log_2 N)$ [47]. Considering that in practical scenarios J is greater than N, our solution is dominated by the execution of HH algorithm for each terminal. Therefore, its worst-case computational complexity is $\mathcal{O}\left(JMN \log_2(N)\right)$.

APPENDIX D
COMPLEXITY ANALYSIS OF THE MEEP HEURISTIC 1

As the MEEP heuristic basically employs the HH algorithm to estimate the EE for each MCS and the MCS is updated until the power runs out, the worst-case computational complexity is the same as the calculated in Appendix C multiplied by the number of MCSs. Therefore, the worst-case complexity of this solution is $\mathcal{O}\left(JM^2N \log_2(N)\right)$.

APPENDIX E
COMPLEXITY ANALYSIS OF THE MEEP HEURISTIC 2

The worst-case computational complexity of the proposed suboptimal solution for MEEP with Anzai's algorithm is clearly dominated by the power allocation steps performed by the adapted HH algorithm of Section III-B2. As the MEEP heuristic solution basically employs the HH algorithm with the iterative algorithm of [38], the worst-case computational complexity is the same of calculated in Appendix C multiplied by the number of iterations. In our simulations, we verified that a low number of iterations is sufficient to achieve the presented performance. Assuming q as the number of iterations, the worst-case complexity of this solution is $\mathcal{O}\left(qJMN \log_2(N)\right)$.

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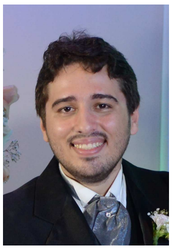

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