A QoE-aware joint resource allocation and dynamic pricing algorithm for Heterogeneous Networks

Panagiotis Trakas*, Ferran Adelantado*, Nizar Zorba†, Christos Verikoukis‡
*Open University of Catalonia (UOC), Barcelona, Spain
†Qatar University, Doha, Qatar
‡Telecommunications Technological Centre of Catalonia (CTTC/CERCA), Castelldefels, Spain
Email: ptrakas@uoc.edu, ferranadelantado@uoc.edu, nizarz@qu.edu.qa, cveri@cttc.es

***Abstract*—The rise of third-party content providers and the introduction of numerous applications has been driving the growth of mobile data traffic in the past few years. The applications' various Quality of Service (QoS) requirements as well as the use of multiple devices per user have increased the traffic heterogeneity, pressing the telecommunications industry to the deployment of dense Heterogeneous Networks (HetNets). At the same time, the content providers' rise has also led to the decrease of the Mobile Network Operators' (MNOs) revenues. Under these circumstances, the MNOs need to guarantee the users' Quality of Experience (QoE) requirements, while ensuring the sustainability of HetNet investments. To this end, we consider a HetNet deployment where MNOs offer a multitude of services with diverse pricing. We propose a heuristic, joint QoE-aware resource allocation and dynamic pricing algorithm with overall user satisfaction constraints to maximize the MNO profit, while providing high QoE. Simulation results show that the proposed algorithm can handle traffic heterogeneity by achieving substantial profit and QoE gains, compared to a state of the art algorithm. Moreover, we demonstrate the benefits of our dynamic pricing scheme and its applicability on other resource allocation algorithms.**

***Index Terms*—Resource Allocation, Dynamic Pricing, Traffic Heterogeneity, QoE.**

I. INTRODUCTION

The emergence of numerous independent content provider applications used by smart devices connected to mobile networks has been driving the ever-increasing rise in mobile data traffic. Each application may have different Quality of Service (QoS) requirements, which along with the use of multiple devices per user [1] increase the heterogeneity of the traffic demand. In order to address these challenges, Mobile Network Operators (MNOs) invest in the densification of their networks with Small Cell (SC) infrastructure, deploying Heterogeneous Networks (HetNets). Although it may seem contradictory, the described traffic boost has increased the content providers' profits while, simultaneously, has diminished the MNOs' revenues [2]. This occurs because the MNO's basic services (voice and messaging) have been gradually replaced by their third-party counterparts. Moreover, the MNO's data service prices have been decreasing over the years, due to the market competition. Furthermore, the content providers only reap the benefits of using the MNO infrastructure without cost, as they do not subsidize its deployment and operation. However, despite these conditions, the MNOs must provide seamless connectivity and high Quality of Experience (QoE) to their users, which is one of the key elements that has been attracting the interest of the telecommunication market the past years [3].

Therefore, MNOs face a two-fold challenge: meet the QoE requirements and maximize the profit. It has been proven that the relation between QoS and QoE has a non-linear nature [4]. This means that small degradations in the received QoS can impact significantly the perception of QoE. Yet, QoE is influenced by other factors such as pricing or device characteristics [5]. In this context, it is necessary to design network and economic functionalities adapted to the new requirements, such as QoE-aware Radio Resource Management and Dynamic Pricing (DP) strategies, and always trying to maximize the profit (to compensate the diminished MNOs' revenues and the increasing deployment investment).

The majority of works on Resource Allocation (RA) and scheduling focus mainly on the provision of high QoS or QoE and other network aspects (e.g. power allocation, fairness etc.), without taking into account the impact of their proposals on economic aspects [6], [7]. Two user-oriented joint subcarrier and Power Allocation (PA) algorithms for OFDMA systems are proposed in [6]. The first algorithm guarantees that all users share the same QoE, whereas the second algorithm provides the trade-off between the appropriate QoE level and the system spectral efficiency. Similarly, a QoE-aware joint RA and PA algorithm with a satisfaction factor that determines the percentage of served users is proposed in [7]. However, there is a limited number of works on RA or scheduling that consider both network and economic aspects. A downlink packet scheduling scheme for QoS provisioning in wireless networks is proposed in [8]. The scheme's objective is the satisfaction of users with various QoS requirements and priority classes, and the minimization of the network operator's revenue loss. A method for the simultaneous RA in both licensed and unlicensed bands in the SCs of a HetNet is proposed in [9]. The authors solve the concurrent RA problem twice; first they maximize the SC users' sum rate, and then the MNO revenue, with constraints on the interference to the macrocell tier, and the SC users' rate requirements.

Regarding dynamic pricing, most schemes in the literature are based on time or location-dependent pricing, aiming to steer the traffic demand from peak to off-peak traffic hours and locations [10], [11]. That is, DP is used as a tool to motivate the users change their data consumption habits, thus avoiding network congestion. However, such approaches cannot provide high customer satisfaction during inevitable congestion periods. A different approach has been studied in [12] for the scheduling of computational resources in cloud computing data centers. In [12], the cloud provider discovers how much a client is willing to pay for a particular service degradation, and uses scheduling algorithms that combine partial degradation of the computational power, and price reduction.

In this paper, we jointly study the RA and DP problems in HetNets composed of macrocell and SC base stations (BSs), dynamic traffic described by numerous QoS/QoE demands, and diverse pricing (i.e. various service prices and different types of pricing). In order to address the challenge of traffic heterogeneity, we propose a joint RA-DP, heuristic algorithm that exploits the QoE-awareness and the network's economic aspects. The proposed algorithm maximizes the MNO profit under overall user satisfaction constraints in a real-time scale, during congestion. Our proposal on DP provides immediate results and can be applied on the RA and pricing type the MNO already uses.

The rest of the paper is organized as follows. We present the system model in Section II. Section III describes the MNO's objectives. We formulate the profit optimization problem in Section IV, and propose a QoE-aware profit maximizing joint RA-DP algorithm in Section V. We validate our algorithm in Section VI, and conclude the paper in Section VII.

II. System Model

The considered network is composed of a set of macrocells and a set of SCs, all of them deployed by a single MNO. We denote this set of all the BSs as $\mathcal{B} = \{1, 2, \ldots, N_B\}$, where N_B is the total number of BSs. The bandwidth allocated to each BS $i \in \mathcal{B}$ is hereafter referred to as b_i (in Hz).

The MNO serves a set of users $\mathcal{U} = \{1, 2, \ldots, N_U\}$, where N_U is the total number of users. It is assumed that users are not served by more than a single BS simultaneously, and therefore we define the set of users served by BS $i \in \mathcal{B}$ as $\mathcal{U}_i$, where $\mathcal{U} = \cup_{i\in\mathcal{B}}\mathcal{U}_i$ and $\cap_{i\in\mathcal{B}}\mathcal{U}_i = \emptyset$. MNOs have put the focus on the QoS and QoE as the target Key Performance Indicators (KPIs) in the design of networks [3]. Accordingly, in our model each user has a contract with the MNO that specifies a desired QoE for each service, denoted in the sequel as *Service Profile* (SP). If we define the set of services as $\mathcal{S} = \{s : s = 1 \ldots S\}$ and the set of QoE classes as $\mathcal{Q} = \{q : q = 1 \ldots Q\}$ ($\mathcal{Q}$ is assumed to be a discrete and finite set), a generic SP can be defined as $\pi_k = (s_k, q_k, p_k)$, where p_k is the price of the service (in €), $s_k \in \mathcal{S}$ and $q_k \in \mathcal{Q}$. Focusing on p_k, it is worth noting that its definition depends on the service s_k. Thus, some services are charged based on the amount of transmitted/received data and some others are based on the connection time. Let us define the price for a data-based charged service as θ_k^B (in €/MB) and for a time-based charged service as θ_k^t (in €/sec). Moreover, we denote by $\mathcal{U}_i^B$,$\mathcal{U}_i^t \subseteq \mathcal{U}_i$ the sets of data-based and time-based charged users served by BS i, respectively (i.e. $\mathcal{U}_i^B \cup \mathcal{U}_i^t = \mathcal{U}_i$ and $\mathcal{U}_i^B \cap \mathcal{U}_i^t = \emptyset$). In order for the MNO to apply DP on a real-time basis, the users' service price must be reduced during short time periods T. To that end, a BS i determines the percentage of p_k a user $j \in \mathcal{U}_i$ will pay at a time period T, which we denote by $\lambda_{ij} \in [0, 1]$. The general expression of p_k for a time period T can be expressed as

$$p_k = \begin{cases} T\lambda_{ij}\theta_k^t & \text{If user } j \in \mathcal{U}_i^t \\ \frac{T\cdot r}{8}\lambda_{ij}\theta_k^B & \text{If user } j \in \mathcal{U}_i^B, \end{cases} \quad (1)$$

where r (in Mbps) is the user transmission rate. As for the perceived QoE, in general any user with a service profile π_k has a target QoE level, Q_k^{tg}, and a minimum QoE level below which the session is dropped, Q_k^{drop} (in the MOS scale [4]).

Although the perceived QoE is influenced by multiple factors, as it will be detailed in Section III, we now focus on the impact of the user device. Nowadays, a single user can get connected to the network with different devices (tablet, laptop, smartphone, etc), each one with specific characteristics. These characteristics of the device, such as the screen quality or screen size, are relevant since they may improve or worsen the perceived QoE. For instance, to perceive similar QoE levels, lower image resolution and hence lower transmission bit rate (i.e. lower QoS) is required for a user using a video service in a small-size screen smartphone than for the same user with a large screen tablet [13]. Therefore, we define the set of devices as $\mathcal{D} = \{d : d = 1 \ldots D\}$, and the mapping function that links the device-SP pair with the required transmission rate, r_{kd}, as $f : (\pi_k, d) \to r_{kd}$. According to the definitions, the QoE perceived by a user $j \in \mathcal{U}$ with a SP π_k and using a device $d \in \mathcal{D}$, namely Q_j^{kd}, will be higher than the target QoE Q_k^{tg} if the transmission rate from the serving BS to the user j is higher than r_{kd}. In other words, the target QoE is met at time period t if $r_j(t) = w_{ij}(t)\varepsilon_{ij}(t)b_i \geq r_{kd} = f(\pi_k, d)$, where $r_j(t)$ is the actual transmission rate of user $j \in \mathcal{U}_i$ (in Mbps), $w_{ij}(t) \in [0, 1]$ is the portion of BS $i \in \mathcal{B}$ radio resources allocated to user j, and $\varepsilon_{ij}(t)$ is the spectral efficiency of the link between user j and BS i (in bps/Hz).

Note that the QoE classes differentiate the perceived quality by offering different maximum rate values for the same service (e.g. SD and HD video). That is, the user can opt between Q quality levels for every service and create a *user profile*, since each service may be of different importance to the user (e.g. preference for high browsing speed but SD video).

Based on the definitions stated above, it is clear that the satisfaction of users is tightly coupled with the perceived QoE. Specifically, if the satisfaction of user j served by BS i, namely $\sigma_{ij}(t)$ is defined within the interval [0,1], when $Q_j^{kd}(t) = Q_k^{drop}$, the session is dropped and the satisfaction is equal to 0. Conversely, when $Q_j^{kd}(t) \geq Q_k^{tg}$, the satisfaction is equal to 1. Thus, according to [5], the satisfaction can be defined as

$$\sigma_{ij}(t) = \begin{cases} 0 & \text{if } Q_j^{kd}(t) \leq Q_k^{drop} \\ \frac{Q_j^{kd}(t) - Q_k^{drop}}{Q_k^{tg} - Q_k^{drop}} & \text{if } Q_j^{kd}(t) \in (Q_k^{drop}, Q_k^{tg}) \\ 1 & \text{otherwise} \end{cases} \quad (2)$$

III. MNO Objectives

In order to propose a RA-DP scheme based on network and economic functions, we first need to identify and analyse the MNO's objectives. It is true that MNOs have two-fold objective. First, they must offer users the QoE agreed in the

SP. Second, the network must be managed so as to maximize their economic profit. In the following, the analyses of the QoE, overall user satisfaction and the profit are detailed.

A. User QoE and overall user satisfaction

Based on the analysis described in [5], the perceived QoE $Q_j^{kd}(t)$ can be divided into two components: the QoS-based component ($\widehat{Q}_j^{kd}(t)$) and the price-based component ($Q_p(p_k)$).

$$Q_j^{kd}(t) = \widehat{Q}_j^{kd}(t) \cdot Q_p(p_k). \tag{3}$$

The QoS-based component, $\widehat{Q}_j^{kd}(t) \in [1,5]$ (in the MOS scale), shows the effect of QoS level on QoE. In the literature, the connection between QoE and QoS is usually modelled according to the IQX hypothesis [4], which defines it as an exponential relationship. Using the transmission rate $r_j(t)$ as the reference QoS metric, and according to the IQX hypothesis, we can express $\widehat{Q}_j^{kd}(t)$ as

$$\widehat{Q}_j^{kd}(t) = \alpha_{k_j d_j} e^{-\beta_{k_j d_j} \Delta r_j(t)} + \gamma_{k_j d_j}, \tag{4}$$

where $\Delta r_j(t) = r_{kd} - r_j(t)$, and $\alpha_{k_j d_j} > 0$, $\gamma_{k_j d_j} > 0$ (both in the MOS scale), $\beta_{k_j d_j} > 0$ (in sec/bit) are SP-device dependent constants. Regarding the price-based component, it captures how the perception of the quality improves (worsens) as the price falls (rises). As in [5], $Q_p(p_k)$ is modelled as

$$Q_p(p_k) = 1 - v_{k_j} p_k, \tag{5}$$

where $v_{k_j} > 0$ is an adjusting factor measured in €$^{-1}$. We assume that v_{k_j} and hence $Q_p(p_k)$ can be different for each user j, in order to capture the effect of p_k on each user individually. As it can be observed in (5), if the user does not pay for the service (i.e. $p_k = 0$), the price-based component will reach the maximum value, $Q_p(0) = 1$, thereby increasing the perceived QoE in (3). That is, the more a user pays for a service, the higher her expectations on the received QoS are.

Overall User Satisfaction: We define the sum of the satisfaction of all the users in a BS i as the Overall User Satisfaction (OS), $OS_i = \sum_{j \in \mathcal{U}_i} \sigma_{ij}$. Similarly, the OS in the system is given by the satisfaction of all users, $OS = \sum_{i \in \mathcal{B}} OS_i$.

Given a particular association of users in a BS i at time period t, the corresponding maximum overall satisfaction $OS_i^{max}(t) = \max_{w_{ij}} \{OS_i(t)\}$ depends on the users' rate requirements r_{kd} and their current spectral efficiency $\varepsilon_{ij}(t)$. Based on the definition, the OS achieved with a specific RA can be expressed as a fraction of the maximum value. Therefore, we define the relative overall user satisfaction $\phi_i(t) = OS_i(t)/OS_i^{max}(t) \in [0,1]$ as a QoE-aware performance metric. The objective of the MNO is then given by

$$\phi_i(t) \geq \phi^{min}, \forall i \in \mathcal{B}. \tag{6}$$

where ϕ^{min} is a minimum threshold defined by the MNO.

B. MNO Profit

The objective of the MNO is the maximization of the profit while satisfying the QoE required by the users. Specifically, the total profit $P(t)$ is the sum of the individual profits of each BS $P_i(t)$, i.e. $P(t) = \sum_{i \in \mathcal{B}} P_i(t)$. In [14], $P_i(t)$ is expressed as the revenue obtained from the traffic served at time t, $R_i(t)$, minus the cost incurred when serving the traffic, which depicts the bandwidth utilization cost, $CB_i(t)$. Therefore,

$$P(t) = \sum_{i \in \mathcal{B}} P_i(t) = \sum_{i \in \mathcal{B}} (R_i(t) - CB_i(t)), \text{ [€]}. \tag{7}$$

The revenue of BS i, $R_i(t)$, is usually the price of the services paid by the users in $\mathcal{U}_i$. That is, $R_i(t) = \sum_{j \in \mathcal{U}_i} R_{ij}(t)$, where $R_{ij}(t) = p_k$ is the revenue paid by user j when connected to BS i at time period t, for a duration of T seconds. With regard to $CB_i(t)$, it is a convex and increasing exponential function of the total resources used by BS i, $w_i(t) = \sum_{j \in \mathcal{U}_i} w_{ij}(t)$ [14], and for a duration of T seconds it can be written as

$$CB_i(t) = c_i e^{h_i w_i(t) b_i} T, \tag{8}$$

where c_i (in €*/sec*) and h_i (in MHz^{-1}) are adjusting factors that capture the differences in the operational cost of the different BSs (e.g. macrocells and SCs have different transmit power, maintenance cost, site rent, etc). Substituting (8) into (7), and denoting the SP of a generic user j as π_{k_j}, the profit of BS i at time period t, with a duration of T seconds when $Q_j^{k_j d_j}(t) \in (Q_{k_j}^{drop}, Q_{k_j}^{tg}]$ is given by

$$P_i(t) = \sum_{j \in \mathcal{U}_i} p_k \mathbb{1}(\sigma_{ij}(t) > 0) - c_i e^{h_i \sum_{j \in \mathcal{U}_i} w_{ij}(t) b_i} T, \tag{9}$$

where $\mathbb{1}(\cdot)$ is the binary indicator function, which is equal to 1 if the condition is true and 0 otherwise. We use the binary indicator function in order to emphasize that a BS i will not receive revenue if the allocated resources to user j, $w_{ij}(t)$, do not suffice for a satisfactory service with $\sigma_{ij}(t) > 0$. It can be seen in (9) that the profit is impacted by multifarious factors, such as the perceived QoE (which in turn depends on multiple factors), the cost, the radio resources usage, etc.

IV. Profit Optimization

As explained in the previous Section, the MNO aims to maximize the profit $P(t)$ while satisfying the required QoE of all users. However, when not all users can be served with the required QoE due to network congestion, the MNO must provide the highest possible OS. Let us define the association of user j to BS i at time period t as $x_{ij}(t)$, where $x_{ij}(t) = 1$ if user j is served by BS i and $x_{ij}(t) = 0$ otherwise. The profit maximization problem at time t is formulated as

$$\max \quad P(t) = \sum_{i \in \mathcal{B}} (\sum_{j \in \mathcal{U}} x_{ij}(t) p_k - c_i e^{h_i b_i \sum_{j \in \mathcal{U}} x_{ij}(t) w_{ij}(t)} T), \tag{10}$$

$$s.t. \quad \sum_{i \in \mathcal{B}} x_{ij} \leq 1, \; \forall i \in \mathcal{B}, \; \forall j \in \mathcal{U}, \tag{10a}$$

$$w_i \in [0,1], \; \forall i \in \mathcal{B}, \tag{10b}$$

$$\phi_i(t) \geq \phi^{min}. \tag{10c}$$

In the optimization problem, users cannot be connected to more than a single BS (10a), the maximum bandwidth allocated by BS i is b_i, that is $\sum_{\forall j : x_{ij}(t)=1} w_{ij}(t) = w_i(t) \leq 1$ (10b), and the relative overall user satisfaction must be higher than the minimum threshold ϕ^{min} (10c). Since we use the binary indicator function in $P_i(t)$, the optimization problem in (10) is a Mixed-Integer Non-linear Programming (MINLP) problem, whose computational complexity is NP-hard [15].

V. Profit Maximizing Resource Allocation & Dynamic Pricing

As explained in Section III-A, the service price is one of the key factors that affects the users' QoE perception. Particularly, by observing expressions (3), (4) and (5), we notice that when p_k is lowered (increased), the QoE's price-based component ($Q_p(p_k)$) increases (decreases). For instance, when the charging is lowered to $p'_k < p_k$, Q_p increases (i.e. $Q_p(p'_k) > Q_p(p_k)$). Thus, a particular target QoE level Q_k^{tg} can be achieved by offering the same service with lower price and rate $r'_j < r_{kd}$, that is, $Q_k^{tg} = \widehat{Q}_j^{kd}(r_{kd})Q_p(p_k) = \widehat{Q}_j^{kd}(r'_j)Q_p(p'_k)$. Conversely, when p_k is raised, it is not possible to achieve the highest QoE levels, even when the QoS reaches its peak (i.e. $r_j = r_{kd}$).

Therefore, reducing p_k (i.e. $\lambda_{ij} \in [0,1)$) allows for the reduction of a user's rate $r_j(t)$ without lowering her satisfaction, which in turn reduces her resource utilization $w_{ij}(t)$. The released resources can be then used on other users to improve the OS during congestion. Moreover, DP can be used to increase $P_i(t)$. When we use DP, we decrease both $R_{ij}(t)$ and $CB_i(t)$. Hence, when the cost reduction is higher than the revenue loss, $P_i(t)$ becomes higher. Finally, this form of DP can be applied on the existing pricing schemes a MNO uses along with the employed RA scheme.

To this end, we propose a low complexity algorithm $O(n^3)$, presented in Algorithm 1, which takes as input the BS i's users' SP-device pair (p_{k_j}, d_j), to maximize the MNO profit for a minimum relative OS level ϕ^{min} through RA and DP. The rationale is to initially determine the RA that maximizes BS i's $OS_i(t)$. Subsequently, using as input this allocation, the algorithm determines the RA and pricing (i.e. λ_{ij}) that maximize P_i for the required OS constraint (i.e. $\phi_i(t) \geq \phi^{min}$).

Initially, Algorithm 1 calculates the $w_{ij}(t)$ needed to serve each user with the maximum $\sigma_{ij}(t)$ (step 1). Subsequently, it allocates resources starting from the user with the least resource requirements towards the user with the highest (steps 3-11). Finally, either all users are satisfied (i.e. $OS_i = N_U$) or the resources are depleted. Next, the algorithm sets $OS_i^{max}(t) = OS_i(t)$, $\phi_i(t) = 1$, and the discrete set $\Lambda = \{0, 0.1, \ldots, 1\}$ of λ_{ij} values that BS i can use for pricing.

In the following iterative procedure (steps 13-28), each user's satisfaction is decreased (step 15) and increased (step 16) with σ_{step} (the RA $w_{ij}(t)$ is calculated from (2) and (3)). For both satisfaction values, we reduce p_k for the λ_{ij} values in Λ, and calculate the corresponding profit (steps 14-21). Only $\sigma_{ij}(t)$ values that increase the profit are considered as feasible results. This procedure is repeated iteratively for each user and for different values of σ_{step} as long as the relative overall user satisfaction is above the minimum threshold. The RA and pricing are updated with the distribution of resources and the λ_{ij} values that provide the maximum profit for a relative user satisfaction level above ϕ^{min}.

Algorithm 1: Profit Maximizing RA-DP Algorithm

1 Calculate $w_{ij}(t) \leq 1$ for maximum $\sigma_{ij}(t), \forall j \in \mathcal{U}_i$
2 $w_i(t) = 0$
3 **forall** *$j \in \mathcal{U}_i$ in ascending order of $w_{ij}(t)$* **do**
4   **if** $w_{ij}(t) \leq 1 - w_i(t)$ **then**
5         $w_i(t) = w_i(t) + w_{ij}(t)$
6   **else if** *$\sigma_{ij}(t) \geq \sigma^{min}$ for $w_{ij}(t) = 1 - w_i(t)$* **then**
7         $w_{ij}(t) = 1 - w_i(t)$ and $w_i(t) = 1$
8   **else**
9         $w_{ij}(t) = 0$
10   **end**
11 **end**
12 Set $OS_i^{max}(t) = OS_i(t)$, $\phi_i(t) = 1$, $\sigma_{step} = \sigma_{step}^{max}$ and $\Lambda = \{0, 0.1, \ldots, 1\}$
13 **while** $\phi_i(t) \geq \phi^{min}$ **and** $\sigma_{step} \geq \sigma_{step}^{min}$ **do**
14   **for** $j \in \mathcal{U}_i$ **do**
15         $\sigma_{ij}^{-}(t) = \max\left(\sigma_{ij}(t) - \sigma_{step}, 0\right)$
16         $\sigma_{ij}^{+}(t) = \min\left(\sigma_{ij}(t) + \sigma_{step}, 1\right)$
17   **for** $\lambda_{ij} \in \Lambda$ **do**
18   Calculate the total profit $P_i(t)$ and $\phi_i(t)$ with $\sigma_{ij}(t) = \sigma_{ij}^{-}(t)$ and $\sigma_{ij}(t) = \sigma_{ij}^{+}(t)$
19   Store the maximum profit $P_i(t)$ s.t. $\phi_i(t) \geq \phi^{min}$ and $w_i(t) \leq 1$ in $P'_{ij}(t, \lambda_{ij})$ and the corresponding $\phi_i(t)$ and $\sigma_{ij}(t)$ in $\phi'_{ij}(t, \lambda_{ij})$ and $\sigma'_{ij}(t, \lambda_{ij})$
20   **end**
21   **end**
22     $(j^*, \lambda_{ij}^*) = \underset{j, \lambda_{ij}}{\arg\max}\left(P'_{ij}(t, \lambda_{ij})\right)$
23   **if** $P'_{ij^*}(t, \lambda_{ij}^*) > P_i(t)$ **then**
24         $P_i(t) = P'_{ij^*}(t, \lambda_{ij}^*)$, $\phi_i(t) = \phi'_{ij^*}(t, \lambda_{ij}^*)$, $\sigma_{ij^*}(t) = \sigma'_{ij^*}(t, \lambda_{ij}^*)$ and the corresponding $w_{ij}(t), \lambda_{ij}(t)$ values are updated
25   **else**
26   Reduce σ_{step}
27   **end**
28 **end**

VI. Performance Evaluation

The scenario used for the performance evaluation consists of a cluster with 6 SCs deployed in the coverage area of a macrocell sector. The cluster is circular shaped and centred at location $c = (x_c, 0)$, as shown in the layout depicted in Fig. 1. Along simulations, x_c is randomly selected according to a uniform distribution with $x_c \in [100, 190]m$. The Inter-Site Distance (ISD) between SC equals $R_{ISD} = 50m$.

Users are uniformly distributed within a radius of 75m from c, and the SP of each user is selected with equal probability among the SPs defined in Table I. As it can be observed in Table I, three services are considered, each one with two QoE classes $\mathcal{Q} = \{$Basic, Premium$\}$: Service 1 is a data-based charged service, and Services 2 and 3 are time-based charged services. Likewise, 3 different devices are considered, and the corresponding transmission rates associated to each SP, r_{kd}, are also included in Table I. Note that for each SP, r_{kd} is the transmission rate required to perceive a QoE equal

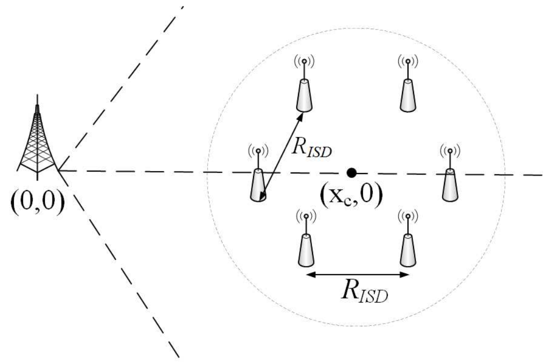

Fig. 1: Simulation scenario topology

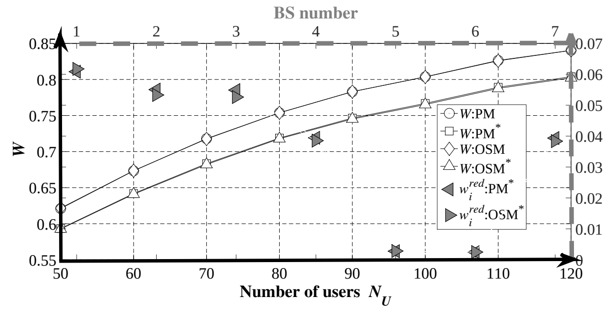

Fig. 2: System Bandwidth Utilization W and w_i reduction

TABLE I: Service Profiles' parameters

Service	QoE class	$\{\mathbf{r_{k1}}, \mathbf{r_{k2}}, \mathbf{r_{k3}}\}$ (Mbps)	$\theta_{\mathbf{k}}^{\mathbf{t}}$ or $\theta_{\mathbf{k}}^{\mathbf{B}}$
Service 1 (Data Based)	Basic	7	1.5€/GB
	Premium	9	2€/GB
Service 2 (Time Based)	Basic	$\{4.5, 5, 6.5\}$	4€/h
	Premium	$\{5, 6, 7\}$	7€/h
Service 3 (Time Based)	Basic	$\{6, 7, 7.5\}$	4€/h
	Premium	$\{6.5, 7.5, 8.5\}$	7€/h

TABLE II: BS parameters

Parameter	Macrocell	Small cell
c_i (€)	$5 \cdot 10^{-5}$	$5 \cdot 10^{-5}$
h_i (MHz^{-1})	0.3	0.295
b_i (MHz)	20	20
Transmission Power (dBm)	43	30

to Q_k^{tg}. In the simulations, the transmission rate that results in a perceived QoE equal to Q_k^{drop} is set to $r_{kd}^{drop} = 0.7 r_{kd}$ for all SPs. Moreover, v_k is selected randomly so as to have $Q_p(p_k) \in [0.8, 0.9]$ in (5), and

$$\begin{cases} \alpha_{kd} = \frac{Q_k^{tg}}{Q_p(p_k)} - \gamma_{kd} & \text{(11a)} \\ \beta_{kd} = -\frac{1}{\Delta r_j^{drop}} \ln\left(\frac{Q_k^{drop} - \gamma_{kd} Q_p(p_k)}{Q_k^{tg} - \gamma_{kd} Q_p(p_k)}\right), & \text{(11b)} \end{cases}$$

where $\Delta r_j^{drop} = r_{kd} - r_{kd}^{drop}$, and $\gamma_{kd} = 1$, for all π_k, $d \in \mathcal{D}$ and (Q_k^{tg}, Q_k^{drop})=$(3.5, 2.5)$ for Basic QoE class and $(Q_k^{tg}$,$Q_k^{drop})$=$(4.5, 3.5)$ for Premium QoE class of all services.

Parameters used for the BSs, both eNBs and SCs, are listed in Table II. We assume dedicated spectrum allocation per tier, adopted 3GPP LTE-A's channel models described in [16], and set the Antenna gains to 0 dB. For the cell selection, we associate the users to the BS with the highest SINR, as it is common practice in mobile networks [17].

The following results were acquired through Monte-Carlo simulations. We compare our proposed algorithm (referred to as PM) with a QoE maximizing algorithm, referred to as OSM [7]. OSM is a RA algorithm that maximizes the user QoE through an iterative procedure, which in each iteration allocates enough resources to satisfy a single user, starting from the user with the highest spectral efficiency towards the user with the lowest. In order to show the benefits of our DP scheme, we provide results for both algorithms with and without applying DP (the symbol * refers to the algorithms with DP applied). For PM, when DP is not applied, it is $\Lambda = \{1\}$. For PM, the values for the change in user satisfaction are $\sigma_{step} = \{0.01, 0.05\}$. Moreover, the minimum acceptable satisfaction level for all algorithms is $\sigma_{ij}^{min} = 0.01$. It should be noted that we provide results for PM with $\phi^{min} = 1$, aiming to offer the users the service agreed in their SPs.

Fig. 2 shows the expected total utilization of the spectrum (in the black-coloured, separate axes), which is defined as $W = \mathbb{E}\left[W(t) = \frac{\sum_{i \in \mathcal{B}} w_i(t) b_i}{\sum_{i \in \mathcal{B}} b_i}\right]$ versus the number of users N_U. We observe that PM and OSM consume the same portion of the bandwidth whether DP is applied or not. Regarding the gain from DP, we see that both PM* and OSM* use $[4.46, 4.92]\%$ less of their total resources compared to PM and OSM respectively.

Fig. 2 also depicts (in the grey-coloured markers and separate dashed axes) the bandwidth utilization reduction of each BS i (w_i^{red}), when DP is used, where $i = 1$ denotes the macrocell BS. In order to produce the presented results, we averaged w_i^{red} of each BS i for all simulated N_U values. We observe that both algorithms share similar W and w_i^{red} gains, when DP is applied. This occurs because the reduction in $w_{ij}(t)$ depends on the users' individual parameters, that is, her current spectral efficiency $\varepsilon_{ij}(t)$, her rate requirement r_{kd}, and the impact that the service price has on her QoE perception Q_p. We further notice that there is a high deviation in w_i^{red} among the BSs. Particularly, w_i^{red} at BSs 5 and 6 is almost zero. This is a result of low load in these two BSs. Due to the use of the SINR-based cell selection scheme, the SCs closer to the eNB are associated with a small number of users. Hence, they have low spectrum requirements, and if DP is applied, the revenue loss will be higher than the cost reduction.

Fig. 3 shows the algorithms' performance on the MNO profit P and the overall user performance OS. We see that our proposal outperforms OSM in terms of profit, and shows a slight gain over OS as well ($[1.65, 2.83]\%$ gain). As mentioned earlier, OSM sorts the users according to their spectral efficiency $\varepsilon_{ij}(t)$, and then allocates the resources until they are exhausted. This means that OSM will first serve the users with the highest $\varepsilon_{ij}(t)$ regardless of their service's requirements. Conversely, PM sorts the users according to their resource requirements $w_{ij}(t)$ for serving them with their maximum $\sigma_{ij}(t)$. OSM performs well when there is a single rate requirement. However, in a scenario with heterogeneous traffic as well as diverse pricing, a more elaborate algorithm such as PM is required in order to serve the users with even

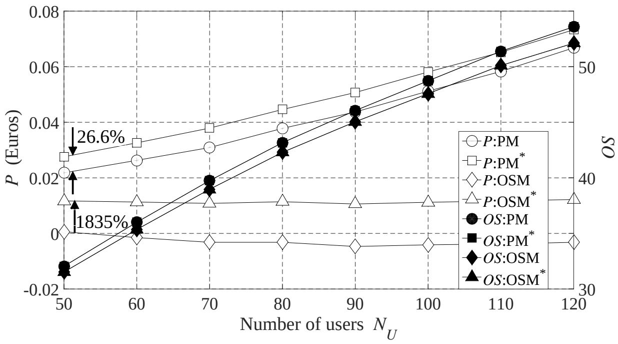

Fig. 3: MNO profit P and Overall User Satisfaction OS

higher satisfaction, while gaining large MNO profit.

Regarding the effect of DP, we observe that both PM* and OSM* perform the same as PM and OSM respectively, in terms of OS. Conversely, PM* and OSM* provide substantial gains in the MNO profit P ($[9.7, 26.6]\%$ gain for PM* and $[325, 1835]\%$ gain for OSM^{*1}). For PM, this is explained by the fact that the decisions on RA and DP are made in order to maximize the BS profit while achieving a minimum OS performance (refer to Alg. 1's steps 32-34). Therefore, PM* provides the same OS as PM, however for lower W and cost. As for OSM, we applied our DP scheme on the RA determined by the original algorithm. Hence, we obtain the same OS, but for a higher profit owing to the cost reduction. If DP was applied within the original OSM algorithm, the BS revenue would be significantly low (even zero), as the algorithm would always reduce the service price (i.e. low λ_{ij}) in order to maximize OS.

Our proposed algorithm manages to offer significantly higher profit for a similar network performance compared to the reference algorithm, because it bases its decisions on both technological (i.e. QoS/QoE requirements) and economic (i.e. pricing and profit) context of the network. Moreover, our proposal on DP has been proven to complement RA schemes in order to increase substantially the MNO profit. Additionally, in a different application of DP the released resources can be used to increase the QoE of the users, while maintaining high MNO profits.

VII. Conclusions

In this paper, we studied the joint resource allocation and dynamic pricing problem in a single MNO's HetNet described by traffic heterogeneity, and diverse pricing. Our objective was the maximization of the MNO's profit, while providing high QoE to the users. Thus, we proposed a heuristic, joint RA-DP algorithm, which bases its decisions on profit maximization, while satisfying a constraint on overall user satisfaction. We evaluated the performance of the proposed algorithm with and without applying DP by comparing it with a state of the art RA algorithm. Our results verify the adaptability of the proposed algorithm to traffic heterogeneity, by providing higher OS and profit than the algorithm in comparison. Finally, we show that our proposal on DP can be applied on different algorithms, allowing them to improve either the MNO profit or the OS performance.

[1] The high gains observed for OSM* are explained by the fact that OSM's profit is significantly low and close to 0.

Acknowledgment

This work has been funded by the MSCA-ITN-ETN Project SPOTLIGHT (722788), Project CellFive (TEC2014- 60130-P), Project SGR (2014-SGR-1551), and the Spanish Ministry of Economy and the FEDER regional development fund under SINERGIA project (TEC2015-71303-R).

References

[1] Appier Research Report: *"Cross-Screen User Behavior Insights, Asia 1H 2015",* Aug. 2015
[2] Mobile Squared, *"Annual Market Review 2014 and PRS market outlook 2015,"* Jul. 2015
[3] Ofcom, *"Measuring mobile voice and data quality of experience,"* 2013
[4] R. Imran, M. Odeh, N. Zorba and C. Verikoukis, *"Quality of Experience for Spatial Cognitive Systems within Multiple Antenna Scenarios,"* in IEEE Transactions on Wireless Communications, vol. 12, no. 8, pp. 4153-4161, August 2013.
[5] Reichl, P.; Maille, P.; Zwickl, P.; Sackl, A., *"On the fixpoint problem of QoE-based charging,"* in Performance Evaluation Methodologies and Tools (VALUETOOLS), 2012 6th International Conference on , pp.235-242, 9-12 Oct. 2012
[6] M. Rugelj, U. Sedlar, M. Volk, J. Sterle, M. Hajdinjak and A. Kos, *"Novel Cross-Layer QoE-Aware Radio Resource Allocation Algorithms in Multiuser OFDMA Systems,"* in IEEE Transactions on Communications, vol. 62, no. 9, pp. 3196-3208, Sept. 2014
[7] V. F. Monteiro, D. A. Sousa, T. F. Maciel, F. R. M. Lima, E. B. Rodrigues and F. R. P. Cavalcanti, *"Radio resource allocation framework for quality of experience optimization in wireless networks,"* in IEEE Network, vol. 29, no. 6, pp. 33-39, Nov.-Dec. 2015
[8] B. Al-Manthari, H. Hassanein, N. A. Ali and N. Nasser, *"Fair Class-Based Downlink Scheduling with Revenue Considerations in Next Generation Broadband Wireless Access Systems,"* in IEEE Transactions on Mobile Computing, vol. 8, no. 6, pp. 721-734, Jun. 2009
[9] A. R. Elsherif, W. P. Chen, A. Ito and Z. Ding, *"Resource Allocation and Inter-Cell Interference Management for Dual-Access Small Cells,"* in IEEE Journal on Selected Areas in Communications, vol. 33, no. 6, pp. 1082-1096, Jun. 2015
[10] C. Chang, P. Lin, J. Zhang and J. Jeng, *"Time dependent adaptive pricing for mobile internet access,"* IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS), Hong Kong, 2015, pp. 540-545
[11] Y. Li and F. Xu, *"Trace-driven analysis for location-dependent pricing in mobile cellular networks,"* in IEEE Network, vol. 30, no. 2, pp. 40-45, Mar.-Apr. 2016
[12] J. Simao and L. Veiga, *"Partial Utility-Driven Scheduling for Flexible SLA and Pricing Arbitration in Clouds,"* in IEEE Transactions on Cloud Computing, vol. 4, no. 4, pp. 467-480, Oct.-Dec. 2016
[13] Abdul Rehman ; Kai Zeng and Zhou Wang, *"Display device-adapted video quality-of-experience assessment,"* Proc. SPIE 9394, Human Vision and Electronic Imaging XX, 939406 (March 17, 2015)
[14] Iosifidis, G.; Lin Gao; Jianwei Huang; Tassiulas, L., *"A Double-Auction Mechanism for Mobile Data-Offloading Markets,"* in Networking, IEEE/ACM Transactions on , vol.23, no.5, pp.1634-1647, Oct. 2015
[15] Gunluk, O.; Linderoth, J.; *"Perspective Reformulation and Applications,"* in Mixed Integer Nonlinear Programming, Springer New York, pp.61-89, 2012
[16] 3GPP TR 36.814 v9.0.0, *"Evolved Universal Terrestrial Radio Access (E-UTRA); Further advancements for E-UTRA physical layer aspects,"* Mar. 2010
[17] J. G. Andrews, *"Seven ways that HetNets are a cellular paradigm shift,"* in IEEE Communications Magazine, vol. 51, no. 3, pp. 136-144, Mar. 2013