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User Driven Multiclass Cell Association in 5G HetNets for Mobile & IoT Devices

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ABSTRACT Fifth generation (5G) needs to support plenty of applications and services with a wide variety of quality of service requirements. The deployment of ultra-dense small cells' networks as a part of the heterogeneous networks architecture is one of the key technologies to achieve this. In such a dense architecture, associating devices with the network is challenging. The traditional cell association algorithms use signal-to-interference-plus-noise ratio metric. However, this is not appropriate for 5G, especially with the reduction in the cells size and the growing number of the user equipment (UE) and the Internet-of-Things (IoT) devices. In this paper, we propose a distributed multiclass user-driven cell association algorithm based on the multi armed bandit game (CA-MAB) to connect devices with different requirements to the network. Here, we focus on two classes of devices: UE devices and low-power IoT devices. The proposed algorithm is evaluated in static and mobile environments, where the convergence and equilibrium are achieved. Our performance results are validated against the central cell association method that is complex and requires a huge amount of information exchange. The results show that CA-MAB throughput and energy efficiency are within 10% of the centralized solution. These values increase by less than 5% in the case of mobility. However, they reduce with more network densification.

INDEX TERMS 5G, ultra-dense networks, cell association, energy harvesting, game theory.

I. INTRODUCTION

Mobile data traffic continuously grew by 74% in 2015 and is expected to multiply eight times by 2020. Only 26% smart-phones (from global mobile devices) generate about 88% of the entire mobile data traffic [1]. Users' continuous changing behavior and the emerging high bandwidth-hungry applications including, but not limited to, video streaming and multimedia have put future wireless cellular networks under tremendous pressure [2]. The expected increase in wireless communications traffic volume motivates a lot of research on the fifth generation (5G) cellular networks. Eight major requirements of 5G systems are identified through different industries and academic research initiatives, those requirements are represented in offering several Gbps data rates in real networks, 1 ms round-trip latency, high bandwidth in unit area, an enormous number of connected devices, 99.999% of perceived availability, almost 100% coverage for anytime anywhere connectivity, reduction in energy usage by almost 90% and high battery life [3]. 5G architecture is required to break the Base Station (BS) centric network paradigm in order to achieve the sub-millisecond latency requirements and to overcome the traditional wireless spectrum bandwidth limitation. This can be done by moving from BS centric to a device-centric network.

Mobile cellular networks are designed to support data-intensive Human-Type Communications (HTC). HTC in general, User Equipment (UE) Mobile devices traffic specifically, differs than Machine-Type Communications (MTC) traffic from its size, quality, sensitivity, and requirements. Therefore, cell association mechanism should take communication types and classes requirements into consideration [4]. MTC as the Internet of Things (IoT) applications typically exchange small data packets in smart environments; the energy consumption required to transmit small data packets over cellular communication is considered a serious obstacle that faces large-scale IoT deployment. Heterogeneous Network (HetNets) represents the major direction of 5G network design. Cell association is a major part of 5G HetNets resource management [5]. Traditional cell association is performed depending on Signal-to-Interference-Plus-Noise Ratio (SINR). However, the network load is not taken into account in SINR based cell association [6]. Users and devices are required to associate with the cell(s) (e.g., a macrocell or

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small cells) based on different criteria such as, but not limited to, the lowest transmission power required.

Multiple emerging technologies provide the potential to support 1000× wireless traffic volume increment in the future wireless communication. Massive Multiple-Input Multi-Output (MIMO) antenna emerging technology will present a key feature to improve the spectrum efficiency [7]. Massive MIMO offers a sufficient number of antennas for BS through the use of a linear and simple signal processing techniques [8]. Network densification is also required for the 5G networks to meet its goals [7]. Fast interference coordination and cancellation, Software Defined Networking (SDN), Cognitive Radio Networks (CRNs) and Self Organizing Networks (SONs) are promising techniques that will enable dense network management [8]. Coordinated multipoint (CoMP) technology is a primary element on the Long-Term Evolution (LTE) road-map beyond Release 9 [7] that is used to decrease inter-site interference and enhance spectrum efficiency [9]. The full-duplex transmission will also be used to increase spectral efficiency [10]. Cloud Radio Access Networks (C-RAN) is an architecture envisioned for network densification that will enable CoMP implementation and can also be utilized for load balancing.

In this work we propose a multiclass distributed Cell association algorithm which uses Multi-Armed Bandit (CA-MAB) to connect devices with different requirements to the network. We argue that devices with different energy constraints and rate requirements in a 5G Ultra-Dense Small Cell Networks (UD-SCN) architecture will have a variety of optimization problems that need to be formulated as a distributed decision-making problems in a multi-agent system. For each class of devices that share a common constraint, the solution is corresponding to the interactions of a large number of devices under the energy uncertainty and dynamic mobility. Our contributions are summarized as follows:

1) We derive a multiclass Cell Association method based on Multi-Armed Bandit game in order to associate devices with different constraints and requirements to the network with minimum exchange of information between devices and the network.
2) We also show that performing cell association for all classes of devices jointly improves equilibrium and convergence of the whole systems compared to allocating specific resources for each class of devices.
3) We validate the proposed CA-MAB at environments with mobile devices and devices with uncertain resources (energy harvesting). We also show the attainable throughput gains and energy saving of CA-MAB.

The reminder of this paper is organized as follows. In Section II, we discuss 5G cellular networks and related emerging technologies. In Section III, we explain non-conventional game theory types and compare their potential applications. Section IV offers an overview about cell association techniques and some related work. In Section V, we present the proposed algorithm and formulate mathematically the system model. Section VI evaluated the CA-MAB using various test scenarios. Finally, the paper is concluded in Section VII.

II. PRIMER ON 5G

5G network design should enable the achievement of large cellular network capacity, ultralow latency, and heterogeneous device support in order to fulfill the new emerging applications. The foreseen 5G network will be composed of different types of overlapped cells and therefore will require an efficient cell association mechanisms. Cell association is a major part of 5G HetNets resource management and will be performed in conjunction with different emerging technologies in order to achieve efficient use of spectrum, capacity maximization, and energy efficiency. Resource management in 5G HetNets can be divided on one hand into cell association, required to decide which of HetNet cells should provide service to the user, and on the other hand into resources allocation including antenna, power, and channel performed after the user connection has been established [5]. A general observation of the researchers has concluded that most mobile subscribers stay outside for approximately 20% of the time and inside for approximately 80% of the time. Performing an inside and outside setups is a recent technique which came into existence in order to apply the 5G cellular architecture [11]. Such a technique will slightly reduce through walls penetration loss. This technique will be supported with massive MIMO technology, which offers a geographically dispersed tens or hundreds of antenna units arrays deployment [12]. Both outdoor antenna arrays and indoor access points will significantly enhance energy efficiency, data rate, cell average throughput, and spectral efficiency of the wireless cellular system; but with additional infrastructure cost [11]. 5G networks will encompass a few new features and technologies including HetNets new architecture design, UD-SCN, new access technologies , flexible spectrum management, and mobile cloud.

HetNets are the major direction of 5G network architecture design, which consists of different types of cell points with different technologies, capabilities, and constraints. HetNets mix up current macrocells with new deployed low power remote nodes including picocells and femtocells which enables offloading the macrocells traffic, improving user performance, indoor coverage, and enhancing spectral efficiency through spectrum reuse [13]. HetNets will play an important part to achieve ultra-dense networks due to their dynamicity. Though, interference, mobility and backhauling are going to represent new challenges that will rise due to the dense and dynamic heterogeneous networks. User-independent algorithms offer promising solutions to meet those challenges. So future smart devices are designed to be able to learn and take decisions on how to manage connectivity [12].

III. PRIMER ON GAME THEORY

Game theory is a traditional method applied to achieve effective analysis for the interactive decision making of different players with conflict of interests. Traditional learning and game-theoretical models are used in different situations including efficient resources management for different wireless heterogeneous networks, Machine to Machine (M2M) communications, and sensor networks. Such models are not suitable enough to describe and model large-scale systems because they suffer from many pitfalls and shortcomings including limited slow convergence, analysis capabilities, and excessive overhead due to large information exchange. Therefore, non-conventional models are required to handle and model the characteristics of future wireless networks in order to face distributed resource allocation problems in ultra-dense IoT systems [6]. However, non-conventional models have pros and cons that allow them to be suitable for solving specific problems more than others. Many of those games cannot be applied to cell association problems. Evolutionary games, for example, are unable to model the inhomogeneity of IoT and UE mobile devices. They are also incapable of modeling uncertainty and the stochastic nature of parameters such as energy harvesting. Auctions games are unable to model the inhomogeneity of devices. It also requires the existence of a coordinator. While Minority games have a limited binary action set which limits its selection choices [6]. In this work, we employee the mean field multi-armed bandit model to solve our optimization problem.

A. MEAN FIELD GAMES

The analysis of the interactions between players is required to achieve equilibrium for rational devices trying to take their best decision based on other players actions. However, such analysis in large-scale systems as in IoT needs intensive information exchange and leads to high complexity. Mean Field Games (MFGs) analyze the interactions of a massive number of rational entities and effectively model them [14]. The ability to summarize and describe the behavior of a single massive system with only two equations represents the most significant aspect of MFGs when modeling massive IoT systems in order to solve resource allocation problems. In the models where information exchange between devices is limited, MFG is capable to execute as offline algorithms. In fact, at the initialization phase, the devices shall gather the required information. This feature lets MFGs even more suitable to overcome the backhaul/fronthaul connectivity limitations. However, MFG formulations face difficulties in taking the incompleteness of information into account [6].

B. MEAN FIELD BANDIT GAMES

Mean Field Bandit game is a canonical model used for studying and learning in uncertain environments [15]. The Multi-Armed Bandit (MAB) games are defined as a class of sequential optimization problems, where a player pulls an arm from a given group of arms in successive rounds in order to receive a priori unknown Bernoulli reward. The player watches only the reward of his played arm. The player select arms according to some decision-making policy in order to optimize some regret-based target function over the game time. Upper Confidence Bound (UCB) is a policy which is developed specially to handle stochastic stationary bandit problems and to balance between obtaining and exploiting information in order to achieve a better reward in the future [16]. The UCB policy, described in Algorithm 1 estimates a fixed confidence level upper bound of the mean reward of each arm $m \in \mathcal{M}$ at every selection round. The highest estimated bound arm is then played, and its rewards observed and bounds updated. Conventional Bayesian and Nash equilibrium notions are infeasible to be used in models with large number of players due to the long convergence time and excessive complexity required. In mean-field bandit games, every player considers the rest of the world as being stationary and do not consider players' individual moves an important detail [6]. Mean-field bandit games are able to consider the stochastic nature of the system, to overcome the backhaul/fronthaul connectivity limitations, and to model the inhomogeneity of IoT devices.

Algorithm 1 Upper Confidence Bound Selection Policy [17]

Deterministic policy: UCB1;
Initialzation: Pull each arm once;
Loop;
- Pull arm j that maximizes $\bar{x}^j + \sqrt{\frac{2 \ln n}{n^j}}$ where $\bar{x}^j$ is the average value of the reward obtained from arm j, n^j is the number of times arm j has been pulled so far, and n is the overall number of pulls done so far;

Mean field MAB game is an efficient mathematical model used to analyze UD-SCNs. This model is suitable for 5G HetNets as users do not need prior information about network traffic or channel quality thus no massive information exchange among players is required. The model also is not complex for a massive number of users and does not suffer from slow convergence. Besides all of this, it is able to handle uncertainty and guarantee convergence to equilibrium. In mean-field games, regeneration means that a player quits or leaves the game and a new player enters and takes its place. Thus, each player regenerates at a random time which follows geometric distribution with parameter $1 - \alpha$, $\alpha \in [0, 1)$. At time t, the population profile is defined as $f^t = [f_1^t, f_2^t, \ldots, f_M^t]$ where f_m^t is the ratio of players pulling arm m at time t. An arbitrary player $n \in \mathcal{N}$ has a type $\theta_n^t \in [0, 1]^M$ at time t sampled from distribution W. It also has a state Z_n^t representing the total number of successes and failures of pulling arm m up to round t. At regeneration, Z_n^t is reset to zero. However, in any other trial, the type remains unchanged and a random selection policy is used to map state Z_n^{t-1} to an action a_n^t. After each action the player status is updated and a Bernoulli distribution random reward with success probability $Q(f_m^t, \theta_n^t)$ is produced. This mean-field dynamics is summarized in Algorithm 2 [10]. Achieving Mean Field Equilibrium (MFE) in mean-field dynamics require a stationary system for every player through maintaining a fixed population profile f [15].

Algorithm 2 Mean-Field Dynamics for Multi-Armed Bandit Games [10]

if *t is a regeneration trial,* **then**
  The players' type θ_n^{t+1} is sampled from some distribution W.
  The state Z_n^{t+1} is reset to zero.
else
  Use a selection policy δ to map Z_n^t to some action a_n^t. The mapping δ can be any standard bandit policy such as the UCB selection policy, illustrated in Algorithm 1. Monitor the reward. Update Z_n^t to Z_n^{t+1}.
end

IV. CELL ASSOCIATION

Cell association approaches are categorized based on who takes the association decision. In Network-Driven association approaches [18]–[21], a network side entity takes the decision on whether to serve/let access the new user or not. This approach offers the operator a full network control required to achieve particular objectives. Roche in [18], proposed cell association policy for an Orthogonal Frequency Division Multiple Access (OFDMA)-based small cell with hybrid access mode. Cheung *et al.* [19] association approach was based on users' distance to the BS using closed and open access modes. Niyato in [20] assumed cell association based on resources allocation and power adaptation using Nash game theory equilibrium. While Madan in [21] considered cell association based on channel allocation in order to increase the average utility value for all users through cells. On the other hand, in User-Driven cell association approach, the user/device has the privilege to make the decision to which BS to connect. In [22], devices decide to associate with the BS based on the highest SINR reported from all nearby BSs. However, devices in [23] form coalitions which decide independently on which cell to join based on their individual up-link transmission power consumption, and decide to switch their cell automatically if they observed performance degradation. Rakshit in [24] used a human walk mobility model based on 226 daily GPS traces collected from 101 volunteers in five different outdoor sites in New York city illustrated in [25] using a user-driven cell association described in [10]. Their work was only concentrated on representing the mobility effect for UE devices with a stable power source. Network and User-driven association approaches can be applied together under what is known as the Hybrid cell association approach. In this approach users select the BS or cell of their preference. However, the networks make the decision of accepting or rejecting devices [5]. The authors, in [26] used an auction process to allow devices to bid for radio resource through sending requests to a target BS while the BSs collecting all bids and determining the resource allocation for all bidders.

Cell association implementations are categorized based on where does the association decision take place. Association decision can be implemented either centralized, decentralized or distributed. In the centralized implementation, a central network entity makes a global cell association decision for all cells and devices [5]. This implementation provides complete information about networks and devices required to achieve optimal network performance. However, this approach relies on intensive information exchange and gathering [5]. In addition, it will be challenging to trace the different system parameters including quality-of-service (QoS), energy requirements, and interference conditions [24]. On the other hand, the decentralized implementation divides the network into smaller parts capable of making cell association decision for its members using controllers. This approach aims to achieve a network-wide objective but with limited information exchange. While the distributed implementation differs from the centralized and decentralized implementations as each network entity can make it's own decision independently with least information exchange [5]. Maghsudi proposed in [10] an approach based on mean-field multi-armed bandit games in order to solve the uplink cell association problem for energy harvesting for IoT devices in a UD-SCN. Their work introduced a distributed cell association approach using UCB selection policy based on received data rate. This work is motivated by the analysis and results of their work. In [27], Dong optimized the device association matrix through using quantum particle swarm optimization. Similarly, in [28], two different algorithms based on the total cost function and access points density are proposed in order to jointly optimize user association and BS operation in heterogeneous networks. Cell association access modes are categorized based on how the access to the associated cells is managed. Those modes are open, closed, and hybrid. In the open access mode, all users are treated equally and can access the small cell depending on the availability of resources. Devices in the closed access mode will receive higher access priority if they belong to Closed Subscriber Groups (CSG) and will be limited only to emergency calls if they do not belong to CSG. In the hybrid access mode, part of the resources are reserved for the small cell subscribers while also allowing access to non-subscribers, users subscribed to the small cell may get preferential charging compared to users not subscribed to the cell that receive service from it. Guruacharya in [23] introduced cell association using coalition formation game. In this scheme, HetNets use a self-control strategy that allows devices to decide and chose the cell to join independently based on its individual performance and to switch to another cell automatically if performance degradation is observed due to any congestion. Guruacharya used a Markov chain analysis to obtain a stable cell association of users. Cell association is also discussed in [5] and [10]. Wang proposed in [5] an antenna allocation and cell association algorithm depending on the evolutionary game theory which provides equilibrium solutions. Wang algorithm balanced between devices need and network need for high data rate and high revenue, respectively; but didn't consider IoT devices for low power communication need.

In our work. we proposes a user-driven distributed cell association approach that is suitable for multiclass of user devices in an open and hybrid access modes. It relies on mean field MAB game theory model using UCB selection policy based on minimum required data rate or transmission power as a reward. We show that our method is most suitable for dense and ultra-dense networks and can be used in mobile environments.

V. CELL ASSOCIATION USING MEAN FIELD MAB SYSTEM MODEL

Our system model assumes a dense small cell network which consists of M SBS, including macro cells. The network also includes N_I IoT devices and N_U UE devices. Every device n intends to transmit data packets in the uplink direction. At every transmission period j, each device transmits to the SBS selected by the device itself in which it applies a distributed cell association decision. $\mathcal{N}^j_{I,m}$ and $\mathcal{N}^j_{U,m}$ represents the set of IoT and UE devices associated to SBS m at round j, respectively. In this work, we assume IoT devices depends on energy harvesting to collect the required power for transmission. We also assume that each IoT device consumes all the stored harvested energy during each transmission period. Due to the opportunistic nature of energy harvesting, the amount of harvested energy and hence transmission power, denoted by $P^j_{I,k}$, is unknown prior for IoT device k at round j. In the system model, $P^j_{I,k}$, $j = 1, \ldots, J$, is assumed to be independent identically distributed (i.i.d.) random variables. Each of these random variable follow half-normal distribution with parameter $\sigma_n^2 > 0$ [10]. On the other hand, batteries of UE devices offer a stable energy source compared to the energy available through harvesting. This allows UE devices to perform association decisions based on the highest data rate available. The UCB policy allows devices to learn the minimum power required for transmission and the highest affordable data rate through both exploitation and exploration trials. If a device quits transmission, it is replaced by another device in order to maintain fixed population profile required for keeping MFE. This mean-field game model regeneration process is achieved through a stationary system and through keeping the number of connected devices in the network always equal to N [10].

For the communication channel, we assume a zero-mean additive white Gaussian noise with variance σ_0^2 inside every small cell as the only transmission distortion parameter in the network. We also consider the inter-cell interference experienced by device n in SBS m denoted by $I_{n,m} \geq 0$ to be fixed noise during the entire transmission period. A frequency non-selective block fading channel is used in this work where the fading channel coefficient between device n and SBS m denoted by $h_{n,m}$ follows Rayleigh distribution with parameter $\frac{1}{\sqrt{2\beta_{nm}}}$ and remains constant during transmission period. We assume that $h_{n,m}$ doesn't change for static devices. However, it changes at every transmission period for mobile devices. The random channel gain $g_{n,m} = h^2_{n,m}$ then follows an exponential distribution with parameter β_{nm}. For simplicity, the Gaussian noise, inter-cell interference, and channel gain distribution are represented by one random variable denoted by $\theta^j_{n,m} = \frac{g^j_{n,m}}{I^j_{n,m}+N_0}$ which represents the type (or ability in MAB games) of every device.

Let $f^j_m = \frac{N^j_{I,m}+N^j_{U,m}}{N}$ be the fraction of devices associated with SBS m at round j. $N^j_{I,m}$ and $N^j_{U,m}$ are the size of $\mathcal{N}^j_{I,m}$ and $\mathcal{N}^j_{U,m}$, respectively. Based on Shannon Hartley theorem formulated in [10], the achievable transmission rate $r^j_{n,m}$ can be expressed as:

$$r^j_{n,m} = \frac{W_m}{Nf^j_m} \log(1 + P^j_n \theta^j_{n,m}) \tag{1}$$

where P^j_n is the transmission power of device n at transmission period j. We assume that UE devices share the available spectrum equally in an orthogonal manner, but not equally with IoT devices. In this model, cell association decision depends on the number of IoT and UE devices connected to each SBS and the data rate for each class of devices. Therefore, weighing the IoT devices to the UE devices associated with a specific cell is required based on the proportion of the average data rate between UE devices and IoT devices. This is achieved by obtaining $N^j_m = (N^j_{I,m} + \frac{\bar{r}_U^{(j-1)}}{\bar{r}_I^{(j-1)}} N^j_{U,m})$ where $\bar{r}_I^{(j-1)}$ and $\bar{r}_U^{(j-1)}$ represents the mean data rate at the previous transmission period for IoT and UE devices, respectively. Every device requires a specific QoS for data transmission that is expressed in terms of a minimum acceptable data rate denoted as $r_{n,min}$. Therefore, probability of success for device n to transmit at period j is $p^j_{n,m} = Pr[r^j_{n,m} \geq r_{n,min}]$.

The QoS can be also correlated with the available transmission power. Based on Shannon Hartley theorem [10], the minimum power required to guarantee $r_{n,min}$ can be expressed as:

$$P^j_{n,min} = \frac{1}{\theta^j_{n,m}}(e^{\frac{Nf^j_m r_{n,min}}{W_m}} - 1) \tag{2}$$

Considering $r^j_{n,m} \geq r_{n,min}$, the probability of success $p^j_{n,m} = Pr[P^j_n \geq P^j_{n,min}]$ can be computed using the error function as:

$$p^j_{n,m} = 1 - \text{erf}[\frac{P^j_{n,min}}{\sqrt{2}\sigma_n}] \tag{3}$$

Due to the congestion model, the probability of success for IoT devices $p^j_{n,m}$ is directly proportional to $\frac{\theta^j_{n,m}}{f^j_m}$. However, for UE devices, the success probability is proportional to the achievable rate $r^j_{n,m}$. The success probability of every device n when selecting SBS m at transmission round j can be expressed as:

$$p^j_{n,m} = \begin{cases} 1 - \mathrm{erf}[\frac{P^j_{n,min}}{\sqrt{2}\sigma_n}] & r^j_{n,m} \geq r_{n,min}, n \in \text{IoT}, \\ 1 - (\frac{r_{n,min}}{r^j_{n,m}}), & r^j_{n,m} \geq r_{n,min}, n \in \text{UE}, \\ 0, & \text{otherwise} \end{cases} \quad (4)$$

In our model, IoT devices use the learned power in updating the UCB index while UE devices use the achieved data rate to update the UCB index. The power which IoT devices learn and use is actually the estimated minimum power required for offering minimum data rate transmission between each device and each SBS expressed in (2). However, the absence of prior information about channel gain and SBS population require each device to estimate the minimum power as:

$$P^j_{n,min} = \frac{P^{j-1}_n (e^{f^j_m r_{n,min}} - 1)}{(e^{f^j_m r^{j-1}_n} - 1)} \quad (5)$$

IoT devices in this model will transmit at a fixed minimum data rate while reducing transmission power based on learned minimum transmission power required to connect to surrounding SBSs and therefore minimizing the probability of successful association with undesired SBS. On the other hand, UE devices will use a fixed transmission power and apply UCB to increase confidence level with SBSs offering higher data rate and therefore minimizing the probability of successful association with undesired SBS.

Distributed cell association allow each device to take its own decision independently with minimal information exchange. In this model, devices do not have any prior knowledge of channel quality, interference level, and congestion levels. In successive rounds of the mean-field MAB, a device (player) decide to associate to a cell (pulls an arm) from a given set of cells (arms) in order to perform cell association (select the best arm to exploit after exploring all the available arms) based on it's confidence level in the cell. IoT devices (low resources players in MAB games) associate to cells which offer the minimum required data rate with least transmission power; such behavior is similar to exploiting the machine that offers a reward with highest success probability and lowest cost or offers frequent low fixed rewards within a small portion of time. On the other hand, UE devices (greedy players in MAB games) associate to cells which afford the highest data rate (highest available resources to allocate), such cells are similar to the less crowded machines in MAB game or machines with the reputation of offering a worthy reward within a fixed portion of the time. Therefore, we can imagine transmission power resources in our model as time in MAB games and data rate in our model as the reward in MAB games.

Each device decides to associate to a cell according to some decision-making policy in order to optimize some regret-based objective function over the game horizon. Each device decision is determined through the joint action profile of other devices and not only through its own actions. Therefore, the payoff of every cell association decision/selection for every device relies on the type or ability of that specific device and the number of devices selecting that cell. The confidence level is built and updated through the UCB policy which estimates an upper-bound of the mean reward of each SBS at some fixed confidence level. This is done through obtaining an index for every SBS m at round j, denoted by index $C^j_{n,m}$; $C^j_{n,m} = \overline{u}^{j-1}_m + \sqrt{\frac{2\ln j}{T^{j-1}_m}}$, where T^{j-1}_m is the total number of rounds SBS m is selected, and $\overline{u}^{j-1}_m$ is the average reward of SBS m, both up to round j-1. The $\sqrt{\frac{2\ln j}{T^{j-1}_m}}$ part is related to the size of the one-sided confidence interval for the average reward within which the truly expected reward falls with overwhelming probability [17]. As a result, SBS with the highest estimated bound is selected for association, and bounds are updated after observing the reward. The selection is done by finding the arguments of the largest index "$\arg\max\{C^j_{n,m}\}$".

Using data rate transmission as a reward to build a confidence level based on UCB is practical. However, for IoT devices, the randomly harvested energy will impact the data rate and therefore effect the confidence level credibility. Therefore, we propose to use the inverse of the minimum transmission power required for minimum data rate obtained from (5) in the UCB equation in Algorithm 1 ($\overline{u}^{j-1}_m + \sqrt{\frac{2\ln j}{T^{j-1}_m}}$) for IoT devices. For the rest of this work, we will refer to CA-MAB which uses the data rate as a reward of the UCB policy for IoT and UE as MAB_{rr}. While we refer to CA-MAB which uses minimum transmission power for IoT and minimum data rate for UE as a reward of the UCB policy as MAB_{pr}.

VI. SYSTEM PERFORMANCE EVALUATION

In this work we apply mean field game model on devices in Small Cell Network (SCN) using UCB selection policy as described in Section V. We evaluate the proposed model which consists of IoT and UE devices using various network densification scenarios and the multi-class Mean Field MAB cell association approach. We benchmark our approach against centralized informed and random cell association schemes. In our model, we used $W_m = N$, $\sigma_n = 1$ and $r_{n,min} = 0.75$ for all devices. We assumed a random selection in the first five rounds before applying the CA-MAB algorithm in order to initialize statues Z^j_n randomly. We added regeneration following a random time over the game horizon [10].

A. CA-MAB AND NETWORK DENSITY

In this subsection we evaluate the equilibrium of CA-MAB dynamics. The CA-MAB (MAB_{rr}) is applied to a network with 1000 IoT devices, 200 UE devices, and 5 SBS. The percentage of devices associated to each SBS is shown in figure 1. Equilibrium in the network is observed as the

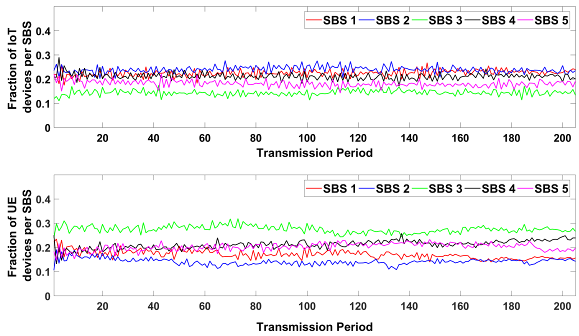

FIGURE 1. Convergence and equilibrium of cell association in mean field MABs dynamics for 1000 IoT and 200 UE devices.

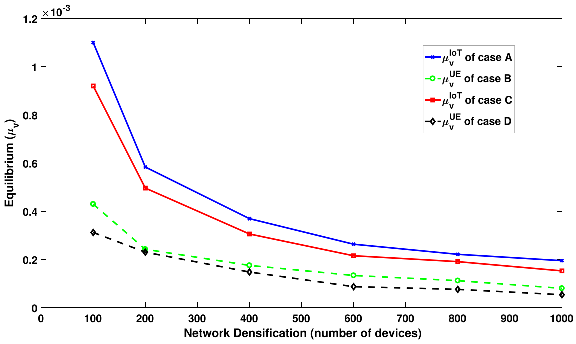

FIGURE 2. The affect of network densification on equilibrium. Cases A and C represent changing the number of IoT devices while fixing UE to 200 and 500 devices, respectively. Cases B and D represent changing the number UE of devices while fixing IoT to 200 and 500 devices, respectively.

TABLE 1. BD gains.

Scenario	IoT	UE
A	100 - 2000	200
B	200	100 - 2000
C	100 - 2000	500
D	500	100 - 2000

fraction of devices associated to each cell changes only marginally. However, to quantify convergence and hence equilibrium, we measure the variance of the number of IoT and UE devices associated to each SBS denoted as V_m^{IoT} and V_m^{UE}, respectively. In figure 2, we present the mean of V_m denoted as μ_{v} for 5 SBS network and different densification scenarios as described in table 1. CA-MAB achieves μ_{v} less than 0.12% for all test scenarios which means that the number of devices associated to each SBS doesn't change significantly over iterations and hence equilibrium. We also observe that μ_{v} reduces as network densification increases. Besides, μ_{v}^{IoT} decreases as number of IoT devices in the network increases while the number of UE devices doesn't change as in case A and C. Similarly, μ_{v}^{UE} decreases as number of UE devices in the network increases while number of IoT devices is fixed as in case B and D. This makes

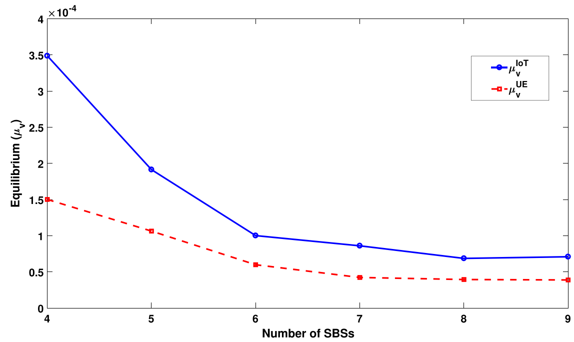

FIGURE 3. The affect of increasing number of SBSs and hence network resources on equilibrium. 5000 IoT and 1000 UE devises are used to obtain μ_{v}.

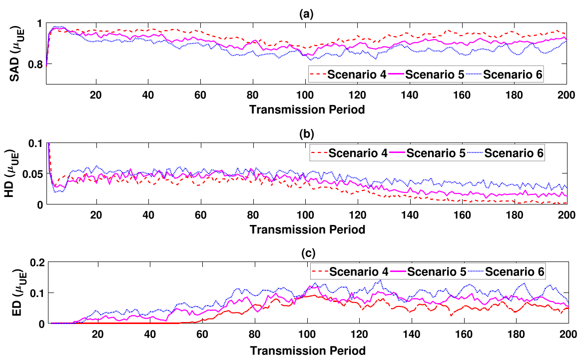

FIGURE 4. Scenarios 4, 5, and 6 for UE devices representing μ_{UE} for (a) SAD (b) HD (c) ED.

the proposed cell association approach suitable for heterogeneous IoT and 5G networks. In addition to that we notice that μ_{v}^{IoT} is greater than μ_{v}^{UE} which is justified due to the uncertainty associated with energy harvesting of IoT devices. Increasing the number of SBSs and hence increasing the available resources in the network improves equilibrium of CA-MAB as shown in figure 3. The abundance of network resources in this case enabled devices including disconnected IoT (due to low harvested power) to reconnect to the same SBS.

B. CA-MAB DYNAMICS AND MOBILITY EFFECT

In this subsection, we evaluate the equilibrium of CA-MAB (MAB_{rr}) dynamics in presence of mobile UE devices. Mobility affect is introduced in the CA-MAB model by varying the channel gain $g_{n,m}^{j}$ at every iteration. In this work, we assumed only a fraction of UE devices (20% to 40%) are outdoor and hence mobile [11]. At every iteration, fraction of devices remain connected to the same SBS, we refer to these as stable cell association devices (SAD). Other devices which move to a new SBS as a result of handover, we refer to them as handed over devices (HD). The remaining devices enter into exploring SBSs mode following a regeneration trial, we refer to them as regenerating devices (ED). In table 2, we present the mean (μ) and variance (σ^2) for IoT and UE devices at these three modes considering six test scenarios. We argue

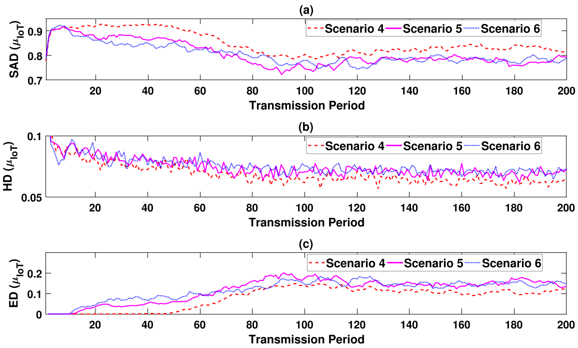

FIGURE 5. Scenarios 4, 5, and 6 for IoT devices representing μ_{IoT} for (a) SAD (b) HD (c) ED.

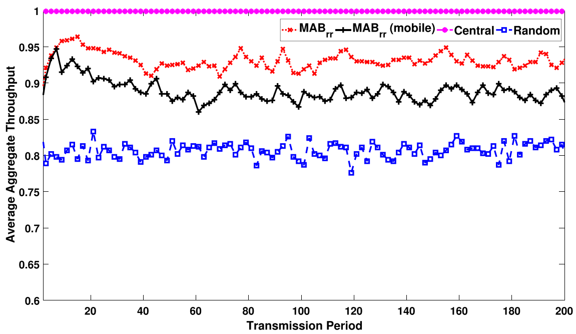

FIGURE 6. Throughput performance of UE devices. CA-MAB throughput is within 10% and 15% of central association for static and mobile environments, respectively.

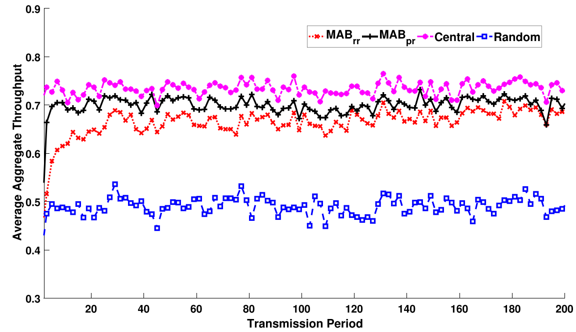

FIGURE 7. Throughput performance of IoT devices. CA-MAB throughput is within 10% of central association. It improves to within 5% when the confidence bounds are updated based on the minimum transmission power.

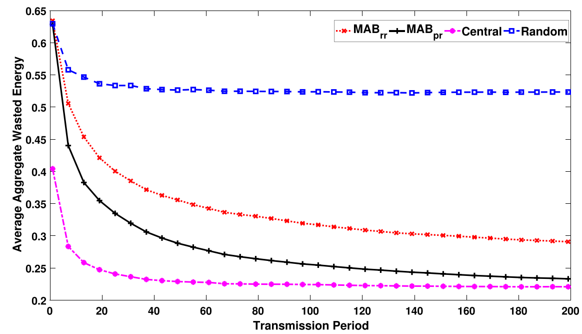

FIGURE 8. Average aggregated wasted energy of IoT devices. CA-MAB results are within 10% of central association. The wasted energy reduces to within 1% of central association when the confidence bounds are updated based on the minimum transmission power.

that increasing μ with small σ^2 of SAD lead to more stability in the network.

In some of the test scenarios, CA-MAB is applied to IoT and UE devices jointly in the same system (merged). In other scenarios CA-MAB is applied to each type of these devices independently (isolated) where resources are split between IoT (γ) and UE (1-γ) devices. CA-MAB achieves more stability in merged scenarios as more devices tend to remain connected with the same SBS (higher μ_{IoT} and μ_{UE}) in SAC. We also vary the percentage of mobile UE with and without regeneration trials. Devices in scenarios with regeneration perform handover to new SBS less frequently (less μ_{IoT} and μ_{UE} in HD) and thus system attains better stability. As expected, mobility of UE as in scenarios 5 and 6 reduces stability. However, increasing the fraction of mobile UE has marginal affect on stability of IoT devices. Equilibrium in the presence of UE mobility can be observed in figure 4 and figure 5 for UE and IoT devices, respectively. It is evident in figure 4 that μ_{UE} of SAD converges within 20% and reduces as the number of mobile devices increases. On the contrary, μ_{UE} of HD and ED increases with mobility.

C. CA-MAB THROUGHPUT PERFORMANCE AND ENERGY SAVING

In this subsection, we evaluate the throughput and energy saving of CA-MAB through measuring the ratio of successful transmissions to total trials and the energy consumed over unsuccessful transmissions (wasted energy). In here, we assume a system with 1000 IoT and 1000 UE devices and 5 SBSs. The throughput and energy savings of CA-MAB are compared to centralized and random cell association. The centralized association scenario offers the optimum performance despite the fact of its complexity and huge amount of information exchange. This scenario relies on a central unit with complete information about the system and thus offers the highest successful transmission probability. On the other hand, random association scenario does not rely on such complexity or exhaustive searching overhead. In this scenario, each device associates with an SBS randomly without any prior information about channel gain or SBSs population. As can be observed for UE devices in figure 6, the throughput performance of CA-MAB is within 10% and 15% as compared to the centralized association for the scenarios of static and mobile UE devices, respectively. Similar throughput performance is attained for IoT devices as presented in figure 7. In term of energy savings, the average aggregate wasted energy is shown in figures 8. At the beginning of transmission (first few iterations of MAB where bounds are random), the amount of wasted energy is similar to random association. However, after few trail periods the confidence bounds are updated using MAB_{rr}

TABLE 2. **Stability, handover, and exploring of IoT and UE devices in different scenarios IoT devices $N_1 = 5000$ and UE Mobile devices $N_2 = 1000$.**

Scenario	Scenario Description γ	Mobility	Merged	Regeneration	SAD μ_{IoT}	σ^2_{IoT}	μ_{UE}	σ^2_{UE}	HD μ_{IoT}	σ^2_{IoT}	μ_{UE}	σ^2_{UE}	ED μ_{IoT}	σ^2_{IoT}	μ_{UE}	σ^2_{UE}
Scenario 1	20%	No	No	No	56.23%	2.91%	93.05%	0.06%	9.22%	0.49%	2.97%	0.05%	0.00%	0.00%	0.00%	0.00%
	25%	No	No	No	88.62%	0.43%	95.07%	0.02%	11.38%	0.43%	4.93%	0.02%	0.00%	0.00%	0.00%	0.00%
	30%	No	No	No	88.96%	0.27%	95.18%	0.02%	11.04%	0.27%	4.82%	0.02%	0.00%	0.00%	0.00%	0.00%
	35%	No	No	No	91.19%	0.02%	94.88%	0.02%	8.81%	0.02%	5.12%	0.02%	0.00%	0.00%	0.00%	0.00%
	40%	No	No	No	94.46%	0.02%	95.99%	0.02%	5.54%	0.02%	4.01%	0.02%	0.00%	0.00%	0.00%	0.00%
Scenario 2	20%	No	No	Yes	58.03%	2.67%	93.00%	0.07%	9.34%	0.49%	2.76%	0.05%	32.62%	5.39%	4.24%	0.08%
	25%	No	No	Yes	63.25%	1.58%	92.69%	0.07%	9.31%	0.41%	2.86%	0.05%	27.44%	3.45%	4.45%	0.09%
	30%	No	No	Yes	68.05%	1.64%	93.36%	0.07%	8.96%	0.28%	2.86%	0.05%	22.98%	2.85%	3.78%	0.07%
	35%	No	No	Yes	81.35%	0.21%	92.98%	0.08%	8.13%	0.04%	3.04%	0.06%	10.52%	0.28%	3.98%	0.08%
	40%	No	No	Yes	86.91%	0.11%	93.63%	0.06%	5.24%	0.02%	2.34%	0.05%	7.85%	0.14%	4.03%	0.07%
Scenario 3	-	No	Yes	No	92.67%	0.02%	95.15%	0.02%	7.33%	0.02%	4.85%	0.02%	0.00%	0.00%	0.00%	0.00%
Scenario 4	-	No	Yes	Yes	84.99%	0.21%	93.43%	0.07%	6.94%	0.02%	2.56%	0.04%	8.06%	0.27%	4.01%	0.08%
Scenario 5	-	20%	Yes	Yes	80.60%	0.24%	90.57%	0.08%	7.48%	0.01%	3.39%	0.03%	11.92%	0.31%	6.04%	0.10%
Scenario 6	-	40%	Yes	Yes	80.49%	0.16%	87.70%	0.12%	7.59%	0.01%	4.35%	0.02%	11.92%	0.21%	7.95%	0.13%

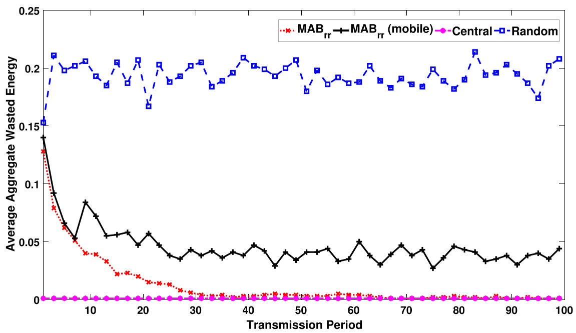

FIGURE 9. **Average aggregated wasted energy of UE devices. CA-MAB wasted energy converge to that of the central cell association method after few transmission periods. However, using minimum transmission power in CA-MAB results is an increase in the wasted energy within 7% of central association.**

and the wasted energy reduces and converges within 10% of central association. Further reductions in the wasted energy (5% of central) can be achieved using MAB_{pr} as bounds are updated based on the minimum transmission power for IoT devices. This improvement will be on the expense of reduction in throughput as shown in figure 7. In figure 9, energy savings are evaluated in the presence of mobility for UEs. Although, the wasted energy can't but eliminated, it is kept within 7% of the centralized association.

VII. CONCLUSION

We present a distributed multiclass user-driven cell association method based on the Mean Field Bandit game. Given that our method considers different constraints for each class of devices, it is well suited for HetNets such as the 5G cellular networks. Our method is also appropriate for system models with uncertainty such as energy harvesting of IoT devices. In this work, we presented a mathematical formulation for our method followed by extensive performance evaluation of the proposed CA-MAB algorithm at different scenarios. Equilibrium and fast convergence for dense networks are attained using CA-MAB without any prior information about channel status or SBS population. CA-MAB evaluation results show that considering constraints of all classes jointly in a merged scenario leads to better equilibrium. The CA-MAB has also been evaluated in the presence of mobile devices where equilibrium, throughput, and energy savings are marginally affected by mobility. We have also leveraged on the proposed algorithm such that the UCB policy is updated based on transmission power requirements. This achieved some savings in the wasted energy on the expense of some reductions in throughput.

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