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A Game Theoretic Approach For Optimizing Density of Remote Radio Heads in User Centric Cloud-Based Radio Access Network

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Abstract—In this paper, we develop a game theoretic formulation for empowering cloud enabled HetNets with adaptive Self Organizing Network (SON) capabilities. SON capabilities for intelligent and efficient radio resource management is a fundamental design pillar for the emerging 5G cellular networks. The C-RAN system model investigated in this paper consists of ultra-dense remote radio heads (RRH) overlaid by central baseband units that can be collocated with much less densely deployed overlaying macro base stations (BS). It has been recently demonstrated that under a user centric scheduling mechanism, C-RAN inherently manifests the trade-off between Energy Efficiency (EE) and Spectral Efficiency (SE) in terms of RRH density. The key objective of the game theoretic framework developed in this paper is to dynamically optimize the trade-off between the EE and the SE of the C-RAN. More specifically, for an ultra-dense C-RAN based HetNet, the density of active RRHs should be carefully dimensioned to maximize the SE. However, the density of RRHs which maximizes the SE may not necessarily be optimal in terms of the EE. In order to strike a balance between these two performance determinants, we develop a game theoretic formulation by employing a Nash bargaining framework. The two metrics of interest, SE and EE, are modeled as virtual players in a bargaining problem and the Nash bargaining solution for RRH density is determined. In the light of the optimization outcome we evaluate corresponding key performance indicators through numerical results. These results offer insights for a C-RAN designer on how to optimally design a SON mechanism to achieve a desired trade-off level between the SE and the EE in a dynamic fashion.

Index Terms—C-RAN, SON, Outage Capacity, Energy Efficiency, RRH density, Game theory, Nash Bargaining Solution.

I. INTRODUCTION

By the year 2020, the growth in mobile data is expected to increase by more than 1000 folds as compared to 2010 [1]. Consequently, the emerging 5G wireless networks should be able to support this massive proliferation of mobile devices and triggered exabyte flood. Therefore, 5G technology is expected to: 1) be able to support 1000 times of traffic density more than today's networks; 2) be capable of serving 10 to 1000 times more terminals than today's networks; 3) achieve better network coverage. In order to make the capacity demands required for the upcoming 5G technology possible, networks densification will be an essential part of 5G [2]. It

is envisioned that such densification will be realized through the ultra-dense deployment of small cells. Cloud-based Radio Access Networks (C-RANs) are expected to facilitate the densification of cellular networks through the deployment of distributed Remote Radio Heads (RRHs) [3], [4]. The main characteristic of C-RAN architecture is that the baseband processing unit (BBU) is separate from the distributed RRHs. Each RRH is connected with the cloud BBU pool via a front-haul which is often a fiber optic cable. Such a centralized RAN architecture enables the implementation of complex coexistence and scheduling mechanisms. The net overhead of implementing such mechanisms is less than what would occur in traditional autonomous small cell networks. Another benefit that C-RAN architecture provides is that it enables significant energy savings. It is established that RRHs do not require energy expenditure compared to traditional macro-BSs where cooling and running of computing systems results in significant energy consumption. This distributed architecture carried by a central management unit enables the implementation of advanced interference mitigation schemes, such as interference alignment [5]. All of these features which can be exploited from implementing C-RAN have triggered intensive research in this area including [5]–[8]. Another new cellular networks design philosophy in context of 5G is to transform the clustering scheme from a base station centric approach to be user-centric [9], [10]. Benefits of following such an approach are dynamic coverage and higher link success probability. Dynamic coverage is provisioned by turning on only the RRHs which are needed to serve the desired user at a certain quality of service (QoS). A higher link success probability is achieved due to higher gain in the received signal strength (RSS) at the mobile user (MU). This diversity enabled gain is attained from having several active RRHs in the user-centric cluster. This clustering scheme has been explored by [10], [11]. There are several key performance indicators (KPI) that can be used to quantify C-RAN performance. The most important of these KPIs is the spectral efficiency (SE). A study on the SE in terms of outage capacity (OC) was conducted by [10], which shows how the OC relates to the density and to the employed transmission power of RRHs in each tier. Another

important KPI that needs to be taken into consideration during C-RAN's design and deployment is the energy efficiency of the network. Power consumption in C-RAN has been a subject of intensive research. Such research attempted to characterize and reduce the power needed to perform tasks such as joint downlink and uplink user-AP association and beamforming [12], decoding data [13], and resource allocation [14]. A study on energy efficiency in dense small cells networks for different on/off schemes has been studied in [15].

II. CONTRIBUTIONS & ORGANIZATION

In this work, we study the inherent trade-off between the SE and the energy efficiency (EE) in C-RAN where user-centric clustering is performed. In particular, we examine how the two KPIs, the SE and the EE, vary with the density of active RRHs in a C-RAN network. Firstly, we summarize a user-centric clustering scheme and present an analytical framework that characterizes the SE in form of an OC formula. Thus, we will use the terms SE and OC interchangeably throughout this paper. The next step, is to characterize the cost of implementing a user-centric clustering mechanism. This is achieved by deducing a formula that quantifies the EE on the holistic level of the network. Our formula quantifies the energy that is needed for selecting the best RRH which will serve the MU in each user-centric cluster. We demonstrate that there exists a trade-off between the EE and the SE in terms of RRH density. The key objective of this study is to provide a SON capability for the selection of RRH density per tier that would provide the best trade-off between the SE and the EE. To achieve this goal, we utilize a game theoretic formulation to find the RRH density value by modeling the problem as a bargaining problem. We find the Nash bargaining solution (NBS) which achieves the best balance between those two KPIs.

As discussed in the introduction section, a number of prior studies have explored the EE and the SE in context of macro and small cell networks [5], [10]–[15]. However, to the best of our knowledge, this paper presents the first study of its kind that investigates the trade-off between the EE and the SE in the context of C-RAN, where user centric clustering is implemented, and utilizes a game theoretic framework to optimize the solution. This paper builds on very recent results presented in [5], [10]–[15].

The rest of the paper is organized as follows: In section III, we describe the user-centric clustering scheme and characterize cell OC. In section IV, we quantify the effect of RRH density on power consumption in the network. We examine the trade-off between the two performance metrics in section V. In section VI, we formulate the problem as a bargaining game and validate the required axioms for it to have a Nash bargaining solution. Numerical results of NBS and discussion are presented in section VII. The paper is concluded in section VIII.

III. OUTAGE CAPACITY UNDER USER-CENTRIC CLUSTERING MECHANISM

In this paper, we consider the downlink operation of a large scale cellular network provisioned by a dynamic user-centric clustering scheme. Under such mechanism, the first tier is constituted by macro BSs and the remaining $(k - 1)$ tiers correspond to small cells that consist of RRHs. It is assumed that dissimilar RRH densities and transmission powers are employed per tier. Various user-centric clusters can be formed within each tier. The total bandwidth is divided into sub-bands where each sub-band is assigned to one cluster. Sub-bands are allocated to clusters in a manner that cross-tier interference is eliminated. The user-centric clustering mechanism is managed by the C-RAN control center. For an arbitrary MU, the C-RAN central controller locates the best tier that can serve the MU under a specific QoS requirement. The QoS requirement is captured by having the MU as a center of a cluster that does not contain any other scheduled users except for the targeted MU. Each cluster is represented by a circle with radius R and is centered around the MU. The average number of RRHs inside each cluster is assumed to be greater than unity. The operation of forming a user-centric cluster proceeds as follows: The macro BS that is closest to the MU transmits a pilot signal to it. The MU, in return, retransmits the pilot signal to all RRHs contained within its cluster. The corresponding RRHs examine the received strength of the pilot signal. The RRH selection mechanism chooses the RRH which will be able to provide the targeted MU with the highest RSS among the group of RRHs located within the cluster. It is worth noting that none of the RRHs contained within the cluster are allowed to concurrently serve any other MUs until the targeted MU finishes its current activity. The benefits attained from applying this mechanism can be summarized as:

- 1) RRH selection diversity enables a higher gain in the received signal at the targeted MU.
- 2) Since each cluster uses its own sub-band and no overlapping clusters are allowed, this permits an effective mitigation of both co-tier and cross-tier interference. Any users who belong to overlapping clusters are scheduled to be served later.
- 3) The dynamic scheduling employed in this scheme enables energy savings. Only the best RRH is activated, while the rest of RRHs are put in sleep mode.

We characterize the relationship between RRH density and the cell outage capacity in a k -tier C-RAN, where the propagation channel suffers from Rayleigh fading complemented with large scale power-law path-loss, by the following proposition:

Proposition 1. For a desired reliability constraint ρ , the outage capacity is defined as the maximum downlink throughput which can be obtained in the network such that the outage probability for the MU remains below a per-designated reliability threshold ρ . The upper-bound on the outage capacity

under ρ is given as

$$C_\rho \leq \log_2 \left(1 + \frac{(\pi\delta\Gamma(\delta) \sum_{i=1}^k \lambda_i P_i^\delta)^{\delta-1}}{\sigma^2 \ln(1/\rho)^{\delta-1}} \right), \quad (1)$$

where the noise at the receiver is assumed to be additive white Gaussian noise (AWGN) represented by a random variable with Gaussian distribution of $\mathcal{N}(0, \sigma^2)$; δ is a path loss dependent constant given as $\delta = 2/\alpha$ for path loss exponent $\alpha > 2$. k is the number of tiers in the C-RAN. We assume that the RRH density in each subsequent tier is denser than its antecedent tier. Thus, we denote λ_i as the RRH density for tier $i \in k$. This can be stated in terms of the baseline density λ_l , where $\lambda_i = \eta^i \lambda_l$ for $\eta \geq 1$. P_i is the transmitted power per tier $i \in k$ which can be calculated by $P_i = \beta^i P_l$, where $\beta \leq 1$ and P_l is the baseline power employed at the parent tier. It is assumed that RRHs in each tier consumes less power than its parent tier.

Proof: Please refer to [10] ■

IV. POWER CONSUMPTION IN C-RAN

It is important to quantify the cost of implementing the user-centric clustering scheme in terms of power expenditure. This allows us to compare the attained diversity gain with the consumed power in the network. One penalty for having diversity gain is that all RRHs in the cluster have to be active during the RRHs selection phase. The more active RRHs are available to choose from, the higher is the achieved diversity gain, but the more total power is consumed per cluster. This process creates a trade-off between the EE and the SE of the user-centric clustering mechanism. The EE of the network can be quantified as the cost function of implementing the clustering mechanism. In order for our evaluation to be valid, we only focus on the energy consumed during RRH selection phase, as it represents the overhead caused by the user-centric clustering scheme.

A. Power consumption model

Power consumption of various types of wireless networks has been investigated in [16]. The authors in [17] focus on power consumption for multi-input multi-output discontinuous transmission in C-RAN. We extend the formula described in [17] in order to quantify power consumed in the network during the discovery process of the RRH, which can be quantified as:

$$P_{CRAN} = \xi_{CRAN} + \Delta_\mu P_\mu + P_{0\mu}, \quad (2)$$

where P_μ is the transmit power employed by the MU. Δ_μ is a parameter that relates power consumption with the employed radio frequency. $P_{0\mu}$ is the fixed power consumed by the hardware of the MU. ξ_{CRAN} is the C-RAN coefficient, which represents the total consumed power by every active RRH in all k -tiers of the network. It shows the proportional relation between power consumption on the wide network level and the density of RRHs and their employed transmission power per tier. The C-RAN coefficient is also proportionally related to θ , which represents the efficiency of the implementation. Hence,

the C-RAN coefficient ξ_{CRAN} is expressed by the following equation:

$$\xi_{CRAN} = \theta \sum_{i=1}^k \lambda_i P_i, \quad 0 \leq \theta \leq 1, \quad (3)$$

where $\theta = 0$ represents the most energy efficient implementation.

B. Energy Efficiency

The energy efficiency measures the number of bits transmitted per unit of bandwidth at the expense of one Joule during one second. We quantify EE according to the following proposition:

Proposition 2. We can express the energy efficiency at the network level by the following analytical expression:

$$\omega_{EE} = \frac{BC_\rho}{\theta \sum_{i=1}^k \lambda_i P_i + \Delta_\mu P_\mu + P_{0\mu}}, \quad (4)$$

where the transmission bandwidth B is normalized to unity.

Proof: Proof of this proposition directly stems from the definition of EE at the network holistic level, that is: The ratio of sustainable throughput for each scheduled user to the power consumed at the user mobile device and the RRHs during the RRH selection phase. In other words EE is the ratio of [bits/s/Hz] over consumed units of [Joule]. ■

V. TRADE-OFF BETWEEN OUTAGE CAPACITY AND ENERGY EFFICIENCY

To examine the effect of RRH density in each tier, we start by examining the effect of baseline RRH density λ_l on the OC and EE. We analyze OC as expressed in (1) and the EE as expressed in (4) for various values of baseline RRH density λ_l . We perform the analysis using the parameters from Table I with different variations of η and β . Figure 1a depicts the impact of RRH density per tier on OC. It can be concluded from the corresponding graphs that OC increases as RRHs become denser. Figure 1a consolidates the observation that after certain RRH density, the corresponding OC plot becomes saturated and no significant gain can be obtained from increasing RRH density any further. The optimal RRH density for maximum OC and the corresponding peak OC values are shown in the second and third columns of Table II. Figure 1b shows the changes in EE with an increase in RRH baseline density. It can be observed from figure 1b that EE increases with RRH density up to a certain RRH density threshold. Intuitively, for a large increment rate η in RRH density, EE drops significantly. Columns 2 and 3 from Table III show the optimal RRH density values which result in peak EE values. By examining the second column from Tables II and III for each case study, we notice a major difference in the optimal RRH density values. This simple comparison clearly demonstrates that there exists an inherent trade-off between the two performance determinants, EE and OC in C-RAN under user centric clustering. A self-organizing capability is essential here to guarantee that the best throughput and energy efficiency are achieved and maintained in the C-RAN. This

self-organizing feature should be able to dynamically select the most appropriate number of RRHs that should be active in each tier to achieve the desired level of balance between OC and EE, while taking into account spatio-temporally changing channel and user distributions. In the next section we will employ a game theoretic framework to solve this dilemma.

VI. GAME THEORY FRAMEWORK

In the previous section, we concluded that selecting the best baseline RRH density would require a trade-off between the OC and the EE. Therefore, a SON mechanism for Cloud BBU pool must be devised such that the baseline RRH density strikes a desired balance between those two performance determinants. As we will see, a game theoretic approach can provide a solution to this dilemma. We propose modeling the two performance metrics as virtual game players. Cell OC is modeled as the first player with (1) as its utility function, and the EE is modeled as the second player with (4) as its utility function.

A. Game Formulation

Each player's payoff is affected by the selection of baseline RRH density λ_l made by the other player. Benefiting from the centralized management in C-RAN, we can define the problem as a cooperative game. The two players will have to negotiate for the value of λ_l . Both players mutually benefit from reaching an agreement over the optimal baseline RRH density. Thus, both cell OC and EE can reach an optimal trade-off. We prove that this negotiation process can be modeled as two-player Nash Equilibrium bargaining game.

B. The Bargaining problem

Let $\mathbb{N} = \{1, 2\}$ be the set of the players, where player $i = 1$ denotes OC and player $i = 2$ denotes EE, and S_i denotes the set of all feasible payoffs to a user i , as:

$$S_i = \{U_i | U_i = U_i(\lambda_l), \lambda_l \in \mathbb{R} : \lambda_l > 0\}. \quad (5)$$

Let's define the space S as the set of all feasible payoffs that player $i \in \mathbb{N}$ can achieve when they work together is:

$$S = \{U = (u_1, u_2) | u_1 \in S_1, u_2 \in S_2\}, \quad (6)$$

where u_1 is the utility of the first player and u_2 is the utility of the second player where

$$s_1 = u_1 = C_\rho(\lambda_l), \quad (7)$$

$$s_2 = u_2 = \omega_{EE}(\lambda_l), \quad (8)$$

and $\lambda_l \in \mathbb{R} : \lambda_l > 0$. We also define the disagreement space ($D \in S$) as the set of the two disagreement points $d = (d_1, d_2)$, where $d_1 = u_1(D)$ and $d_2 = u_2(D)$ represent the payoff for each player if the bargaining process failed and no outcome is reached. For our game we set $d = (0, 0)$. Therefore, we give both players the same bargaining power in the game.

Proposition 3. The problem described by (18) and (19) is a two-player bargaining problem defined by the pair (S, D) where $S \subset \mathcal{R}^2$ and $D \in S$.

Proof: For a bargaining problem to be defined, S should be

a convex and a compact set [18]. Since it is clear that S is compact, we only need to prove that it is a convex set:

$\forall \epsilon : 0 \leq \epsilon \leq 1$ and if $U^a = (u_1^a, u_2^a) \in S$ and $U^b = (u_1^b, u_2^b) \in S$, then $\epsilon U^a + (1 - \epsilon)U^b \in S$.

Since $u_1 = \log_2(1 + \frac{(\pi \delta \Gamma(\delta) \sum_{i=1}^k \lambda_i P_i^\delta)^{\delta^{-1}}}{\sigma^2 \ln(1/\rho)^{\delta^{-1}}})$, we denote the SIR as γ and re-write it as: $u_1 = \log_2(1 + \gamma)$ where $\gamma \leq \rho$. Without loss of generality we can apply the condition of convexity on $1 + \gamma$. Since taking the logarithmic values of a convex set will not change its convexity property:

$$\epsilon u_1^a + (1 - \epsilon)u_1^b = 1 + \bar{\gamma}, \quad (9)$$

where $1 + \bar{\gamma} = 1 + \frac{(\pi \delta \Gamma(\delta) \sum_{i=1}^k (\epsilon \lambda_i^a + (1 - \epsilon) \lambda_i^b) P_i^\delta)^{\delta^{-1}}}{\sigma^2 \ln(1/\rho)^{\delta^{-1}}}$, where $0 < \lambda_i^a$ and $0 < \lambda_i^b$, thus it can be easily concluded that values of $1 + \bar{\gamma}$ form a convex set and that the same applies to the values of $\log_2(1 + \bar{\gamma})$. Hence, we prove that:

$$\epsilon u_1^a + (1 - \epsilon)u_1^b \in S_1. \quad (10)$$

As for the utility of the second player, we use the same aforementioned definition for γ and $\bar{\gamma}$ from above. Similarly we find:

$$u_2 = \frac{B \log_2(1 + \gamma)}{\theta \sum_{i=1}^k \lambda_i P_i + \Delta_\mu P_\mu + P_{0\mu}}. \quad (11)$$

we already proved that the outcome of the numerator is convex set, as for denominator:

$$\theta \sum_{i=1}^k \bar{\lambda}_i P_i + \Delta_\mu P_\mu + P_{0\mu}, \quad (12)$$

where $\sum_{i=1}^k \bar{\lambda}_i P_i = (\sum_{i=1}^k \epsilon \lambda_i^a + \sum_{i=1}^k (1 - \epsilon) \lambda_i^b) P_i$ thus, we write

$$\epsilon u_2^a + (1 - \epsilon)u_2^b = \frac{B \log_2(1 + \bar{\gamma})}{\theta \sum_{i=1}^k \bar{\lambda}_i P_i + \Delta_\mu P_\mu + P_{0\mu}}, \quad (13)$$

Since $0 < \lambda_i^a$ and $0 < \lambda_i^b$, we find that the denominator is also convex. Thus, we conclude that:

$$\epsilon u_2^a + (1 - \epsilon)u_2^b \in S_2, \quad (14)$$

from (10) and (14) we conclude that the $\epsilon U^a + (1 - \epsilon)U^b \in S$ and the set S is convex. ■

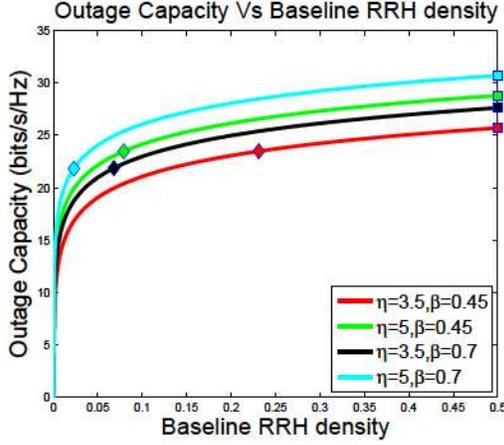
C. Nash Bargaining Solution

In order for a bargaining problem to have a solution $U^* = (u_1^*, u_2^*)$ for the disagreement space $D = (d_1, d_2)$, Nash has specified four axioms that the bargaining outcome must satisfy [18]:

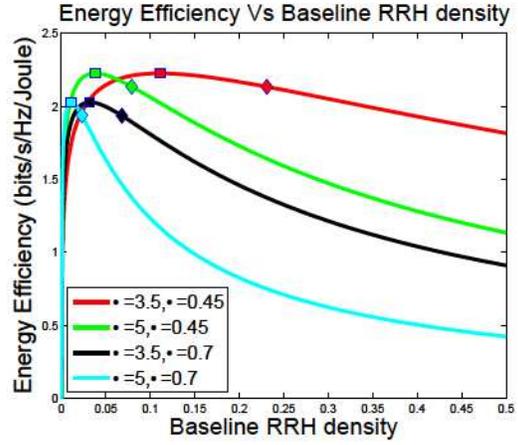
- 1) *Pareto Efficiency:* The Nash bargaining solution must be Pareto-optimal. This means that there cannot be a solution where utilities of both players can be improved in the same time. This concept can be mathematically expressed as:

$$(U_1, U_2) > U^* \Rightarrow (U_1, U_2) \notin S. \quad (15)$$

- 2) *Symmetry:* The solution of the bargaining problem should remain the same if the roles of the two players



(a) Outage capacity with varying RRH baseline density λ_l



(b) Energy efficiency with varying RRH baseline density λ_l

Fig. 1: The effect of varying RRH baseline density on OC and EE for various case studies. The peak and NBS values for each graph are consecutively denoted by '■' and '◆' of the same corresponding color

were to be switched. In other words, the bargaining solution does not discriminate between the players if they were indistinguishable.

- 3) *Invariance to equivalent utility representation*: The Nash bargaining solution must satisfy the following condition for any strictly increasing linear function F

$$U^*[F(S), F(D)] = F[U^*(S, D)]. \quad (16)$$

- 4) *Independence of irrelevant alternatives*: Let's consider \hat{S} a smaller set of S where U^* is still part of \hat{S} then U^* will not change:

$$U^*(S, D) \in \hat{S} \subseteq S \Rightarrow U^*(\hat{S}, D) = U^*(S, D). \quad (17)$$

We now search for the unique Nash Bargaining Solution that satisfies the axioms above. We start by defining the Nash product [18] which is expressed as:

$$\max_{(s_1, s_2)} (s_1 - d_1)(s_2 - d_2), s.t. (s_1, s_2) \in S \geq (d_1, d_2). \quad (18)$$

We select the disagreement points as $(d_1, d_2) = (0, 0)$. By substitution, we get:

$$\max(C_\rho(\lambda_l)) \times (\omega_{EE}(\lambda_l)). \quad (19)$$

Equation (19) represents the final Nash product which we want to maximize for $\lambda_l \in \mathbb{R} : R > 0$

VII. RESULTS & DISCUSSION

Nash product defined in (19) and is plotted in figure 2. The NBS value that we are looking for is RRH baseline density λ_l , which maximizes the Nash product. Using the network parameters' values from Table I, we create four case studies to be examined. Each case study represents a different set of values of η and β . The obtained NBS value of λ_l and its corresponding outage capacity values are shown in columns 4 and 5 of Table II. The NBS value of λ_l and its corresponding energy efficiency values are shown in columns 4 and 5 of

TABLE I: List of parameters used in the analysis

Parameter	Value
k	3
α	4
σ^2	10^{-5}
η	{3.5, 5}
β	{0.45, 0.7}
ρ	0.2
P_l	1 Watts
P_μ	1 Watts
Δ_μ	4
$P_{0\mu}$	4.3 Watts
θ	0.5

TABLE II: Peak and NBS outage capacity values and their corresponding RRH density values

Case	λ_l^{opt}	C_ρ^{peak}	λ_l^{NBS}	C_ρ^{NBS}	%Loss
$\eta = 3.5 \& \beta = 0.45$	0.5	25.71	0.23	23.48	8.67%
$\eta = 5 \& \beta = 0.45$	0.5	28.80	0.07	23.47	18.5%
$\eta = 3.5 \& \beta = 0.7$	0.5	27.62	0.06	21.87	20.81%
$\eta = 5 \& \beta = 0.7$	0.5	30.71	0.02	21.83	28.91%

TABLE III: Peak and NBS energy efficiency values and their corresponding RRH density values

Case	λ_l^{opt}	ω_{EE}^{peak}	λ_l^{NBS}	ω_{EE}^{NBS}	%Loss
$\eta = 3.5 \& \beta = 0.45$	0.11	2.22	0.23	2.13	4.05%
$\eta = 5 \& \beta = 0.45$	0.03	2.22	0.07	2.13	4.05%
$\eta = 3.5 \& \beta = 0.7$	0.03	2.02	0.06	1.93	4.45%
$\eta = 5 \& \beta = 0.7$	0.01	2.02	0.02	1.93	4.45%

Table III. By comparing fourth and fifth columns between the Tables II and III, we find that, both OC and EE have dropped

by a some amount from its peak value. The loss percentage in each KPI has been calculated for each study case and is shown in the sixth column in Table II and Table III. A simple comparison between the loss percentages in OC and EE show that the impact of the bargaining process on outage capacity is more pronounced as compared to its impact on EE. If it is desired to create a bias in the outcome towards one of the KPIs, a threshold on acceptable-loss percentage can be defined. Such threshold is reflected by a new set of disagreement points. Each of d_1 and d_2 can be given a value $0 \leq d_1 \leq C_\rho^{peak}$ and $0 \leq d_2 \leq \omega_{EE}^{peak}$ consecutively. The process then can be repeated by using this new disagreement space D . However, it is intuitively obvious that any improvement in the utility of one player will cause a deterioration in the utility of the second player. Hence, such thresholds should be carefully designed when integrating this dynamic trading mechanism between EE and SE as a self-organizing capability of the C-RAN based deployment of 5G.

VIII. CONCLUSION

In this work, we have developed an analytical framework for characterizing Energy Efficiency (EE) and Outage Capacity (OC) using game theory in cloud radio access network (C-RAN). C-RAN model considered in this paper exploits ultra-dense Remote Radio Read (RRH) deployments to dynamically perform user-centric clustering mechanism for radio resource scheduling and Energy Efficiency (EE). Our analysis shows that there exists values of active RRHs densities which can maximize EE and OC. However, an inherent trade-off between maximizing OC and EE needs to be addressed. We solve this dilemma of optimizing two conflicting objectives, i.e., EE and OC, by modeling the problem as a bargaining game. The two performance indicators, EE and OC were modeled as virtual game players in a bargaining game. Our analysis shows that a Nash bargaining solution exists in such a game. Several scenarios for the game have been examined. We use the loss percentage between peak and NBS values in each player's utility as a comparison metric. Thus, we evaluate the results and conclude that RRHs density obtained from the NBS provides a reasonable trade-off. We show that the bargaining game model also enables the possibility of shifting the solution to a more preferable trade-off level dictated by networks performance requirements.

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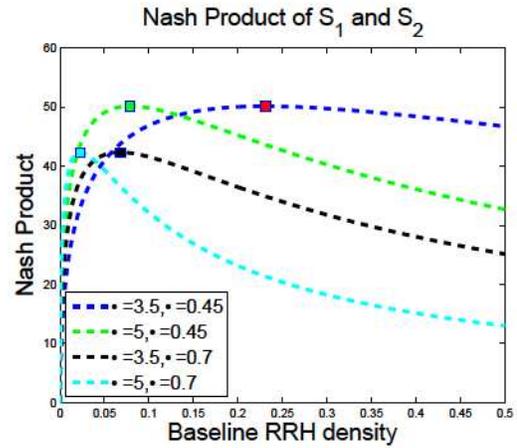


Fig. 2: Nash Product for each case study. The peak value for each graph is denoted by '■' of the same corresponding color

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