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USER DRIVEN CELL ASSOCIATION IN 5G HETNETS FOR MOBILE AND IoT DEVICES

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MASTER THESIS

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Declaration of Authorship

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قل إن صلاتي ونسكي ومحياي ومماتي لله رب العالمين

Abstract

In the near future, users prime objectives and demands of being connected will exceed the current cellular networks capabilities. This requires continuously enhancing the techniques and technologies used to build these networks. For example, the fourth generation (4G) cellular networks will be replaced with fifth generation (5G) cellular networks which will use the latest emerging technologies. The idea to shift toward new cellular networks is based on the need to address different challenges that are not effectively addressed by the preceding cellular networks. For 5G, those challenges include higher capacity, higher data rate, lower end-to-end latency, massive device connectivity, reduced cost and consistent quality of experience provisioning. 5G cellular networks design assumes Heterogeneous Network (HetNets) architecture which consists of different types of cells (e.g., macrocells and small cells). This design takes into consideration the current and foreseen growth of User Equipment (UE) traffic on one hand, and the massive increase in the number of connected Internet of Things (IoT) devices on the other hand. The capabilities and needs of these two classes of devices vary, and thus this should be efficiently considered when connecting or associating each of them with the emerging 5G cellular networks. This work addresses the cell association decision problem aiming to improve throughput and reduce consumed energy.

Ordinary cell association ensures that all connected devices and the new connected devices will have an acceptable performance level. However, Signal-to-Interference-Plus-Noise Ratio (SINR) is used for traditional Cell association without taking into account different devices requirements and priorities which include, but not limited to, maximum possible data rate and minimum transmission power. This work reviews 5G foreseen Hetnets architecture, emerging technologies, cell association approaches, implantations, and access modes. In addition, it reviews a set of non-conventional game theories capable of handling a massive number of players scenarios. Then, this work proposes a distributed Cell Association using Multi-Armed Bandit (CA-MAB) algorithm which allows each IoT and UE device to take its own association decision based on Mean-Field Multi-Armed Bandit (MAB) game approach. The convergence and equilibrium of this algorithm are evaluated over different network scenarios. In addition, this work studies the throughput performance and energy saving of the CA-MAB algorithm. It also validates the performance of CA-MAB in static and mobile environments. This work results show an enhancement in throughput efficiency by 3% and energy efficiency by 5% for IoT devices through building association confidence on minimum transmission power required. In addition, this work results show degradation in throughput efficiency by 4.3% and energy efficiency by 3.5% for UE devices when 20% of those devices start mobility. The results are also compared against random and centralized association solutions.

المستخلص

في المستقبل القريب، سيتجاوز المستخدمون الأهداف الرئيسية ومتطلبات الاتصال قدرات الشبكات الخلوية القائمة. هذا سيتطلب تحسين مستمر للتقنيات والأساليب المستخدمة في بناء هذه الشبكات. فعلى سبيل المثال، شبكات الجيل الرابع الخليوية سيتم استبدالها بشبكات الجيل الخامس الخليوية التي ستستخدم أحدث التقنيات. تقوم فكرة التحول نحو شبكات خلوية جديدة على الحاجة لمجابهة التحديات التي تعجز عن تجاوزها الشبكات الخليوية القائمة بكفاءة. بالنسبة لشبكات الجيل الخامس، هذه التحديات تتضمن سعات اعلى، وسرعات اعلى، وانخفاض زمن نقل الإشارة من الطرف الى الاخر ، والاتصال بعدد هائل من الاجهزة، وانخفاض تكلفة واتساق جودة التجربة الموفرة. يتوقع اتسام شبكات الجيل الخامس الخليوية بالغير متجانسة المكونة من اكثر من نوع من الخلايا (على سبيل المثال، الخلايا الصغيرة والخلايا متناهية الصغر). هذا التصميم يأخذ بالاعتبار النمو الحالي والمرتقب لحركة بيانات أجهزة المستخدمين المتنقلة من جهة، والنمو الهائل لاعداد أجهزة انترنت الأشياء من جهة أخرى. ان مطالب واهداف هذين النوعين من الأجهزة هو متنوع، لذلك ينبغي النظر في ذلك عند ربط او اتصال أي من هذه الاجهزة بشبكات الجيل الخامس الخليوية الحديثة. خلال هذا العمل، ندرس معضلة اتخاذ قرار الارتباط بالخلية بهدف تحسين توفر البيانات وتخفيض استهلاك الطاقة لدى الأجهزة.

ان الارتباط المعتاد بالشبكة يضمن مستوى أداء مقبول لكافة الأجهزة المتصلة والجديدة التي سيتم وصلها بالشبكة. ولكن يتم استخدام معدل الإشارة الى التشويش في تنفيذ عمليات الارتباط التقليدي بخلايا الهاتف المتنقل دون الأخذ بعين الاعتبار متطلبات الأجهزة المختلفة والأولويات التي تشمل، على سبيل المثال لا الحصر، أقصى قدر ممكن من معدل تناقل البيانات والحد الأدنى من الطاقة المطلوبة للارسال. خلال هذا العمل، نراجع شبكات الجيل الخامس الغير متجانسة المرتقبة، التقنيات الحديثة، توجهات وتطبيقات وأساليب الارتباط بالخلايا. بالإضافة، نراجع عدد من نظريات الألعاب الغير تقليدية القادرة على التعامل مع السيناريوهات المكونة من عدد كبير من اللاعبين. ثم ، نطرح خوارزمية الارتباط الموزع

بالخلايا باستخدام نموذج لعبة عصابة اللصوص متعددة الايدي والتي تتيح لكل من أجهزة انترنت الأشياء وأجهزة المستخدمين اتخاذ قراراتهم الخاصة بالارتباط بالخلايا. ان اتزان هذه الخوارزمية يقيم عبر سيناريوهات شبكات مختلفة. بالإضافة، ندرس أداء توفر البيانات وحفظ الطاقة من خلال الخوارزمية المقترحة. كما ونوثق أداء الخوارزمية المشار اليها في ظروف سكون وحركة الأجهزة. نتائجنا تشير الى تحسن كفاءة توفر البيانات بنسبة ٣ % و حفظ الطاقة ب ٥ % بالنسبة لأجهزة انترنت الأشياء عبر بناء الثقة بالارتباط بالاعتماد على الحد الأدنى للطاقة المطلوبة للارسال لكل خلية. بالإضافة، تشير نتائجنا الى انخفاض كفاءة توفر البيانات بنسبة ٣.٤ % و حفظ الطاقة بنسبة ٤.٣ % عند بدأ ٢٠ % من الأجهزة بالحركة. نقارن نتائجنا مقابل حلول الارتباط بالخلية المركزية والعشوائية.

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List of Abbreviations

1G First Generation

2G Second Generation

3G Third Generation

3GPP 3rd Generation Partnership Project

4G Fourth Generation

5G Fifth Generation

BS Base Station

CA-MAB Cell Association using Multi-Armed Bandit

CDMA Code Division Multiple Access

Cloud-RAN Cloud Radio Access Networking

CoMP Coordinated Multipoint

C-Plane Control Plane

C-RAN Cloud Radio Access Networks

CSG Closed Subscriber Groups

D2D Device to Device

DoS Denial of Service

EH node Energy Harvesting node

FDMA Frequency-Division Multiple Access

FinTech Financial Technology

GSMA Group Special Mobile Association

HetNets Heterogeneous Network

HTC Human-Type Communications

i.i.d. independent and identically distributed

IoT Internet of Things

IoV Internet of Vehicles

LTE Long-Term Evolution

LTE-A Advanced Long-Term Evolution

M2M Machine to Machine

MAB Multi-Armed Bandit

MCS Modulation and Coding Scheme

MFE Mean Field Equilibrium

MFG Mean Field Games

MIMO Multiple Input and Multiple Output

mmWave millimeter Wave

MTC Machine-Type Communications

NOMA Non-Orthogonal Multiple Access

OFDMA Orthogonal Frequency Division Multiple Access

OMA Orthogonal Multiple Access

QoS Quality of Service

RRH Remote Radio Heads

SBS Small Base Station

SCN Small Cell Network

SDN Software Defined Networking

SINR Signal-to-Interference and Noise Ratio

SONs Self Organizing Networks

UCB Upper Confidence Bound

UD-SCN Ultra-Dense Small Cell Networks

UE User Equipments

U-Plane User Plane

WiFi Wireless Fidelity

Chapter 1

Introduction

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Mobile data traffic continuously grew by 74% in 2015 and it is expected to multiply eight times by 2020 [1]. Ericsson reported a 70% growth in the global mobile data traffic between 2016 and 2017, and expects an annual growth rate of 42% through to 2022; which is an 8-fold increase compared to 2016 [2]. Only 26% smart-phones (from global mobile devices) generate about 88% of the entire mobile data traffic. Actually, over than half of the entire mobile traffic was generated after 2012 in the form of video traffic [1]. By 2020, it is estimated that ordinary mobile user will download around 1 terabyte of data annually. The continuous spread and increasing popularity of the IP based smart devices and smartphones had let Long-Term Evolution (LTE) mobile networks be a part of our everyday life. Therefore, a new generation of mobile user-oriented multimedia applications is rising up including, real-time online gaming, video conference applications, health-care applications, and video streaming. Those emerging applications open new business opportunities for mobile operators allowing them to obtain more revenue in addition to their users' requirements satisfaction [3]. 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 [4]. In addition, it is expected that various types of applications in different fields will come up. Those fields include augmented reality, Device to Device (D2D) communications, IoT, Machine to Machine (M2M) communications, e-healthcare, Internet of Vehicles (IoV) and Financial Technology (FinTech). Supporting this huge and fast increase in connectivity and data usage is a very difficult task in modern cellular systems [3].

This thesis presents a distributed, user driven, cell association algorithm in 5G HetNets using Mean-Field MAB game approach. This algorithm is CA-MAB. The main part of this thesis describes the 5G cellular networks technologies, cell association techniques, and related game theory methods. This introduction briefly describes the main challenges which face the operating cellular networks and emerging technologies developed to use in the foreseen 5G cellular networks. Moreover, it briefly describes the cell association problem in 5G HetNets with the deployment of massive IoT.

1.1 5G Requirements and Emerging Technologies

The expected increase in wireless communications traffic motivates a lot of research on 5G cellular networks. To meet the high specifications and overcome the tremendous challenges that will be facing 5G networks, its design should include emerging technologies and additional spectrum in a high dense architecture. This design should enable the increase of speed of wireless data transmission, bandwidth, coverage, and connectivity, with a huge reduction in latency and increase in energy efficiency. Group Special Mobile Association (GSMA) is cooperating with many partners in order to reach a final formation of 5G [3]. Eight major requirements of next-generation 5G are identified through different industries and academic research initiatives. Those requirements are represented in affording several Gbps data rates in real networks, 1 ms round-trip latency, high bandwidth in unit area, 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 [5]. 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. It is expected that 5G networks will reach the Gigabit data rate level in future cellular networks, and to offer high capacity, high reliability, increase battery life, number of connected devices, mobility, and reduce latency. Multiple emerging technologies provide the potential to support 1000x 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 [6]. Massive MIMO offers a sufficient number of antennas for BS through the use of a linear and simple signal processing techniques. The grid of antennas is capable of directing vertical and horizontal beams [3]. Network densification is also required for the 5G networks to meet its goals [6]. Fast interference coordination and cancellation, Software Defined Networking (SDN), Cognitive Radio Networks and Self Organizing Networks (SONs) are promising techniques that will enable dense network management [3]. Coordinated multipoint (CoMP) technology is a primary element on the LTE road-map beyond Release 9 [6], it is used in small cells in order to decrease the inter-site interference and enhance spectrum efficiency [7] and energy efficiency [4], it facilitates a fast cooperative data transmission [3]. Full-duplex transmission will also be used to increase spectral efficiency [8], improve feedback and latency mechanism while maintaining security in the physical layer. 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. It also improves system architecture, coverage performance, mobility, and energy efficiency while reducing the network deployment cost and operation [3].

1.2 Game Theory

1.2.1 Traditional Game Theory

The game theory represents the study and analysis of the interactive decision-making processes mathematical models. It facilitates the investigation of the massive decentralization optimization problem. Moreover, game theory offers a useful tool for self organizing/dynamic networks applications. In general, algorithms converge is a possible task to achieve despite the fact that it doesn't necessarily provide an optimal solution due to inefficient use in combination with large overhead costs. Therefore, due to the fact that game theory focuses on strategic decision making, there is no specific form or expression that can be used to characterize the relationship which connects the performance metric and the network parameters. Despite the fact that game theory does not represent the optimal design or analysis tool for HetNet load balancing, but it could provide an understanding of how uncoordinated IoT and UE and BSs should associate [9].

1.2.2 Non-conventional Game Theory

The extensive analysis of interactive decision makers with conflicting interests has been applied through traditional learning and game-theoretical models. However conventional game models are not adequate to model large-scale systems required for IoT. Mean field bandit model is one of those non-conventional game models; it does not require prior knowledge for decision makers. Therefore, this model is very suitable for any IoT systems. Mean field bandit model is a class of sequential optimization problems, wherein successive rounds a player pulls an arm from a given set of arms in order to receive a priori unknown reward and observes only the reward of that played arm. Due to information shortage, a difference may exist between the maximum possible reward and the played arm reward. This difference is referred to as player regret. By selecting arms using a decision making policy, the player tries to optimize its objective and reduce regret values over the game horizon. Thus, the issue is to reach to dissection whether to start gathering immediate rewards or to keep obtaining information required for achieving a large reward in the future. This problem is referred to as the exploration-exploitation dilemma [10]. This will be discussed further in more details in chapter 3.

1.3 Problem Statement

Mobile cellular networks, in general, and Advanced Long-Term Evolution (LTE-A) recently, are designed to support data-intensive Human-Type Communications (HTC). HTC in general, UE Mobile devices traffic specifically, are different from Machine-Type Communications (MTC) from its data size and quality requirement. In general, MTC refers to the communication used for IoT devices. On the other hand, mobile users in different classes have different data rate requirements. Therefore, cell association mechanism should take communication types and classes' requirements into consideration [11]. The ubiquitous nature of IoT is responsible for draining out energy from its resources [12]. IoT applications typically exchange small data packets in smart environments; the energy consumption required for transmitting those small data packets over cellular communication is considered a serious obstacle that faces large-scale IoT deployment.

HetNets represents the major direction of 5G network design. They are composed of many types of cells including, but not limited to, macrocells and small cells. Cell association is a major part of 5G HetNets resource management. In a HetNet, a macrocell overlaps with small cells [13]. Traditional cell association is performed depending on SINR. Such traditional association is referred to as SINR-based association. A user in SINR-based association associated with the cell which has the highest SINR in order to obtain the best transmission quality and highest possible data rate. However, the network load is not taken into account in SINR based association [10]. Users and devices have different data rate requirements and they will choose to associate with the cell(s) (e.g., a macrocell or small cells) based on different criteria such as the lowest transmission power required. If users and/or devices are under any of the small cell coverage, they can decide to connect to either the macrocell or the small cell. Cell Association algorithms need to take into account UE Mobile devices willing to achieve the highest data rate possible and IoT willing to reduce power transmission. Cell association algorithms need to be aware of the IoT clusters' head need for higher data rate compared to individual IoT devices. Cells also have to allocate resources in terms of antennas to different users or devices to optimize and maximize their resource utilization [13].

1.4 Thesis Contribution

This work reviews 5G foreseen Hetnets architecture, emerging technologies, cell association approaches, implantations, and access modes. This thesis provides a comparative review of different game theories that can be used as mechanisms to analyze the interactive decision making in cell association. Also, it proposes CA-MAB cell association algorithm based on Mean-Field MAB game theory approach. This game theory approach is suitable for a large number of agents because it uses a mean-field approximation, every agent in such approximation considers the rest of the world as being stationary, dealing with other agents individual moves as unimportant details. Therefore, this model is very appropriate for scaling massive IoT systems. Matlab simulation is used to obtain the results of the CA-MAB algorithm in terms of achieving equilibrium, achievable data rate and consumed power. Simulation results are compared with centralized informed and random cell association schemes. Applying game theory methods aim to maximize the allocated data rate for mobile devices and minimize power consumption for IoT devices using minimum information exchange overhead. Thus power consumption and data rate are the two considered parameters for optimization.

1.5 Thesis Organization

The rest of this thesis is organized as follows. Chapter 2 discuss 5G cellular networks features and emerging technologies. Chapter 3 presents the related game theory methods and compare their potential applications. Chapter 4 discuss cell association types and presents related work. Chapter 5 defines and analytically formulates the problem of cell association in 5G addressed in this work. In addition, it contains mathematical formulation for the CA-MAB algorithm. Chapter 6 evaluates CA-MAB algorithm. At last, Chapter 7 concludes the major results of this thesis and illustrates its importance.

Chapter 2

Primer on 5G

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This chapter presents the required 5G cellular networks architecture and the different emerging technologies. It describes 5G cellular networks design deliverables, motivations. Then, it describes some of the 5G Network features and emerging technologies including new access technologies and flexible spectrum management system.

2.1 5G Cellular Networks

5G network design should enable the achievement of large cellular network capacity, ultra-low latency, and heterogeneous device support. This is basically needed in order to fulfill the new emerging applications of 5G networks including but not limited to, video streaming and Internet access. The foreseen 5G network will compose of different types of overlapping cells (e.g., macrocells and small cells) and therefore will require efficient cell association mechanism. 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 for the user, and on the other hand into resources allocation including antenna, power, and channel performed after the user connection has been established [13].

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. Communication for inside or outside mobile user in the present wireless requires an outside BS in the middle of a cell. The communication between inside users and outside BS requires the signals to travel through walls leading to significant penetration loss, which correspondingly costs with the reduction in wireless communication energy efficiency, data rate, and spectral efficiency. Performing an inside and outside setups is a new technique which came into existence in order to apply the 5G cellular architecture [14]. Such a technique will slightly reduce the 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 [15].

In addition, large antenna arrays will be installed outside every building in order to facilitate a line of sight communication with outdoor BSs. Those large outdoor antenna arrays will be connected with indoor wireless access points for communicating through cables. 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. Within this new architecture, indoor users will only need to connect with indoor wireless access points while the outside large antenna arrays will manage the communication with the close BSs [14].

Several technologies including WiFi, visible light communications, small cell ultra wideband are widely utilized for short-range communication due to their large data rates capabilities. The high required and utilized frequencies for Millimeter Wave (mmWave) and visible light communication technologies limit their use for cellular communications. In addition, it is inefficient to use high-frequency waves for outdoor long-range applications due to their wave limited ability to infiltrate through dense materials and can be dispersed by gases, rain droplets, and flora. As a result of those limitations, visible light communications and mmWaves technologies are utilized for enhancing indoor setup data rate due to their large bandwidth [15].

Since cells are overlapped and heterogeneous in 5G cellular architecture; the mobile small cell is an essential component of the 5G cellular network. The mentioned architecture will be partially comprised of small cell and mobile relay concepts. It is introduced to serve high mobility users while inside automobiles and trains. High mobility users issue can be solved through installing mobile cells in automobiles and trains to provide connectivity for users inside while setting up large antennas MIMO units outside in order to connect with near

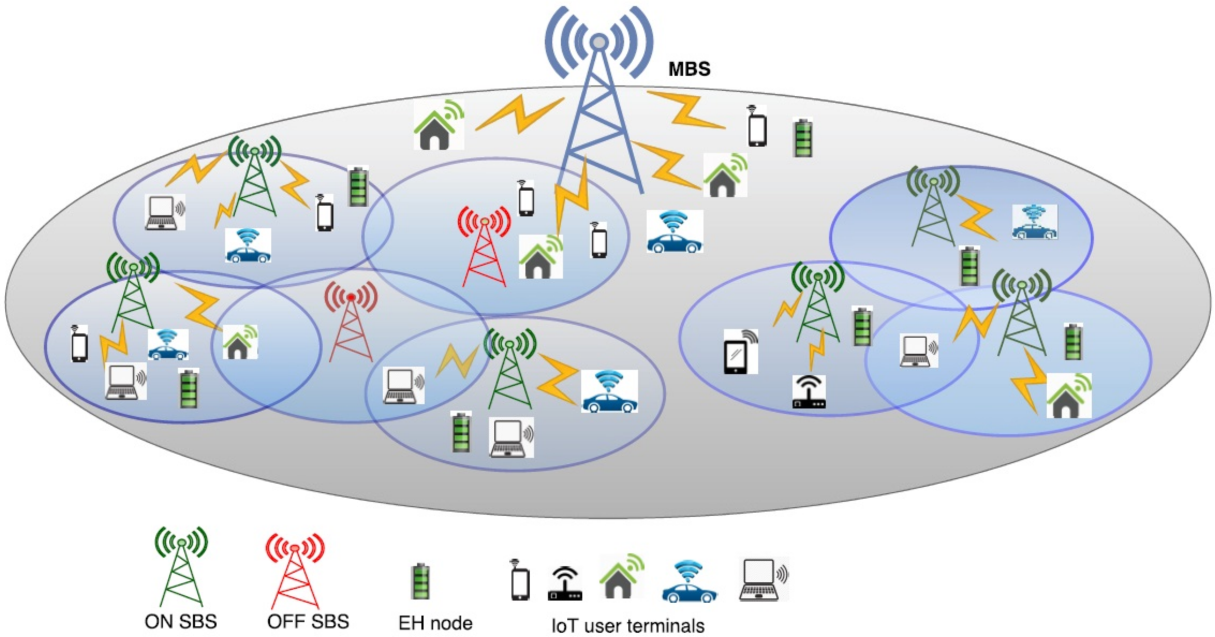

Figure 2.1: Cell planning and user association in IoT UD-SCNs with energy harvesting.

BSs. 5G wireless cellular radio network architecture is formed from a cloud network logical layers and a radio network logical layers and other multifunction components [15].

Capacity maximization and energy efficiency methods, which consider the quality of experience level, represents a fundamental problem in Small Cell Networks (SCNs) and it is taking a rising attention in recent researches. However, such problems are rarely addressed or studied under the scenarios that consider Small Base Station (SBS) and/or users complete rely on ambient energy harvesting as power resources [8]. The 5G cellular network architecture has equal importance in terms of front-end and backhaul network respectively. In this thesis, a general 5G cellular network architecture, including Energy Harvesting nodes (EH nodes), has been proposed similar to what is shown in Figure 2.1. It describes the different types of overlapped cells connecting IoT harvesting devices and UE devices in Ultra-Dense Small Cell Networks (UD-SCN).

2.2 5G Network Features and Emerging Technologies

5G network emerging technologies are proposed to achieve the ultimate goal of the next generation network; which is offering a higher throughput. That ultimate goal is in addition to the higher capacity required and the ultra-low latency needed. To meet these goals, 5G networks will encompass a few new features as mentioned in the bellow subsections.

Types of nodes	Transmit power	Coverage	Backhaul
Macrocell	46 dBm	Few km	S1 interface
Picocell	23–30 dBm	< 300 m	X2 interface
Femtocell	< 23 dBm	< 50 m	Internet IP
Relay	30 dBm	300 m	Wireless
RRH	46 dBm	Few km	Fiber

Table 2.1: Main HetNets elements specifications

2.2.1 HetNets

HetNets are the major direction of 5G network architecture design. A HetNet is a network which consists of different types of cell points with different technologies, capabilities, and constraints. The foreseen 5G networks serious traffic demand require to be managed through a cost-effective solution. HetNets offer this solution by mixing up current macrocells with new deployed low power remote nodes including and not limited to picocells and femtocells. This mixed network deployment enables offloading the macrocells traffic, improving user performance, indoor coverage, and enhancing spectral efficiency through spectrum reuse. This architecture developed from LTE-Advanced multi-tier network which includes different types of remote radio heads (RRH), picocells and femtocells overlapped by a macrocellular layout. Table 2.1 summarize the specifications of the different components of the HetNets [16].

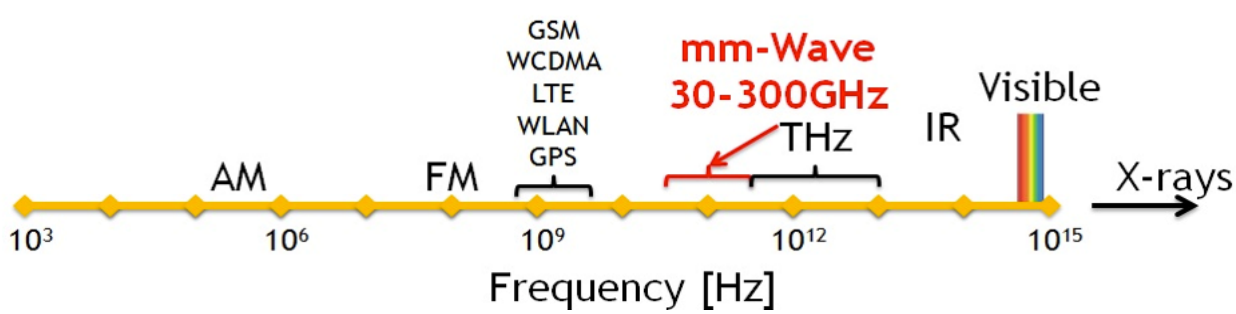

Figure 2.2: mmWave Frequency

2.2.2 New Access Technologies

The foreseen 5G networks we are heading towards are heterogeneous. The integration of many different radio access technologies is the main attractive aspect. 5G devices need to be backward technology compatible to support operation over Third Generation (3G), different releases of 4G, various types of WiFi, and direct device to device communication networks with their different spectral bands in addition to supporting of 5G new mmWave frequencies. Therefore, defining the standards and using the spectrum in which the BS or users will be a very difficult task for the network [15].

To achieve higher throughput, a couple of candidate access technologies are being considered, including massive MIMO and mmWave [17]. The sufficient mmWave bandwidth range presented in figure 2.2 can provide much better performance due to the large bandwidth of up-band, around 30 to 50 GHz [13]. The mmWave spectrum was and remain underutilization until 2018. mmWave spectrum unsuitability for cellular communications is the main reason for its underutilization. mmWave spectrum is not stable in unfriendly channel conditions which include path loss effect, atmosphere, and rain absorption, small diffraction, and penetration about obstacles and through objects respectively. Moreover, strong phase noise and excessive apparatus costs are another reasons for unsuitability. On the other hand, the large unlicensed band around 60 GHz are appropriate for very short range transmission. Therefore, the attention had been given for both fixed wireless applications in the 28, 38, 71–76 and 81–86 GHz band and WiFi using the 802.11ad standard in the 60 GHz band. This attention increased the growth of the short-range standards and semiconductors evolution leading to a rapid decrease in their costs and power consumption values [15].

On the other hand, Massive MIMO can improve network performance with a great number of antennas to multiplex traffic [13]. Massive MIMO is the evolving and upgraded technology of current MIMO technology. Current MIMO systems use either two or four antennas, while massive MIMO systems will utilize the advantages of a large array of antenna elements in order to obtain huge capacity gains. The major objective of Massive MIMO technology is to obtain all MIMO features but on a larger scale. Due to its energy efficiency, robustness and spectrum efficiency massive MIMO is the evolving technology of next-generation networks. Massive MIMO relies heavily on spatial multiplexing, which depends on the BS for channel status information in both the uplink and downlink. Constructing a large massive MIMO network require fitting the outside BSs with large antenna arrays among them in addition to some dispersed around the hexagonal cell and connected to the BS through optical fiber cables, aided by massive MIMO technologies. Outside, mobile users fitted with a number of antenna units cooperating with a large constructed virtual antenna array forms virtual massive MIMO links with BS antenna arrays [15]. Therefore, the recent use of mmWave with massive MIMO will enhance the feasibility of massive MIMO in an uplink band which will allow the implementation of a line-of-sight transmission and short-range services with small cell coverage. Such implementation is preferred for backhaul connections due to the large propagation loss in addition to the limited space for large array size at the BS and lower cost. This implementation will increase both energy efficiency and throughput on one hand, and decrease round-trip latency on the other hand [13]. The enhancement of massive MIMO feasibility, when combined with mmWave technology, will significantly increase when used through a developed multiple access technique.

Multiple access techniques are a key technology which distinguishes between different mobile generations. First Generation (1G) mobile systems used frequency-division multiple access (FDMA), while Second Generation (2G) mobile systems used time-division multiple access (TDMA), 3G mobile systems used code division multiple access (CDMA), and 4G mobile systems used orthogonal frequency- division multiple access (OFDMA). These traditional multiple access techniques allocate orthogonal resources including time, frequency, and code to different users. This allocation allows to avoid inter-user interference and to multiple users gain with acceptable complexity. To address the various challenges facing the new 5G mobile systems, Third Generation Partnership Project (3GPP) studied in their Rel-13 study the development of a new multiple access technology. This new multiple access technology is Non-Orthogonal Multiple Access (NOMA). NOMA was developed to allow a multi-user superposition transmission through enabling share of time and frequency resources between multiple users. NOMA technology has many features including improving spectral efficiency, handling massive connectivity, and reduction of transmission latency. NOMA eliminates the need for a user to send a scheduling request to BS as in conventional Orthogonal Multi-Access (OMA) with a grant-based transmission. This elimination offers a free uplink transmission that enables the reduction of transmission latency and signaling overhead [18].

2.2.3 Device to Device Communication

D2D Communication system can be explained by imagining a two-level 5G cellular network, device level, and network entity level. The network entity level consists of the BS of the HetNets cell to device communications as in a traditional cellular system. The device level consists of a device to device communications. Devices linking the cellular network directly through the BS are operating in the entity cell level. On the other hand, devices linking the cellular network through another device or apprehends its transmission through the support of other devices are on what is referred to as the device level. A BS can either have a full or partial control over resource allocation or none at all in the device level communications. Therefore, the device-level communications can be categorized to more levels based on BS control [15].

Orsino focused on IoT efficiency in [11] and proposed a wise use of Modulation and Coding Scheme (MCS) to move data efficiently over both the D2D and the uplink LTE-A towards the eNodeB. It also proposed the use of short-range D2D communications for energy efficient IoT data collection on one side, and the clustering of the IoT devices to perform the far range communication on the other side. However, Orsino assumed that all users and/or devices are associated with one cell only.

2.2.4 Densely Deployed Small Cells

Many operators start the process of densification of the infrastructure taking it into account as a prior aspect of 5G communications which require to cover the increasing traffic demands caused by the continuous increase in the number of users. Heterogeneous networks will play an important part to achieve ultra-dense networks. The heterogeneous networks are becoming more dynamic after the introduction of moving networks and ad-hoc social networks. Though, interference, mobility and backhauling are going to represent new challenges that will rise due to the dense and dynamic heterogeneous networks. To overcome these challenges, it is necessary to design a new network layer functionalities in order to maximize the performance from the design of the current physical layer [15].

The small cell network concept requires the reliable placement of small cells Control Plane (C-Plane) by the macrocell while keeping the massive deployment of small cells for higher energy efficiency in a User Plane (U-Plane) separately. This virtual cell approach (e.g., soft cell) will substitute the classical concept of the hexagonal cell and will employ a hierarchical placement that will achieve frequency separation, easier spectrum reuse, and interference control [19]. Increasing density of nodes and interchanging connectivity options raised up new challenges which need to be met. To meet those challenges, user-independent algorithms are required. So future smart devices are designed to be able to learn and take decisions on how to manage the connectivity [15].

2.2.5 Flexible Spectrum Management

Different interference mitigation techniques are used in present networks. LTE, as an example, use techniques like autonomous component carrier selection and enhanced InterCell Interference Coordination. However, these techniques have limited flexibility and are applied only for nomadic and dense small cell deployments. Therefore, interference mitigation techniques in 5G networks need to be more flexible and open toward changes in the traffic and ready to handle the foreseen rapid deployment [15].

Many cellular wireless communication systems specifications rely on the reuse concept in order to obtain efficient utilization for limited resources [15]. Spectrum reuse is required in the closely located small cells of 5G SCN in order to obtain spectral efficiency [14]. load sharing efficiency between macro cells and local access networks will be enhanced through the introduction of both reuse and densification concept. On the other hand, all these advantages have come up with the considerable and corresponding problem of increase in receiver terminals co-channel interference in the network (especially at the boundaries of cells) due to the high density and load of the network [15]. Thus, the interference from neighboring cells will increase despite the strong signal received from the large number of SBSs within the network. Therefore, not only intra-cell interference but also inter-cell interferences should be mitigated in order to reach the expected capacity of UD-SCNs and high satisfaction level for users [14]. Under the cognitive radio concept in which a transceiver can intelligently detect which communication channels are in use and which are not on one hand, and can be adapted to support flexible and intelligent spectrum management on the other hand; flexible spectrum management enable network entities to observe, learn, adapt, and optimize their spectrum usage in order to improve transmission efficiency and resource utilization. In addition, it enables network entities to meet dynamic traffic demand from users with different requirements and applications [14].

To fulfill the performance targets of future mobile broadband systems, a much wider scope and wider bandwidth than the current spectrum of performance are required. So to overcome this difficulty, another spectrum management technique is introduced, spectrum sharing; spectrum will be made available under horizontal or vertical spectrum sharing systems. The importance of spectrum sharing will possibly increase, while dedicated licensed spectrum access is expected to stay the baseline approach for mobile broadband which provides investment certainty and reliability for cellular mobile broadband systems. Network components that use a common spectrum are likely to play a role in balancing [15].

2.2.6 Mobile Cloud

The support of mobile services and applications in the 5G networks require integration between radio resource access and data processing. Cloud computing can facilitate efficient data access and processing and can enable radio access networks to provide flexible communication between the interacted components of the 5G HetNets. This utilization of cloud computing in radio access networks is Cloud Radio Access Networking (Cloud-RAN). The interaction between multiple small cells and macrocell in 5G HetNets is critical to facilitate user connection and resource management. In addition, it will enable 5G HetNets to achieve optimal performance, meet user demands and application requirements, and ensure fairness. The typical resource management framework consider QoS requirements, radio resource limitations, energy consumption, and cost/profit [13].

This chapter illustrates the required 5G cellular networks design, and emerging technologies and features. The model proposed in this work reflects UD-SCN which can utilize from the new NOMA technique for fast access to the network by avoiding the need for sending scheduling requests. Avoiding excessive complexity, it doesn't reflect CoMP and MIMO in this model despite its ability to be included and represented. The next chapter describes briefly some different types of the non-conventional game models and applies a comparative review between them. Moreover, it illustrates the features of those different types of game theory and its potential applications in IoT massive deployment systems. It explains the reasons and features beyond choosing Mean-Field MAB game approach in this work proposed cell association algorithms in 5G cellular HetNets with the massive deployment of IoT devices.

Chapter 3

Primer on Game Theory

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This chapter explores some non-conventional game theoretic models that correspond to the basic characteristics of the widely anticipated large-scale IoT systems. It discusses and describes evolutionary games, mean field games, minority games, mean field bandit games, and mean field auctions. This chapter describes few basics of each of these game models and describes the potential IoT-related resource management problems that can be managed using these models. In addition, this chapter also discusses challenges, slips, and future research directions.

Game theory is the traditional method applied to achieve effective analysis for the interactive decision making of different agents with conflict of interests [10]. Traditional learning and game-theoretical models have been widely used over the last decade for analyzing interactive decision making of different agents with conflicting interests. Such models are used in different situations including efficient resource management for different wireless heterogeneous networks, M2M communications, and sensor networks [10]. Even though, traditional game 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 [10]. Those shortcomings make traditional game models insufficient to analyze the associated problems with the rising ultra-dense network infrastructures and created arguments against using different traditional game models for massive scale systems include, but are not limited to:

- The immense overhead caused by the information acquisition
- The slow convergence to equilibrium
- The inefficiency of equilibrium in terms of social welfare
- The excessive computational complexity
- The theoretical complexity of characterizing the equilibrium set

Therefore, it is necessary to move toward less conventional models that can handle and model the characteristics of future wireless networks in order to face distributed resource allocation problems in ultra-dense IoT systems [10]. Such less conventional game models are:

- Evolutionary games
- Mean field games
- Minority games

Furthermore, for large-scale multi-agent systems:

- Mean field bandit games
- Mean field auctions with learning

3.1 Evolutionary Games

The evolutionary game was first developed to model and study the evolving populations behavior in the biological entities. This type of game allows limited rationality players to learn from the surrounding environment and make their own individual decisions for their own behavior. In this game, players strategically replicate the more successful actions or behaviors rather than the possible outcomes of every joint action profile, that is, the more frequently used actions among the players. In an evolutionary game, ”population” is referred to the set of players. Moreover, at each step, ”population state” is referred to the collection of fractions of the player’s population selecting different actions at that given step. Players adapt their strategies by repeating the most successful actions in terms of the occurrence frequency until the system equilibrium is obtained. ”Replicator dynamics” is referred to the process of action selection modeled by some ordinary differential equations. Evolutionary equilibrium is the fixed point of this replicator dynamics. Usually, in games that assume full rationality of players, players need to track the moves of each other. Therefore, using conventional games to model resource allocation problems in massive IoT systems require very complicated algorithms and too much feedback information exchange due to the massive number of interconnected devices. However, in evolutionary games, players simply adapt their moves relying only on the systems average utility rather than relying on knowing other players decisions. This characteristic nominates the evolutionary game model as a suitable candidate for developing resource allocation algorithms with low complexity and suitable enough for large IoT systems with limited backhaul/fronthaul connectivity [10].

Moreover, evolutionary equilibrium guarantees identical resources for all players in the system through its resource management schemes which guarantee fairness between all players. There are many possible applications of evolutionary games suitable for modeling massive IoT, those applications include Power control, medium access control/sub-carrier allocation and joint power-subcarrier allocation, transmission mode/network selection, and system behavior analysis under Denial of Service (DoS) attacks. Evolutionary-game-based algorithms can handle a limited amount information of exchange delay [20]. However, evolutionary-game-based algorithms performance under such a limited amount of information delay is totally dependent on the system and network parameters, including but not limited to, channel gains and the number of devices in the network. Nonetheless, evolutionary game models may not be able to model the stochastic nature of parameters such as queue dynamics and the uncertainty of the non-guaranteed energy supply, such as energy collected through harvesting. Moreover, evolutionary games face difficulties to model the interconnection of different types of IoT devices due to its assumption of homogeneity of the players [10].

Here, it is necessary to point out that the reason behind the prevention of using Evolutionary games in characterizing the relations between the parties, UE mobile and IoT devices, in cell association during 5G HetNets is due to its inability to model the inhomogeneity of IoT devices and UE mobile devices. Moreover, Evolutionary games are incapable of modeling uncertainty and the stochastic nature of parameters that challenge IoT devices during cell association in 5G HetNets situations. The uncertainty challenge in those situations is due to the uncertainty of energy harvesting and limited computational capabilities [10].

3.2 Mean Field Games

Conventional games need to analyze the interactions between players to achieve the efficient equilibrium required for rational IoT devices trying to make the best decision based on other agents actions. However, such analysis, in large-scale systems as in IoT systems, needs intensive information exchange and leads to high complexity. Mean Field Games (MFGs) concept recently developed to deal with the mentioned issues, which will analyze the interactions of a massive number of rational entities and effectively model them [21]. In MFGs each player has a state, a control policy and group of actions [10]. Every state is mapped through control policy into an action over a specified period of time. MFG models each individual player interaction with the effect of the mean behavior of all the other players instead of modeling it with every other player. Therefore, the mean field simply represents the fraction of players at every state at each step of the game. The target of each player in MFGs is to get a sophisticated control in order to maximize its utility over a limited amount of time while taking into consideration other players collective behavior. The Mean Field Equilibrium (MFE) can be achieved by solving mean field equations simultaneously. There is no general technique that can solve mean-field equations. Therefore, it is challenging to obtaining the MFE.

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 resource allocation problems. In addition, those mean-field equations are able to model the system behavior over a period of time. MFG represents one of the special forms of differential games. Therefore, MFG is able to consider the stochastic nature of the system (battery and channel dynamics, Queue length variation, etc.) when applied to solve the problem of resource allocation. This ability allows the MFG to be a good candidate for developing resource allocation techniques while taking the system's dynamic nature into account. There are many possible applications of MFGs in massive IoT systems. Those applications include, but are not limited to, Energy-aware power control, resource management for mobile IoT devices, and queue-aware resource allocation. In the models where information exchange between devices is limited, while algorithm execution, MFG is possible to derive offline algorithms. In fact, at the initialization phase, the devices shall gather the required information in order to execute the algorithm. This feature let MFGs even more suitable and required to overcome the backhaul/fronthaul connectivity limitations. However, it is highly important to mention that MFG formulations face difficulties in taking the incompleteness of information into account [10].

3.3 Minority Games

Minority games are one type of game theory which models the behavior of entities with limited rationality similarly to evolutionary games. Belonging to populations minority is more advantageous in minority games scenarios [10]. The minority game was developed as a mathematical model which let an odd number of players to participate in a repeated game, where at every single iteration or trial, each player decides whether to join his group to a cafe or not. On one hand, no one will enjoy the cafe if it is too crowded, so it is better to simply avoid going to the cafe with his group. On the other hand, if the cafe is empty, everyone in the cafe will enjoy it; therefore, it is desirable to go to the cafe. This setting let staying in the minority group to be always more beneficial. The general setting of a minority game is similar to the scenario where an odd number of limited rational players have two different actions from which to select. In this game, winners are the players who select the minorities action at every iteration. Each player knows the winning side and the outcome of the game at the end of each step. This information is referred to as the player winning history. The winning history will be used by each player in order to decide the action of the next step. Therefore, players do not evaluate every joint action profile possible outcome, instead, they use a strategy in order to find the best mapping of each possible winning history of an action. Thus, implementing inductive learning at every player in a distributed manner can be used to obtain the mapping of each action possible winning history [22].

Minority game model differs from the two previously mentioned game models in its ability to implement resource allocation algorithms in the scenarios that tolerate imperfect information. The simple inductive learning algorithm allows the corresponding resource allocation technique to be scalable. However, the applications of minority games can be limited due to having a limited binary action set. Minority games can be used to model large-scale IoT limited resource management problems. For instance, slotted ALOHA transmission decision, interference management, and transmission mode/network selection in large-scale IoT. Moreover, minority games are similar to evolutionary games in being unable to model the inhomogeneity of IoT devices. However, it is possible to model the resource allocation problem as a hierarchical game when multiple categories of devices exist in the system, [10]. Here, it is necessary to point out that the reason behind the prevention of using Minority games in characterizing the relations between the parties, UE mobile and IoT devices, during cell association in 5G HetNets is due to its limited set of possible actions. In 5G HetNets association, devices association decision is taken depending on multiple parameters which include associating with one of the overlapping HetNets cells and which cannot be shortened or simplified in a limited set of actions. Another shortage in minority games, which limit its use in 5G HetNets cell association problem formulation, is its inability to model the inhomogeneity of IoT devices and UE mobile devices as in evolutionary games.

3.4 Mean Field Auctions Games

An auction matches to the process of selling or buying goods, where the goods are offered by the auctioneer, participants (bidders) offer or suggest bids, those offers adjust prices, and finally, the goods get sold to the participant or the player who make the highest bid. The actual paid price by the bid winner relies on the auction rule. For instance, in the regular first-price auction, the winner pays his highest offered price. However, in a second-price auction, only the second highest price is paid. While in static auctions, bids are done only once as a one time bid. On the other hand, dynamic auctions are performed repeatedly. Such replication enables a model incorporating learning theory where bidders have no prior estimation of the item being sold. Nevertheless, the agents react to each other as in a natural dynamic setting, so the system needs to converge and reach an equilibrium or steady state. Researchers have used various auction models intensively in order to model different wireless networking problems, especially spectrum allocation auction. Nonetheless, dynamic auctions become computationally infeasible in a small number of agents scenarios as for any other multi-agent setting due to its need for an auctioneer to solve for best prices of a large group of bids. Therefore, mean field approximation can be used to deal with this issue and make the problem easier. Mean field auctions are similar to mean field bandits in its suitability to address the decision problems under information shortage. However, mean field auctions require the existence of a coordinator in order to execute the auction process. There are many potential applications for mean field auctions game models in massive IoT systems. Those applications include, but not limited to, load balancing, Channel access, resource allocation, and backhaul/ fronthaul channel allocation for mobile cloud computing. It is important to mention that game models can sometimes be applied to a specific problem in order to get rid off some of the shortcomings. As mentioned before, modeling the randomly deployed IoT devices is challenging. [10]. Here, it is necessary to point out that the reason behind the prevention of using mean field auctions games in characterizing the relations between the parties, UE mobile and IoT devices, during cell association in 5G HetNets is due to it's requirement to the existence of a coordinator in order to execute the auction process. Relying on a coordinator to perform cell association in 5G HetNets with massive is IoT deployment is impractical and will generate high signaling overhead.

3.5 Mean Field Bandit Games

MABs are a canonical model for studying and learning in uncertain environments [23]. Moreover, MABs 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. Those arms are at the side of MAB games as shown in figure 3.1. The player watches only the reward of his played arm. However, a significant difference between the maximum reward that can be achieved and the actually achieved reward of the played arm is possible because of the shortage of information. This difference is usually referred to as regret. The player selects arms according to some decision-making policy in order to optimize some regret-based target function over the game time. In order to solve the stochastic bandit problem, many different methods have been developed so far that are based on mathematical models including the Upper Confidence Bound (UCB) policy [24]. The UCB policy is developed specially to handle stochastic stationary bandit problems. Thus, the constraint is to balance between obtaining and exploiting information in order to achieve a better reward in the future, known as the exploration-exploitation dilemma. The basic bandit problem, (stationary, stochastic model), is related to only one agent and its main objective is to learn the best arm quickly [23]. However, the problem can be generalized to a multi-agent situation, where the agents affect every other agents' rewards arbitrarily. Thus, reaching some sort of system equilibrium or stability is important. Conventional equilibrium notions, such as correlated, perfect Bayesian equilibrium, or Nash are practical when applied to a limited number of agents bandit game model. However, such equilibrium notions are infeasible in a large number of agents bandit game model due to the long convergence time and excessive complexity required. Therefore, mean field approximation is useful and can

Figure 3.1: Multi Armed Bandit Games.

be used, similar to games with complete information, for analyzing large-scale bandit games and to overcome the equilibrium challenges in a large number of agents bandit game models. In mean-field bandit games, as is conventional games, every agent considers the rest of the world simply as being stationary and don't consider agents individual moves an important detail [10].

Algorithm 1: Upper Confidence Bound Selection Policy [25]

Deterministic policy: UCB1;
Initialzation: Pull each arm once;
Loop;
- Pull arm j that maximizes $\overline{x}_j + \sqrt{\frac{2 \ln n}{n_j}}$ where $\overline{x}_j$ 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;

A policy, or allocation strategy in MABs games is the algorithm used to select the next machines to play depending on the sequence of the played machines and obtained rewards. While the regret is known as the expected loss due to the fact that the policy does not always select the best machine to play. The set of each arm instantaneous rewards in the UCB policy is independent and identically distributed (i.i.d.) random variables. The UCB policy 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. Hence, under UCB policies the optimal machine is exploited and played exponentially more often than any of the other machines. These policies work by associating an upper confidence index quantity for each machine. In general, it is not easy to compute such an index. In fact, it depends on every machine entire sequence of offered rewards. Once the index is computed for each machine, the policy use this index in order to estimate the corresponding reward expectation, selecting for the next machine with the current highest index to play [25]. Theorem 1 from reference [25] represent the seminal UCB policy and is shown in Algorithm 1.

Table 3.1 offers a brief summary of the main features of the game models discussed so far. Moreover, Table 3.2 illustrates which game model would be able to solve the wireless IoT-specific challenges and constraints described before. However, it is important to mention that sometimes game models can be used to a specific problem in order to get rid of some of the shortcomings. Another important issue to note is that no single game model is able alone to address all the challenges that appear when designing massive IoT distributed resource management schemes. However, it is always possible to address those challenges by modifying those game models. Therefore, the use of mean field bandit games in addressing the conflict and cooperation relations between the parties, UE mobile and IoT devices, during cell association in 5G HetNets is practical due to different capabilities. Those capabilities include its ability to consider the stochastic nature of the system, to overcome the backhaul/fronthaul connectivity limitations, to model the inhomogeneity of IoT devices, and due to the absence of limitation on the set of actions to be modeled.

Game model	Random deployment	Scalability	Limited back-haul/fronthaul	Inhomogeneity	Non-guaranteed energy supply	Uncertain and incomplete information
Evolutionary games	Yes	Yes	Yes	No	No	No
Mean field games	Yes	Yes	Yes	Yes	Yes	No
Minority games	Yes	Yes	Yes	No	No	No
Mean field bandit games	Yes	Yes	Yes	Yes	Yes	Yes
Mean field auctions	Yes	Yes	Yes	Yes	Yes	Yes

Table 3.1: Summary of each game model main features.

3.5.1 Multi-Agent Multi-Armed Bandits

Mean-field multi-armed bandit game is an efficient mathematical model to analyze UD-SCNs. This model does not need massive information exchange among agents; it does not

Game model	Equilibrium concept	Information requirement	Rationality	Remarks	Potential IoT applications
Evolutionary games	Evolutionary equilibrium	Average system utility	Bounded	Guaranteed fairness, linear time complexity, tolerant to information delay	Power control, spectrum/subcarrier allocation, transmission mode/network selection
Mean field games	Mean field equilibrium	Initial distribution of the players' states	Full	Stochastic awareness, performance evaluation for a time period, complicated mean field equations	Energy/queue/channel-aware resource allocation, resource management under mobility
Minority games	Public perfect equilibrium	Successful action	Bounded	Binary action set, tolerant of imperfect information	Scheduling, transmission mode/network selection, interference management
Mean field bandit games	Mean field equilibrium	None	Bounded	No information, binary reward set	User association, scheduling, channel allocation
Mean field dynamic auctions	Mean field equilibrium	Bids	Bounded	No information on utility function, an auctioneer is required	User association, scheduling, channel allocation

Table 3.2: Summary of massive wireless IoT challenges that can be addressed by each game model.

suffer from slow convergence in a medium/large number of actions and agents. Users in this model do not need any prior information about network traffic or channel quality. Also, this mathematical model is not complex for a massive number of users, are able to work with the uncertainty, and guarantee convergence to equilibrium. In a multiple agents bandit game, agents affect and influence each other in the sense that the reward achieved by each agent is determined through the joint action profile of other agents and not only through its own actions. Therefore, the payoff of every arm to each agent relies on the ability or type of that specific agent and the number of agents selecting that arm. As an example, the individual rewards might decrease in a congestion model if multiple agents select the same arm, while the reward might increase in a coordination model. Reaching to system stability and equilibrium is as important as minimizing the regret in a multi-agent setting. For a small number of agents, reaching to system stability and equilibrium is possible in multi-agent multi-armed bandit games through correlated, Nash, and Perfect Bayesian equilibrium, where the last equilibrium is heavily used with learning games in conjunction. On the other hand, for multi-armed bandit games with a large number of agents, those mentioned equilibrium notions are not practical due to their excessive complexity requirements and long convergence time. For example, for a multi-armed bandit game, each agent needs to observe and monitor the joint action profile of other agents and expect their future moves in order to converge to correlated equilibrium [8].

3.5.2 Mean-Field Model for Multi-Agent Multi-Armed Bandits

In general, mean-field models are used to analyze games with a large number of agents. As mentioned above, every agent in mean-field models considers the rest of the world as being stationary and do not take into account the individual moves of other agents. Instead, mean-field analysis confirms game theory as an interaction of every individual agent with the group of other agents. On the other hand, applying multi-armed bandit games with mean-field analysis of games with perfect information is a recently-emerging research direction. In mean-field games, regeneration means that an agent quits or leaves the game and a new agent enters and takes his place. Thus, each agent regenerates following a random time which follows a geometric distribution with parameter $1 - \alpha$, $\alpha \in [0, 1)$. The regeneration process can capture the changes in the type of each agent. At time t, the population profile $f_t = [f_{1,t}, f_{2,t}, ..., f_{M,t}]$ evolves as the agents choose over time their actions. An arbitrary agent $n \in \mathcal{N}$ with agents type $\theta_{n,t}$ in mean-field dynamics is sampled from distribution W and its state $Z_{n,t}$ is reset to zero if the trial is a regeneration trial. However, in any other trial the type remains unchanged and a random selection policy, UCB as an example, is used to map state $Z_{n,t-1}$ to an action $a_{n,t}$. The selection policy should be applied by all agents. Each agent selection deliverers a Bernoulli distribution random reward with success probability parameter $Q(f_{m,t}, \theta_{n,t})$, and update the state $Z_{n,t}$. This mean-field dynamics is summarized in Algorithm 2 [8]. Achieving MFE in mean-field dynamics require a stationary system for every agent through maintaining a fixed population profile f [23, 26].

Algorithm 2: Mean-Field Dynamics for Multi-Armed Bandit Games [8]

for $t = 1, 2, ...$**do**
if *t is a regeneration trial,* **then**
  The agents' type $\theta_{n,t+1}$ 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

After the brief description on each different game theory, it is important to note that ability of mean field bandit model to handle the lack of prior available knowledge for decision making, allows this model, to be very suitable for IoT systems with low backhaul/fronthaul connectivity. Many problems which can be handled by different game theories include transmission power, user association and spectrum allocation for transmission mode selection, wireless IoT devices, and channel access. Also, game theory can be used to model and analyze the distributed control problems (for instance the cell association problem, among many others) in IoT-driven UD-SCNs. To this end, this work develops a mean field multi-armed bandit model for the uplink cell association problem in a UD-SCN, where a large number of IoT devices (human-driven or machines) try to select an appropriate SBS to become connected to the Internet. Next Chapter illustrates the different cellular networks cell association approaches and how they are implemented and accessed.

Chapter 4

Related Works

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This chapter presents various cell association approaches, implementations, and access modes. First, it describes and compares between user-driven and network-driven cell association approaches. Then, it discusses the pros and cons of centralized, decentralized and distributed cell association implementations. It also defines closed, hybrid and open cell association access modes that are used under different implementations and approaches. Moreover, this chapter review how cell association approaches, implementations, and access modes were applied in the literature.

4.1 Cell Association Approaches

Cell association approaches are categorized based on where the association decision is performed. In Network-Driven association a network side entity makes the decision on whether to serve/let access the new user or not. The decision can also refer to the cell that the user is linked to. This approach offers the operator a full network control required to achieve particular objectives [13]. Authors in [27–30] used network driven cell association. In [27, 28], authors introduced two simple cell association policies, the first was for an OFDMA-based small cell with hybrid access mode; while the second was based on the users' distance to the BS using closed and open access modes. However, the work in [29, 30] assumed cell association is performed jointly between resources allocation and adaption issues; in [29] power adaptation is based on Nash game theory equilibrium, while in [30] channel allocation is considered jointly with cell association to increase the average utility value for all users through cells.

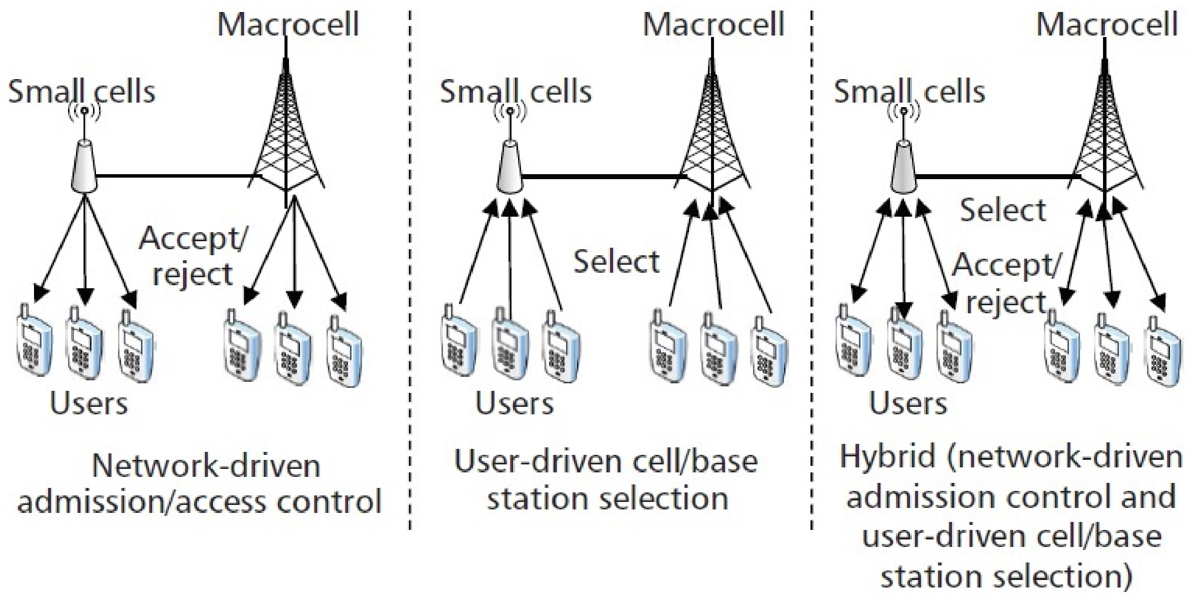

Figure 4.1: Cell association approaches

The other type of cell association approaches is User-Driven cell association. In this approach, the user has the privilege to make the decision to which BS or access point to connect after observing and estimating the performance of all nearby cells. This approach allows taking users preferences into account [13]. In [31], users decide to associate with the BS based on the highest SINR reported from all nearby BSs. However, users in [32] decide independently on which cell to join based on their individual performance, and decide to switch their cell automatically if they observed performance degradation. Rakshit in [33] 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 [34] using a user-driven cell association described in [8]. Their work was only concentrated on representing the mobility effect for UE devices with a stable power source and without the existence of a different type of devices population fluctuation. Network and User-driven association approaches can be applied together under what is known as the Hybrid cell association approach. In this approach users from their side select the BS or cell of their preference. However, the networks from the other side make the decision of accepting or rejecting the users [13]. Chun-Han Ko used in [35] an auction process to allow users 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. The three mentioned approaches are shown in Figure 4.1. This thesis proposes a user-driven cell association algorithm, it aims to minimize the growing cell association overhead due to the foreseen massive deployment of IoT devices which wasn't considered in any of the aforementioned public work.

4.2 Cell Association Implementations

The three Cell Association approaches mentioned above 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 users [13]. This decision is done by calculating the cellular association metrics for each device on SBS and disseminates this information to each individual SBS [33]. This implementation provides complete information about networks and users required to achieve optimal network performance. However, this approach relies on intensive information exchange and gathering [13]. In addition, it will be challenging to trace the different system parameters including quality-of-service requirements of individual tiers, energy requirements, and interference conditions [33]. On the other hand, the decentralized implementation divides the network into smaller parts capable of making cell association decision for its members using those part's controllers. This approach aims to achieve a network-wide objective but with limited information exchange and self-interest. 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. However, this distributed implementation gives the individuals performance the priority upon the entire network performance [13]. Therefore, it is computationally scalable and feasible and is widely used to consider load balancing, signal strength optimization, transmission success probability maximization, and transmission energy efficiency. In addition, it enables the utilization of the information about each device energy usage and mobility patterns stored within each of those IoT and UE Mobile devices in order to perform an active participation in UD-SCN for efficient energy optimization and efficient mobility [33].

The above three mentioned implementations can be adopted for the network-driven cell association while taking into account network configuration and system setting. On the other hand, user-driven cell association typically adopt the distributed implementation approach in order to limit information exchanged. For the centralized, decentralized, and distributed implementations with network-driven and user-driven cell association approaches, the performance of the network and the individual user should be taken into consideration and evaluated in order to take the right decisions. For the same considerations, cell selection/association schemes are designed jointly with power control and channel allocation [13]. Maghsudi outlined in [8] the major challenges for distributed cell association in IoT-driven UD-SCNs where the IoT devices will need to perform cell association in a distributed manner in the presence of uncertainty (e.g., limited knowledge on channel/network), energy harvesting and limited computational capabilities. They proposed 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. They provided some theoretical results as well as preliminary performance evaluation results for the proposed approach. However, that work proposed cell association algorithm based on IoT devices consuming all the harvested power for transmission and not willing to minimize transmission power consumption, it considered IoT devices scenario perspective only, without taking into account Mobile devices willing to achieve the highest data rate through cell association.

A great majority of studies neglect the energy efficiency problem by excluding the randomness of energy harvesting from their analysis. Thus, for energy-harvesting UD-SCNs, it is useful to formulate the (joint) uplink and downlink cell association as distributed optimization problem under uncertainty. In [36], Dong optimized the user association matrix through using quantum particle swarm optimization. Similarly, in [37], 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. However, none of these took into consideration energy harvesting in the system model. In addition, Maghsudi suggests in [38] a distributed mode selection method in heterogeneous networks through the use of multi-armed bandit theory, where users have only very limited information; nonetheless, energy harvesting is not used in the system model. This work proposed a user-driven cell association algorithm is implemented in a distributed manner in order to let each IoT and UE device take its own decision independently with minimal information exchange. It aims to minimize the growing cell association overhead due to the foreseen massive deployment of IoT devices.

4.3 Cell Association Access Modes

Regarding cell association access modes, there are basically three different cell association access control modes in which a small cell could be operated in HetNets: 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. However, the small cells will differentiate users in the closed access mode. Users 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 [39]. The user-driven distributed CA-MAB algorithm proposed in this thesis does not consider reserved resources as in closed access mode. It considers shared resources under congestion model. Such an algorithm can be helpful to apply for all users in open access mode and for non-subscribed users in hybrid mode. In both cases; users will be treated equally depending on the resources availability. Although, this algorithm assumes 5G system architecture treat users equally if operating in open access mode or if belong to non-subscribed users in hybrid mode. However, CA-MAB algorithm allows them to behave differently based on their needs. Mobile devices and IoT devices different needs drive them to take different individual decisions for cell association. The Mean-Field MAB game approach is applied to solve mobile and IoT cell association and to maximize the allocated data rate for mobile devices and minimize power consumption for IoT devices. Different types of game models are illustrated in paper [10], it also discussed the potential IoT-related resource management problems that can be solved by using those different models. On the other hand, Semasinghe didn't discuss the potential of Mobile devices-related different subscriber groups or behaviors in [10].

Guruacharya in [32] introduced cell association using coalition formation game. In this scheme, HetNets use a self-control strategy that allows users to decide and choose 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 [13] and [8]. Wang proposed in [13] an antenna allocation and cell association algorithm depending on the evolutionary game theory which provides equilibrium solutions. These solutions ensure that the users cannot gain a higher data rate by changing their cell association neither the cells can gain higher total revenue by changing their antenna allocation. It relied on two different algorithms, user-driven, and network driven algorithm. That paper balanced between users need and network need for high data rate and high revenue, respectively; but didn't consider IoT devices for low power communication need into account. On the other hand, Maghsudi proposed in [8] a user-driven cell association approach using mean-field multi-armed bandit games in order to solve the uplink cell association problem for energy harvesting IoT devices in a UD-SCN. This approach is particularly suitable to analyze large multi-agent systems under uncertainty and lack of information. However, UE Mobile devices cell association was not addressed. UE mobile devices have much less energy consumption concern when compared to IoT devices.

This chapter illustrates major cellular networks cell association approaches, implementations, and access modes. It clarifies the use of a user driven distributed cell association approach in this work. Such an approach will be suitable for open and hybrid access modes. This work main contribution can be summarized in developing an IoT and UE Mobile devices user-driven cell association algorithm in 5G HetNets based on Mean Field MAB approach and UCB selection policy. This algorithm is developed in order to be used by both IoT and UE mobile devices while taking into account these devices different cell association requirement and goal. This different requirement is to maximize the data rate for UE Mobile devices at fixed power consumption while to minimize power consumption for IoT devices at a fixed data rate. The next chapter describes the mathematical formulation of cell association in UD-SCN.

Chapter 5

Problem Formulation

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The majority of the existing cell association methods are designed for downlink transmission, consume a significant amount of information at SBSs, and depend on a central controller. The foreseen 5G networks should be able to handle the massive growing amount of IoT devices and meet their uplink transmission needs. 5G networks will be formed of highly distributed UD-SCN and need to reduce dependency on centralized control. Therefore, developing a distributed association method capable of dealing with information shortage as well as a very large network size (number of SBSs and/or users) and can be used by IoT is highly required. Moreover, the uncertainty problem caused by the random energy availability in energy harvesting networks should be addressed through an efficient solution. Such a solution should also consider UE mobile devices need to associate with the SBS that can offer the highest data rate [8].

5.1 System Model Design and Assumption

This model considers a dense small cell network which consists of a set $\mathcal{M}$ of M SBS, including the macro cell, and a set $\mathcal{N}_1$ IoT devices and a set $\mathcal{N}_2$ UE Mobile devices of N devices. Every device $n \in \mathcal{N}_1$ or $\mathcal{N}_2$ intends to transmit $J_n \leq J$ data packets in the uplink direction in a successive transmission rounds. At every transmission round j, each device transmits one data packet to an SBS of its choice, implying that the association is performed in a distributed manner. Multiple devices can be served through single SBS. $\mathcal{N}_{1m,j}$ represents the set of IoT devices to be served by SBS $m \in \mathcal{M}$ at round j, and $\mathcal{N}_{2m,j}$ represents the set of UE Mobile devices to be served by SBS $m \in \mathcal{M}$ at round j. On one hand, every IoT device obtains the energy through ambient energy harvesting by applying harvest and use strategy; in which it uses all of the harvested energy for transmission in every transmission round if high data rate transmission is required. Devices can also use a harvest store-use strategy, in which devices store temporarily energy and use the minimum amount required to prolong IoT devices operation time. In both cases, energy harvesting is independent across IoT devices. Without loss of generality, this model assumes that the power used by IoT devices for transmission equals to the energy harvested if harvest and use strategy is deployed to achieve the highest data rate. Also, this model considers that the IoT devices use all the harvested power and learn the amount of power needed for minimum data rate transmission in order to prolong operation time. This learning continues even during the exploitation trials. This enables IoT devices to use the minimum amount of power through learning and without obtaining channel status and SBS population information. Due to the opportunistic nature of energy harvesting, the amount of harvested energy, denoted by $P_{n1,j}$, is unknown prior for every IoT device $n \in \mathcal{N}_1$ and at every round j. In this system model $P_{n1,j}$, $j = 1, ..., Jn$, is assumed to be i.i.d. random variables. Since half-normal distribution is always positive and follows an ordinary normal distribution $N(0, \sigma^2)$, $P_{n1,j}$ follows half-normal distribution with parameter $\sigma_n^2 > 0$. This assumption is not restrictive and can be replaced by any other distribution without affecting the solution approach [8]. On the other hand, UE Mobile devices batteries offer a stable energy source compared to the energy available through harvesting, and this will allow UE Mobile devices to perform association decision based on the highest data rate available. UE Mobile devices learn the available data rate that can be achieved from each SBS through regeneration trials and during the exploitation trials through UCB policy. When UE Mobile devices battery power level drops to a certain battery power level, UE Mobile devices can simply start acting as IoT devices to preserve the energy left. If a device quits transmission, it is replaced by another device in order to maintain a 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 devices always equal to N. Regeneration mathematical details used in this model are as in [8].

Transmissions are corrupted only by zero-mean additive white Gaussian noise with variance N_0 inside every small cell. The inter-cell interference experienced by every device $n \in \mathcal{N}_{m,j}$ for each small cell $m \in M$ denoted by $I_{nm} \geq 0$, is considered as noise and assumed to be fixed during the entire transmission period. Dealing with interference as noise is commonly used for SCN in many references. At round j, channel gain between device $n \in \mathcal{N}_{m,j}$ and small cell $m \in M$ is denoted by $h_{nm,j}$. In addition, the frequency is assumed as non-selective block fading channel model, where the random variable h_{nm} follows a Rayleigh distribution with parameter $\frac{1}{\sqrt{2\beta_{nm}}}$, and remains constant during the transmission of every packet $j = 1, ..., Jn$, for every $n \in N$ and $m \in M$, and changes from one transmission round to another. The random channel gain $h'_{nm} = h^2_{nm}$ then follows an exponential distribution with parameter β_{nm}. The type (or ability in MAB games) of every device $n \in N$ is defined as the collection of its channel gains towards SBSs, i.e., $h'_{n,j} = (h'_{n1,j}; h'_{n2,j}, ..., h'_{nM,j})$, $h'_{n,j} \in (0, 1]^M$. For simplification, the type of every device $n \in \mathcal{N}$ at every round j can be denoted by $\theta_{n,j}$

$\in (0;1]^M$, and is defined as the collection $\theta_{n,j} = (\theta_{n1,j}, \theta_{n2,j}, ..., \theta_{nM,j})$ where for $m \in \mathcal{M}$, $\theta_{nm,j} = \frac{h'_{nm,j}}{I_{nm,j}+N_0}$. If $I_{nm,j}$ is deterministic, the type still follows the same distribution as h'_{nm} but with different parameters. If $I_{nm,j}$ is a random variable, the distribution of type can be calculated by using simple rules of probability. Let $f_{m,j} = \frac{\mathcal{N}_{m,j}}{N}$ denote the fraction of devices that select SBS m at round j. Thus, for each $n \in \mathcal{N}_{m,j}$ and for transmitting every data packet j, the achievable transmission rate is given by

$$r_{nm,j} = \frac{W_m}{N f_{m,j}} \log(1 + P_{n,j}\theta_{nm,j}) \tag{5.1}$$

It is important to remember that in the distributed cell association method each network entity can make its own decision independently with minimal information exchange. Therefore, devices do not have any prior knowledge of channel quality and/or interference level and on the congestion levels in the SBS. In other words, the type and the fraction of devices in each SBS are unknown a priori. W_m is the available bandwidth at SBS $m \in M$. Maghsudi assumed in [8] that $W_m = \mathcal{N}_m w_m = \mathcal{N}_m$ in a system that contains only a set IoT devices $\mathcal{N}_m$ to be served by SBS $m \in M$; his assumption was based on that all devices which select any SBS $m \in M$ share the available spectrum resources equally in an orthogonal manner and based on $w_m = 1$, w_m represents the amount of resources located per each IoT device. If [8] assumption is considered, where all devices (IoT and UE Mobile devices) act as IoT devices and share the available resources equally $W_m = w_{m1} = w_{m2}$ then $W_m = \mathcal{N}_m w_m = (\mathcal{N}_{m1} w_{m1} + \mathcal{N}_{m2} w_{m2})$ and $\mathcal{N}_m = (\mathcal{N}_{m1} + \mathcal{N}_{m2})$; where w_{m1} is the amount of resources located for each IoT device $n_{m1} \in \mathcal{N}_{m1}$ of the set $\mathcal{N}_{m1}$ IoT devices to be served by SBS $m \in M$, and w_{m2} is the amount of resources located per each UE mobile device $n_{m2} \in \mathcal{N}_{m2}$ of the set $\mathcal{N}_{m2}$ UE mobile devices to be served by SBS $m \in M$. Regarding the data rate in [8] where all the system devices are IoT devices or acting as IoT devices, and assuming that the minimum data rate used for IoT devices is $r_{n,min} = 0.75$ then $r_{m,total} = \mathcal{N}_m\ r_{n,min} = 0.75\ \mathcal{N}_m = 0.75(\mathcal{N}_{m1} + \mathcal{N}_{m2})$. Moreover, the maximum data rate available by each SBS is $r_{m,total} = \mathcal{N}_m\ r_{n,min} = 0.75\ \mathcal{N}_m$ and $\mathcal{N}_m = (\mathcal{N}_{m1} + \mathcal{N}_{m2})$ again.

However, this is not exactly the same case in the system used in this work, because the devices in this system are not IoT devices only, there will be UE Mobile devices also. This model assumes that UE Mobile devices also share the available spectrum resources equally in an orthogonal manner, but not equally with IoT devices $w_{m1} \neq w_{m2}$. Despite that, assuming the opposite where both IoT and UE devices sharing the available spectrum resources equally in a distributed cell association scenario based on Mean Field MAB games approach is possible. This assumption simply means that both types of devices are different types of MAB game players with a different attitude or way of playing but will be offered similar resources. In this assumption, in addition to the effect of the devices population fraction from the same type in each SBS on each other, the variance in the fraction of IoT/UE devices associating to an SBS and the proportion of average data rate between those two types will be meaningful and will make difference. Therefore, weighing the amount of IoT devices compared to the amount of UE devices which select a specific cell is required to be done based on the proportion of the average data rate between UE Mobile devices and IoT devices. This is done through a simple linear equation $\mathcal{N}_m = (\mathcal{N}_{m1} + \frac{\overline{r}_{2_{t-1}}}{\overline{r}_{1_{t-1}}}\mathcal{N}_{m2})$. $\overline{r}_{1_{t-1}}$ represents the mean of the IoT devices data rate and $\overline{r}_{2_{t-1}}$ represents the mean of the UE devices data rate in the previous round. This will limit UE Mobile devices data rate availability and bound it between the limitations of the SBS resources on one side and the fraction of IoT and UE Mobile devices associated with each SBS $m \in M$.

Moreover, as stated before, $P_{n,j}$ is the transmission power of device n at trial j. This equals the amount of energy harvested at that trial for every IoT device if the highest data rate is needed in IoT devices. It can also equal to the minimum estimated power required to achieve the minimum data rate if operation time extending is needed. On the other hand, it equals the transmission power possible for every UE Mobile device. For transmission of every data packet, every device $n \in N$ requires a specific quality of service (QoS) that is expressed in terms of a minimum data rate $r_{n,min}$. Hence, for any device $n \in N$, at every transmission round j, the reward of selecting SBS $m \in M$ is defined in equation 5.2 as

$$u_{n,j}(m) = \begin{cases} 1, & \text{if } r_{nm,j} \geq r_{n,min}. \\ 0, & \text{otherwise.} \end{cases} \tag{5.2}$$

The success probability of device n given in equation 5.3, for all devices $n \in N$ in general, is when selecting SBS m at every transmission round j.

$$p^{(s)}_{nm,j} = Pr[r_{nm,j} \geq r_{n,min}] \tag{5.3}$$

and the failure probability yields $p^{(f)}_{nm,j} = 1 - p^{(s)}_{nm,j}$. Thus, successful transmission is a Bernoulli random variable with parameter $p^{(s)}_{nm}$. Equation 5.4 represents the power required to guarantee the minimum data rate $r_{n,min}$ for any specific $f_{m,j}$ and $h'_{nm,j}$ is derived from equation 5.1

$$P_{n,j,min} = \frac{1}{\theta_{nm,j}}(e^{\frac{Nf_{m,j}r_{n,min}}{W_m}} - 1) \tag{5.4}$$

yields $r_{n,m,j} \geq r_{n,min}$. Thus, equation 5.5 reflects also the probability of success for any IoT device $n \in N_1$

$$p^{(s)}_{nm,j} = Pr[P_{n,j} \geq P_{n,j,min}] \tag{5.5}$$

By the half-normal assumption on the harvested energy of IoT devices, the probability of success equation can be derived as in equation 5.6 below

$$p^{(s)}_{n_1m,j} = 1 - \text{erf}[\frac{P_{n,j,min}}{\sqrt{2}\sigma_n}] \tag{5.6}$$

So that roughly, $p^{(s)}_{n1m,j} \propto \frac{\theta_{nm,j}}{f_{m,j}}$ which, as expected, corresponds to a congestion model.

However, in UE Mobile devices, the success probability of device n when selecting SBS m at every transmission round j is

$$p^{(s)}_{n_2m,j} = \begin{cases} 1 - (\frac{r_{n,min}}{r_{n,m,j}}), & \text{if } r_{nm,j} \geq r_{n,min}. \\ 0, & \text{otherwise.} \end{cases} \tag{5.7}$$

In this model, IoT devices UCB (Algorithm 1) use the inverse of the power learned in updating the UCB index while UE Mobile devices use the data rate achieved in updating the UCB index. The use of the inverse of power for updating the UBC reward is examined below in section 6.6 vs the use of the data rate for updating UCB. The power IoT devices learn and use is actually the estimated minimum power required for offering minimum data rate transmission between each device and each SBS as in equation 5.4. However, the absence of prior information about channel gain and SBS population require each device to estimate its value as illustrated in equations 5.8 and 5.9:-

$$\frac{P_{n,j,min}}{P_{n,j-1}} = \frac{\frac{1}{\theta_{nm,j}}(e^{\frac{Nf_{m,j}r_{n,min}}{W_m}} - 1)}{\frac{1}{\theta_{nm,j}}(e^{\frac{Nf_{m,j}r_{n,j-1}}{W_m}} - 1)} = \frac{(e^{\frac{Nf_{m,j}r_{n,min}}{W_m}} - 1)}{(e^{\frac{Nf_{m,j}r_{n,j-1}}{W_m}} - 1)} \tag{5.8}$$

$$P_{n,j,min} = \frac{P_{n,j-1}(e^{f_{m,j}r_{n,min}} - 1)}{(e^{f_{m,j}r_{n,j-1}} - 1)} \tag{5.9}$$

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

5.2 Mean-field Equilibrium of the Multi-armed Bandit Game Model

According to the system model described in the previous section, considering a multi-agent multi-armed bandit game G that consists of a set $\mathcal{M}$ of M cells and a set $\mathcal{N}$ of N devices; including IoT and UE Mobile devices. At every round j, each agent $n \in \mathcal{N}$ decides to associate to a cell (an action), denoted by $a_{n,t}$, from the predefined set of $\mathcal{M}$ cells, and receives some a priori unknown reward. The reward for IoT devices is the successful association to a cell with minimum transmission power requirement, however, for UE mobile devices the reward is the successful association to a cell with maximum data rate. In the mean-field model of a game G, at every round j, each device $n \in \mathcal{N}$ is characterized by some type defined as the collection of its channel gains towards SBSs, $h'_{n,j} \in (0,1]^M$and some state $Z_{n,j} = (w_{1,j}, l_{1,j}, ..., w_{M,j}, l_{M,j})$, with $w_{m,j}$ and $l_{m,j}$, m , being the total number of successes and failures of arm m up to round j, when selected by agent $n \in \mathcal{N}$. Hence, unlike the type, the state is known to the agent. At every round j, every agent $n \in \mathcal{N}$ use some (randomized) selection policy (for example, UCB algorithm [25]) to map $Z_{n,j\text{-}1}$ to some action $a_{n,j}$. The state of each device is simply its game history, i.e., its past cell association decisions (actions) and rewards. $f_{m,j}$ denotes the fraction of devices that associate to cell $m \in \mathcal{M}$ at trial j.

In successive rounds of this mean-field MAB system, a device (player) decide to associate to a cell (pulls an arm) from a given set of cells (a given set of 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(arm). IoT devices (low resources players in MAB games) associate to cells which can afford 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 mobile 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, transmission power resources in this work model can be imagined as time in MAB games and data rate in this model as the reward in MAB games. Each device (player) decide to associate to a cell (pulls an arm) according to some decision-making policy in order to optimize some regret-based objective function over the game horizon. In mean-field bandit games, every device considers the rest of the other devices as being stationary and dont consider devices individual cell associations an important detail. In the system used in this work, IoT and UE Mobile devices affect each other in the sense that the reward achieved (minimum transmission power for IoT devices, the highest data rate for UE mobile devices) by every device is determined through the joint action profile of other agents 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. Again, for example, the individual rewards might decrease in a congestion model if multiple devices select a cell (multiple players select an arm), while the reward might increase in a coordination model.

Confidence level assumes a starting point. It can starts with an average expected reward value or from zero. The confidence level is built and updated into a machine/cell through the UCB policy which estimates an upper-bound of the mean reward of each arm/SBS $m \in \mathcal{M}$ at some fixed confidence level. This is done through calculating an index of every arm $m \in \mathcal{M}$ at round j, denoted by index $I_{m,j}$; $I_{m,j} = \overline{u}_{m,j-1} + \sqrt{\frac{2 \ln j}{T_{m,j-1}}}$, where $T_{m,j1}$ is the total number of rounds arm/SBS m is selected, and $\overline{u}_{m,j-1}$ is the average reward of arm/SBS m, both up to round j-1. The $\sqrt{\frac{2 \ln j}{T_{m,j-1}}}$ part is related to the size of the one-sided confidence interval for

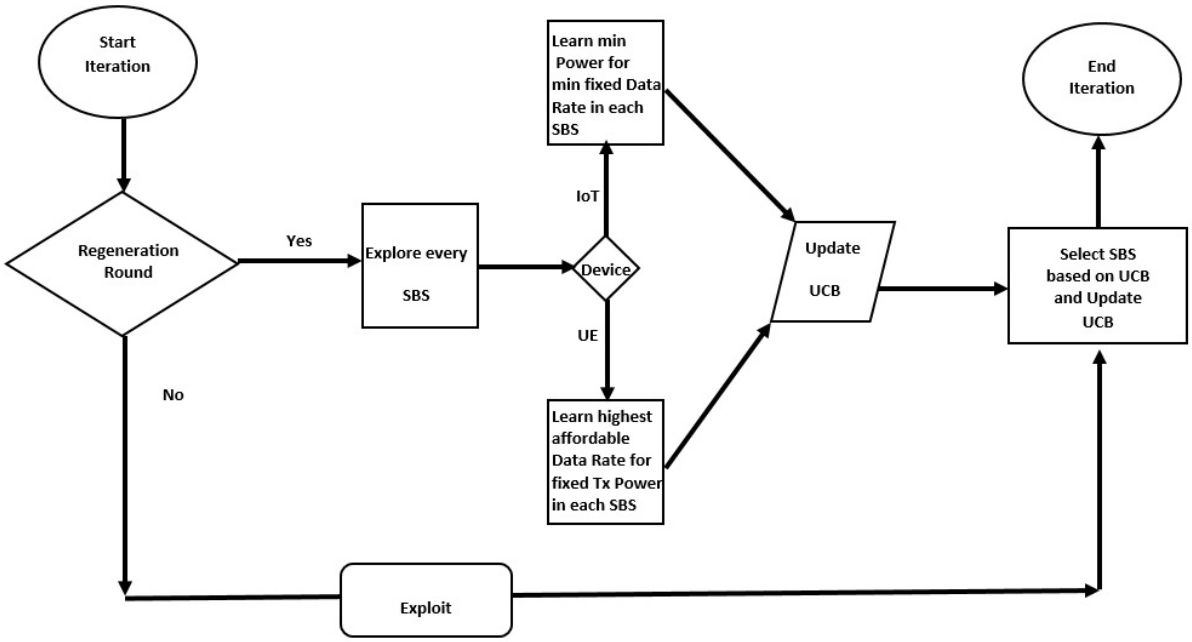

Figure 5.1: Applying Algorithm 2 using UCB described in Algorithm 1

the average reward within which the truly expected reward falls with overwhelming probability [25]. As a result, the arm/SBS with the highest estimated bound is then played, and bounds are updated after observing the reward. The selection is done by finding the arguments of the largest index "$\arg\max I_{m,j}$". The player/device receives some random reward following a Bernoulli distribution with parameter (success probability) $Q(f_{m,j}, \theta_{n,j})$, and the state vector $Z_{n,j}$ is updated.

Formalizing this work problem into Mean Field MAB games can be summarized as follow:-

- **Player:-** Refers to IoT and UE Mobile devices which are trying to select a SBS. IoT and UE Mobile devices refer to two different types of players from the perspective of their resources (power or/and rate) and required reward
- **Machines:-** Refers to SBSs in 5G UD-SCN, where all SBSs share a load of all the devices (Players).
- **Gaming Hall:-** Refers to the UD-SCN including the macro cell and few SBSs.
- **Confidence level:-** Refers to each player (devices) impression toward or expectation from each machine (SBSs) in Mean Field MAB games.
- **Reward:-** Refers to Lowest power consumption required to achieve a fixed data rate (minimum) for IoT devices on one hand. On the other hand, it refers to the highest

data rate to be achieved within a fixed transmission power consumption level.

- **Playing Strategy:-** Player in the Mean Field MAB gaming hall select the Machine which is believed or expected to afford the highest possible reward.

Figure 5.1 represents the flow chart of the explore and exploit model used in every round without any prior information about channel gain or SBS population. Simply, a new device (player) to the network (game hall) explore each SBS (machine) once and learn depending on his game play type and build confidence based on the results of the exploration stage and then start exploiting.

Chapter 6

System Setup and CA-MAB Evaluation

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This chapter evaluates the proposed cell association algorithm, investigates the convergence and equilibrium in mean field MABs dynamics, investigates the effect of the change in the number of devices on the performance of the equilibrium, investigates the effect of change in the number of SBSs on the performance of the equilibrium, and investigates the mean field MAB games throughput performance and energy performance for IoT devices and UE Mobile devices. Each of those investigation results was collected through the mean of a ten different iterations.

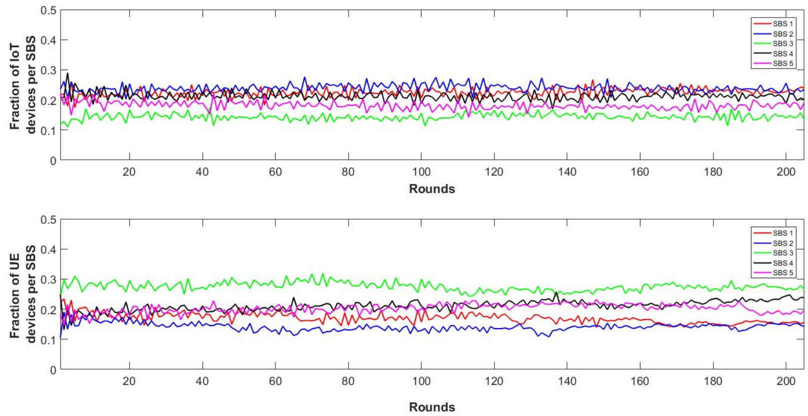
6.1 System Setup

This work applies mean field game model on devices in SCN as described in Chapter 5 using UCB selection policy illustrated in Algorithm 1. This work builds a model which combines IoT devices and UE devices depending on the mathematical model proved in [8] and described in Chapter 5. This work uses Matlab to build the model which consists of 5 SBS and 3 SBS scenarios under Mean Field MAB approach while performing association to SBSs through different assignment schemes. Those schemes are UCB, centralized informed and random cell association schemes. The system used in this work use $W_m = N$, $\sigma_n = 1$ and $r_{n,min} = 0.75$ for all devices (IoT and UE) and m SBSs. On the other hand, the set of channel gains $h'_{n,j} = (h'_{n1,j}; h'_{n2,j}, ..., h'_{nM,j})$ for each device $n \in \mathcal{N}$ are randomly selected from a Rayleigh distribution. The channel gains are independent and i.i.d. for each device $n \in \mathcal{N}$ and for every SBS $m \in \mathcal{M}$. This model tied the relation between the IoT devices and UE devices in the same SBS through the fraction of each type of devices in the same SBS while taking into consideration the ratio between the average data rate for both types. Also, it assumes a random selection in the 1st few rounds before applying CA-MAB algorithm in order to initialize status $Z_{n,j}$ randomly. In addition, it adds a regeneration following a random time over the game horizon following the proofed proposition in [8]. The mentioned proposition represents in the existence of a unique mean-field and convergence of mean-field dynamics from any initial point. This additional complexity affected equilibrium but reflected a more realistic approach.

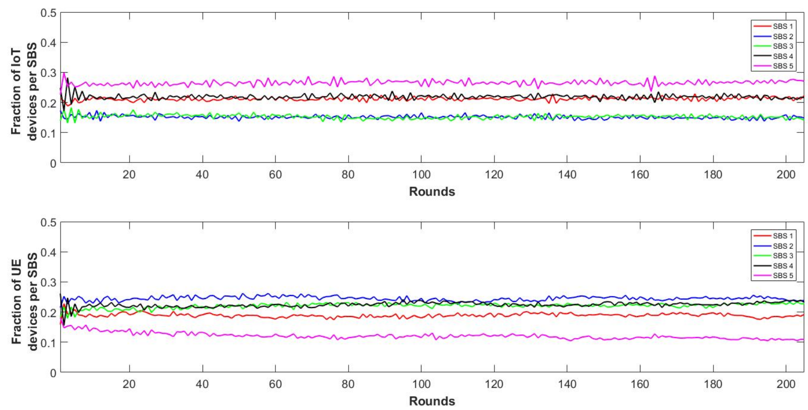
This work proposes to use the inverse of the power learned for the same amount of data rate as the reward for IoT devices. This had enabled IoT devices to build a higher confidence level for SBSs which require the lowest transmission power consumption for the same specified amount of data rate.

6.2 CA-MAB and Network Density

Convergence and equilibrium are the first performance indicators required to investigate in mean field MABs dynamics. Therefore, the simulation is performed for a different number of devices (players) who associate or select each SBS (arm). Figure 6.1a and 6.1b show the effect of the number of devices in SCN on the equilibrium performance. With increasing the number of devices in the system from $N_1 = 1000$ IoT device to $N_1 = 10^5$ and $N_2 = 200$ UE Mobile device to $N_2 = 1000$, the decrease in fluctuations reflect the effect of this change, specifically improving the performance of mean-field dynamics. Therefore, fluctuations decrease with the increase in the number of devices in mean-field dynamics due to its main property in which each device deal with the rest of the surrounding as stationary and ignoring individual's changes. This observation can lead to conclude that the performance can decrease in smaller systems with a low number of devices. In such low population systems, individual changes may cause a non-neglect-able impact. Despite the possible decrease in the performance following a decrease in the number of devices; but it is still acceptable and can be controlled through more strict policy. Regeneration and population change of similar and different devices between SBSs represent another fluctuations factors which effect IoT and UE Mobile devices. The difference between IoT devices performance fluctuations compared to UE devices performance fluctuations in both figures 6.1a and 6.1b is due to the effect of the energy harvesting uncertainty in IoT devices compared to the stable energy used in UE. In order to confirm that this algorithm converges better with the increase in the number of devices in each SBS, this work defines variable $V_m = \text{var}[f_{m,j}]$ which refers to the variance or fluctuation of the users' population in each SBS. The mean value of V_m describes the



(a) 1000 IoT and 200 UE device



(b) 10^5 IoT and 1000 UE device

Figure 6.1: The effect of the number of devices on the performance of mean-field dynamics

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

Table 6.1: Number of IoT and UE devices in different scenarios

fluctuation effect. This effect is tested over four different cases as described in Table 6.1. Thus, Figure 6.2 illustrates the fluctuation response to the increase in the number of devices of IoT and UE Mobile devices. The curves show how fluctuation of cell association change when increasing one type of devices while fixing the other. All cases in Figure 6.2 provide sufficient evidence which supports this work observation and ensures that convergence and equilibrium increase with the increase in the number of devices in the network.

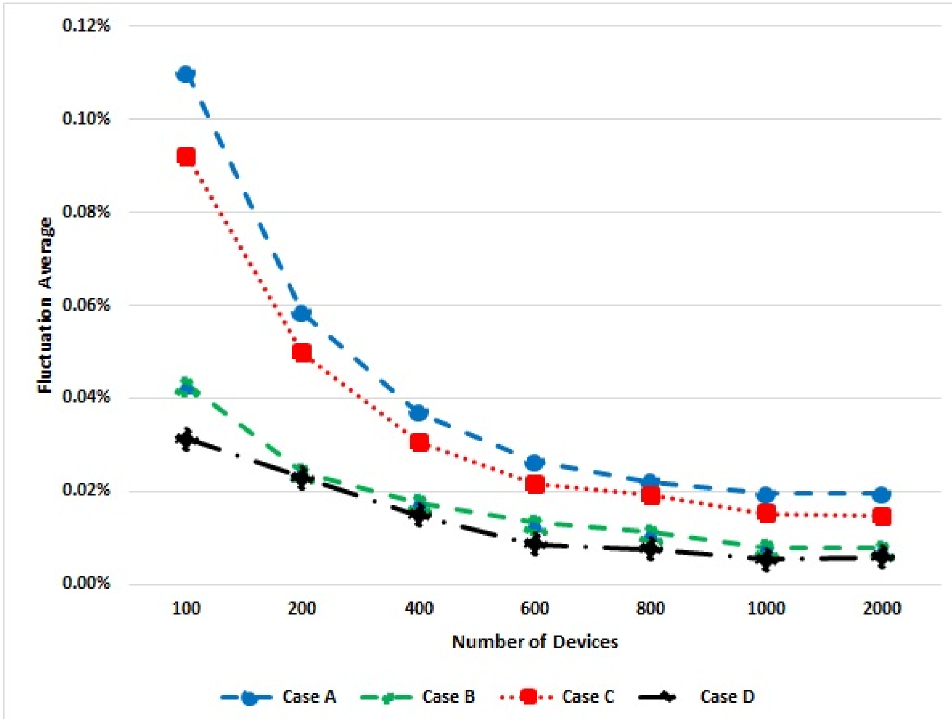


Figure 6.2: Cases A and C represent changing the number of IoT devices while fixing UE to 200 and 500 devices, respectively. Cases B and D represent changing the number UE of devices while fixing IoT to 200 and 500 devices, respectively.

6.3 CA-MAB and Number of SBSs

This section investigates the effect of changing the number of SBSs on the performance of the equilibrium while fixing the number of IoT devices $N_1 = 10^5$ and UE Mobile devices $N_2 = 1000$. This change is presented in Figure 6.4. No significant difference in the performance fluctuations can be detected following the change in the number of SBSs. Therefore, this change doesn't significantly effect on the mean field dynamics equilibrium when compared to 5 SBSs system presented in Figure 6.1b. In order to confirm the stability of convergence in this algorithm while changing the number of SBSs in the system, fluctuation of devices population comparison with a different number of SBSs is performed in the system in Figure 6.3. The decay of average fluctuation in Figure 6.3 is high when number of SBSs is low [5,6]. The average fluctuation can be ignored for large networks at which number of SBSs is high. Therefore, the change in the number of SBSs will not make a significant effect the mean field dynamics equilibrium compared to the change in the number of devices in the previous section.

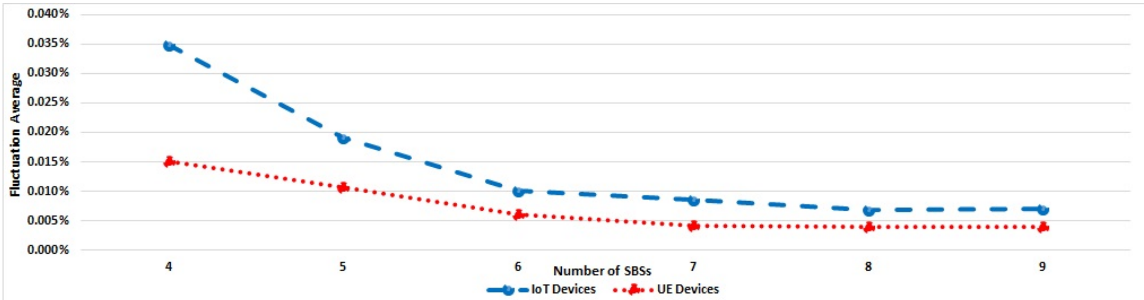


Figure 6.3: Convergence performance vs number of SBSs

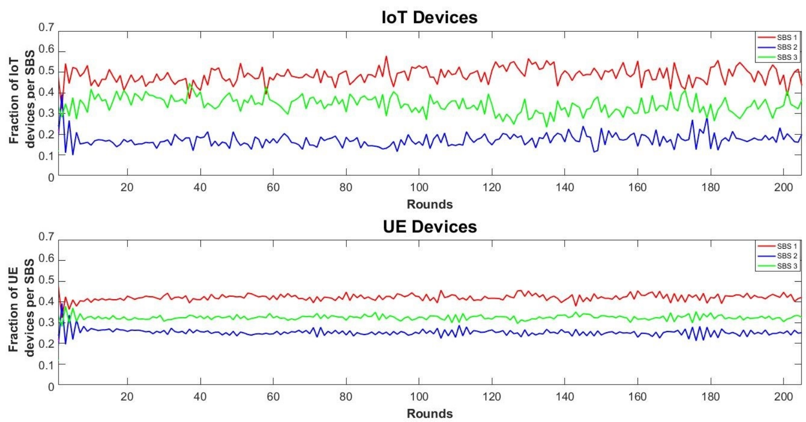
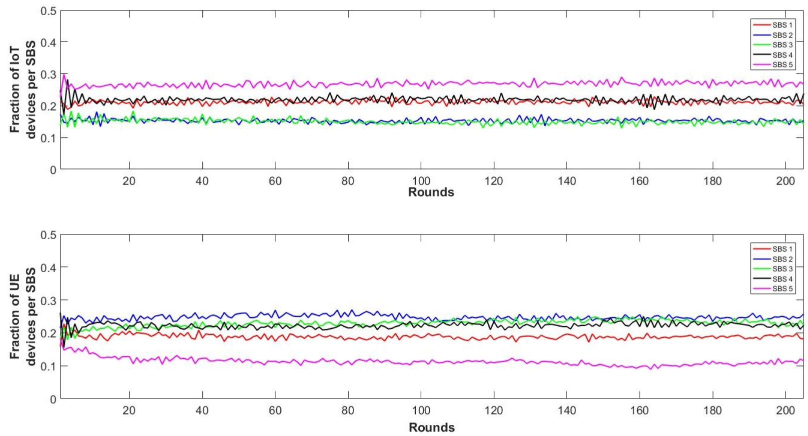


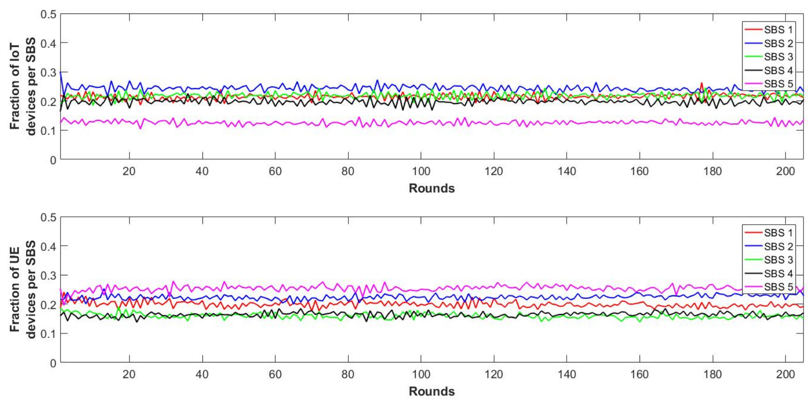
Figure 6.4: Equilibrium performance of mean-field dynamics in a 3 SBS system

6.4 CA-MAB Mobility Effect

This section investigates the mobility effect on the performance of the equilibrium while fixing the number of IoT devices $N_1 = 10^5$ and UE Mobile devices $N_2 = 1000$ in the system. Channel status between each device and SBS denoted by $\theta_{nm,j} = \frac{h'_{nm,j}}{I_{nm,j}+N_0}$ as described in Chapter 5 represents the factor that will change when devices move. To emulate the mobility of devices in the system, this model assumes that a proportion of the devices in the whole systems are mobile and thus the channel gain which includes the fading coefficient is randomly generated at each iteration for those devices. Therefore, mobility effect is reflected simply through switching channel status between moving devices and each SBSs every single round. This change is limited to wireless users/devices who are outdoors. This part of model simulation assumes that 20% of wireless users/devices are outdoor based on the studies which estimate that wireless users stay indoor for about 80% of the time, while stay outdoors about 20% of the time [14]. This reflection assumes that each moving device moves to the next device position in the next round. It can reflect mean-field dynamics convergence ability in the dynamic channel status. Specifying channel status change between each user/device on one side and each SBS on the other side require a mobility model in order to achieve a realistic mobility behavior and characteristics.



(a) 20% Mobility percentage



(b) 40% Mobility percentage

Figure 6.5: The effect of regenerating channel status for 20% and 40% of the devices on the performance of mean-field dynamics

Comparing to Figure 6.1b, fluctuations will increase slightly as long as the percentage of the devices' regenerating their channel statues increase each round as presented in Figure 6.5a and Figure 6.5b. In order to study devices association, handover and exploring different SBSs, six different scenarios are constructed as presented in Table 6.2. These scenarios differ from the perspective of including regeneration factor, mobility and being merged IoT and UE devices model or isolated model. Through the different scenarios, it is possible to obtain the mean and variance of the IoT devices and UE Mobile devices which selected the same SBS as in the previous round, devices which selected a different SBS than the previous round (Handover), and devices which are exploring different SBSs following to a regeneration round. For both IoT devices and UE Mobile devices, handover decreases in scenario 2 compared to scenario 1 as new devices enter the system after a recent exploring. While handover

	Senario 1	Senario 2	Senario 3	Senario 4	Senario 5	Senario 6
Mobility	No	No	No	No	Yes 20%	Yes 40%
Merged Model	No	No	Yes	Yes	Yes	Yes
Regeneration	No	Yes	No	Yes	Yes	Yes
Mean of IoT Same SBS Association	94.46%	86.91%	92.67%	84.99%	80.60%	80.49%
Var. of IoT Same SBS Association	0.02%	0.11%	0.02%	0.21%	0.24%	0.16%
Mean IoT Different SBS Association "Handover"	5.54%	5.24%	7.33%	6.94%	7.48%	7.59%
Var. of IoT Different SBS Association "Handover"	0.02%	0.02%	0.02%	0.02%	0.01%	0.01%
Mean of IoT Exploring SBSs	0.00%	7.85%	0.00%	8.06%	11.92%	11.92%
Var. of IoT Exploring SBSs	0.00%	0.14%	0.00%	0.27%	0.31%	0.21%
Mean of UE Same SBS Association	95.99%	93.63%	95.15%	93.43%	90.57%	87.70%
Var. of UE Same SBS Association	0.02%	0.06%	0.02%	0.07%	0.08%	0.12%
Mean UE Different SBS Association "Handover"	4.01%	2.34%	4.85%	2.56%	3.39%	4.35%
Var. of UE Different SBS Association "Handover"	0.02%	0.05%	0.02%	0.04%	0.03%	0.02%
Mean of UE Exploring SBSs	0.00%	4.03%	0.00%	4.01%	6.04%	7.95%
Var. of UE Exploring SBSs	0.00%	0.07%	0.00%	0.08%	0.10%	0.13%

Table 6.2: Stability, handover, and exploring of IoT and UE devices in different scenarios

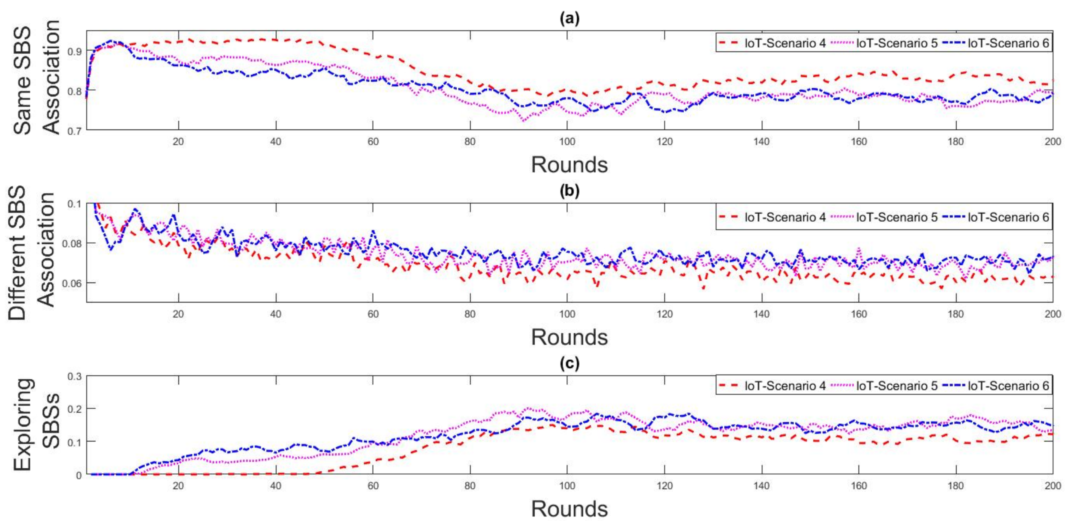


Figure 6.6: Scenarios 4, 5, and 6 for IoT devices representing **(a)** same SBS association **(b)** different SBS association **(c)** exploring SBSs.

increases in scenario 3 compared to scenario 1 due to the effect of population changes of the other devices type. Scenarios 4, 5, and 6 illustrate the effect of the contentious change of channel status on handover. For these last mentioned scenarios, Figure 6.6 for IoT devices and Figure 6.7 for UE devices describe the portion of devices which associated to the same SBS as in the previous round, devices which selected different SBS than the previous round, and devices which are exploring different SBSs following to a regeneration round. Certainly, handover mean will keep increasing as long as more devices channel statues keep changing following to a mobility effect. Therefore, the next two sections investigate more in order to figure out the effect of this change on the throughput and energy performance.

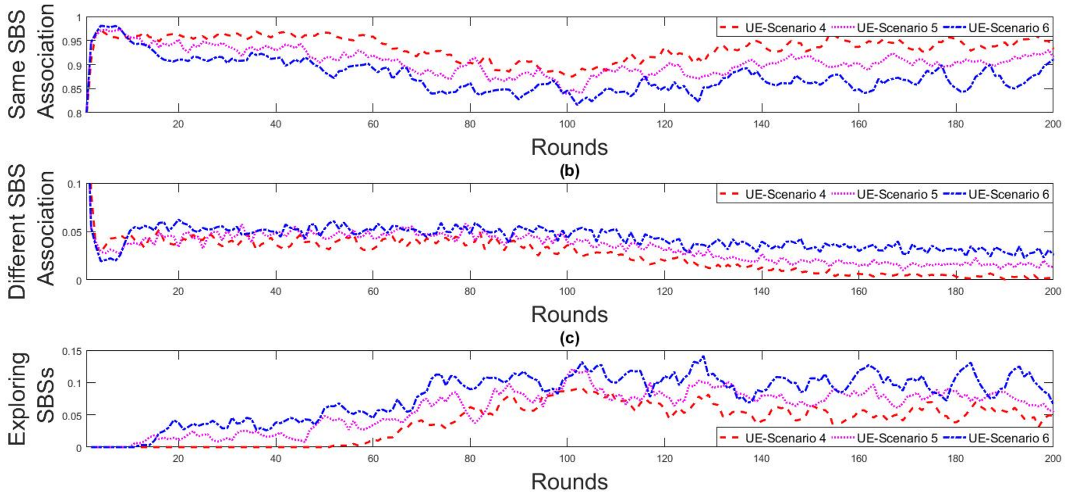


Figure 6.7: Scenarios 4, 5, and 6 for UE devices representing **(a)** same SBS association **(b)** different SBS association **(c)** exploring SBSs.

6.5 CA-MAB Throughput Performance

This section investigates the mean field MAB approach throughput performance through the average number of successful transmissions for a $N_1 = 1000$ IoT devices system and another separated $N_2 = 1000$ UE Mobile devices system over $M = 5$ SBSs. This mean field MAB performance for the IoT devices and the UE Mobile devices is compared against both centralized and random association. Centralized association scenario is assumed to offer the optimum performance despite the fact of its complexity and high required overhead. This scenario relies on a central unit that replies to each device exhaustive search in order to be assigned to the cell which has 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 randomly selects the required SBS to associate without any prior information about channel gain or SBS population. Mean field MAB approach doesn't have this prior information. However, using a simple selection policy and associating based on the comparison of the previous rewards; mean field MAB approach throughput performance can approach closer to centralized optimum performance after enough convergence time as can be observed in Figure 6.8 and Figure 6.9.

For IoT devices, in addition to centralized and random association scenarios, this section compares the mentioned mean field MAB throughput performance which uses UCB of IoT devices (data rate as the reward, referred to in the figure as MAB) against itself after using UCB differently (using the inverse of the minimum required power for minimum data rate, referred to in the figure as MAB2) based on equation 5.9 in the previous chapter. Equation 5.9 is used in order to estimate the minimum required power for minimum data rate due to

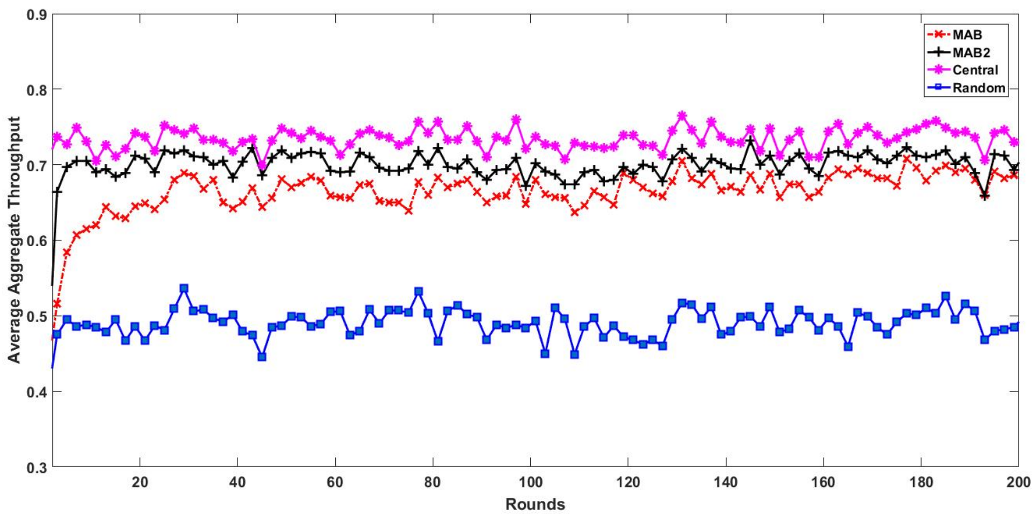


Figure 6.8: The throughput performance of the mean-field MABs approach for IoT devices compared with modified UCB, centralized, random association.

the absence of prior information about channel gain and each SBS population. Building a confidence level based on data rate transmission as a reward in UCB is practical. However, IoT devices in this model depend on a randomly harvested energy. This randomly harvested energy will impact the data rate and the confidence level. Therefore, using the inverse of the minimum required power for minimum data rate obtained from equation 5.9 in the UCB equation in Algorithm 1 ($\overline{x}_j + \sqrt{\frac{2 \ln n}{n_j}}$) provides more accurate confidence level. The 2nd part of the UCB equation reflects the degradation of confidence level for each time other arms or SBSs are selected. This part needed to be scaled in order to fit with the new reward concept. The old reward concept (data rate) was twice the amount of the new reward concept (the inverse of the minimum required power). Therefore, the scaling was done by multiplying the 2nd part of the UCB with a variable which reflects the ratio between the minimum required power and the data rate achieved in the last round.

In UE Mobile devices system, this work use data rate as a reward in UCB without using the minimum required power to represent the UCB reward as done for IoT devices above. The use of a fixed power source in the simulation of UE Mobile devices mean-field MAB approach was the reason for not replacing UE conventional UCB reward. Also, this section compares UE Mobile devices mean field MAB throughput performance approach after switching the channel status of part of the devices together trying to reflect mobility effects on the mean field MAB approach. This comparison is shown in Figure 6.9 as MAB2 added to the compassion against both centralized and random association.

In Figure 6.8 and Figure 6.9, it is clear that within enough convergence time the mean field MAB performance for IoT devices and UE Mobile devices denoted in the figures as

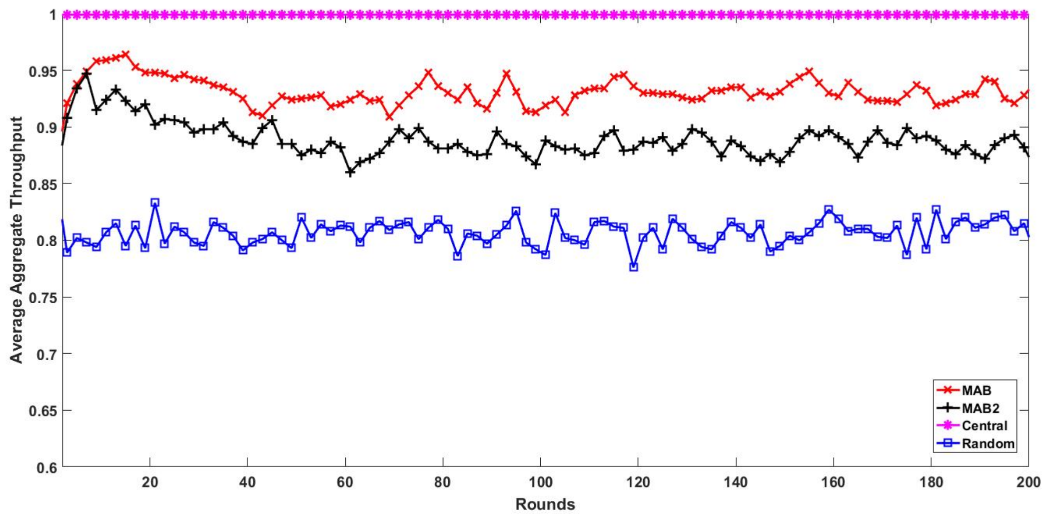


Figure 6.9: The throughput performance of mean-field MABs approach for UE devices compared centralized, random association, and channel status switching approach.

"MAB " enhance compared to random association approach over time and offer a performance close to centralized association approach. However, it is important to ensure that despite the better performance of the centralized solution, it requires excessive overhead in order to gain the required information and with a significant increase in complexity. Centralized solution throughput performance in the UE devices system is much better than the IoT devices system due to the stability of the power source and not relying on harvested energy. "MAB 2" in the IoT devices system, presented in Figure 6.8, represents enhancements on the traditional UCB use "MAB" (based on data rate as a reward). This simple change in UCB described above, drive throughput performance to enhance faster toward the performance of the centralized solution. On the other hand, "MAB 2" in UE Mobile devices system, presented in Figure 6.9 reflect a degradation in the throughput performance due to the switching of the channel status of 20% of the devices (trying to reflect mobility effect).

6.6 CA-MAB Energy Saving

This section investigates the mean field MAB games energy performance over successful transmission for $N_1 = 1000$ and $N_2 = 1000$ over $M = 5$ SBSs. As in the previous section, mean-field MAB energy performance for the IoT devices and the UE Mobile devices is compared against both centralized and random association. And again, centralized association scenario offers the optimum energy performance despite its complexity while random association offers the least performance despite its simplicity. In addition to centralized and random association scenarios, this section compares the mean field MAB energy performance of IoT devices against itself after using UCB differently (inverse of the minimum required power as the reward); and it compares the mean field MAB energy performance of UE devices against what is referred to in section 6.4 as mobility effect (through switching the channel status of part of the devices together) starting from round 10 as described in the previous section.

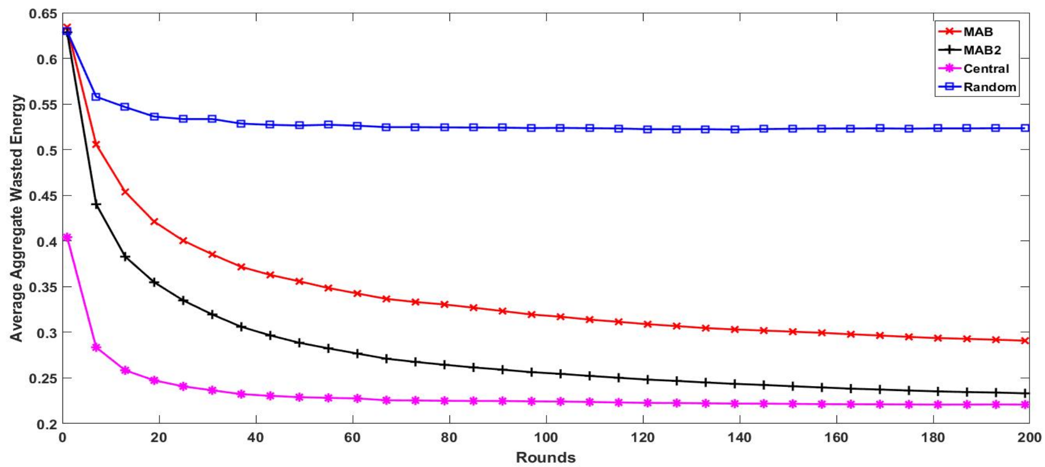


Figure 6.10: The average aggregated wasted energy in IoT mean-field multi-armed bandits model compared with modified UCB, centralized, random association

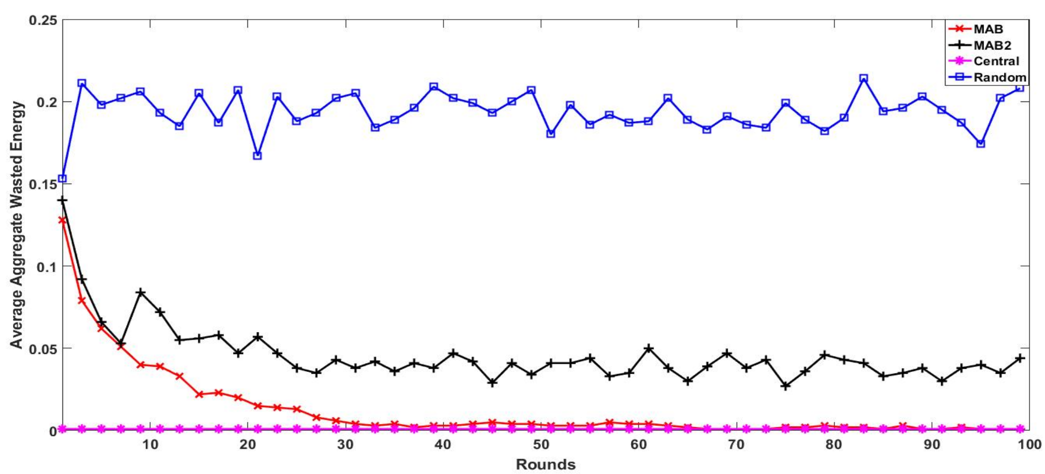


Figure 6.11: The average aggregated wasted energy in UE mean-field multi-armed bandits model compared centralized, random association, and channel status switching approach.

Within enough convergence time, the mean field MAB energy performance for IoT devices and UE Mobile devices denoted in both figures as "MAB " enhance compared to random association approach over time and offer performance close to centralized association approach. This can be noticed in both Figures 6.10 and 6.11. Also, centralized solution energy performance in the UE devices system is much better than the IoT devices system due to the stability of the power source and not relying on harvested energy. "MAB 2" in the IoT devices system energy performance in Figure 6.10 prove that the mentioned modification in UCB reward enhanced the energy efficiency and drive devices to achieve semi-optimal efficiency faster. On the other hand in Figure 6.11, "MAB 2" in the UE devices system; which reflects the energy performance under the change of 20% of devices' channel status starting from round 10 reflects; present the degradation of energy performance compared to the stationary UCB devices. The enhancement in throughput and energy performance over time using this mean-field MAB in the previous and this section reflect the expected QoS indicators testing to this model.

6.7 Summary and Discussion

This work investigated the convergence and equilibrium of IoT devices and UE Mobile devices together in the same system using mean-field MABs dynamics and UCB for selection and presented the effects of changing the number of devices and changing the number of SBSs on convergence and equilibrium. It compared the mean field MAB games throughput performance for UE Mobile devices and the mean field MAB games energy saving for IoT devices. In addition, this work modified the UCB selection policy by using the inverse of the minimum required power as the reward instead of the data rate. Moreover, this work reviewed others work mobility effect and simulated similar effects.

Mean Field MAB approach convergence allow users to switch between SBSs based on their confidence level by applying the UCB. Actually, this switching represents handover from an SBS to the another within one macrocell area. Handover using UCB is smooth, simple and fast and doesn't require a previous inquiry about channel gain and SBS population. This is possible through the initial confidence level built about each SBS after a regeneration trial. Those mentioned features will increase properly with the increase in the number of the devices in the system compared to the centralized solution. It is important to mention that applying UCB to a moving device between macrocells will require trying each of the new SBSs at least once as a mandatory initial step in UCB. This doesn't violate Mean Field MAB approach but can require using other selection methods else UCB in high mobility or between macrocells. Or, one of the MIMO antennas can be assigned for exploring every new SBSs and updating UCB. Through MIMO, UCB can support and get use of CoMP and can update confidence level continuously and facilitate handover or switching to a primary SBS. CoMP and MIMO were not applied in any of this work experiments and the study of their effect is out of the scope of this work. However, UCB can use those technologies and may not be a barrier in front of using them.

Chapter 7

Conclusion and Perspective

The main part of this thesis demonstrated the foreseen 5G cellular networks design, emerging technologies, different cell association approaches and summarized some of the non-conventional game theoretic models. This thesis proposed a cell association algorithm for IoT and UE devices based on Mean Field MAB game theory approach independent of channel gain or SBS population information inquiry. CA-MAB algorithm facilitates the handling of the massive deployed IoT devices and enables IoT devices to select SBS which offer minimum required data rate for lower power consumption without prior information about channel gain and SBS population inquiry. Moreover, this algorithm enables UE mobile devices to select SBS which offer higher data rate without prior information about channel gain and SBS population.

In the coming few years, the exponential increase in the capacities and number of devices associating to mobile networks and requesting more and more information will exceed the capabilities of mobile networks and need to be addressed. The massive deployment of devices, especially the IoT devices and the increasing demands on capacity on one side is a huge concern from the perspective of control and signaling. The decrease in BSs sizes is another issue that makes this concern even more serious. This issue requires a creative solution. Letting devices select their preferred SBS through performing distributed association using Mean Field MAB approach and mathematical selection model is one of the trending solutions for those matters. The 5G foreseen multi-access technique "NOMA" described in section 2.2.2 promote this trending solution by adding another additional abilities and authorities to devices. NOMA eliminates the need for devices to send a scheduling request enabling free uplink transmission that reduce transmission latency and signaling overhead. User-driven distributed association and NOMA new devices abilities and authorities do not neglect or bypass network boundaries or limits. Networks can set different limits through different access mode types as presented in section 4.3. Such model can be applied in addition to other selection models for some subscribers depending on the access mode used. This model fits most for non-subscribers in Hybrid access modes.

This work ensures again the ability to achieve convergence and equilibrium through distributed association built on the proposed approach for IoT and UE mobile devices. This work had successfully used the UCB for two different types of devices with different targets, better energy efficiency for IoT devices and better data rate efficiency UE Mobile device. Compared to others works, this work enhanced throughput efficiency almost by 3% and energy efficiency by 5% for IoT devices using harvested energy through a simple change in reward concept used in conventional UCB selection policy. This thesis offers enough evidence that distributed user-driven cell association in the 5G cellular networks is suitable through Mean Field MAB approach to achieve good energy and throughput efficiency results despite its simplicity and independence from massive information exchange. It is also, capable of dealing with uncertainty power sources scenarios, regeneration, mobility and fast handover. In addition, this model proved its ability to work under congestion and improve equilibrium as long as the number of users increases. It is important to mention that despite the results do not show any significant effect on the equilibrium while changing the number of SBSs, but the increase in the number of SBS explored through UCB will simplify handover in one hand but will require longer exploring time on the other hand. Finally, this trade-off balance study is out of the scope of this thesis and can be investigated in future work.

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