Adaptive Monte Carlo Algorithm to Global Radio Resources Optimization in H-CRAN

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***Abstract*—We propose an Adaptive Monte Carlo algorithm to perform global energy efficient resource allocation for Heterogeneous Cloud Radio Access Network (H-CRAN) architectures, which are forecast as future fifth-generation (5G) networks. We argue that our global proposal offers an efficient solution to the resource allocation for both high and low density scenarios. Our contributions are threefold: (*i*) the proposal of a global approach to the radio resource assignment problem in H-CRAN architecture, whose stochastic character ensures an overall solution space sampling; (*ii*) a critical comparison between our global solution and a local model; (*iii*) the demonstration that for high density scenarios Energy Efficiency is not a well suited metric for efficient allocation, considering data rate capacity, fairness, and served users. Moreover, we compare our proposal against three state-of-the-art resource allocation algorithms for 5G networks.**

I. Introduction

Projections on cellular network service requirements foretell a 10-fold expansion in coverage area, a 100-fold increase in User's Equipment (UEs), as well as a 1000-fold raise in data rate transmission capacity by 2020 in comparison with current cellular networks specifications [1][2]. Current network architectures are unable to meet the preconized requirements. Luckily, the dense deployment of small cells is reckoned as a promising solution to reach such stringent improvements since it moves the antennas closer to UEs, thus achieving higher data rates by taking profit of better signal quality at short distances [3]. However, operating a massive number of antennas can significantly increase the energy consumption of the network [4]. Moreover, insertion of a large number of new radios means a buildup on spectral interference between the cells, potentially challenging the gain in spectral capacity [5].

Fortunately, Energy Efficiency (EE), *i.e.,* the relation between spectral capacity and energy consumption, can be managed through a radio resource allocation algorithm that controls transmission power and distribution of spectral Resource Blocks (RBs), *e.g.*, in a Generalized Frequency Division Multiple Access Allocation Scheme [6]. Nonetheless, granting service to UEs through the optimal management of radio resources is a challenging task. For instance, while low transmission powers may preclude UE's connection, high transmission powers may increase interference, thus hindering Spectral Efficiency (SE), *i.e.,* the ratio between transmission capacity and channel bandwidth [7]. Similarly, unplanned reuse of RBs may also intensify interference, resulting in low data transmission per RB, while under-reuse of RBs will limit the overall data transmission capacity. These competing effects are at the core of the high complexity of the management of radio resources, and motivate the design of a solution that encompasses control of transmission power, assignment of the spectral RBs, while ensuring service to the UEs.

The radio resource allocation problem has been investigated in the context of Orthogonal Frequency-Division Multiple Access (OFDMA) based systems for traditional and scattered networks [6][8]. Recently, this problem has attracted renewed attention within the community in connection with the trends on cloud-based centralized cellular architectures, *i.e.,* Cloud Radio Access Network (C-RAN) and Heterogeneous C-RAN (H-CRAN). These architectures allow for new control possibilities and crucially depend on global network knowledge [3][4]. Shi, Zhang, and Letaief [4] presented a global optimization model for C-RAN aiming to reduce the energy consumption of the network through a joint selection of active cell and minimization of the transmit power. Peng et al. [3] investigated the H-CRAN architecture problem aiming at single cell (*i.e.,* local) EE optimization through iterative RBs distribution with minimal power assignment.

The above solutions represent an important step forward. Yet, given resource competition between the cellular radios, EE landscape is highly complex. In view of this competition, we argue that in EE optimization approaches to H-CRAN environments, the investigation of a global and heterogeneous solution is an exaction. Moreover, due to the heterogeneity of antennas and UEs relative spatial distribution, consideration of a fairness constraint in the optimization problem is necessary, to avoid EE optimal solutions to favor UEs closest to antennas, being detrimental to the farthest UEs. Evidently, service is guaranteed by a UE demand constraint.

We propose a global approach to the radio resource allocation problem in a multi-cell H-CRAN model. As the main contribution of this paper, we present an Adaptive Monte Carlo (AMC) algorithm to the optimal radio resources allocation model. Stochastic approaches, such as AMC, provide an efficient way of sampling highly complex solution spaces, as is the case for the EE landscape in the resource allocation problem for H-CRAN. Moreover, we also demonstrate that for high density scenarios EE is not a well suited metric for efficient allocation, considering data rate capacity, fairness, and served users. We evaluate our solution in a scenario defined by the 3rd Generation Partnership Project (3GPP) for the latest definition of Long-Term Evolution (LTE-A) with small cell deployment [9]. We compare the AMC proposal against three state-of-the-art resource allocation algorithms. The results of our evaluation show that the global solution improves the efficiency of the radio access network when compared to a local model.

The remainder of the paper is organized as follows. The system model is analyzed in Section 2 while our proposed solution is presented in Section 3. Our solution is then evaluated in Section 4. Finally, conclusions are presented in Section 5.

II. System Model

H-CRAN architecture adopts Remote Radio Heads (RRH) that digitize and forward the signal samples to be processed at a centralized Base Band Unit (BBU) pool [3]. RRHs are simple antennas with a lower cost of deployment and operation when compared to traditional base stations. In practice, several RRHs acting as Low Power Nodes (LPNs), will be deployed in the coverage area of High Power Nodes (HPNs) to increase the network bit rate in hot spot areas, *i.e.,* holding a large number of UEs and high traffic demand [4]. Fortunately, the coupling of RRHs to a centralized BBU enables the use of cloud computing concepts to centralize decisions and achieve global optimization of resources [10].

Despite the advantages offered by RRH malleability, studies indicate that the densification of RRHs can significantly increase the energy consumption of the network [4]. Beside linearly scaling with the number of RRHs, energy consumption also depends on energy demands of a high-performance optical network connecting RRHs to remote BBUs [3]. Reducing energy consumption is possible by dynamically decreasing the RRHs transmission power through global cloud control solutions [4]. Nevertheless, energy consumption alone cannot be taken as a metric for network efficiency. Indeed, limiting the transmission power reduces Signal-to-Noise Ratio (SNR), possibly restraining the data transmission capacity, thus demanding more spectral RBs to meet a target UE demand [4][11]. The network EE is pointed as an important metric to evaluate the system performance, balancing the energy consumption and ensuring service to the UEs.

In an OFDMA-based downlink system, with a total of K RBs per antenna, L LPNs and H HPNs attending U UEs, the network total data capacity can be written as:

$$C(a,p) = \sum_{t=1}^{L+H} \sum_{u=1}^{U} \sum_{k=1}^{K} a_{t,u,k} \cdot S_{sh}(p_{t,u,k}), \tag{1}$$

where $t \in \{1, ..., L+H\}$ denotes the LPN and HPN cell transmitters, $u \in \{1, ..., U\}$ corresponds to UEs, and $k \in \{1, ..., K\}$ denotes the respective RB in a given antenna (LPNs and HPNs). Matrices $a = [a_{t,u,k}]_{(L+H)\times U \times K}$ and $p = [p_{t,u,k}]_{(L+H)\times U \times K}$ represent a feasible RB and power allocation possibility, respectively. The element $a_{t,u,k} \in \{0,1\}$, *i.e.,* $a_{t,u,k} = 1$ indicates that the kth RB in the tth LPN or HPN is assigned to the uth UE, and the element $p_{t,u,k}$ denotes the respective transmition power. Whenever $a_{t,u,k} = 0$, for a given (t,u,k), *i.e.,* kth RB belonging to tth antenna is not assigned to UE u, the corresponding power $p_{t,u,k} = 0$.

For each $a_{t,u,k} = 1$, $p_{t,u,k} > 0$, and we have a transmission bit capacity $S_{sh}(p)$, as defined by Shannon's theorem [3]:

$$S_{sh}(p_{t,u,k}) = B_0 \log_2 \left(1 + \frac{p_{t,u,k} P_{t,u}^{(pl)}}{I_{t,u,k} + N_0} \right), \tag{2}$$

where $I_{t,u,k}$ represents the power interference due to the assignment of the kth RB to other UEs ($u' \neq u$) by adjacent LPNs or HPNs ($t' \neq t$). $P_{t,u}^{(pl)}$ is the system path loss coming from the inverse square law decay of signal intensity with distance between uth UE receptor and tth transmitter. Finally, B_0 and N_0 are fixed system bandwidth and noise, respectively.

Each cell type has a different total power consumption. Considering transmission, circuit, and front-haul power, the total power consumption of an LPN (HPN) is defined as $P_L(a,p)$ ($P_H(a,p)$) is defined as [3]:

$$P_L(a,p) = \sum_{l=1}^{L} \left(\varphi_{\text{eff}}^{L} \sum_{u,k} a_{l,u,k}\, p_{l,u,k} + P_{\text{c}}^{L} + P_{bh}^{L} \right), \tag{3}$$

$$P_H(a,p) = \sum_{h=L+1}^{L+H} \left(\varphi_{\text{eff}}^{H} \sum_{u,k} a_{h,u,k}\, p_{h,u,k} + P_{\text{c}}^{\text{H}} + P_{bh}^{\text{H}} \right), \tag{4}$$

where $l \in \{1, ..., L\}$ denotes LPN cells while $h \in \{L+1, ..., L+H\}$ denotes HPN cells. The constants φ_{eff}^{L} (φ_{eff}^{H}), P_{c}^{L} (P_{c}^{H}), and P_{bh}^{L} (P_{bh}^{H}) denote, respectively, the power amplifier efficiency, circuit power, and power consumption of the front-haul link for LPNs (HPNs) [3].

The overall EE performance of a system is obtained by the sum of the network transmission capacity (1) divided by the total power consumption, equations (3) and (4). We represent EE by Γ^E, which for an H-CRAN can be written as:

$$\Gamma^E(a,p) = \frac{C(a,p)}{P_L(a,p) + P_H(a,p)}. \tag{5}$$

An allocation problem to optimize the overall efficiency of the radio resources can be formulated with constraints on RB assignments, maximum transmission power per cell, minimum required UE demand, and fairness among UEs data rate. RB assignment and maximum transmission power constraints are hard physical limitations enforced strictly. However, the minimum required UE demand and fairness data rate are soft constraints, yet essential for service ensurance. The latter constraints are fundamental to guarantee service to all UEs avoiding that UEs closer to antennas be prioritized. The EE constrained maximization problem can be formulated as:

$$\max_{\{\mathbf{a},\mathbf{p}\}} \quad \Gamma^E(a,p) = \max_{\{\mathbf{a},\mathbf{p}\}} \frac{C(a,p)}{P_L(a,p)+P_H(a,p)}, \tag{6}$$

s.t.

$$\sum_{u} a_{t,u,k} \leq 1, \qquad a_{t,u,k} \in \{0,1\},\ \forall\, k,\ \forall t, \tag{7}$$

$$\sum_{t} a_{t,u,k} \leq 1, \qquad \forall\, u,\ \forall\, k, \tag{8}$$

$$\sum_{u,\,k} p_{l,u,k} \leq P^{L}_{\max}, \qquad 1 \leq l \leq L, \tag{9}$$

$$\sum_{u,\,k} p_{h,u,k} \leq P^{\mathrm{H}}_{\max}, \qquad L+1 \leq h \leq L+H, \tag{10}$$

$$\sum_{k} S_{sh}(p_{t,u,k}) \geq \eta_{\mathrm{u}}, \qquad \forall\, u,\ \forall\, t, \tag{11}$$

$$\frac{\left(\sum_{t,\,u,\,k} S_{sh}(p_{t,u,k})\right)^2}{U \cdot \sum_{u}\left(\sum_{t,\,k} S_{sh}(p_{t,u,k})\right)^2} \geq \eta_f. \tag{12}$$

Constraint (7) expresses that each RB in a given LPN (HPN) can be assigned to at most one UE. Constraint (8) limits assignment of the same RB to a given UE by at most one LPN (HPN). Constraints (9) and (10) limit to $P^L_{\max}$ (P^H_{max}), the maximum transmission power of LPNs (HPNs). Constraint (11) sets UE demand η_{u} as a lower limit to uth UE data rate. Lastly, constraint (12) denotes the fairness restriction for the spectral RBs distribution among the UEs, $\eta_f = \frac{1}{U}$ being the worst case fairness, and $\eta_f = 1$ being the best case fairness.

In view of the complexity of the model (6)-(12), we argue that finding the optimal RB assignment and power allocation, $\mathbf{a}^*$ and $\mathbf{p}^*$, constitute a non-convex optimization problem. Classical convex optimization methods are not well suited to explore the complex EE landscape. Stochastic methods, however, appear as a suitable approach to address the solution space landscape sampling problem.

III. Adaptive Monte Carlo

The AMC algorithm is an example of a stochastic approach to the radio resource allocation problem. Random sampling is an efficient way of solving complex constrained optimization through the generation of an ensemble of initial conditions (sample solutions) randomly exploring the solution space [12]. A stochastic dynamics is then defined that allows for some rate of violation of the target function maximization. Each sample is evaluated considering model (6)-(12) to find the best possible resource assignment. Algorithm 1 provides an overview of our AMC proposal, which we describe in the remaining of this section.

Parameters $I_{max}, B, \Lambda, \Upsilon$ (line 1) represent, respectively, the number of Monte Carlo Steps (MCSs), AMC weights for EE, data rate, and fairness. The samples' EE is computed after I_{max} MCSs (lines 2-18). The ensemble of sample solutions S contains $K \cdot U$ initial conditions (line 3). For each sample solution S, we define adaptive weights $\beta_S, \lambda_S, \upsilon_S$ that tune the solution design priorities, *i.e.,* EE, data rate, and fairness, all initialized to 1 (line 4). Each MCS is represented by a set of moves. We randomly select an antenna t, a random UE u in t's coverage area, and a random RB k (line 6), *i.e.,* a triplet t, u, k. A candidate move is an attempt to change the RBs allocation of a sample (*e.g.,* vacating it or assigning it to a UE u connected to the antenna t). We store B_s of the original state, to be able to restore it eventually (line 7).

Algorithm 1 Adaptive Monte Carlo

1: Set $I_{max}, B, \Lambda, \Upsilon$;
2: **for** $i = 0$ **to** I_{max} **do**
3:   **for** $S = 0$ **to** $K \cdot U$ **do**
4:     **if** $i == 0$ **then** $\beta_S = 1, \lambda_S = 1, \upsilon_S = 1$;
5:     **for** $j = 0$ **to** $K \cdot (H+L)$ **do**
6:       $t, u, k = rand(S.antennas, S.ues, S.rbs)$;
7:       $B_s = store(S)$;
8:       **if** $S.a_{t,:,k}$ **is** *assigned* **then**
9:         $S.a_{t,:,k}$ = 0; $S.p_{t,:,k}$ = 0;
10:       **else**
11:         $S.a_{t,u,k}$ = 1; $S.p_{t,u,k}$ = *minpower*(t,u,k);
12:       $\Gamma^{[E,D,F]} = W(S.a, S.p, B, \Lambda, \Upsilon)$;
13:       **if** $A(S, B_s, \beta_S, \lambda_S, \upsilon_S) \geq$ *rand*() **then**
14:         $\Gamma^{[E,D,F]}_S = \Gamma^{[E,D,F]}$;
15:       **else**
16:         S = *restore*(B_s);
17:       *update*$(S, \beta_S, \lambda_S, \upsilon_S)$;
18:   Γ^E_i = *select*(S^*);

Having randomly selected RB k belonging to antenna t, it will either be vacated with some probability (if initially assigned to some UE u - line 9), or assigned to a UE u' connected to t with some probability (if initially vacant - line 11), whence, constraints (7) and (8) are always satisfied. After assignment, the minimum power $p_{t,u',k}$ to communicate the UE u' with the antenna t through kth RB is obtained considering path loss, received interference, and maximum transmission power. The minimum power thus defined ensures constraints (9) and (10).

The optimal solution S^* must encompass optimal EE, user data rate constraint (11), and fairness constraint (12). These are enforced in a single function W, given as:

$$\begin{aligned} &W(a,p,B,\Lambda,\Upsilon) = \\ &B \cdot \Gamma^E(a,p) + \Lambda \cdot \Gamma^D(a,p) + \Upsilon \cdot \Gamma^F(a,p), \end{aligned} \tag{13}$$

where B, Λ, and Υ are constant AMC weights, and

$$\Gamma^D = \min\left\{0, \sum_{u}\left(\sum_{t,\,k} a_{t,u,k} S_{sh}(p_{t,u,k}) - \eta_{\mathrm{u}}\right)\right\}, \tag{14}$$

$$\Gamma^F = \frac{\left(\sum_{t,\,u,\,k} S_{sh}(p_{t,u,k})\right)^2}{U \sum_{u}\left(\sum_{t,\,k} S_{sh} h(p_{t,u,k})\right)^2} - 1. \tag{15}$$

Function W (line 12) allows one to tune the priority given to each term through the relative size of AMC weights. Once UE data rate and fairness constraints are satisfied by a sample solution S, AMC dynamics is lead by EE maximization. The W definition is inspired by Lagrange Multipliers for constrained variational problems.

Functions Γ^E, Γ^D, and Γ^F provide quality indices of a sample state. Given a candidate move, its acceptance rate (line 13) is:

$$A(S, B_s, \beta_S, \lambda_S, \upsilon_S) \tag{16}$$
$$= \mathcal{P}_{\beta_S}(\Gamma^E_{B_S} \to \Gamma^E_S) \cdot \mathcal{P}_{\lambda_S}(\Gamma^D_{B_S} \to \Gamma^D_S) \cdot \mathcal{P}_{\upsilon_S}(\Gamma^F_{B_S} \to \Gamma^F_S),$$

where $\mathcal{P}_\xi(\Gamma_i \to \Gamma_f) = \min\{1, \exp(\xi\ (\Gamma_f - \Gamma_i))\}$. Hence, it is possible to accept a move which decreases EE, UE data rate relative to UE demand, and/or fairness with some finite probability, tuned by adaptive weights $\beta_S, \lambda_S, \upsilon_S$. Symbols Γ^E_S ($\Gamma^E_{B_s}$) are the candidate (stored) EE state of the sample solution, Γ^D_S ($\Gamma^D_{B_s}$) are the corresponding candidate (stored) neglected UE demand, and Γ^F_S ($\Gamma^F_{B_s}$) are the corresponding candidate (stored) fairness. Candidate sample solution S is accepted with probability A (line 14), and rejected with probability $1 - A$, in which case S is restored to B_S (line 16). Each MCS amounts to $K \cdot (H + L)$ move attempts.

The adaptive weights $\beta_S, \lambda_S, \upsilon_S$ are updated (line 17) between MCSs according to the current state of the sample solution. We compute the average values $\langle\Gamma^E\rangle$, $\langle\Gamma^D\rangle$, and $\langle\Gamma^F\rangle$ over the ensemble of sample solutions $\{S\}$. For each sample solution S, if $\Gamma^E_S < \langle\Gamma^E\rangle$ (respectively, $\Gamma^D_S < \langle\Gamma^D\rangle$, $\Gamma^F_S < \langle\Gamma^F\rangle$), the corresponding adaptive weight β_S (respectively, λ_S, υ_S) is increased by a fixed factor. Moreover, if Γ^E_S (respectively, Γ^D_S, Γ^F_S) relative fluctuations over a number of MCSs are small, then the respective weight is increased by a larger factor, than in the opposite situation. Conversely, if $\Gamma^E_S > \langle\Gamma^E\rangle$ (respectively, $\Gamma^D_S > \langle\Gamma^D\rangle$, $\Gamma^F_S > \langle\Gamma^F\rangle$), and the relative sample solution fluctuations are small, then the corresponding weight is decreased by a fixed factor. This method is similar to a Simulated Annealing method in Markov Chain Monte Carlo [13].

The AMC dynamics solution is chosen as the best among all sample solutions generated throughout the AMC history (line 18). The best sample will be the solution to the radio resource allocation problem for an H-CRAN architecture. The proposed AMC will find a solution in polynomial time.

IV. Evaluation

In the following, we describe a realistic scenario for simulations and tests methodology. In the sequence, numerical results are presented and then analyzed and discussed.

A. Scenario

We simulate an H-CRAN scenario assuming 3GPP technical specifications for LTE-A radio access networks with small cell deployment [9]. A dense scenario must contain at least 7 HPNs, each one with three sectors. HPNs are uniformly distributed respecting a minimum distance of 500 meters between each pair of HPNs. A minimum of two Hot Spots ($H_s = 2$) must be deployed inside the HPN coverage area, at a minimum distance of 90 meters from the center of the corresponding HPN. A Hot Spot can be defined as a densely populated area, *e.g.,* a city downtown or a shopping mall. Each Hot Spot has a set of four LPNs randomly deployed with a minimum distance of 10 meters between each pair of LPNs. Moreover, the UEs located in a Hot Spot area are randomly placed with minimum distances of 30 meters to the HPN and 5 meters to the nearest LPN. Two thirds of UEs are forcibly placed within the Hot Spot area, the remaining UEs being randomly placed in the HPN coverage area. A typical scenario following the 3GPP specification is exemplified in Fig. 1.

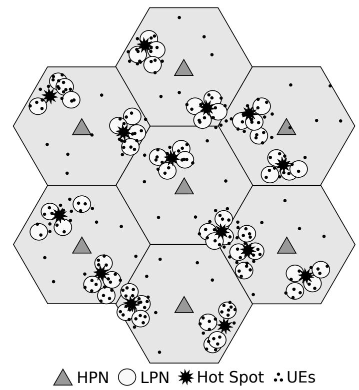

Fig. 1. H-CRAN scenario.

We also define minimal power and interference models. We compute the interference caused by the sum of the adjacent cell powers at the kth RB assigned to UE u as:

$$I_{t,u,k} = \sum_{u' \neq u} \sum_{t' \neq t} a_{t',u',k}(p_{t',u',k} P^{(pl)}_{t',u}).$$

We assume the following definition for the minimal power of LPNs (HPNs):

$$p_{t,u,k} = \min\{R_t, (I_{t,u,k} + N_0) \cdot T_{sinr} + P^{(pl)}_{t,u}\},$$

where

$$R_t = \begin{cases} P^L_{max} - \sum_{u,\,k} p_{t,u,k}, & \text{if } \ 1 \leq t \leq L, \\ P^H_{max} - \sum_{u,\,k} p_{t,u,k}, & \text{if } \ L+1 \leq t \leq L+H. \end{cases}$$

T_{sinr} is a fixed target Signal-to-Interference-plus-Noise Ratio (SINR) adopted for all system transmissions. The path loss $P^{(pl)}_{t,u}$ is given by the 3GPP TR 36.814 definition (for more details see [14]). Finally, our UEs are stationary and the transmission is restricted to a single-input downlink system.

We compare the performance of the proposed AMC radio resource allocation against a Locally Optimal (LO) algorithm, and two algorithms initially presented by Peng et al., namely Fixed Power and Sequential [3]. The LO algorithm assigns RBs to UEs, aiming at local interference mitigation and minimal power assignment. By local interference we mean that quality assessment of an allocation solution is done considering only received interference, which strongly hinders solution robustness. The Fixed Power algorithm equally distributes the transmission power among all K RBs of LPNs and HPNs. The Sequential algorithm relies on RBs assignment to UEs in a sequential manner with minimal power. The criteria for these choices are twofold: (*i*) to make a parallel between our global proposal and a local solution; (*ii*) considering commonly presented algorithms in the literature. The three algorithms are restricted to constraints (7)-(12) and execute the same number I_{max} of iterations as our proposal. Simulation and algorithm parameters are enumerated in Table I.

TABLE I
SIMULATION AND ALGORITHM PARAMETERS

Parameter	Value	Parameter	Value
H/Hs	7 / 2	B_0	180 Hz
L	$4 \cdot (H \times Hs)$	N_0	-110 dB
U	$[10, 100 : 10] \cdot (H \times Hs)$	$\varphi_{\mathrm{eff}}^{H}/\varphi_{\mathrm{eff}}^{L}$	4 / 2 W
P_{max}^{H}/P_{max}^{L}	46 / 23 dB	$P_{\mathrm{c}}^{\mathrm{H}}$ / P_{c}^{L}	10 / 6.8 W
T_{sinr}	16.5	P_{bh}^{H} and P_{bh}^{L}	3.85 W
η_{u} / η_f	1 Mbit/s / 1	I_{max}	10
K	100 (20 MHz, 0.5 ms)	$[B, \Lambda, \Upsilon]$	[1, 10, 1]

B. Numerical Results

We present numerical results considering system EE and SE, fraction of served UEs (*i.e.,* ratio of minimal data rate constraint fulfillment), and fairness in the resource distribution. We gradually increase the UE density from 10 to 100 UEs per Hot Spot. Fig. 2 shows the results of a total of 30 repetitions with 95% confidence intervals.

In Fig. 2 (a) we present comparative results regarding normalized EE as a function of density of UEs. AMC solution achieves the best EE results among the four compared models up to 60 UEs per Hot Spot. Beyond 50 UEs per Hot Spot, the increasing behavior of the normalized EE of the AMC proposal is replaced by a steep decreasing. For densities equal to 70 UEs per Hot Spot and higher, AMC proposal achieves lower normalized EE than the LO solution. For 80 UEs per Hot Spot and beyond, AMC proposal normalized EE also lies below normalized EE achieved by the Sequential algorithm.

In Fig. 2 (b) we show a similar comparison regarding normalized SE as a function of UE density. Again, at low densities (50 UEs per Hot Spot and below) our proposal achieves the highest normalized SE, when compared to any of the other three models. At higher UE densities, AMC's normalized SE is surpassed by Fixed Power model, which achieves the highest normalized SE in this density regime. This behavior is explained when considering that Fixed Power model attains very low transmission power, as shown in Fig. 2 (a), resulting in a scenario with minimal interference. Yet, above 50 UEs per Hot Spot, AMC's normalized SE attains the second best results among the compared models. We also observe that the normalized SE of the LO model saturates at a density of 60 UEs per Hot Spot.

Fig. 2 (c) regards fraction of served UEs as a function of UE density. At low densities (up to 40 UEs per Hot Spot), both AMC and LO are able to attend all UEs. For increasing densities, fraction of served UEs decreases for both algorithms, though decrease for the LO is steeper. At very high densities (for 70 UEs per Hot Spot and beyond), fraction of served UEs attained by AMC is the highest among the four models.

In the last analysis, presented in Fig. 2 (d), we present fairness results. At low UE densities, *i.e.,* where available resources are abundant, AMC solution tends to an unequal resource assignment among UEs. In this density regime, LO model is the fairest among the compared solutions. Beyond 60 UEs per Hot Spot, however, AMC solution becomes the fairest among solutions, and remains almost constant throughout the high density regime, while LO steeply decreases attaining a baseline comparable with the worst performing algorithm, considering fairness, *i.e.,* Sequential algorithm.

C. Analysis

In the following we present a correlated analysis, considering all aspects of the allocation solution. We identify three distinct regimes, namely, Low Density (LD), Moderate Density (MD), and High Density (HD), based on solution characteristics, as highlighted on top of Fig. 2.

• LD regime: Corresponds to 40 UEs per Hot Spot or less. Sequential and Fixed Power algorithms perform poorly in this regime. We show that the EE of our proposal (Fig. 2 (a)) is highest among all algorithms, LO's EE being the second best. Both algorithms are able to serve the total UE demand. Nonetheless, LO's solution is EE inefficient, due to its local knowledge of solution space. Fig. 2 (b) shows that LO's SE is only slightly above the worst performing algorithm's. Indeed, LO has only access to received interference, thus limits its solutions to the minimum data rate. Meanwhile, LO achieves the highest fairness (Fig. 2 (d)), but only because it is unable to explore data rates beyond the minimum.

In this resource abundant scenario, AMC achieves both highest EE and SE. This means that, on the one hand, given the abundance of resources in the LD regime, AMC is able to grant data rate beyond the minimum UE demand. On the other hand, given the global knowledge of the algorithm, it is also able to mitigate interference with intelligent resource allocation. This raises transmission capacity more than the corresponding energetic cost, whence achieving the highest EE. AMC's fairness (Fig. 2 (d)) degrades when the UE density is low, *i.e.,* despite all UEs having their minimum demand attended (Fig. 2 (c)), some UEs receive more data than others.

• MD regime: Between 40 and 70 UEs per Hot Spot, we reach a crossover regime, which goes from resource abundant to scarce. Mitigating interference becomes difficult, transmission cost grows to attain the target SINR, hindering EE. AMC is able to find solutions with increasing SE, to supply UE demand and fairness, up to a point. Radio resources are not enough to service all UEs, so AMC solutions divide resources prioritizing fairness. On the other hand, LO, given its limited knowledge on interference, is unable to locally reconfigure its network allocation in this saturation regime, the interference due to RB reuse increases and its SE saturates. This means the number of UEs LO solutions are able to serve saturates as well, and fraction of served UEs decreases steeply with increasing density.

• HD regime: Beyond 70 UEs per Hot Spot, the steep decrease in EE (Fig. 2 (a)) for the AMC solution is explained

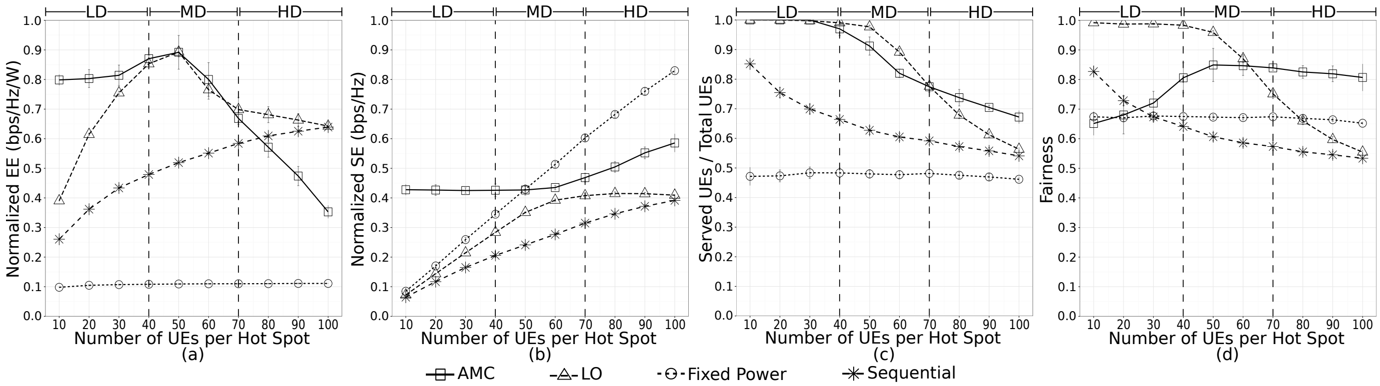

Fig. 2. Quality assessment for UEs densification in a fixed H-CRAN scenario with 7 HPN and 4 LPNs per Hot Spot

by a corresponding increase in SE (Fig. 2 (b)), with a resulting increase in energy cost. When the number of unattended UEs grows, the AMC solution sacrifices EE (including below Sequential's EE) to achieve higher SE, to serve more UEs with also higher fairness (Fig. 2 (c), (d)). Indeed, our solution provides the best fairness among all models. In contrast, the LO solution decreases the fairness and ratio of served UEs, due to its limited local knowledge. This means that solutions limited to local knowledge are unable to explore all the network reconfiguration capacity (limiting SE), as opposed to global solutions that can promote greater SE to the network.

High EE is easy to achieve, when considered alone, as can be seen from the fact that the Sequential algorithm is able to provide the same normalized EE as the LO. Had we considered EE only, we would have mistakenly inferred the AMC solution to provide a bad resource allocation strategy at high UE densities. However, this behavior is justified in view of our solution prioritizing served UEs and fairness, as forecast in 5G networks.

V. Conclusion and Future Works

In this paper, we proposed an AMC algorithm to perform global EE resource allocation for *e.g.,* H-CRAN architectures. We compared our solution against three state-of-the-art resource allocation algorithms for 5G networks, following the guidelines defined by the 3GPP. We showed that our proposal achieves the highest EE when the UE density is low; whereas, for high density networks, our proposal achieves an EE similar or lower to LO algorithms. However, our solution is able to guarantee higher fraction of served UEs with the highest fairness. We also proved that our algorithm provides the best SE due to overall knowledge and control of the network. We showed that in highly dense scenarios, EE maximization does not provide the best allocation solution, considering fraction of served UEs and fairness. Thus, EE alone is not a well suited metric for efficiency of resource allocation. We conclude that our proposal is the best suited, among all models considered, to meet 2020 cellular network requirements. For future works, we envisage the application of the AMC solution to a scenario with user mobility and the modeling of the horizontal handover as a function of the radio resource allocation problem.

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