Towards User QoE-Centric Elastic Cellular Networks: A Game Theoretic Framework for Optimizing Throughput and Energy Efficiency

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***Abstract*—User-centric network architectures are a key proponent to enable the uniform Quality of Experience (QoE) requirement for future dense heterogeneous network (HetNet) deployments. However, catering to spatio-temporally varying user service demands arising from the plethora of diverse mobile applications remains a challenge in such network architectures. In this paper, we propose a QoE-centric elastic framework for a dense multi-tier cellular network deployment. The framework leverages the control and data plane separation architecture (CDSA) for enabling selective data base station (DBS) activation within user equipment (UE)-centric virtual cells (also referred to as service zones). The allocation of these virtually elastic service zones around selected UEs is conducted via a central control base station (CBS) and modeled through two game techniques, namely evolutionary and auction games. Both the games are based on a utility minimization problem which is a function of weighted mean UE throughput and usage based UE service demands. To illustrate the trade-offs between the game models, network level performance is compared in terms of aggregate throughput, energy efficiency, algorithm convergence speed and mean UE scheduling probabilities.**

***Index Terms*—User-centric architectures, Control and Data Plane separation, evolutionary game, auction game**

I. Introduction

Network densification through the use of small cells is considered a viable solution for meeting the capacity targets in future cellular networks (i.e. 5G). While densification is inevitable, it has a couple of major associated problems that persist as a bottle neck in network planning: i) high inter-cell interference and ii) low energy efficiency [1]. Though upcoming 5G technologies such as massive multiple input multiple output (MIMO) and millimeter wave (mmWave) offer promising prospects for increased system capacity [2], they may not address the aforementioned issues. Redesigning the network orchestration in cell planning from the traditional base station (BS)-centric to a user equipment (UE)-centric approach [3] has been recently envisioned as a first step to address these challenges [4]. This user-centric (UEC) architecture guarantees a higher energy efficiency (EE) along with location-independent uniform Quality of Experience (QoE). Analysis in [5] has shown that the cell density that yields optimal EE is different than that which yields maximum outage capacity. In [6], we leverage this analysis to propose a UEC network deployment solution where an ultra-dense network is deployed, and is then orchestrated between EE and area spectral efficiency (ASE) optimal modes by intelligently switching OFF/ON small cells. This switching ON and OFF is done by creating non-overlapping exclusion zones around high priority UEs within which only one small cell is turned ON during each scheduling instant. The size of the exclusion zone is then used as a control parameter to realize the desired compromise between EE and ASE. However, due to diversity in mobile data usage trends, a static network wide optimal exclusion zone size does not offer the elasticity to optimize individual user's QoE in different spatio-temporal zones.

In this paper, we present and introduce a second tier of elasticity within UEC systems that integrates non-uniform exclusion zones centered around users. These non-uniform exclusion zones, which we call as service zones (S-Zones), cater for data demand disparity between spatio-temporal zones as well as the diversity of data requirements from user applications (for instance HD video streaming v/s whatsapp messaging) within a single spatio-temporal zone. The basic premise behind deploying virtual flexible service zones around mobile users is to control the interference limit that a user can experience while still getting the throughput sufficient for its data needs. For instance, high definition real-time gaming applications will require a high throughput and low latency communication link, which can be guaranteed if the signal to interference ratio (SINR) is sufficiently high. To ensure that, the controller will assign this user a large service zone to not only assign it larger number of resources, but also to reduce interference from concurrent downlink transmissions for other users. The same is true other way round for

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IoT based sensor devices that require low throughput transmission, and hence a relatively moderate SINR. Consequently, a smaller service zone would suffice for their data requirements.

This demand based UEC scheme is an ideal candidate for implementation in a control-data separation architecture (CDSA) [7] where small cells referred to as data base stations (DBSs) provide data services to UEs while macro base stations also referred to as control base stations (CBSs) provide necessary control and signaling. While CBSs provide the essential coverage, intelligent activation/de-activation of the DBSs enables potential for significant energy savings in CDSA. In addition to this, CDSA can offer better spectral efficiency mainly because of selection diversity that stems from large number of DBSs in dense deployments. Centralized coordination at the CBS solves the cell discovery problem for DBSs in a conventional BS-centric architecture. In the proposed UEC framework, this allows for turning DBSs ON/OFF, depending upon an individual UE's S-Zone size and the propagation link quality between that UE and the DBSs within its S-Zone.

The analysis of strategies UEs may adapt while competing for downlink (DL) resources to meet their data requirements in a UEC CDSA is the focus of this paper. To this end, we investigate the application of game theoretic techniques which have been well known for resource management and interference mitigation in dense small cell networks [8] [9]. In particular, we apply auction and evolutionary game techniques (referred to as AGT and EGT respectively), with users as game players adapting strategies to secure DL scheduling within virtually interference free S-Zones. While there has been significant research in user-centric networks in recent times [10],[11], to the best of our knowledge, analysis of second tier elasticity in user-centric CDSA that caters to non-uniform user demands remains a terra incognita. This work is a first attempt to analyze the tradeoff of game theoretic techniques for UE level demand based CDSA architecture. The contributions and findings of this work are summarized as follows:

A. Contributions

- The analysis of UE-centric systems with a CDSA architecture requires incorporating the idiosyncrasies of the dynamic activation/de-activation of DBSs within a two-tier network. We present a system model that links the activation of DBSs to user requirements as well as the level of interference in the environment surrounding the scheduled users (Section II-A,B,C,D).
- Contrary to our previous UEC models in [4], [5] and [6] that were based on static first tier exclusion zone modelling, this work takes a step further and incorporates the effect of non-uniform user demands across and within spatio-temporal zones (Section II-E).

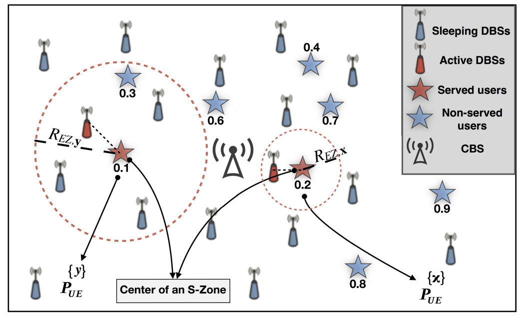

Fig. 1. S-Zones concept illustration in UE-centric CDSA architectures.

- In order to evaluate mechanisms for integrating throughput demand disparity in S-Zone assignment, we perform a detailed comparative analysis using two game theoretic techniques, namely evolutionary game and auction theory (Section III). Both the games are based on a distributed utility minimization problem. The evolutionary game involves iterative action strategy adjustment by the UEs, whereas the auction game comprises of UEs bidding their true valuation with the aim of winning the auction and securing virtual S-Zones for DL scheduling.
- Simulation results are presented for performance evaluation of the algorithms in terms of aggregate system throughput, energy efficiency, user scheduling ratio and mean algorithm convergence time (Section IV). We show that the proposed QoE based user-centric service zone provisioning yields better performance as compared to a UE-centric network with static system-wide service zone area. Our analysis advocates integration of an intelligent self-organizing network (SON) engine [12] within the proposed UEC CDSA network architecture. The SON engine would optimize a network efficiency metric by dynamically shifting game strategies with respect to network dynamics and spatio-temporally varying operator's business model.

II. System Model

A. UE-Centric CDSA Network

Fig. 1 shows a UE-centric based CDSA network model where users having a high payoff (used interchangeably with utility) and scheduling priority are served by a single DBS providing best channel quality (e.g. CQI (channel quality indicator) measure) within their virtual service zones respectively. Each scheduled UE is the center of an S-Zone with an active DBS. The remaining DBSs within and outside the S-Zones are turned OFF to reduce inter-cell interference as well as lower overall power consumption. The area of S-Zones around scheduled UEs is adjustable based on individual UE's throughput requirements. This two-tier CDSA with elastic service zone model consists of a central CBS providing essential control and signaling functionalities to the UEs while the DBSs serve the UEs with DL data transmissions. Based on the channel feedback by the UEs, the CBS allocates S-Zones to scheduled users based on outcome of game models (Section III) during each transmission time interval (or TTI).

B. Network Model

Borrowing from well established tools in stochastic geometry [13], we model the spatial distributions of DBSs and UEs using two independent stationary Poisson point processes (SPPPs): $\Pi_{\text{DBS}} \in \mathbb{R}^2$ and $\Pi_{\text{UE}} \in \mathbb{R}^2$ with intensities λ_{DBS} and λ_{UE} respectively. Specifically, at an arbitrary time instant, the probability of finding $n_i \in \mathbb{N}, i \in \{\text{DBS,UE}\}$ DBSs/UEs inside a typical macro-cell with area foot-print $\mathcal{A} \subseteq \mathbb{R}^2$ follows the Poisson law with mean measure $\Lambda_i(\mathcal{A}) = \lambda_i v_2(\mathcal{A})$ [4]. The mean measure is characterized by the average number of DBSs/UEs per unit area (i.e., $\lambda_{\text{DBS}} \backslash \lambda_{\text{UE}}$) and the Lebesgue measure [13] $v_2(\mathcal{A}) = \int_{\mathcal{A}} d\boldsymbol{x}$ on $\mathbb{R}^2$, where if $\mathcal{A}$ is a disc of radius r then $v_2(\mathcal{A}) = \pi r^2$ is the area of the disc.

C. Channel Model

The channel between a DBS $\boldsymbol{x} \in \Pi_{\text{DBS}}$ and an arbitrary UE $\boldsymbol{y} \in \Pi_{\text{UE}}$ is modeled by $h_{\boldsymbol{xy}} l(||\boldsymbol{x} - \boldsymbol{y}||)$. Here $h_{\boldsymbol{xy}} \sim \mathcal{E}(1)$ is a unit mean exponential random variable which captures the impact of a Rayleigh block-fading channel between $\boldsymbol{x}$ and $\boldsymbol{y}$. The small-scale Rayleigh fading is complemented by a large-scale path-loss modeled by $l(||\boldsymbol{x}-\boldsymbol{y}||) = K||\boldsymbol{x}-\boldsymbol{y}||^{-\alpha}$ power-law function. $||\boldsymbol{x} - \boldsymbol{y}||$ is the Euclidean distance between $\boldsymbol{x}$ and $\boldsymbol{y}$, K is a frequency dependent constant and $\alpha \geq 2$ is an environment/terrain dependent path-loss exponent. The fading channel gains are assumed to be mutually independent and identically distributed (i.i.d.). Without any loss of generality, we assume $K = 1$ for the rest of this discussion. Furthermore, we assume that all DBSs employ the same transmit power.

D. UE-Centric DBS Scheduling

The first step in DBS scheduling is identification of high priority users to be scheduled in a given TTI. The second step is creation of non-overlapping circular S-Zones centered around each UE selected to be served in that TTI. The size of the S-Zone is the parameter of optimization and will be discussed later. Each UE is then served by a DBS within its S-Zone that provides strongest received signal power. The remaining DBSs are switched off. The size of circular S-Zone around a scheduled UE $\boldsymbol{x}$ is characterized by a variable radius $R_{\text{SZ},\boldsymbol{x}}$ which is a function of $\boldsymbol{x}$'s data requirements and the interference from nearby active DBSs. The CBS is responsible for control signaling to all the UEs within its footprints. In addition, the CBS also assigns scheduling priorities in the form of a mark/tag $p_{\text{UE}} \sim \mathcal{U}(0, 1)$ to each UE. The marked PPP [13] formed as a result of user-centric scheduling impacts the downlink scheduling priority of the UEs. More specifically, the lower the value of the mark, the higher is the priority of the UE to be scheduled. Effectively, these marks can be thought of as the timers corresponding to each UE that are decremented in each time slot where DL service to this UE is deferred. Based on the channel quality measure between the DBSs and the UEs, the CBS decides and activates the relevant DBSs for DL transmission to the scheduled UEs. The advantages of such UEC scheduling is two-fold: firstly, due to non-overlapping S-Zones, the interference experienced by a scheduled UE is considerably reduced and secondly, on-demand activation of DBSs provides the network self-organizing capabilities to cope with spatio-temporal variations in user demography.

One might argue that such a one-to-one UE-DBS association within a non overlapping user-centric S-Zone scheme may result in service holes, i.e. there may exist UEs that are not associated with any DBSs due to empty UE-centric S-Zones. Since we are considering dense small cell deployments with λ_{DBS} and λ_{UE} of the same order, UE-centric S-Zones with realistic areas will hardly be void. In the unlikely scenario of a void S-zone though, user clustering strategies [14] may be employed where nearby UEs are grouped together and optimization is performed on the UE clusters rather than individual UEs. Furthermore, it is known that best DBS activation with a proximity constraint provides dual benefits of low outage probability and high power efficiency in dense deployment scenarios [15].

E. UE's payoff function and S-Zone size for Game formulation

Payoff function: We model the payoff of a UE $\boldsymbol{x}$ as $u_{\boldsymbol{x}} = \delta(\bar{\tau} - \tau_{\boldsymbol{x}}(R_{\text{SZ},\boldsymbol{x}})) + (1 - \delta)(\tau_{d,\boldsymbol{x}} - \tau_{\boldsymbol{x}}(R_{\text{SZ},\boldsymbol{x}}))$; where $\tau_x(R_{\text{SZ},\boldsymbol{x}})$ is the achievable data throughput for $\boldsymbol{x}$, $\bar{\tau} = \frac{1}{N}\sum_{n=1}^{N} \tau_{\boldsymbol{n}}$ is the mean achievable user throughput (considering N active UEs) of the spatio-temporal zone estimated through a central entity (such as the CBS) and $\tau_{d,\boldsymbol{x}}$ is $\boldsymbol{x}$'s variable throughput demand based on the application usage. $0 \leq \delta \leq 1$ is a weight priority index, controllable via CBS, with factor δ enforcing uniform throughput regardless of service demand disparity while $1 - \delta$ allows users with high scheduling priority to selfishly meet their data demands at the expense of non-priority users.

The first component of the payoff measures the utility of a UE in terms of the penalty (positive / negative) depending upon how much lesser / greater the UE's achievable throughput is to the mean achievable throughput of all UEs. Similarly, the second component of the payoff determines the penalty associated with how deviant the achievable throughput is to the UE's actual service based throughput demand at a given S-Zone radius. Using this novel characterization of payoff, we can formulate the optimization problem to be solved by the game models for a UE $\boldsymbol{x}$'s payoff as a function of $R_{\text{SZ},\boldsymbol{x}}$ and given as

$$\min_{R_{\text{SZ},\boldsymbol{x}}} |\delta(\bar{\tau} - \tau_{\boldsymbol{x}}(R_{\text{SZ},\boldsymbol{x}})) + (1-\delta)(\tau_{d,\boldsymbol{x}} - \tau_{\boldsymbol{x}}(R_{\text{SZ},\boldsymbol{x}}))|. \quad (1)$$

S-Zone radius: The achievable throughput for a UE $\boldsymbol{x}$ is expressed using Shannon's theorem as

$$\tau_x(R_{\text{SZ},\boldsymbol{x}}) = \log_2(1 + \text{SINR}(R_{\text{SZ},\boldsymbol{x}})), \tag{2}$$

where the S-Zone size dependent received SINR at $\boldsymbol{x}$ when served by DBS $\boldsymbol{y}$ can be written as follows:

$$\text{SINR}(R_{\text{SZ},\boldsymbol{x}}) = \frac{max_{\boldsymbol{y}\in\Pi_{\text{DBS}}\cap(\boldsymbol{x},R_{\text{SZ},\boldsymbol{x}})} h_{\boldsymbol{xy}} l(||\boldsymbol{x}-\boldsymbol{y}||)}{N_o + \sum_{\boldsymbol{z}\in\Pi_I} h_{\boldsymbol{xz}} l(||\boldsymbol{x}-\boldsymbol{z}||)}. \tag{3}$$

$\Pi_{\text{DBS}} \cap (\boldsymbol{x}, R_{\text{SZ},\boldsymbol{x}})$ is the thinned PPP representing the DBSs within the UE-centric virtual circular cell of area $\pi R^2_{\text{SZ},\boldsymbol{x}}$ around $\boldsymbol{x}$, Π_I denotes the thinned PPP of interfering DBSs, i.e. the active DBSs in S-Zones other than that centered around $\boldsymbol{x}$, and N_o is the variance of the additive white Gaussian noise at $\boldsymbol{x}$.

To ensure that the UE-centric S-Zones are within practical dimensions, we tried several mathematical formulations of $R_{\text{SZ},\boldsymbol{x}}$ as a function of λ_{DBS}, λ_{UE} and $\gamma_{\boldsymbol{x}}$. Drawing insights from extensive simulation based experiments with different DBS and UE densities, we propose the following model to characterize the S-Zone area around a UE $\boldsymbol{x}$ served by a DBS $\boldsymbol{y}$[1]:

$$R_{\text{SZ},\boldsymbol{x}} = \frac{||\boldsymbol{x}-\boldsymbol{y}|| \ln(\lambda_{\text{DBS}})}{(1-\gamma_{\boldsymbol{x}}) \ln(\lambda_{\text{UE}})}, \tag{4}$$

where $0.1 \leq \gamma_{\boldsymbol{x}} \leq 0.9$ is the application based variable UE demand with normal distribution $\mathbb{N}(0.5, 0.1)$. The limits on the UE demand ensures avoiding circumstances when UEs with extremely high/low service demands request impractically high/low S-Zone radii.

III. Game Formulations for UE-centric Service Zone Scheduling

We leverage both evolutionary (EG) and auction (AG) games to determine optimal S-Zone sizes by solving the optimization problem in (1). Let **N**={1,2,...,N} denote the set of UEs participating in each game iteration. Each UE $\boldsymbol{x}$ demands a certain throughput $\tau_{d,\boldsymbol{x}}$, which is a function of the variable demand variable $\gamma_{\boldsymbol{x}}$, such that $\tau_{d,\boldsymbol{x}} \propto \gamma_{\boldsymbol{x}}$. For this work, we consider a linear relationship, $\tau_{d,\boldsymbol{x}} = K\gamma_{\boldsymbol{x}} + \epsilon$, where ϵ is the UE specific noise in the throughput demand. The throughput demand $\tau_{d,\boldsymbol{x}}$ in turn determines the S-Zone radius $R_{\text{SZ},\boldsymbol{x}}$ through iterative update in $\gamma_{\boldsymbol{x}}$ until convergence is achieved for the utility in (1). The CBS calculates and communicates $\bar{\tau}$ to every UE within its coverage so that they may adjust $\gamma_{\boldsymbol{x}}$ with the objective of solving (1).

A. Evolutionary Game

In the context of an evolutionary game for S-Zone size optimization, each UE adapts its demand strategy according to the received payoff in (1). This evolution of the game allows the population states to evolve over time. For this work, we are considering two UE population states: over-served and under-served expressed as UE_{OS} and UE_{US} respectively. An over-served UE is characterized by a negative utility in (1) indicating surplus resources in terms of higher achievable throughput as compared to the mean throughput and/or the application based throughput demand. The action strategy for over-served UEs is an adjustment in their S-Zone size through a prefixed step reduction in $\gamma_{\boldsymbol{x}}$. Similarly, the under-served UEs with positive utilities increase their S-Zone areas through a prefixed step increase in $\gamma_{\boldsymbol{x}}$, within the demand constraints (Step 1, Algorithm 1).

The evolutionary game in Algorithm 1 is governed by principles of replicator dynamics [9], according to which the number of UEs selecting a particular strategy will increase if that action yields close to zero payoff. The frequency for a particular action strategy is given by $X_s = \frac{N_s}{N}$. N_s is the number of UEs selecting strategy s where $s \in S = \{\text{increase } \gamma_{\boldsymbol{x}}, \text{ reduce } \gamma_{\boldsymbol{x}}\}$.

Algorithm 1 EG algorithm

1: Each UE chooses a throughput demand $\tau_{d,\boldsymbol{x}}$ based on the application usage. The disparity in $\tau_{d,\boldsymbol{x}}$ is modeled by assuming that the UE demand $\gamma_{\boldsymbol{x}}$ has a normal distribution, i.e. $\gamma_{\boldsymbol{x}} \sim \mathbb{N}(0.5, 0.1)$, and constraints $0.1 \leq \gamma_{\boldsymbol{x}} \leq 0.9$. Iteration counter is set to $i = 1$.
2: Based on the channel gains and $\gamma_{\boldsymbol{x}}$ values, the CBS calculates $R_{\text{SZ},\boldsymbol{x}}$, creates virtual S-Zones around high priority UEs and turns ON a single DBS per S-Zone. Elaborating mathematically, a UE $\boldsymbol{x}$ is scheduled iff $p^{\{\boldsymbol{x}\}}_{\text{UE}} < p^{\{\boldsymbol{x'}\}}_{\text{UE}}; \forall \boldsymbol{x} \in \Pi_{\text{UE}}, \boldsymbol{x'} \in \Pi_{\text{UE}} \cap (\boldsymbol{x}, R_{\text{SZ},\boldsymbol{x}}), \boldsymbol{x'} \neq \boldsymbol{x}$.
3: The scheduled UEs observe $\text{SINR}(R_{\text{SZ},\boldsymbol{x}})$ and subsequently the achievable throughput $\tau_x(R_{\text{SZ},\boldsymbol{x}})$ which is sent to the CBS.
4: The CBS calculates $\bar{\tau}$ and broadcasts it to all UEs.
5: Each scheduled UE computes its utility $u_{\boldsymbol{x}}$ and adjusts $\gamma_{\boldsymbol{x}}$. If $u_{\boldsymbol{x}} > 0$, then $\gamma_{\boldsymbol{x}} = \min(\gamma_{\boldsymbol{x}}+0.05, 0.9)$; if $u_{\boldsymbol{x}} < 0$, then $\gamma_{\boldsymbol{x}} = \max(\gamma_{\boldsymbol{x}} - 0.05, 0.1)$; and left unchanged otherwise.
6: Update $p^{\{\boldsymbol{x}\}}_{\text{UE}}$, increment i and go to step 2 while $i < i_{\text{max}}$.

i_{max} is the maximum number of simulation iterations for a given network configuration. The EG based strategy adaptation algorithm functions in a distributive manner where each UE adapts its individual strategy to optimize (1). Additionally, the algorithm relieves the CBS from centralized optimization computation, making its implementation scalable throughout the network.

B. Auction Game

Auction theory allows players to intelligently select their strategies in order to gain maximum resources. For our work, we adapt the Vickrey Clark Groves (VCG) auction mechanism which is known for ensuring assurance of truthfulness from the players as well as maximization of fairness [16]. Also called the "sealed-bid

[1]Note that the formulation for $R_{\text{SZ},\boldsymbol{x}}$ is done for the parameters considered in Section IV. A different formulation may be required for suburban and sparsely deployed DBS regions.

second-price auction", this auctioning scheme awards the bid to the highest bidder who pays an amount equivalent to the second highest bid. Contrary to the first price auctions, VCG auctions prevent selfish players from cheating because bidding the true valuation is the weakly dominant strategy in this model [17]. This guarantees that under most general circumstances, VCG will yield bid winners as players with highest valuations.

In contrast to EG where S-Zone assignment was dependent upon $p_{\text{UE}}^{\{\boldsymbol{x}\}}$ alone, in AG (Algorithm 2), we integrate the utility $u_{\boldsymbol{x}}$ within the bidders' (or UEs') valuation structure as

$$b_{\boldsymbol{x}} = \frac{1}{p_{\text{UE}}^{\{\boldsymbol{x}\}}[\delta(\bar{\tau} - \tau_x(R_{\text{SZ},\boldsymbol{x}})) + (1-\delta)(\tau_{d,\boldsymbol{x}} - \tau_x(R_{\text{SZ},\boldsymbol{x}}))]}. \tag{5}$$

As seen from (5), the UEs with optimal utilities are rewarded with higher bid values. Each iteration in the AG is a new game as the winners of the conducted auctions are assigned S-Zones by the CBS and barred from further bidding. Because we analyze system level performance metrics, the cost paid by UEs after winning the bids is irrelevant for this work. However, we employ a VCG auction due to its relevance to wireless networks [18]. Moreover, the existing framework can be analyzed in extensions of this work and include the effect of UE cost when modeling the network over large number of TTIs.

Algorithm 2 AG algorithm

Steps 1-4 same as EG algorithm.
5: Each UE participating in the auction calculates its bid value $b_{\boldsymbol{x}}$ and sends it to the CBS.
6: The CBS chooses a player as the winner of the auction if its bid is not lower than any other player that can form a non-overlapping S-Zone with the existing S-Zones, i.e. a UE $\boldsymbol{x}$ is the auction winner iff $b_{\boldsymbol{x}} > b_{\boldsymbol{x'}}; \forall \boldsymbol{x}, \boldsymbol{x'} \in \Pi_{\text{UE}}^{'}$, where $\Pi_{\text{UE}}^{'}$ refers to the UEs whose $R_{\text{SZ},\boldsymbol{x}}$ (and $R_{\text{SZ},\boldsymbol{x'}}$) allow non-overlapping S-Zones with past auction winners.
7: The CBS removes the auction winner in current iteration from future bidding. New bidding round (step 5) continues until there is no new winner.
8: CBS schedules auction winners, updates $p_{\text{UE}}^{\{\boldsymbol{x}\}}$ and i. Go to step 3 and re-evaluate the metrics for existing players. Continue until $i < i_{\max}$.

IV. Simulation Results and Discussion

In this section, we discuss the simulation results for a range of efficiency parameters to evaluate the performance of the game theoretic techniques in question, i.e. EGT and AGT within the elastic CDSA framework. The basic simulation parameters are given in Table 1.

A. Aggregate Throughput performance

The aggregate throughput is calculated numerically as the sum of the achievable throughput of the served UEs within a TTI, i.e. $\lambda_{\text{DBS,Act}}|A| \sum_{1}^{\lambda_{\text{DBS,Act}}|A|} \tau_{\boldsymbol{x}}$ where $\lambda_{\text{DBS,Act}}|A|$ denotes the number of activated DBSs (or served UEs) in the network. The results in fig. 2 reveal contrasting trends with varying δ and DBS densities under considered game theoretic algorithms. While the EGT demonstrates reduction in throughput for the range of DBS densities considered as δ increases, the AGT shows increasing throughput trends for denser DBS deployments with an increase in δ. The trends are disruptive for $\delta = 1$ which is the pure fairness centric scheduling scheme and takes no consideration of users' QoE requirements.

As far the deployment density is concerned, EGT is the superior scheme for $\lambda_{\text{UE}}/8$ DBS density. For denser networks with mean DBS deployment density of $3\lambda_{\text{UE}}/8$, AGT is clearly the preferred game model. The findings highlight the necessity of a SON implementation within the CBS for intelligent and dynamic adaptation of game model as a function of both λ_{DBS} and δ to maximize the system throughput.

TABLE I
SIMULATION PARAMETERS

Parameter	Value
Simulation area dimensions ($\lvert A\rvert$)	100 m x 100 m
$\lambda_{\text{UE}}\lvert A\rvert$	400
$\lambda_{\text{DBS}}\lvert A\rvert$	50, 100, 150
α	4
δ	0, 0.25, 0.5, 0.75, 1
Power consumption parameters P_o, P_u, Δ_u and P_{ou}	6.8, 1, 4 and 4.3 W
θ	0.5
$i_{\max}$	100
No. of Monte Carlo realizations	1000

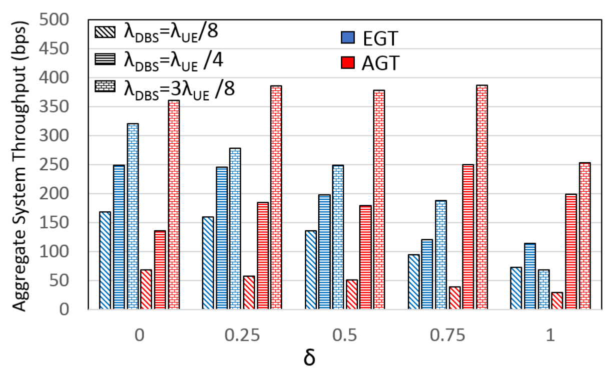

Fig. 2. System throughput comparison of EGT and AGT.

B. Energy Efficiency of the UEC CDSA

To estimate the EE of an elastic CDSA under UE-centric architecture, we take inspiration from the work of award winning European project EARTH [19] and apply relevant modifications to construct a power consumption model for a UE-centric CDSA given as

$$P_{\text{CDSA}} = \lambda_{\text{DBS,Act}}|A|(\theta P_o + \Delta_u P_u + P_{ou}), \tag{6}$$

where P_o, P_u and P_{ou} denote fixed power consumption of an active DBS, transmit power of a UE terminal and circuit power consumed at UE terminal during discovery respectively [20]. $0 \leq \theta \leq 1$ is a system deployment efficiency parameter with $\theta = 1$ capturing least energy efficient deployment. The power consumption of the CDSA as seen from (6) is an increasing function of the DBS density and a decreasing function of the average UE S-Zone area.

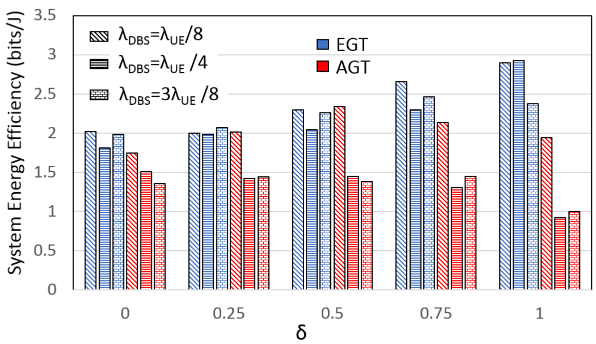

Fig. 3. Energy Efficiency comparison of EGT and AGT.

Although AGT (fig. 3) demonstrates comparable EE performance for $\lambda_{\mathrm{DBS}} = \lambda_{\mathrm{UE}}/4$ and $\delta \leq 0.5$; for most of the simulated scenarios, EGT is a clear winner. This can be attributed to a larger average S-Zone area for the EGT implementation which reduces the average number of concurrent DL transmissions and hence more DBSs are deactivated.

C. Convergence analysis

To analyze the convergence of the algorithms, we plot the average payoff received by UEs using EGT and AGT (fig. 4). It can be seen that the system converges to equilibrium relatively faster with AGT. Particularly at low DBS densities, for instance at $\lambda_{\mathrm{DBS}} = \lambda_{\mathrm{UE}}/8$ in fig. 4b, the mean UE utility converges to 0 almost instantly. Not only does the AGT outperform EGT in convergence speed, but also in achieving optimal UE utility, i.e. by minimizing $|u_{\boldsymbol{x}}|$. Negative utilities for EGT indicate UEs receiving sufficiently high SINR to attain achievable throughputs exceeding the desired levels needed to optimize (1). The root cause for the non-ideal UE utility distribution with EGT can be traced back to UE demand constraints ($0.1 \leq \gamma_{\boldsymbol{x}} \leq 0.9$) which bars the UEs with high negative utilities to further reduce the S-Zone size and increase their utility.

D. UE Scheduling success

The expected delay for a UE waiting to be scheduled is analyzed by plotting the mean served UE ratio ($\frac{\lambda_{\mathrm{DBS,Act}}}{\lambda_{\mathrm{UE}}}$) under variable DBS densities and δ values (fig. 5). The served UE ratio represents the expected number of scheduled UEs after equilibrium is achieved for the EGT and AGT games. The smallest wait time

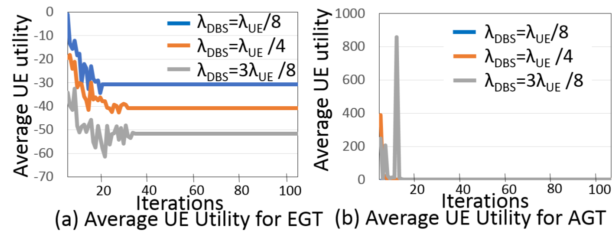

Fig. 4. Convergence of (a) EGT and (b) AGT algorithms for an elastic UEC CDSA network.

is observed for AGT scheme with $\lambda_{\mathrm{DBS}} = 3\lambda_{\mathrm{UE}}/8$ where an arbitrary UE is expected to be re-scheduled after every 5th or 6th TTI. For $\lambda_{\mathrm{DBS}} = \lambda_{\mathrm{UE}}/8$, EGT marginally outperforms AGT while AGT exhibits higher scheduling success for $\delta \geq 0.5$ when $\lambda_{\mathrm{DBS}} = \lambda_{\mathrm{UE}}/4$. The simulation results in fig. 5 once again reiterate the practicality of a SON engine capable of adjusting δ and alternating between game models to yield desired service delay times within UE-centric CDSA.

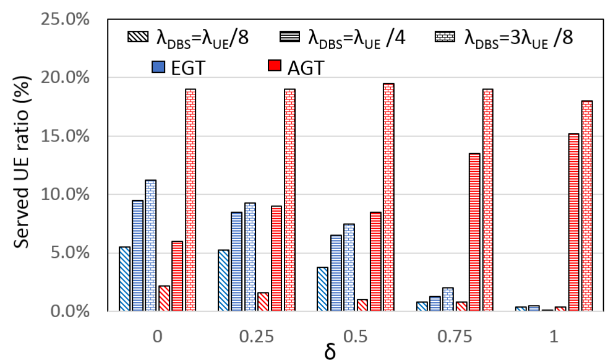

Fig. 5. UE Scheduling Success probabilities with EGT and AGT algorithms.

E. Performance Comparison with first tier user-centric elasticity

Fig. 6 shows the performance gains in terms of aggregate system throughput (fig. 6(a)) and energy efficiency (fig. 6(b)) for the proposed UE-centric elastic CDSA in comparison to the uniform user-centric service regions proposed in earlier works [21]. The network models with fixed user-centric regions in [21] to maximize ASE and EE are referred to as FS(ASE) and FS(EE) respectively. The variable-sized QoE-centric service zones proposed in this work with EGT and AGT implementations are referred to as VS(EGT) and VS(AGT) respectively. Clearly, the proposed model outperforms "one-size fits all" strategy both in terms of system throughout and EE by virtue of assigning flexible user-centric service zones that are appropriately sized to meet an arbitrary UE's data requirements. While AGT yields higher data throughput, particularly at high λ_{DBS}, the EGT is more energy efficient. Once again, this result reiterates the need for an intelligent SON enabled CBS that can switch the game models to support a higher data throughout (or energy efficiency).

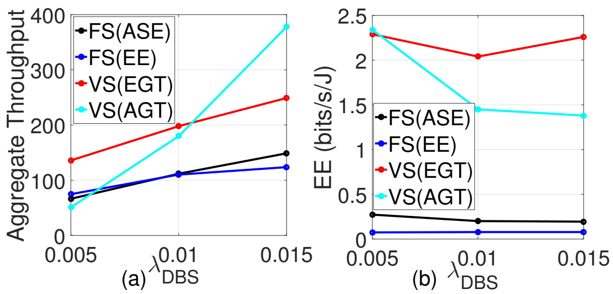

Fig. 6. (a) System throughput and (b) EE comparison of uniform user-centric [21] and QoE-centric service zone approaches with different DBS densities.

V. Conclusion

In this paper, we presented an elastic cellular network framework capable of catering to individual UE QoE requirements. The QoE flexibility is realized through virtual interference free service zones centered around scheduled UEs. We proposed a distributed utility minimization problem to model appropriate S-Zone formations around the UEs. To evaluate the optimization of S-Zone allotment to UEs, we conducted a detailed comparative analysis using evolutionary and auction based game implementations at a centralized CBS. We investigated different key performance indicators including aggregate network throughput, energy efficiency, mean UE scheduling probability and algorithm convergence speed. Results indicated that for each efficiency metric, with variations in DBS density and the priority distribution between a fair UE throughput network versus a service requirement driven throughput network, the game scheme exhibiting superior performance fluctuates. To fully optimize a network efficiency parameter, we advocate a SON enabled CBS that is capable of dynamic adaptation of game modes to offer higher throughput or energy savings, whichever is desired by the network operator. Future works include evaluation of the proposed model at mmWave frequencies and including the associated signaling costs within the optimization framework.

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References

[1] A. Imran, A. Zoha, and A. Abu-Dayya, "Challenges in 5G: how to empower SON with big data for enabling 5G," *IEEE Network*, vol. 28, no. 6, pp. 27–33, Nov 2014.

[2] S. Cetinkaya, U. S. Hashmi, and A. Imran, "What user-cell association algorithms will perform best in mmWave massive MIMO ultra-dense HetNets?" in *2017 IEEE 28th Annual International Symposium on Personal, Indoor, and Mobile Radio Communications (PIMRC)*, Oct 2017, pp. 1–7.

[3] S. Chen, F. Qin, B. Hu, X. Li, and Z. Chen, "User-centric ultra-dense networks for 5G: challenges, methodologies, and directions," *IEEE Wireless Communications*, vol. 23, no. 2, pp. 78–85, April 2016.

[4] S. Zaidi, A. Imran, D. McLernon, and M. Ghogho, "Characterizing Coverage and Downlink Throughput of Cloud Empowered HetNets," *Communications Letters, IEEE*, vol. PP, no. 99, pp. 1–1, 2015.

[5] B. Romanous, N. Bitar, S. A. R. Zaidi, A. Imran, M. Ghogho, and H. H. Refai, "A Game Theoretic Approach for Optimizing Density of Remote Radio Heads in User Centric Cloud-Based Radio Access Network," in *2015 IEEE Global Communications Conference*, Dec 2015, pp. 1–6.

[6] U. S. Hashmi, S. A. R. Zaidi, and A. Imran, "User-Centric Cloud RAN: An Analytical Framework for Optimizing Area Spectral and Energy Efficiency," *IEEE Access*, vol. 6, pp. 19 859–19 875, 2018.

[7] A. Mohamed, O. Onireti, M. A. Imran, A. Imran, and R. Tafazolli, "Control-Data Separation Architecture for Cellular Radio Access Networks: A Survey and Outlook," *IEEE Communications Surveys Tutorials*, vol. 18, no. 1, pp. 446–465, Firstquarter 2016.

[8] J. Zheng, Y. Cai, and A. Anpalagan, "A Stochastic Game-Theoretic Approach for Interference Mitigation in Small Cell Networks," *IEEE Communications Letters*, vol. 19, no. 2, pp. 251–254, Feb 2015.

[9] P. Semasinghe, E. Hossain, and K. Zhu, "An Evolutionary Game for Distributed Resource Allocation in Self-Organizing Small Cells," *IEEE Transactions on Mobile Computing*, vol. 14, no. 2, pp. 274–287, 2015.

[10] J. Cao, T. Peng, Z. Qi, R. Duan, Y. Yuan, and W. Wang, "Interference Management in Ultra-Dense Networks: A User-Centric Coalition Formation Game Approach," *IEEE Transactions on Vehicular Technology*, vol. PP, no. 99, pp. 1–1, 2018.

[11] H. Zhang, Y. Chen, and Y. Liu, "Spatial correlation based analysis of power control in user-centric 5G networks," *IET Communications*, vol. 12, no. 3, pp. 326–333, 2018.

[12] O. G. Aliu, A. Imran, M. A. Imran, and B. Evans, "A survey of self organisation in future cellular networks," *IEEE Communications Surveys Tutorials*, vol. 15, no. 1, pp. 336–361, 2013.

[13] J. M. D. Stoyan, W. S. Kendall and L. Ruschendorf, *Stochastic geometry and its applications*. Wiley Chichester, 1995, vol. 2.

[14] A. Imran, M. A. Imran, A. Abu-Dayya, and R. Tafazolli, "Self organization of tilts in relay enhanced networks: A distributed solution," *IEEE Transactions on Wireless Communications*, vol. 13, no. 2, pp. 764–779, February 2014.

[15] H. He, J. Xue, T. Ratnarajah, F. A. Khan, and C. B. Papadias, "Modeling and Analysis of Cloud Radio Access Networks Using Matern Hard-Core Point Processes," *IEEE Transactions on Wireless Communications*, vol. 15, no. 6, pp. 4074–4087, June 2016.

[16] W. Vickrey, "Counterspeculation, Auctions, and Competitive Sealed Tenders," *The Journal of Finance*, vol. 16, no. 1, pp. 8–37, 1961.

[17] Z. Han, D. Niyato, W. Saad, T. Babar, and A. Hjorungnes, *Game Theory in Wireless and Communication Networks: Theory, Models, and Applications*. Cambridge University Press, 2012.

[18] M. A. Alavijeh, B. Maham, Z. Han, and W. Saad, "Truthful spectrum auction for efficient anti-jamming in cognitive radio networks," in *2017 IEEE Symposium on Computers and Communications (ISCC)*, July 2017, pp. 742–747.

[19] [Online]. Available: https://www.ict-earth.eu/

[20] R. Gupta, E. C. Strinati, and D. Ktenas, "Energy efficient joint DTX and MIMO in cloud Radio Access Networks," in *2012 IEEE 1st International Conference on Cloud Networking*, Nov 2012, pp. 191–196.

[21] U. Hashmi, S. A. R. Zaidi, A. Darbandi, and A. Imran, "On the efficiency tradeoffs in User-Centric cloud RAN," in *IEEE ICC 2018 Next Generation Networking and Internet Symposium (ICC'18 NGNI)*, Kansas City, USA, May 2018.