

A DENSITY-AWARE, ENERGY- AND SPECTRUM-EFFICIENT SCHEDULING
MODEL FOR DYNAMIC NETWORKS

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SCHEDULING MODEL FOR DYNAMIC NETWORKS**

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ABSTRACT

A DENSITY-AWARE, ENERGY- AND SPECTRUM-EFFICIENT SCHEDULING MODEL FOR DYNAMIC NETWORKS

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Future mobile networks have to be densified by employing small cells to handle the upsurge in traffic load. Although the amount of energy each small cell consumes is low, the total energy consumption of a large-scale network may be enormous. To enhance the energy efficiency, we have to adapt the number of active base stations to the offered traffic load. Deactivating base stations may cause coverage holes, degrade the quality of service and throughput while redundant base stations waste energy. That is why we have to adapt the network to the effective density. In this thesis, we show that achieving an optimal solution for adapting density of base stations to the demand is NP-hard. We propose a solution that consists of two heuristic algorithms: a base station density adaptation algorithm and a cell-zooming algorithm that determines which base stations must be kept active and adapts transmit power of base stations to enhance throughput, energy and spectral efficiency. We employ multi-access edge clouds for taking a snapshot of the network state in nearly real-time and for collecting network telemetry over a large area. We show that the proposed algorithm conserves energy up to 12% while the spectral efficiency and network throughput can be en-

hanced up to 30% and 26% in comparison with recent works, respectively.

Keywords: 5G mobile networks, densification, density-aware networking, energy-efficiency, green networks, multi-access edge cloud (MEC), self-organizing network-sal

ÖZ

DİNAMİK GEZGİN AĞLARDA YOĞUNLUK-UYARLI, ENERJİ- VE SPEKTRUM-VERİMLİ ÇİZELGELEME MODELİ

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Gelecekteki mobil ağların, trafik yükündeki artışlarla başa çıkmak için küçük hücreler kullanılarak yoğunlaştırılması gerekmektedir. Her küçük hücrede tüketilen enerji miktarı düşük olmasına rağmen, büyük ölçekli bir şebekenin toplam enerji tüketimi muazzam derecede fazla olacaktır. Enerji verimliliğini arttırmak için aktif baz istasyonu sayısını, trafik yüküne uyarlamak zorundayız . Baz istasyonlarını devre dışı bırakmak kapsama boşluklarına neden olurken, servis ve verim kalitesini düşürecek ancak gereğinden fazla sayıda çalıştırılan baz istasyonları ise enerji israfına yol açacaklardır. Bu tezde, baz istasyonlarının yoğunluğunun talebe uyarlanması konusunda optimum bir başarı elde etmenin NP-zor bir problem olduğunu göstermekteyiz. İki tür sezgisel algoritmadan oluşan bir çözüm önermekteyiz: birincisi baz istasyonu yoğunluğu adaptasyon algoritması ve ikincisi ise ağdaki veri iletim hacmini, enerji ve spektral verimliliği arttırmak için hangi baz istasyonlarının aktif olarak kullanılması gerektiğini belirleyen ve baz istasyonlarının iletim gücünü uyarlayan hücre yakınlştırma algoritmasıdır. Daha geniş bir perspektifle neredeyse gerçek zamanlı olarak belirtilen ağın anlık görüntüsünü almak için çoklu erişim kenar bulutu kullanıyoruz.

Önerilen algoritma ile %12'ye kadar enerji tasarrufu sağlandığı, aynı zamanda spektral verim ve ağ verimliliğinde de yakın zamanlı iki çalışmaya göre %30 ve %26'lık artış sağlandığı gösterilmektedir.

Anahtar Kelimeler: 5G gezgin ağlar, yoğunlaştırma, yoğunluğa-uyarlı ağ iletişimi, enerji verimliliği, yeşil ağlar, çoklu erişim kenar bulutu (MEC), kendi kendini düzenleyen ağ iletişimi

To my family

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TABLE OF CONTENTS

ABSTRACT	v
ÖZ	vii
ACKNOWLEDGMENTS	x
TABLE OF CONTENTS	xii
LIST OF TABLES	xv
LIST OF FIGURES	xvi
LIST OF ALGORITHMS	xix
LIST OF ABBREVIATIONS	xx
LIST OF SYMBOLS	xxii
CHAPTERS	
1 INTRODUCTION	1
1.1 Paradigm Changes in Mobile Communications	1
1.2 Why Does Infrastructure Become Dynamic?	3
1.3 Why Present Architectures Will Fail?	5
1.4 Problem Definition	5
1.5 Contributions	7
1.6 Outline	8

2	BACKGROUND AND RELATED WORK	11
2.1	The Overall View of Mobile Networks	11
2.2	2nd Generation and 3rd Generation of Wireless Networks	12
2.3	4G (LTE) Wireless Networks	12
2.4	Orthogonal Frequency Division Multiple Access	14
2.5	5G Wireless Networks	16
2.6	Multi-Access Edge Cloud (MEC)	16
2.7	Related Work	17
3	DENSITY-, ENERGY- AND SPECTRUM-AWARE RESOURCE SCHEDULING	21
3.1	Density-, energy- and spectrum-aware resource scheduling problem (DESAS)	21
3.2	Base Station Density Adaptation (BDA) Problem	25
3.3	Power Adaptation (PA) Problem	27
4	BASE STATION DENSITY AND POWER ADAPTATION (BDPA) ALGORITHM	31
4.1	Scenarios	31
4.2	Comparison of Distributed, Centralized or Decentralized Solutions	32
4.3	Base Station Density Adaptation (BDA) Algorithm	34
4.4	The Power Adaptation (PA) Algorithm	39
5	RESULTS AND DISCUSSION	45
5.1	Simulation Models and Parameters	45
5.2	Vienna Simulator, Implementation Details	47
5.3	What's happening at MEC?	47

5.4	Validation of the BDPA Algorithm	49
5.5	LP-WUR Sleep Scheduling Technique	49
5.6	Cooperative ICIC (C-ICIC) Technique	50
5.7	Monte-Carlo Simulation Results	50
5.8	Quality of Service (QoS)	50
5.9	Spectral Efficiency	52
5.10	Energy Consumption	54
5.11	User Density	56
5.12	Mobility	57
6	CONCLUSION AND FUTURE WORK	63
6.1	Conclusion	63
6.2	Future Work	64
	REFERENCES	65
	CURRICULUM VITAE	77

LIST OF TABLES

TABLES

Table 4.1	The comparison of implementing a fully distributed, a decentralized or a centralized solution to the DESAS problem.	35
Table 4.2	The SNR-CQI map table.	41
Table 5.1	Simulation parameters and their values.	46
Table 5.2	Traffic types in OFDMA-based networks [1].	47

LIST OF FIGURES

FIGURES

Figure 1.1	Two application scenarios of mobile BSs in future networks are presented. We illustrate how cells on wings or wheels may change the infrastructure of mobile networks. Because of mobility and many other factors we present in this thesis, the infrastructure of mobile networks start resembling ad hoc networks in terms of dynamics. As a consequence, the density of BSs unpredictably change.	2
Figure 1.2	Categorization of power consumption in mobile networks.	6
Figure 2.1	The overview of the LTE network architecture which consist of three main components: The User Equipment (UE), The Evolved UMTS Terrestrial Radio Access Network (E-UTRAN) and the Evolved Packet Core (EPC) [2].	13
Figure 2.2	The OFDMA-based systems downlink frame structure [3].	15
Figure 3.1	The illustration of a network architecture where multi-access edge clouds are employed for self organization.	22
Figure 3.2	The overall methodology.	26
Figure 4.1	Four different scenarios (S1, S2, S3, S4) including: a) reducing energy consumption through macro cell, b) reducing interference, c) enhancing energy conservation through small cells, d) maintaining QoS, that we may face in a HetNet and the effect of applying the BDPA algorithm over these scenarios.	33

Figure 4.2	The mobile edge tasks flow chart.	39
Figure 4.3	The BLER-SINR map for various CQI values.	40
Figure 4.4	The effect of applying fluctuation reduction over the PA algorithm.	42
Figure 5.1	The probability of coverage for different SINR thresholds.	48
Figure 5.2	The effect of applying the BDPA algorithm on network throughput in a sparse network with 100 UEs for different BS densities.	51
Figure 5.3	The effect of applying the BDPA algorithm on network throughput in a dense network with 1000 UEs for different BS densities.	52
Figure 5.4	The effect of applying the BDPA algorithm in a sparse network with 100 UEs on spectral efficiency for different BSs' densities.	53
Figure 5.5	The effect of applying the BDPA algorithm in a dense network with 1000 UEs on spectral efficiency for for different BSs' densities.	54
Figure 5.6	The effect of applying the BDPA algorithm on energy consumption in a sparse network with 100 UEs and bursty traffic for different BSs' densities.	55
Figure 5.7	The effect of applying the BDPA algorithm on energy consumption in a dense network with 1000 UEs and bursty traffic for different BSs' densities.	56
Figure 5.8	The effect of applying the BDPA algorithm on energy consumption in a dense network when traffic load is high for different BS density.	57
Figure 5.9	The effect of applying the BDPA algorithm on network throughput when density of BSs is fixed at $50 BS/km^2$ and UEs' density is varied between 100 to 500.	58
Figure 5.10	The effect of applying the BDPA algorithm on spectral efficiency when density of BSs is fixed at $50 BS/km^2$ and UEs' density is varied between 100 to 500.	59

Figure 5.11	The effect of applying the BDPA algorithm on power consumption when density of BSs is fixed at $50 \text{ BS}/\text{km}^2$ and UEs' density is varied between 100 to 500.	60
Figure 5.12	The effect of applying proposed algorithm on network throughput in a sparse network with 100 UEs for varied velocities.	61

LIST OF ALGORITHMS

ALGORITHMS

Algorithm 1	The base station density and power adaptation algorithm. . . .	38
Algorithm 2	The power adaptation algorithm.	43

LIST OF ABBREVIATIONS

ADSL	Asymmetric Digital Subscriber Line
AMPS	American Advanced Mobile Phone Systems
BDA	Base station Density Adaptation
BDPA	Base station Density and Power Adaptation
BILP	Binary Integer Linear Program
BLER	Block Error Rate
BS	Base Station
C-ICIC	Cooperative Inter-Cell Interference Control
C-RAN	Cloud Radio Access Network
CDMA	Code Division Multiplexing Access
CQI	Channel Quality Indicator
DTX	Discontinuous Transmission
EE	Energy Efficiency
eMBB	enhanced Mobile BroadBand
EPC	Evolved Packet Core
E-UTRAN	Evolved UMTS Terrestrial Radio Access Network
GSM	Global System for Mobile Communication
HetNet	Heterogeneous Networks
ICI	Inter Cell Interference
ICIC	Inter Cell Interference Coordination
IoT	Internet of Things
IP	Internet Protocol
ISI	Inter-Symbol Interference
LP-WUR	Low-Power Wake-up Radio

LTE	Long Term Evolution
MBSFN	Multicast Broadcasting Single Frequency Network
M2M	Machine to Machine
MIMo	Multiple-Input Multiple-Output
MEC	Multiple-access Edge Cloud
MME	Mobility Management Entity
mMTC	massive Machine Type Communications
OFDMA	Orthogonal Frequency Division Multiple Access
PA	Power Adaptation
PDA	Packet Data Network
PCRF	Policy Control and Charging Rules Function
QoS	Quality of Service
RAN	Radio Access Network
RB	Resource Block
RE	Resource Element
SE	Spectral Efficiency
S-GW	Serving Gateway]
T	Time interval
TACS	Total Access Communication Systems
TPA	Transmit Power Adaptation
URLLC	Ultra Reliability and Low latency Communications
UE	User Equipment
WiMAX	Worldwide interoperability for Microwave Access

LIST OF SYMBOLS

α	A fit adjustment on a curve
α_P	A normalized coefficient for power allocation
α_S	A normalized coefficient for spectral efficiency
A_j	Cell's activity factor
A_{mj}	Activity ratio of the macro cell responsible for BS j
β	A shift to adjust peak time
b_τ	Bandwidth of a RB
B_j	Bandwidth of BS j
B_{ij}^*	Min required BW by UE i from BS j
B_j^*	Min required BW of BS j
Δ	The power for adjusting transmission power
δ_j	Load factor of BS j
D	UEs' demand
D_{avg}	Average bitrate in the predefined time interval
g_{ij}	Channel gain between UE i and its associated BS j
i	Index of UE
I_{ik}	Interference received by UE i from BS k
j	Index of BS
λ_b	Density of small BSs
λ_u	Density of UEs
N_{macro}	The number of macro cells
N_{small}	The number of small cells
P	Current allocated power by a BS

P_{avg}	Average of allocated power to a BS
P_{macro}	Power consumed by a macro BS
P_{min}	Minimum required transmission power by a BS
P_{max}	Maximum transmission power of a BS
P_{small}	Power consumed by a small BS
P_{ij}	Downlink transmit power assigned by BS j to UE i
P_{ij}^*	Minimum required power by UE i from BS j
P_{τ_j}	The power allocated by BS j to a resource block
P_j	Maximum transmit power of BS j
P_0	Fixed operational power
$P_C(T)$	Coverage probability when received SINR is T
ϕ	Spectrum efficiency
R	Average rate per UE
R_{ij}^*	The required throughput by UE i from BS j
R_j	Total transmission rate in BS j
σ^2	Noise power
SINR	Signal-to-Interference-Noise-Ratio
$SINR_{ij}$	SINR received by UE i from BS j
τ_j	Total number of available RBs in BS j
τ_{ij}^*	The required number of RBs by UE i from BS j
T_{CQI}	Threshold value for minimum required CQI level
T_{SINR}	Threshold value for minimum received SINR
T_{cov}	Threshold value for minimum coverage probability
U_j	Utility function

CHAPTER 1

INTRODUCTION

The state of the art in a mobile cellular network is the centrally-managed and relatively inflexible architecture that was prosperous albeit not scalable anymore. The present-day networks have already reached the spectrum limitations [4]. We have to densify cellular networks by spatial multiplexing to overcome capacity limitations. Increasing the number of base stations (BS) may cause severe interference and redundant coverage resulting in energy wastage [5]. Centralized configuration or real-time centralized monitoring is not applicable due to the difficulties in acquiring global information about the network and computational complexity of the tasks [6]. Management, coordination and optimization tasks usually require solving NP-hard problems.

As the network enlarges, its management and control become a symptomatic issue [7]. Operator intervention requirements have to be drastically reduced by employing self-organization. There is a research gap between the state of the art and the ambition of achieving a self-organized, adaptive and flexible networking architecture. Moreover, we are on the verge of several key paradigm changes in mobile communications.

1.1 Paradigm Changes in Mobile Communications

One of the significant paradigm shifts happens in the control domain of operators. In the past, network operators used to plan, dimension and install BSs. Before and after the launch of the BSs, optimization was plausible. Performance monitoring, failure mitigation, and correction were carried out by the network operator within the lifetime of a BS. However, this scheme will change substantially in future mobile

networks and operators will partially lose their control on cell deployment as we will explain in this thesis [8].

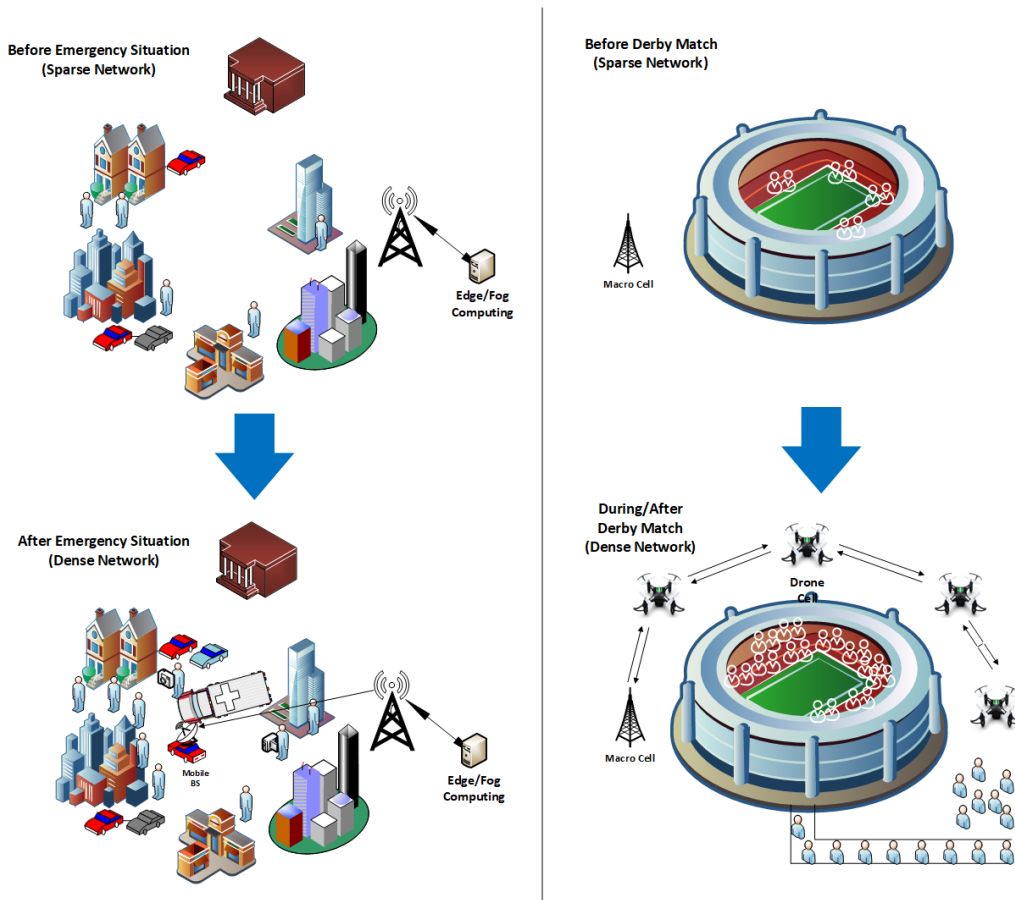


Figure 1.1: Two application scenarios of mobile BSs in future networks are presented. We illustrate how cells on wings or wheels may change the infrastructure of mobile networks. Because of mobility and many other factors we present in this thesis, the infrastructure of mobile networks start resembling ad hoc networks in terms of dynamics. As a consequence, the density of BSs unpredictably change.

Another paradigm change is in the infrastructure of mobile networks [9]. In the past, we used to assume that locations of user equipment (UE) were stochastic, and the network infrastructure was stationary. In the future, BSs may also be mobile yielding a random infrastructure; e.g., drones may provide service to blind spots [10, 11]. We present some example scenarios where the density of UEs and also BSs may change in a dynamic fashion in Figure. 1.1. As can be seen in these scenarios, the density of users may increase suddenly because of some emergency situation such as a car

accident or a sports event. As we can see on the left-hand side of Figure. 1.1, the area seems sparse initially. However, after the car accident, the density of users increases dramatically. Therefore, mobile or nomadic BSs are deployed in the area to maintain the quality of service (QoS) in terms of coverage or capacity. In emergency cases, pre-deployment planning may not be possible. Communication services are of critical importance for public protection and disaster recovery. Man-made or natural disasters such as earthquakes may disrupt communication services that are currently provided by stationary infrastructures. Employing drone BSs can be a viable approach for establishing a communication infrastructure in affected areas and for providing wireless coverage in blind spots. Drone BSs can also be used for gathering data from rural fields where no communication infrastructure exists. For instance, drone cells may act as mobile sinks in applications of the Internet of Things and in massive machine type communication scenarios.

As another scenario, a derby football match can be given. Some flying BSs such as drones may provide coverage and enhance QoS during the event as presented on the right-hand side of Figure. 1.1. Before the event and after the event, the user density in the stadium will be low. However, it will be substantially larger during the match. Instead of incurring the cost of deploying stationary cells inside or nomadic cells around the stadium, cells on wings may be employed on the stadium to satisfy the QoS requirements of users by getting closer to UEs. Depending on the user density, additional BSs can be dynamically deployed that in turn changes the network density.

1.2 Why Does Infrastructure Become Dynamic?

Mobile cells have a huge potential to be employed in future networks. In addition to cells' mobility [12] [11], factors which make a network dynamic are as follows:

- User-controlled BSs (e.g., femtocells bought and controlled by end users): When BSs are deployed in customer premises (such as homes), users may turn them on or off depending on consumption requirements [13].
- Green operation (e.g., sleep scheduling of BSs): BSs may employ duty-cycling for energy conservation. Depending on the employed duty-cycling scheme, the

effective density of BSs will be different over periods of time.

- Incremental deployment: Gradual deployment of BSs will change the network density throughout the deployment time.
- Loss of control and failures in the topology: Deterministic and pre-planning deployment are not probable anymore. The operator may have to strictly comply with the constraints imposed by the urban structure period. Consequently, the deployment can be considered to be stochastic [14].
- Support for various verticals (e.g., automotive, health), multi-tenancy and various scenarios (e.g., megacities versus low average revenue per user (low-ARPU) regions or sporadic events such as Olympics) by network slicing.

The mobile network infrastructure will become stochastic and the location of small cells cannot be pre-planned with the introduction of mobile cells. Considering the scenarios described above and shown in Figure 1.1, we can list the major advantages of employing mobile or nomadic cells as follows.

- Mobile cells may be rapidly deployed to mitigate coverage holes without introducing site-acquisition costs [15].
- Drone cells may facilitate ubiquitous coverage in rural areas [16].
- Mobility of drones cells can be inline with the mobility of the end users providing a better approach for group mobility lowering the mobility management costs.
- Mobile cells together with edge/fog computing may bring processing power closer to end users which can decrease power consumption and provide a higher data rate by obtaining high SINR [17].
- Broadcast data rates can be improved especially for the UEs located at cell edges.

1.3 Why Present Architectures Will Fail?

It is not possible today for present mobile communication networks to address these paradigm changes because of their shortages and limitations [18]:

- Lack of functions for mobile BSs: mobility management of BSs has not been foreseen in standardization yet.
- Inflexible architecture, static and manual configurations: when the infrastructure is dynamic, it is clear static configurations will waste resources. Manual configurations make the network inflexible to dynamics in the topology and are subject to severe human errors. Software networks cast light onto this problems.
- Lack of common control functions and interfaces: real-time and holistic management is almost impossible because of vendor lock-in and vendor-dedicated hardware and software components requiring trained administrators. Network virtualization may help solve this problem.
- Limited backhauling capacity and a shortage of fiber infrastructure in developing countries.

1.4 Problem Definition

Until 2016, over 14 million small cells are deployed in Long Term Evolution (LTE) networks and this number has increased for about 270 percent in 2017 [19]. In heterogeneous networks (HetNets), by employing small cells in addition to macro cells, spectral and energy efficiency (EE) can be enhanced simultaneously [20]. By increasing density of small cells, the distance between base stations and user equipment (UE) can be reduced, which can enhance network area throughput and reduce power consumption. However, increasing density of small cells implies more infrastructure and hardware deployment, which increases the overall circuit energy consumption in the network [21]. During the last decades, mobile networks have grown tremendously and mobile communications have become inseparable technology from our lives. As

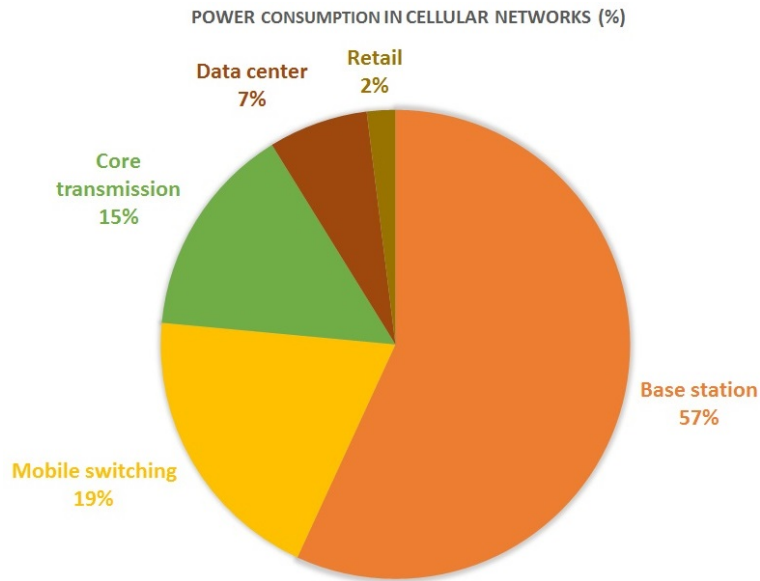


Figure 1.2: Categorization of power consumption in mobile networks.

the number of subscribers increases and the networks grow in size, the amount of energy consumption increases astronomically in mobile networks. Reducing the amount of energy wastage in information and communication technologies (ICT) is important since 2% of the total carbon dioxide-equivalent gas emissions is produced by ICT, and there is an upward trend. The cost of connecting base stations (BSs) that have access to the electrical grid is approximately 3000\$ per year and this may increase up to ten times when BSs are located in rural areas where energy is provided by fuel power generators [22]. As it is shown in Figure. 1.2 the largest portion of energy which is about 57%, is consumed by BSs in mobile networks; while, the amount of energy is consumed by mobile switching, core transmission, and data centers are 19%, 15% and 7%, respectively [23].

Because of mobile/nomadic BSs such as drone cells, user-controlled based BSs (indoor small cells) and sleep scheduling of BSs, the network density may dynamically change in time and space. On the one hand, by increasing the density of small cells, we need to adapt BS density to the network condition for maximizing energy efficiency in the network. On the other hand, future networks need to be smart to adapt themselves to BS density for maintaining the quality of service (QoS) under various conditions when the density of BSs dynamically changes [24]. For instance, when a BS is turned off in a HetNet, the associated traffic load of the deactivated BS needs to

be transferred over to other cells. The demand can be different at each cell because of heterogeneity [25]. Therefore, the impact of turning off a BS on the neighboring cells have to be considered in an adaptive fashion. Turning off a BS may also cause coverage holes that requires the assistance of neighboring cells for providing service to blind spots. In case of network expansion or occasional events (such as a football match), the number (density) of BSs may need to be increased permanently or temporarily. Human intervention may not be possible in a large-scale HetNet. Therefore, future networks need to be equipped with flexible algorithms that can adapt network parameters such as coverage or transmit power to the density of BSs to dynamically react over any changes in the network state [26].

The main idea behind our approach is adapting density of BSs to the network parameters such as coverage and transmit power to provide a highly flexible scheduling model which can enhance energy and spectral efficiency and maintain QoS continuously in the whole network for different conditions. We assume the QoS can be maintained when the minimum throughput by each UE can be satisfied by the network. In this thesis, we define a joint heuristic sleep scheduling and power allocation algorithm for saving energy while satisfying the throughput requirement of users and maintaining the coverage in dynamic heterogeneous networks by considering the density of BSs and employing MEC in the network architecture. The main advantages of this work with respect to old energy efficient techniques are employing MECs in the network architecture and providing a self-organized network which can adapt network parameters including BS transmit power and density of BSs to the network state, that can be categorized as one of the basic requirements of 5G networks. Employing MEC platforms provide higher flexibility, processing power and support multi-tenancy in cellular networks, and can provide self-adaptability in dynamic networks where in addition of density of UEs, density of BSs can be also changed.

1.5 Contributions

The overall contributions of this thesis are as follows.

- We formulate density-, energy- and spectrum-aware base station scheduling

problem (DESAS) in Chapter 3 and we show that providing an optimal solution to this problem for adapting density of BSs to network parameters such as coverage and transmit power to reduce energy consumption and enhance spectral efficiency in the network is NP-hard.

- We propose a heuristic solution named as BS density and power adaptation algorithm (BDPA) that consists of two sub-algorithms named by BS density adaptation (BDA) and power adaptation (PA) in Chapter 4. These algorithms can jointly reduce the amount of power consumption in the network through minimizing the number of active BSs with respect to the cells' load and can enhance the throughput and the coverage in the network by applying a cell-zooming technique in each cell in a distributed manner by adapting transmit power of BSs based on channel conditions and effective density.
- We define a framework for future network infrastructures that employs MECs that facilitate reduction of latency and access a larger amount of data about the state of the network for management and control purposes. On one side, a global optimization is nearly impossible since the DESAS problem is an NP-hard problem. On the other side, solutions carried out individually by base stations lack the required information for achieving an optimal solution. Therefore, we assert that solutions designed on MECs by employing a divide-and-conquer approach are appropriate candidates as we discuss in Chapter 4.2.

1.6 Outline

The outline of this thesis can be categorized as follows.

- In Chapter 2, we reviewed the required basic information regarding wireless network generations, orthogonal frequency division multiple access, Multi-Access Edge Cloud and we compared the proposed algorithm with recent works.
- In Chapter 3, we investigated the resource and power allocation mechanism in wireless networks and we formulate our problem based on that. We also reduce our defined problem to two sub-problems in order to find a joint solution with lower complexity.

- In Chapter 4, we proposed base station density and power adaptation (BDPA) Algorithm.
- In Chapter 5, We validate the BDPA algorithm and compare it with the low-power wake-up radio (LP-WUR) algorithm [27] where base stations activated or deactivated by UEs' request and the cooperative inter-cell interference control (C-ICIC) algorithm [28], which energy consumption is optimized by collaborating among neighbor cells.
- In Chapter 6, we concluded our work and present our expected future works.

CHAPTER 2

BACKGROUND AND RELATED WORK

In this chapter, we overview wireless network generations history, explain orthogonal frequency division multiple access, resource allocation and power adaptation, clarify the advantage of using Multi-Access Edge Cloud in the network and we also compared the proposed algorithm with recent works.

2.1 The Overall View of Mobile Networks

Marvelous growth of wireless networks during last decades, the number of user equipment (UEs) are continuously increasing and even in some regions this number has surpassed the number of citizens because seamless connectivity is a mandatory requirement in the current era [29] [30]. The concept of cellular networks was introduced by Bell Labs. We witnessed their advancement for four generations and nowadays observe their progressive steps toward a complex, very dense, massively connected 5th generation of wireless networks. This path started from 2.4 kbps in the first generation and it dramatically increased to 100 Mbps in the fourth generation while we expect 1000 times improvement in 5G networks.

In the 1980's, the first generation of wireless network (1G) is commercially rolled out [31] [32]. The main object in this generation was providing voice services which were low quality and it has very limited capacity. 1G networks was a fully analog system without any digital processing module and its throughput was limited to 2.4 kbps. Some of the typical 1G implementations are Total Access Communication Systems (TACS) of Britain and American Advanced Mobile Phone Systems (AMPS) [33].

2.2 2nd Generation and 3rd Generation of Wireless Networks

The 2nd generation of mobile networks (2G) were commercially rolled out in the early 1990s [34]. This generation was designed as a digital communication network. Therefore, the 2G's capacity and quality of service were improved noticeably in comparison with the first generation. 2G also provided voice services alongside low data rate communications which provide a fast boot for the market and let it spread it throughout the whole world. 2G networks were implemented based on circuit switching systems and it can provide throughput up to 384 kbps. Some of the typical 2G implementations are European GSM (Global System for Mobile Communication) [35] and the American IS-95 (Interim Standard - 95) [36].

In the early 2000s, Third Generation Partnership Project (3GPP) standardized the third generation of mobile networks (3G). This generation of mobile networks implemented based on the code division multiple access (CDMA) technology which can provide a higher throughput and spectral efficiency with respect to previous generations [37]. Network services in 3G were more data-oriented which allow seamless and high-quality services to be offered to users. The architecture of 3G networks contain both packet switching and circuit switching and the throughput was up to 2Mbps. The major standardized members of 3G in the worldwide are CDMA2000 in America, Wideband CDMA (WCDMA) in Europe, Time Division - Synchronous CDMA (TD-SCDMA) in China [38] and IEEE 802.16e which is known as Worldwide interoperability for Microwave Access (WiMAX) [39].

2.3 4G (LTE) Wireless Networks

In the late 2000's, Third Generation Partnership Project (3GPP) introduced the fourth generation of wireless networks also known as Long Term Evolution (LTE) [40]. 4G networks at first developed based on CDMA communications while, voice services were fully Internet protocol (IP) based and a higher data rate could be achieved in it. To tackle the drawbacks of 3G networks, LTE standards redefined in 2010. By employing multiple-input multiple-output (MIMO) and orthogonal frequency division multiple access (OFDMA) technologies in LTE networks, network throughput

was dramatically enhanced with respect to 3G networks [41] [42]. In this generation of mobile network, the core network is fully developed over the packet-switched structure and all communications including voice and data are IP-based. In LTE, the network throughput can go up to 100Mbps. As it is shown in Figure. 2.1, the LTE network architecture consists of the Evolved UMTS Terrestrial Radio Access Network (E-UTRAN) and the Evolved Packet Core (EPC) [43]. The EPC consists of the Home Subscriber Server (HSS), the Packet Data Network (PDN) Gateway (P-GW), the serving gateway (S-GW), the mobility management entity (MME) and the Policy Control and Charging Rules Function (PCRF) which are responsible for providing a connection with outside networks such as the Internet, apply network policies, UEs registration, mobility management. E-UTRAN consists of radio access network nodes called evolved Node B (eNB) which is responsible for transmitting and receiving data and user planes to and from UEs.

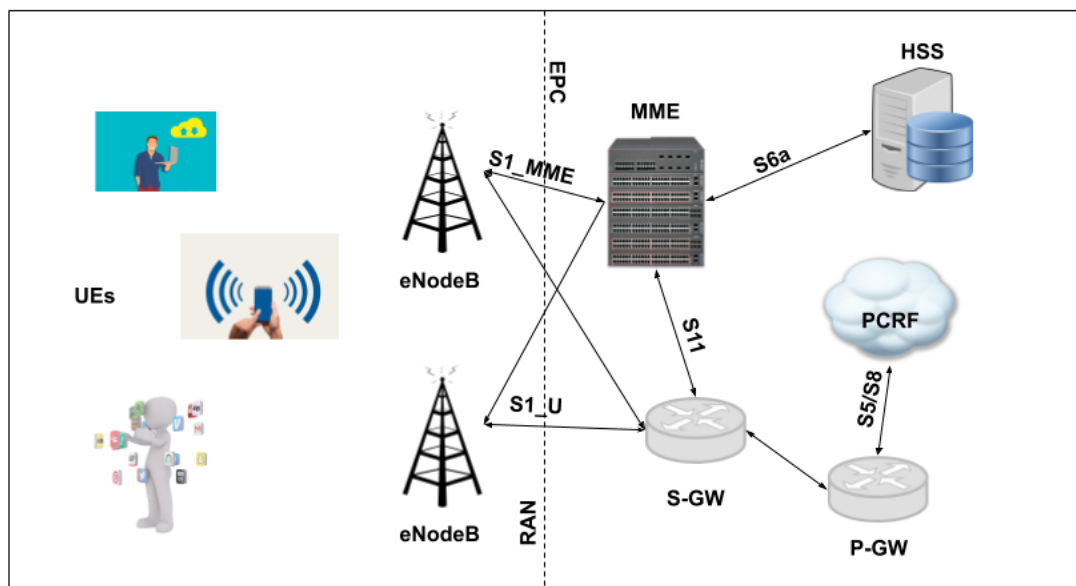


Figure 2.1: The overview of the LTE network architecture which consist of three main components: The User Equipment (UE), The Evolved UMTS Terrestrial Radio Access Network (E-UTRAN) and the Evolved Packet Core (EPC) [2].

2.4 Orthogonal Frequency Division Multiple Access

One of the well-known digitization modulation techniques is Orthogonal frequency-division multiplexing (OFDM) which divide data stream into multiple parallel reduced data rate streams and each of them transmitted on different subcarriers [44]. OFDM has been introduced for about 40 years ago and it was invented during the 1960s and 1970s for coping the interference exist among channels within the same frequency range. OFDM has employed in different wired and wireless networks such as digital audio and video broadcasts as well as asymmetric digital subscriber line (ADSL) [45].

In wireless communications, signals can follow different paths with varied propagation delay. When a signal is reflected by surrounding obstacles during communication, each signal can reach the receiver through different directions that can cause spread delay, fading and inter-symbol interference (ISI) [46]. Therefore, the transmitted rate will be limited by propagation delay in the channel. The OFDM technique has been shown up into a wide variety of wireless communications due to its capability for increasing bandwidth efficiency and handling multi-path delay which can cause a higher bitrate in the network.

OFDMA is developed based on the OFDM modulation technique and it subdivides the overall bandwidth into orthogonal subcarriers in order to carry multiple and independent information during each communication. The frame structure of the LTE system in the time-frequency is represented in Figure. 2.2. As we can see, in the LTE systems length of each frame is 10 ms which is contained 10 subframes with a length of 1 ms . Each of these subframes composes of two 0.5 ms slots. Each of these slots includes seven symbols. The intersection of OFDM symbols and subcarrier can be defined as a resource element (RE) where subcarrier spacing is considered as 15 kHz . A slot of 0.5 ms which represents a group of resource elements that contain 12 subcarriers with overall bandwidth of 180 kHz is defined as a resource block (RB) [47].

The RBs are important because they are the smallest unit of communication that is used during scheduling. Power allocation and scheduling are done periodically by schedulers every transmit time interval (TTI) which is about 1 ms and a RB explicitly

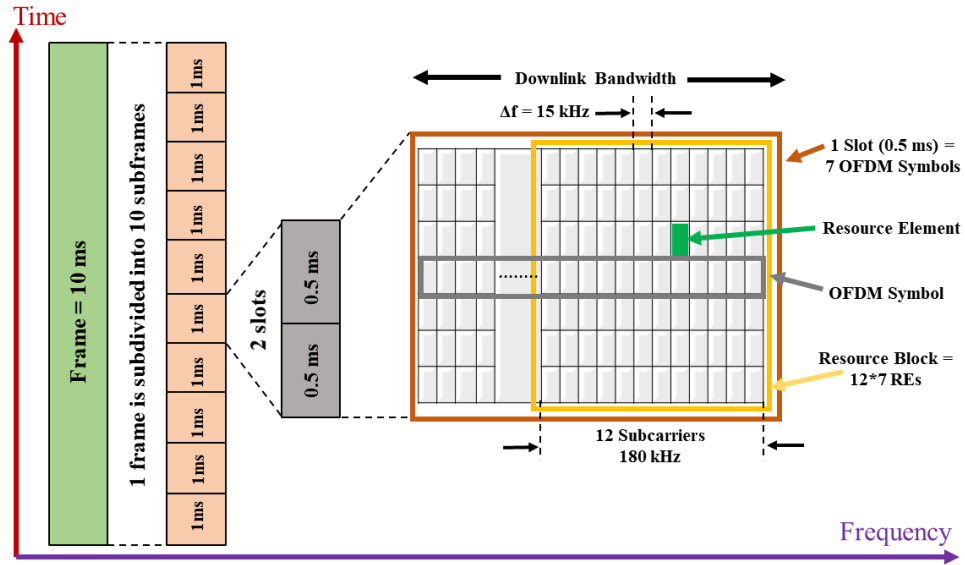


Figure 2.2: The OFDMA-based systems downlink frame structure [3].

will be assigned to each UE in every cell. Although, in multiuser OFDMA systems, packets are transmitted exclusively in different subcarriers, and it can cope the intra-cell interference in networks; but, by employing frequency reuse-1 model, same RB can be assigned to neighbor cells simultaneously which will lead to inter-cell interference (ICI) in the network. The ICI can reduce the overall network throughput because of its negative effect over the received SINR of active UEs [48].

Therefore, providing an efficient ICI coordination (ICIC) model play a vital role in the mobile networks. The ICI coordination models can be categorized into two main groups as it is shown below:

- static ICIC which can be used for to statically managing frequency distribution among cells.
- dynamic ICIC which can be applied by employing dynamic transmit power adaptation (TPA) models and resource allocation schedulers in order to have an efficient model.

In this thesis, we evaluated and analyzed the dynamic ICI management and we investigate centralized, distributed and hybrid models in order to highlight their char-

acteristics. The proposed model includes both dynamic TPA and RB scheduler by considering the density of BSs to tackle the ICI effect in the network. For enhancing the efficiency, we also add the user association in conjunction with TPA and RB scheduler to our model.

2.5 5G Wireless Networks

As we briefly explained, massive development and research have been conducted in wireless mobile networks during the past decades [49] [50]. By changing the functionality of the Internet users from just human-based to the Internet of things (IoT), the amount of machine-to-machine (M2M) communications raised extraordinarily. [51] [52]. Moreover, by introducing ultra-dense networks [16], the density of BSs rapidly increase and size of cells are reduced and cells will be overloaded by huge data communications including high definition videos, multimedia-based applications, online gaming, smart devices, social media and etc. which require a massive data rate and high network capacity. It is predicted in 2021, 86% of traffic load in the cellular networks will be generated by smartphones while 78% of it will be videos [53] [54]. The current LTE networks are not capable of handling such a traffic load and cannot satisfy the minimum requirement of 5G networks such as low latency (1ms) for tactile communications [55] hence, present wireless networks need to be transformed to 5G networks. With respect to LTE networks, the next generation of wireless networks need to be highly energy-efficient due to the fact that the capacity of future networks will be increased up to 1000 times while 90% of energy consumption needs to be reduced [56]. Moreover, alongside a high data rate in 5G networks, the end-to-end latency needs to be reduced for 5 times as well [57].

2.6 Multi-Access Edge Cloud (MEC)

The three main use cases of 5G mobile networks are enhanced Mobile BroadBand (eMBB) [58], Ultra Reliability and Low latency Communications (URLLC) [59], and massive Machine Type Communications (mMTC) [60]. To reach the mentioned requirements in 5G networks, architectures and network topologies need to be placidly

evolved from the current LTE network to an ultra-dense, more complex and heterogeneous network. Multi-access edge cloud (MEC) can be considered as a potential candidate to tackle these issues in the next generation of mobile networks [61]. MEC offers application engineers and substance suppliers distributed computing capacities and an IT administration condition at the edge of the system [62]. This condition is described by ultra-low latency and high data transmission with real-time access to radio system data that can be utilized by applications. Network operators by employing MEC can open their Radio Access Network (RAN) edge to approved third-parties, enabling them to adaptably and quickly convey their imaginative and creative applications and services for their subscribers [63].

2.7 Related Work

In a mobile network, a portion of energy is consumed dynamically by the BSs depending on the amount of the traffic load while another portion of energy is statically consumed in some components such as cooling systems, power supplies or for signal processing. In this thesis, the main focus is on dynamic power consumption in BSs. Power consumption in BSs can be managed by utilizing their resources and adapting density of BSs and transmit power of BSs to the network condition.

Green networking and energy-efficiency have motivated researchers, and their works can be categorized into three main classes: (1) efficient resource allocation models, (2) load balancing models, and (3) bandwidth enhancement models. We will briefly survey these categories in relation to our work in the sequel.

To reduce the energy consumption in BSs by turning off BSs' transceivers in idle times, discontinuous transmission (DTX) models can be employed in the network architecture [64] [65]. In DTX based models Multicast Broadcasting Single Frequency Network (MBSFN) sub-frames are allocated by considering traffic load in the network [66]. Although applying DTX schemes can reduce the energy consumption significantly, DTX does not useful during peak load due to the lack of empty sub-frames and it causes a delay for packet delivery [20]. Moreover, by equipping UEs and BSs with LP-WUR, delay for activation and deactivation of BSs can be re-

duced and BSs can be switched off during their idle periods [27]. Another method for enhancing energy efficiency is the aggregation of RBs [67]. By employing carrier aggregation schemes, the amount of overheads during communication will be reduced, which can increase energy conservation in the network. Another scheme for reducing power consumption in the network is adapting BSs' transmit power to satisfy QoS constraints by minimizing block error rate (BLER) in the network [68]. Also, energy efficiency can be increased by optimizing resource allocation in OFDMA-based networks [69] [70]. In the BDPA algorithm, in addition of adapting BSs transmit power, we adapt density of BSs to network parameters such as throughput and coverage to optimize the network resources more efficiently. Moreover, resource allocation is optimized by increasing cells' utilization factor and deactivating redundant BSs at the same time. Therefore, by adapting density and transmit power of BSs and utilizing the network resources, we simultaneously enhanced the resource management, throughput and coverage in the network from different perspectives. In [71], a joint user scheduling and power control mechanism is proposed which can enhance energy efficiency in ultra-dense networks. Although, in [71], transmit power of base stations and UE allocation are optimized, the density of BSs considered as a pre-configured value which may not applicable in dynamic networks where the density of small cells dynamically changes in time and space. Moreover, by implementing the proposed algorithm in a system level LTE network, we considered the real-life network parameters including traffic models, mobility models and etc. which are not analyzed in the mentioned work. In [72], an energy efficient on-off switching model is proposed where BSs are turned off or on by considering the amount of traffic load in the network. Unlike [72], the main focus is on the effect of increasing density of small cells in future heterogeneous networks in this thesis. Moreover, the proposed algorithm in addition of considering the traffic load and the density of UE dynamicity, it also considers dynamic BSs where the density of BSs may also fluctuate. In the BDPA, network parameters (transmit power) will be adapted to the density of active BSs (PA algorithm) and the density of BSs will be also adapted to the network condition while the QoS (network throughput) can be maintained (BA algorithm).

Moreover, energy can be also conserved by applying load balancing schemes such as distance-aware models in the network architecture [73] [74]. By employing distance-

aware models, when two BSs are competing with each other for registering UEs in their cells, a BS can be switched off when it has a larger distance to UEs and lower traffic load with respect to other BSs. Energy efficiency can be also improved by applying traffic-aware models to adapt energy consumption by considering traffic variations with respect to time in the network [75]. Energy efficiency can be also achieved by applying UE migration techniques to reduce the number of active BSs with the low traffic load which can be implemented in a distributed or centralized manner [76]. In centralized models, by analyzing traffic load among BSs, a BS with the highest load will be determined. After that, in case the selected BS has enough bandwidth for satisfying its neighbor UEs, UEs from a BS with light traffic load will be migrated and the selected BS will be turned off. In contrast, in distributed models, a BS needs to find its pair in a way that the selected BS has a lower traffic load and its traffic load can be handled by its peer. Therefore, by applying UE migration techniques the amount of energy conservation will be increased significantly in the network [77] [78]. In this work, we employed a combination of these methods with a heuristic and fast solution to enhance the network performance. In our scheduling model, we equipped our algorithm with a UE mitigation technique to provide load balancing in the network; but, unlike [73] and [74], UEs are not transferred to other cells just by considering the distance to their neighbor BSs. We consider cell utilization factor and received SINR value to find out the best candidate among BSs to mitigate UEs. We also employ a cell-zooming technique to maintain throughput and prevent any coverage holes in the network. Moreover, the BDPA algorithm, unlike [75], can enhance the network performance and energy conservation even when the traffic load is high due to the resource utilization technique which is employed in this algorithm. Last but not least, our scheduling model is faster than [76] due to its lower complexity and employing MEC instead of a centralized solution.

Bandwidth expansion models can be also employed for enhancing energy efficiency in the network [79] [80]. For instance, in time compression mode (Tcom) algorithm, energy is conserved by reducing overhead caused by control signals during transmission. Moreover, in Tcom by applying high order modulation and coding schemes, RBs are compressed in either of frequency and time domain which can expand the bandwidth in networks. Therefore, BSs can handle their load faster and signal over-

head will be reduced, which can cause energy conservation in the network [81]. In [79] and [80] expanding bandwidth for UEs located at the edge of cells may not be possible due to the high amount of interference received by them from their neighbor cells. In this work, by employing a cell-zooming technique we enhance communication for UEs located at the edges by minimizing interference from other cells and providing high order MCS which can expand bandwidth in each cell individually by considering the network condition.

Moreover, networks can be also optimized by employing MEC platforms in their architectures. Employing MEC platforms provide high flexibility and supporting multi-tenancy in the cellular networks, which can deliver a wide variety of services including cloud computing, network slicing, network function virtualization (NFV) and software-defined networks (SDN) [82]. Due to the heterogeneity of future networks, coordination of dynamic network is difficult which in recent works, authors tackle this issue by employing MEC platforms in networks [83] [84]. MEC can also enable an agile and simple solution to maintain connectivity and enhance service management in the future networks [85]. In recent researches, energy efficiency through MEC platforms is achieved by offloading processing loads from UEs to MECs which can alleviate UEs resource constraints [86]. MEC by providing higher computational power can also be used for enhancing routing data among UEs which can reduce the energy consumption in the network [87] [88] [89]. Moreover, MECs by having higher perspective over the network condition can enhance QoS and interference which can enhance power conservation in the networks [90]. The main advantages of the BDPA algorithm are employing MEC in a distributed manner, implementing it in a system level simulator by considering real-life network parameters (antenna type, height and angle, channel model, shadowing, fading, scheduling, traffic load and etc.) and enhancing the energy efficiency and the throughput by adapting network parameters including transmit power and density of BSs to each other simultaneously through the MEC platform.

CHAPTER 3

DENSITY-, ENERGY- AND SPECTRUM-AWARE RESOURCE SCHEDULING

We define the system model and the density-, energy- and spectrum-aware base station scheduling problem (DESAS) based on the system model presented in this chapter.

3.1 Density-, energy- and spectrum-aware resource scheduling problem (DESAS)

The set $\mathbb{M} = \{1, 2, \dots, T, \dots, M\}$ represents M BSs including T macro BSs and S small cells. The set \mathbb{N} represents N UEs. BSs and UEs are uniform randomly distributed in a two-tier LTE-like environment as shown in Figure.3.1. We assume that no power control is employed in the system and we only focus on the downlink transmission. In LTE-systems [91], BSs schedule their users in 1 ms subframes. A UE is associated to the BS from which it receives the strongest Signal-to-Interference-plus-Noise Ratio (SINR). The experienced SINR by UE i from its serving BS j is

$$SINR_{ij} = \frac{g_{ij}P_{ij}}{\sigma^2 + \sum_{k=1, k \neq j}^M g_{ik}P_{ik}} \text{ dB}, \quad (3.1)$$

where P_{ij} and g_{ij} are the downlink transmit power assigned by BS j to UE i and the channel gain between UE i and BS j , respectively. The amount of noise power is σ^2 and $\sum_{k=1, k \neq j}^M g_{ik}P_{ik} = \sum_{k \neq j} I_{ik}$ is the total received interference by UE i from other BSs.

By considering power is distributed uniformly among resource blocks (RBs) [92], the

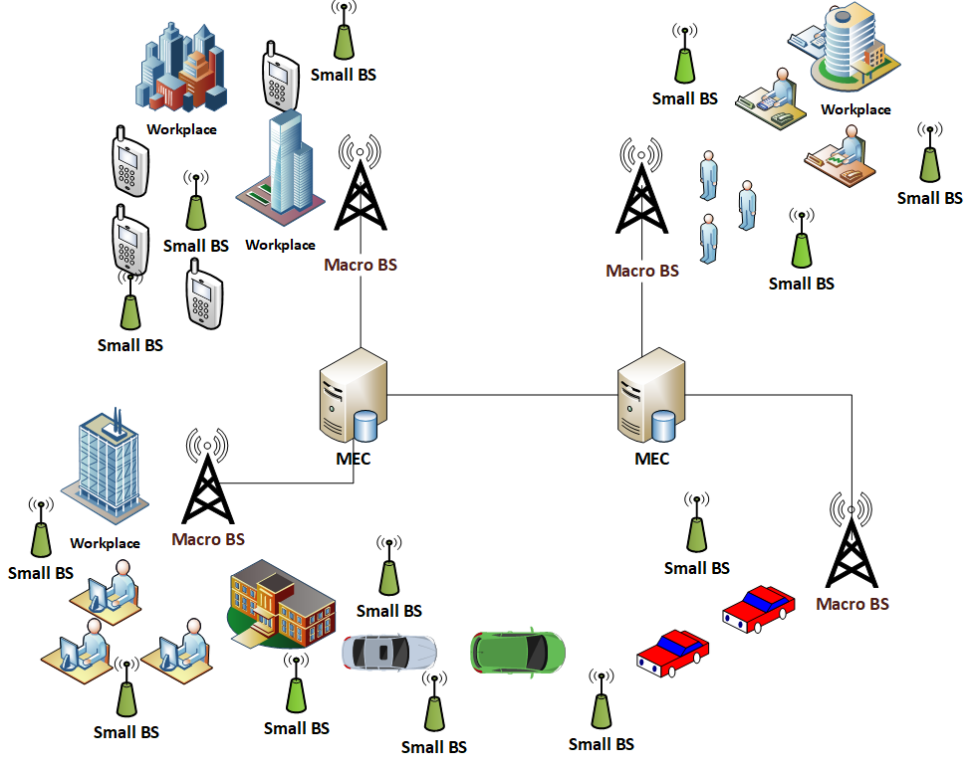


Figure 3.1: The illustration of a network architecture where multi-access edge clouds are employed for self organization.

amount of allocated power in W to each RB can be obtained as:

$$P_{\tau_j} = \frac{P_j}{\tau_j}, \quad (3.2)$$

where P_j is the maximum transmit power of BS j and τ_j is the total number of available RBs in BS j . Then, the number of RBs that has to be allocated to UE i from BS j to satisfy the user's required throughput R_{ij}^* is

$$\tau_{ij}^* = \frac{R_{ij}^*}{b_\tau \log_2(1 + SINR_{ij})}, \quad (3.3)$$

where the denominator provides the maximum achievable data rate and b_τ is the bandwidth of a RB in the network, which is 180 kHz in LTE [93]. By obtaining P_{τ_j} and τ_{ij}^* from (3.2) and (3.3) respectively, we can calculate the minimum amount of power in W that has to be allocated by BS j to UE i as

$$P_{ij}^* = P_{\tau_j} \tau_{ij}^*. \quad (3.4)$$

The dynamic power consumption of BS j can then be computed as

$$P_j = \beta \sum_{i \in \mathbb{N}} P_{ij} + P_0, \quad (3.5)$$

where the constant $\beta \geq 1$ is the inverse of power amplifier efficiency to evaluate amplifier losses and P_0 is the fixed operational power consumed for backhaul signaling and cooling including losses. Although the most influential component of energy consumption in macro cells is the static power, it is not the case for small cells. In small cells, the main part of energy is consumed by the radio transceiver unit due to the absence of cooling system and low-power amplifier [94]. Therefore, we did not analyze the effect of P_0 in this thesis. By considering this fact, we do not need to turn off the small cells completely. While the transmitter of BSs (which consume the major part of energy in small cells) will be turned off completely, other small cells' modules remain active for rapid response to the network condition (we do it per TTI which implicitly sets the timescale to 1 ms). That is why P_0 is considered in the problem formulations. Generally, P_0 is around 500 W and 15 W for macro and small cells, respectively [93]. This model can be expanded by including switching power consumption which is out of scope of this work [95] [96]. Because in our opponents (LP-WUR and C-ICIC) switching power is also not considered. Therefore, for fairness, we did not apply the switching power effect over our power consumption model in this work and we set it a future work item.

The QoS provided to the users can be increased if the amount of interference is lowered. Therefore, we aim in the DESAS at enhancing the received SINR to reach a required threshold T_{SINR} ,

$$\frac{g_{ij}P_{ij}}{\sigma^2 + \sum_{k \neq j} I_{ik}} \geq T_{SINR}.$$

Maximization of energy- and spectral-efficiency can be achieved through minimization of power consumption and the number of required RBs while satisfying UEs' throughput requirements. Therefore, we formulate the DESAS problem given an ini-

tial x_{ij} assignment as

$$\begin{aligned} &\text{finding} && x_{ij}, P_{ij}, z_j \\ &\text{to minimize} && \sum_{i \in \mathbb{N}} \sum_{j \in \mathbb{M}} x_{ij} (\alpha_P P_{ij} + \alpha_S \tau_{ij}) \end{aligned} \quad (3.6a)$$

$$\text{subject to} \quad \sum_{j \in \mathbb{M}} x_{ij} = 1, \forall i \in \mathbb{N}, \quad (3.6b)$$

$$\sum_{i \in \mathbb{N}} x_{ij} \tau_{ij} \leq \tau_j, \forall j \in \mathbb{M}, \quad (3.6c)$$

$$\tau_{ij} \geq \tau_{ij}^*, \forall i \in \mathbb{N}, \forall j \in \mathbb{M}, \quad (3.6d)$$

$$x_{ij} \leq z_j, \quad (3.6e)$$

$$\text{where} \quad x_{ij} = \begin{cases} 1 & \text{if UE } i \text{ is assigned to BS } j \text{ and } z_j = 1 \\ 0 & \text{otherwise} \end{cases}$$

The objective of the DESAS problem is to minimize energy consumption and to reduce the number of required RBs by finding UEs should be assigned to which BSs (x_{ij}), how much power need to be assigned by BSs to their associated UEs (P_{ij}) and which BSs should be kept active (z_j) while maintaining the throughput and satisfying UEs requirements. In (3.6a), we employ normalization coefficients α_P and α_S defined as $w_P \rho_P$ and $w_S \rho_S$ for energy- and spectral-efficiency, respectively [97]; w is a weight for adding a preference among energy- and spectral-efficiency, and ρ is a normalization factor. DESAS is a UE-to-BS assignment problem where each UE has to be served by only one BS (3.6b). To make sure we can assign a UE to a BS, the corresponding BS should have enough available capacity to satisfy the requested RBs by UE (3.6c) and the minimum required RBs of users have to be satisfied (3.6d). A UE can be assigned to a BS only when the BS is active (3.6e).

For simplicity, we did not consider lots of parameters such as velocity, shadowing, fading, packet arrival rates. in the problem formulation, but all of those parameters will be considered during the simulation. The DESAS problem is an integer nonlinear programming problem and can be reduced to the generalized assignment problem with a search space complexity of $O(2^{N \times M} + 2^{N \times M} + 2^M)$ which is an NP-hard problem [98]. By using classical knapsack terminology, we can describe the generalized assignment problem (GAP) [98] as assigning item i to knapsack j with a profit value of P_{ij} . When item i is assigned to knapsack j it has a weight and each knapsack has a

capacity. In the DESAS problem, $(\alpha_P P_{ij} + \alpha_S \tau_{ij})$ can be considered as profit value of assigning UE i to BS j , τ_{ij} is the weight of UE i in case it is assigned to BS j and the capacity of BS j is represented as τ_j . Since the DESAS problem is an NP-hard problem, a global solution to the DESAS is not feasible and practicable. We consequently resort to dividing the DESAS into two separate problems with a lower complexity that we present in the next two sections. These two subproblems are briefly:

- *BS density adaptation (BDA) problem* defines how density of BSs can be controlled based on network capacity and traffic load to conserve energy. By solving the BDA problem, we identify which BSs can be turned off while the minimum required throughput can still be satisfied.
- *Power adaptation (PA) problem* defines how the transmission power of BSs can be adapted by considering the density of BSs while maintaining coverage.

We firstly formulate these problems to evaluate their complexities. After that, we propose heuristic solutions to them. The overall methodology of this thesis is presented in Figure. 3.2.

3.2 Base Station Density Adaptation (BDA) Problem

Let the minimum number of RBs that have to be allocated to UE i by BS j be τ_{ij}^* . Then, the minimum required bandwidth of BS j to satisfy its associated UEs is denoted as B_j^* (Hz) becomes

$$B_j^* = \sum_{i \in \mathbb{N}} B_{ij}^* = \sum_{i \in \mathbb{N}} \tau_{ij}^* b_{\tau}. \quad (3.7)$$

By adapting density of BSs, network resources can be used more efficiently by balancing load among cells and then redundant BSs can be turned off. We have to control BS density for maximizing energy efficiency while preserving throughput. The number of active BSs can be minimized by finding out the whether or not a BS should be

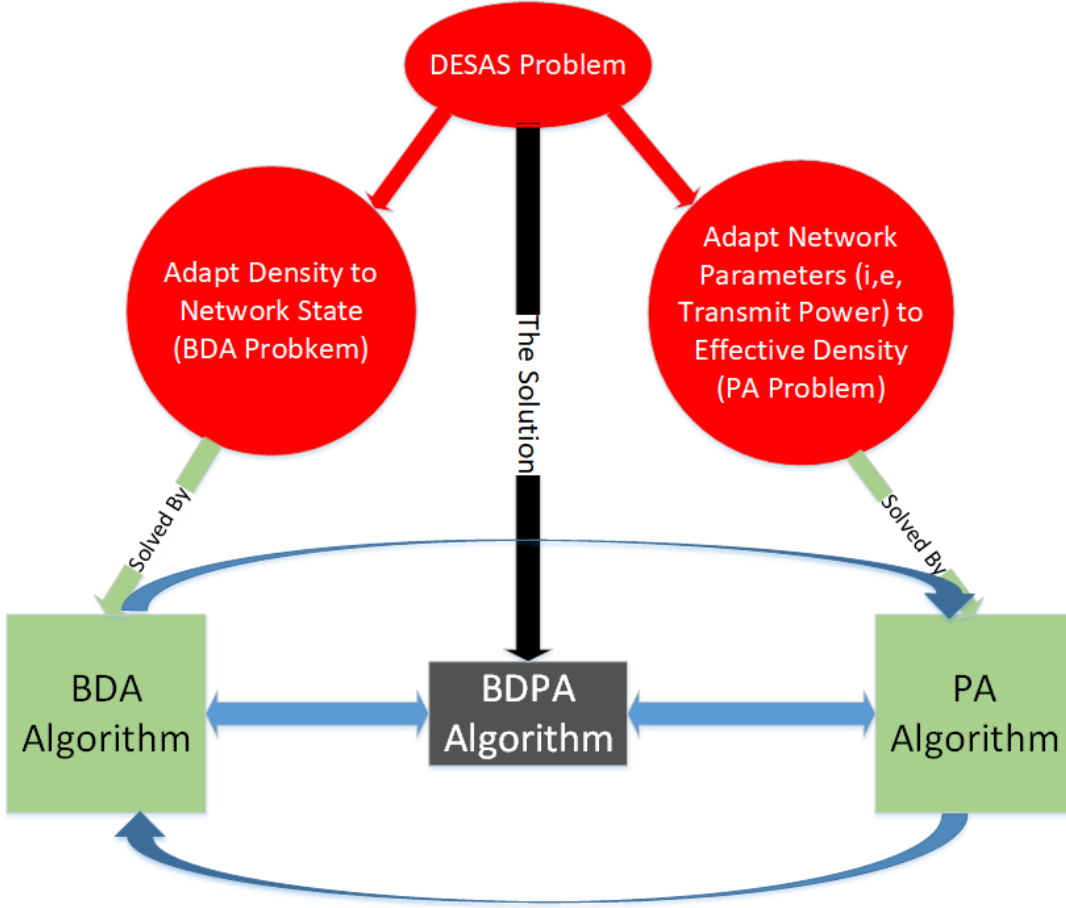


Figure 3.2: The overall methodology.

active (z_j) subject to QoS constraints. Therefore, we define the BDA problem as

$$\begin{aligned} &\text{finding } x_{ij}, z_j \\ &\text{to minimize } \sum_{j \in \mathbb{M}} z_j \end{aligned} \quad (3.8a)$$

$$\text{subject to } \sum_{i \in \mathbb{N}} x_{ij} B_{ij} \leq B_j, \forall j \in \mathbb{M}, \quad (3.8b)$$

$$x_{ij} B_{ij} \geq B_{ij}^*, \forall j \in \mathbb{M}, \quad (3.8c)$$

$$\sum_{j \in \mathbb{M}} x_{ij} = 1, \forall i \in \mathbb{N}, \quad (3.8d)$$

$$\text{given } x_{ij} = \begin{cases} 1 & \text{if UE } i \text{ is assigned to BS } j \text{ and } z_j = 1 \\ 0 & \text{otherwise} \end{cases} \quad (3.8e)$$

In the BDA problem, we try to minimize the number of active BSs (3.8a) by making sure that the amount of bandwidth allocated to UEs are always smaller than the bandwidth (3.8b) allocated to BSs. In other words, the minimum required bandwidth by each UE must be satisfied by its corresponding BS (3.8c). UE i will initially be assigned to BS j if the amount of received SINR value is the highest with respect to its neighbor cells ($x_{ij} = 1$). This is carried out for only initializing the system model and after that UE assignment will be considered as the optimization value in this thesis.

The BDA problem is a binary integer linear program (BILP) with a search space complexity of $O(2^{N \times M} + 2^M)$, that is NP-hard [99] [100] with a smaller search space complexity compared to the DESAS problem. Turning off or on a BS impacts other network parameters such as available bandwidth in other cells or received interference. In case the effect of activation and deactivation of BSs is considered constant, this problem can be reduced to the well-known bin packing problem [101]. In the bin packing problem, the goal is to minimize the number of required bins to be used for packing objects with different sizes and values. In the BDA problem, objects are UEs with different bandwidth requirements (values) and bins are active BSs whose count we try to minimize. Therefore, the BDA problem can be reduced to a multi-dimensional bin packing problem that is NP-hard. To solve this problem, we need to define a utilization factor for each cell to predict network behavior in case of activation and deactivation of a BS. The corresponding utilization ratio will be introduced in the next section.

3.3 Power Adaptation (PA) Problem

In the PA problem, we want to adapt transmit power by considering the effective BS density to maintain network coverage and to prevent coverage holes while satisfying UEs' traffic requirements. This problem can be formulated as the minimization of overall power which is allocated by BS j to its associated UEs.

Assume the overall density of small BSs and density of UEs in the network are represented as λ_b and λ_u , respectively where generally $\lambda_u \geq \lambda_b$. We assume a UE is served

by the BS that provides the highest SINR value. The bandwidth per user depends on the density of UEs (λ_u) and the size of cells. For the sake of simplicity, we assume the whole bandwidth (B) is divided among UEs homogeneously; i.e., $B_u = B \frac{\lambda_b}{\lambda_u}$. Therefore, the average rate per UE i is

$$R_{ij} = B_u \mathbb{E} [\log_2(1 + SINR_{ij})]. \quad (3.9)$$

We define the coverage probability $P_c(T_{SINR})$ as the probability of the received $SINR_{ij}$ by UE i from its closest BS j to be greater than a threshold value T_{SINR} ,

$$P_c(T_{SINR}) = \text{Prob}(SINR_{ij} > T_{SINR}).$$

In the PA problem, we want to find a solution to maximize the energy efficiency while enhancing the spectral efficiency (ϕ) without degrading the provided QoS level in terms of network coverage and UEs' throughput. To maintain the network coverage and satisfy the UEs' throughput requirement, the maximization of energy efficiency can be converted to the minimization of overall power consumption including the transmit power (P_{ij}) for all UEs and the operational power (P_0) in the whole network. Given an initial UE-to-BS assignment x_{ij} , we formulate the PA problem as

$$\begin{aligned} & \text{finding} \quad x_{ij}, P_{ij} \\ & \text{to minimize} \quad \sum_{i \in \mathbb{N}} \sum_{j \in \mathbb{M}} x_{ij} ((P_{ij} + P_0)) \end{aligned} \quad (3.10a)$$

$$\text{subject to} \quad P_c(P_{ij}) \geq (1 - \epsilon) P_c^{max}, \quad (3.10b)$$

$$R_{ij}(P_{ij}) \geq \min \{R, \phi^{max} B_u(\lambda_b)\}, \quad (3.10c)$$

$$x_{ij} \in \{0, 1\}, \forall i \in \mathbb{N}, \forall j \in \mathbb{M}, \quad (3.10d)$$

$$\sum_{j \in \mathbb{M}} x_{ij} = 1, \forall i \in \mathbb{N}, \quad (3.10e)$$

The objective is to minimize the overall power consumption in the network given x_{ij} where $x_{ij} = 1$ if UE i is connected to BS j , and zero otherwise (3.10d), and each UE can be connect to just one BS (3.10e). We need to make sure that the probability of coverage for all UEs should be always higher than an acceptable outage value if the power allocated by BS j to UE i is set to P_{ij} . By considering P_c^{max} as the probability

of coverage when there is no interference, we want $P_c(P_{ij})$ (coverage probability in practice) to be greater than ϵ less of P_c^{max} to achieve the required coverage and to satisfy the throughput requirement of UEs.

By considering an interference limited environment, we assume the maximum achievable spectral efficiency is ϕ^{max} . When the bandwidth allocated to a UE in a network with density λ_b is $B_u(\lambda_b)$, the maximum achievable data rate becomes $\phi^{max} B_u(\lambda_b)$. This is the upper bound for the UEs' demand rate, R . Then, $R_i(P_j)$ is the achievable rate by UE i from its associated BS j when the transmission power of the BS is equal to P_j . It must always be equal or larger than the UEs' demand rate R (3.10c).

The PA problem, similar to the DESAS problem, can be reduced to the GAP. The overall power that is going to be assigned to UEs is the profit value, allocated rate to UE i ($R_i(P_j)$) when transmit power is set to P_j is the weight of assigned power and the maximum achievable data rate by BS j ($\phi^{max} B_u(\lambda_b)$) can be considered as the capacity in the PA problem. Therefore, the PA problem can be reduced to generalized assignment problem with the space complexity of $O(2^{N \times M} + 2^M)$ which is known to be an NP-hard problem [102] with a smaller search space compared to the DESAS problem.

CHAPTER 4

BASE STATION DENSITY AND POWER ADAPTATION (BDPA) ALGORITHM

In this chapter, we present the base station density and power adaptation (BPDA) algorithm to solve the DESAS problem. We first need to evaluate various scenarios that we may face in a dynamic network to justify the BDPA algorithm and show how can we tackle the problems defined in the previous section by adapting density and transmit power of BSs to the network state.

4.1 Scenarios

We define four different scenarios that we may face while running our algorithm among small cells. These four scenarios (S1, S2, S3, S4) and the effect of applying BDPA algorithm is depicted in the left and right side of Figure. 4.1 respectively. We assumed in the figures that macro BSs are connected to a MEC.

- *Scenario S1*: As it can be seen in Figure. 4.1a, when the traffic load in some of small cells is low and in case their assigned UEs are transferred to the associated macro cell, the utilization ratio of macro BS (that we define in Section 4.3) will still remain under the threshold value. In this case, we can turn off redundant small cells and transfer their load to the macro cells.
- *Scenario S2*: Small cells can cause interference to each other that may degrade UE satisfaction as shown in Figure. 4.1b. To enhance QoS and save energy, we may turn off interferer BSs and transfer their UEs to a neighbor BSs with a higher SINR value if the utilization ratio of the neighboring BS still remains

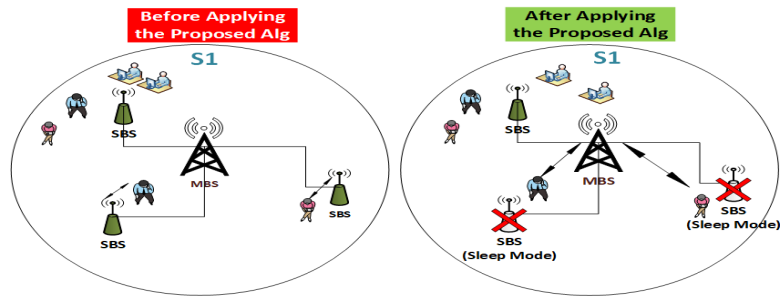
below the expected threshold.

- *Scenario S3*: In the third scenario (Figure. 4.1c), when a small cell's load is below the threshold and if its neighboring small cells can handle its associated UEs without causing any degradation in the coverage and the throughput, and if the macro cell is overloaded, then that small cell can be turned off and its neighbors need to expand their coverage area by amplifying their transmit power until the required received SINR can be obtained for all UEs.
- *Scenario S4*: Maintaining QoS may have a higher priority in comparison to saving energy. If the received SINR in a BS is below the minimum required received SINR value to satisfy UEs, the traffic load needs to be distributed to the neighboring cells to enhance the QoS level. As it is shown in Figure. 4.1d, other cells can boost their transmit power to expand their coverage area for providing service to the unsatisfied UEs located at the edges. The system may force those UEs to handover to their neighboring cells for balancing the load.

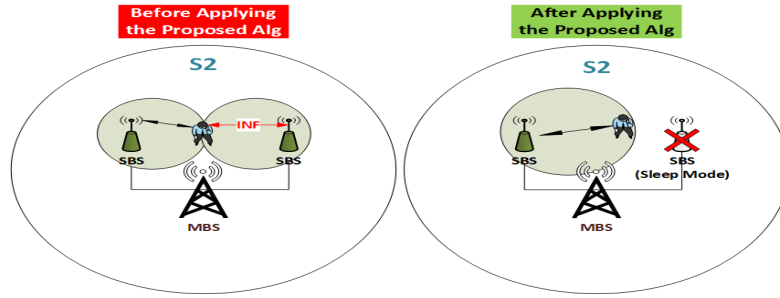
In these scenarios, the main goals are enhancing UEs QoS by lowering received interference and increasing UEs throughput while the transmit power of BSs and the density of active BSs are optimized.

4.2 Comparison of Distributed, Centralized or Decentralized Solutions

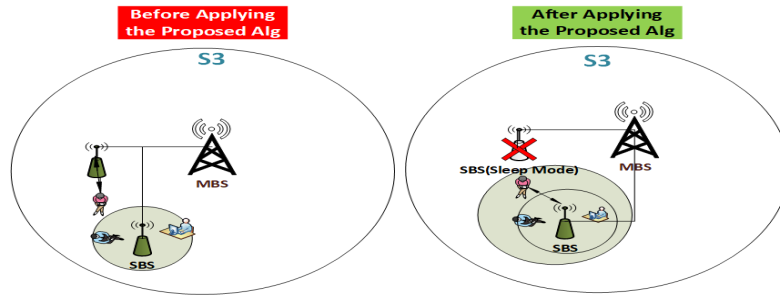
For solving the DESAS problem, there are basically three approaches. One is to design a centralized approach where the input size to the problem is the number of BSs. The other approach is the fully distributed approach where each BS tries to solve the problem individually. Since the DESAS is an NP-hard problem, a centralized solution is not feasible in practice, because of the huge search space. When the number of BS's the increases, the solution space grows exponentially. On the other hand, scheduling BSs for conserving energy may affect the overall network throughput if it is done individually by each BSs in a distributed fashion. Since proposing a fully centralized or a distributed solution is not feasible, we design a hybrid solution using multi-access edge clouds (MECs) to augment the capabilities of BSs. We off-load



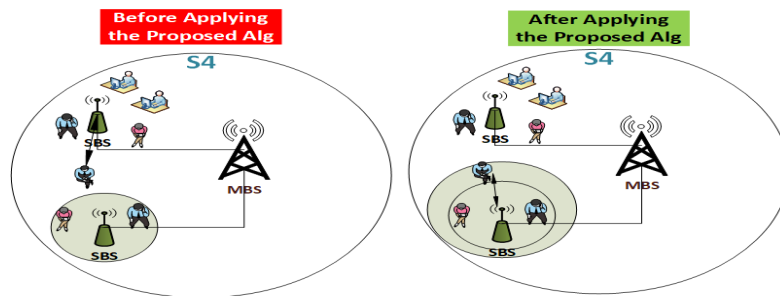
(a) Energy conservation by moving load from small to macro BSs.



(b) Reducing interference (INF) by adapting BS density.



(c) Cell-zooming for conserving energy.



(d) Cell-zooming for user satisfaction.

Figure 4.1: Four different scenarios (S1, S2, S3, S4) including: a) reducing energy consumption through macro cell, b) reducing interference, c) enhancing energy conservation through small cells, d) maintaining QoS, that we may face in a HetNet and the effect of applying the BDPA algorithm over these scenarios.

some management and control tasks such as coverage control and sleep scheduling from the core network to the edges of the network.

MECs, by accessing multiple BSs and communicating with each other, have a larger perspective (accessing data which is not limited to just one cell) over the network state in comparison to distributed models [103]. The overall cost to collect network state for a MEC is lower than a centralized model since the divide-and-conquer approach is employed. Although centralized models have the largest perspective over the network state in comparison to MEC and fully distributed models, they are not scalable; the problems become intractable as the network grows. Since MECs are located to the edge of network and close to the BSs, they can collect information from cells as fast as fully distributed models while the delay for collating the information at the core network is huge. With a similar argumentation, we can claim that the amount of processing power and energy needed by centralized models are large in comparison to MECs. All in all, although centralized models can allocate resources optimally, reaching the optimal result may not always be feasible if the size of network is too large. Therefore, by employing MEC we can reach a sub-optimal solution faster with a lower amount of energy and processing power. The overall comparison among decentralized, MEC and fully centralized solutions are summarized in Table 4.1.

We assume a two-tiered HetNet where under the macro BS's coverage, there are a number of small cells. In the BDPA algorithm, macro BSs will always be up and operational, and the proposed scheduling model will be executed over small cells to maintain the network coverage. The BDPA algorithm consists of BDA and PA algorithms to solve the DESAS problem (3.8a-3.10a).

4.3 Base Station Density Adaptation (BDA) Algorithm

Let us assume the total number of available RBs in BS j during the time interval T is represented as $\tau_j(T)$. The resource utilization ratio of BS j can be defined as the percentage of allocated resource blocks to satisfy the minimum required throughput

Table 4.1: The comparison of implementing a fully distributed, a decentralized or a centralized solution to the DESAS problem.

	Fully Distributed	Decentralized (MEC)	Centralized
Awareness of other cells	Not known	Aware	Aware
Information collection cost	Very low	Low	Very high
Scalability	Scalable	Scalable	Not scalable
Perspective	Per BS individually	Over BSs under its supervision	For the whole network
Time resolution	Very fast	Fast	Very slow
Computational power	Low	High	Very high but not feasible
Resource allocation	Not optimal	Suboptimal	Optimal

in that BS is defined as

$$A_j = \frac{\sum_{i=1}^N \tau_{ij}}{\tau_j(T)} = \frac{\sum_{i=1}^N \frac{R_{ij}^*}{b_r \log_2(1 + SINR_{ij})}}{\frac{b_j T}{b_r}}, \quad (4.1)$$

where b_j is the total available bandwidth of BS j . To incorporate the resource utilization ratio, we can redefine $SINR$ in (3.1) as

$$SINR_{ij} = \frac{g_{ij} P_{ij}}{\sigma^2 + \sum_{k=1, k \neq j}^M A_j g_{ik} P_{ik}}, \quad (4.2)$$

We need to prevent coverage holes when BSs are turned off. By employing MEC, we can calculate the probability of network coverage for different SINR values by considering the density of BSs (λ_b). In this thesis, we validate our results by employing the probability of coverage, $P_C(T_{SINR})$ as proposed in [104],

$$P_C(T_{SINR}) = \frac{2}{\gamma} \int_0^\infty t^{\frac{2}{\gamma}-1} e^{-t\Gamma N_0 \alpha^{-\frac{2}{\gamma}}} e^{-t^{\frac{2}{\gamma}}} \times \left(-\frac{2}{\gamma} \frac{T t^{\frac{2}{\gamma}} F(1, 1 - \frac{2}{\gamma}; 2 - \frac{2}{\gamma}; -T)}{1 - \frac{2}{\gamma}} \right) dt, \quad (4.3)$$

where

$$\alpha = \frac{\lambda_b \pi \mathbf{E}[(P_d S_d)^{\frac{2}{\gamma}}]}{K^2}$$

is the distribution of shadowing S_d that is considered as arbitrary except $E[S_d^{\frac{2}{\gamma}}] < \infty$, and $F(a, b; c; z)$ is the hyper-geometric function [104]. In this model, T is the received SINR value in the network, $K = 6910 \text{ km}^{-1}$ for urban environment, which can be obtained from the COST Walfisch-Ikegami model and γ is a path-loss exponent. Here, $\mathbf{E}[(P_d S_d)^{\frac{2}{\gamma}}]$ is the propagation invariance which S_d and P_d are independent random vectors. S_d represent the effect of propagation of a signal from its origin at S_d and P_d is the transmit power of that signal. The proposed model can be easily evaluated numerically if we consider the noise power zero ($N_0 = 0$) as follows:

$$P_C(T_{SINR}) = \left[-\frac{2 T t^{\frac{2}{\gamma}} F(1, 1 - \frac{2}{\gamma}; 2 - \frac{2}{\gamma}; -T)}{\gamma (1 - \frac{2}{\gamma})} \right]^{-1}. \quad (4.4)$$

In this model, BSs are distributed based on Poisson model and by considering this fact that BSs are not completely turned off (they are always aware of the network condition through the MEC in order to be activated and deactivated during each time interval), the Poisson distribution assumption will still be valid throughout the life-cycle of the network. By obtaining P_C from (4.3), we can find the corresponding required $SINR$ value to keep $P_C \geq T_{SINR}$. In (4.2), $SINR$ depends on the activity ratio of cells. Therefore, we can determine the maximum activity ratio each BS can tolerate to keep the P_C above the network threshold by knowing the required minimum $SINR$ value.

For adapting density of small BSs, we need to make sure user's traffic requirements are satisfied and coverage can still be preserved. For offloading the traffic when a small cell is deactivated, we need to evaluate the capacity of neighboring small cells and the macro BS to find out whether or not they can handle the offloaded traffic. We also need to analyze the effect of applying the scheduling algorithm over the network coverage to prevent holes.

The pseudocode of the proposed BDPA algorithm is presented in Algorithm 1. Due to heterogeneity of the network and variations of BS density, we need to calculate a threshold SINR value to maintain network coverage and minimum cell utilization factor (A_{min}) in each run (line 6). A MEC may access data from a wider range of base stations and it has a larger computation power than base stations. Therefore, the density of BSs can be estimated by using a density estimator at the MEC [105]. By obtaining density of BSs, the minimum T_{SINR} based on the required probability of

coverage (P_c) can be computed; then, it can be used to calculate the minimum cell utilization factor for the next step. We can obtain the minimum required throughput in each small cell (R_{ij}^*) by comparing the achievable throughput in the *basic model* (a network where density and power adaptation is not employed) and set it as R_{ij}^* in the BDPA algorithm. We then check the utilization factor of each BS to compare with A_{min} (line 5). If utilization factor of BS j is above the threshold and if its associated macro BS has enough capacity (A_{mj}) to handle BS j load (line 7) we can turn off that base station and transfer its traffic load to its associated macro BS. If macro BS is overloaded, we can transfer BS j 's load to one of its neighbors, if possible (lines 12-19). However, if its neighbor cannot handle BS j 's traffic load, we need to keep this BS on and use our power adaptation algorithm ($PA()$) that will be explained in the next section. If the utilization factor of BS j is below the threshold and by running our power adaptation algorithm the utilization factor of BS j still remains below the threshold, we can turn on redundant BSs and recalculate A_{min} until we make sure the required QoS (users' traffic requirements) can be satisfied (lines 27-39).

The computational complexity of the joint BDPA algorithm is $O((N_{macro} + N_{small})\tau_{tot})$. Due to the distribution of computational tasks among MECs, each MEC is responsible only for part of BSs and the BDPA algorithm runs in polynomial time.

Algorithm 1: The base station density and power adaptation algorithm.

```
1 From MEC:
2  $\lambda \leftarrow$  density of BSs
3  $T_{SINR} \leftarrow$  find  $T_{SINR}$  such that  $P(T_{SINR}, \lambda) \geq T_{cov}$ 
4 for  $j = 1$ :All BSs connected to MEC do
5    $A_{min} \leftarrow \frac{\sum_{i=1}^N \frac{R_{ij}^*}{b_{\tau} \log_2(1+SINR_{ij})}}{\frac{b_{\tau} T}{b_j}}$ 
6   if  $A_{min} \leq A_j$  then
7     if  $A_{min} \leq A_j + A_{mj} \leq 1$  then
8       Turn off BS  $j$ 
9        $\lambda \leftarrow \frac{N_{small}-1}{Area}$ 
10       $DeactivatedBSs + 1$ 
11    end
12    else
13      Find a neighbor small cell  $k$ 
14      with the highest received SINR
15      if  $A_{min} \leq A_j + A_k \leq 1$  then
16        if  $SINR_k \geq T_{SINR}$  then
17          Turn off BS  $j$ 
18           $\lambda \leftarrow \frac{N_{small}-1}{Area}$ 
19           $DeactivatedBSs + 1$ 
20        end
21        else
22          #Our heuristic cell-zooming #algorithm needs to be run to
23          #maintain QoS in the network
24           $PA()$ 
25        end
26      end
27    end
28  else
29     $PA()$ 
30    if  $A_j < A_{min} \ \&\&$ 
31     $DeactivatedBSs > 0$  then
32      while  $A_j \geq A_{min}$  or  $DeactivatedBSs > 0$  do
33        Turn on a BS
34         $\lambda \leftarrow \frac{N_{small}+1}{Area}$ 
35         $DeactivatedBSs - 1$ 
36         $T_{SINR} \leftarrow$  recalculate  $T_{SINR}$ 
37         $A_{min} \leftarrow \frac{\sum_{i=1}^N \frac{R_{ij}^*}{b_{\tau} \log_2(1+SINR_{ij})}}{\frac{b_{\tau} T}{b_j}}$ 
38      end
39    end
40  end
41 end
```

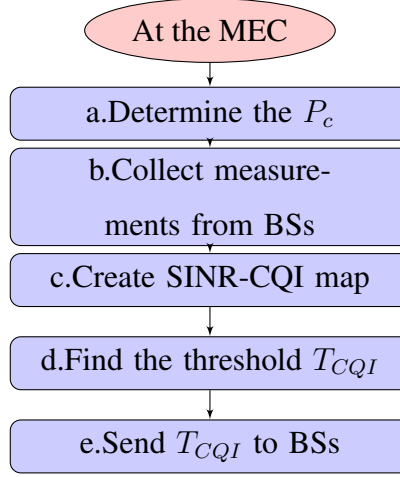


Figure 4.2: The mobile edge tasks flow chart.

4.4 The Power Adaptation (PA) Algorithm

To maintain coverage and reduce interference in a network in addition of considering the capacity of other cells, we employ the cell zooming technique that we partially presented in [106]. In this work, we expand or reduce the cell size for enhancing the overall network throughput.

In the first step, based on the determined SINR threshold from (4.3), we need to adapt transmit power of BSs by finding out an adequate threshold value (T_{SINR}) which can keep P_C above the minimum requirement of network operators (Figure. 4.2, step a) for enhancing the network throughput while the coverage in the whole network is preserved. In the second step, the appropriate modulation and coding scheme (MCS) can be obtained based on the channel quality indicator (CQI) value that can be obtained by BSs from their associated UEs (Figure. 4.2, step b) [107].

After obtaining T_{SINR} , we need to find the corresponding CQI value based on the channel condition. In the third step (Figure. 4.2, step c), the SINR values can be mapped to their corresponding CQI levels by calculating the block error rate (BLER) for each CQI level as it is shown in Figure. 4.3. In Figure. 4.3, we calculate the BLER for each CQI value to find the corresponding SINR value when the BLER reach to 10%. The corresponding SINR-CQI map is shown in Table 4.2.

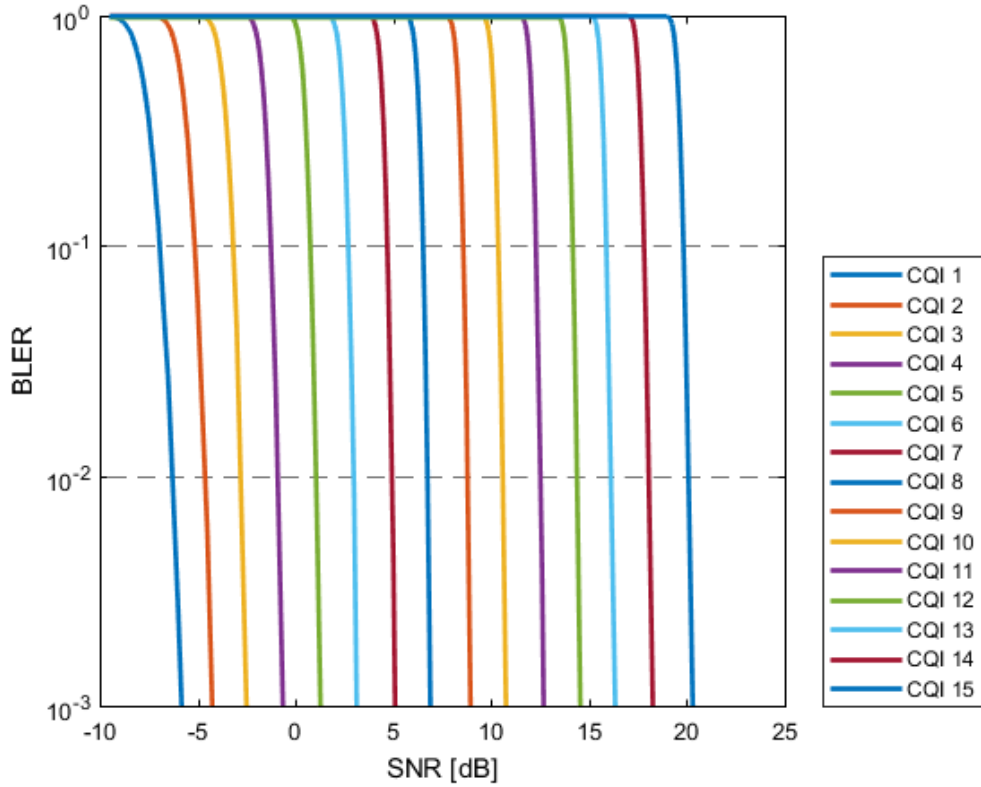


Figure 4.3: The BLER-SINR map for various CQI values.

In the last step of the flowchart shown in Figure. 4.2, at step d, the MEC needs to determine an appropriate CQI value to satisfy network coverage and enhance the throughput simultaneously (T_{CQI}). There is a trade-off between choosing high CQI value and maintaining the network coverage. To maintain the network coverage, we need to use a lower MCS to make sure the received signal is interpretable by the receivers even in low quality channel conditions (low received SINR value). By decreasing the MCS, the size of transport block and the number of bits per symbol will be decreased which can drop the network throughput significantly. Therefore, MEC by considering the probability of coverage and SINR-CQI map which are obtained from previous steps, can choose an appropriate threshold value (T_{CQI}) and inform BSs to adapt their modulation and coding schemes and their power consumption based on it (Figure. 4.2, step e).

This procedure has to be repeated in case of any changes in the network topology such as increasing the amount of maximum transmit power, type of base stations, density

Table 4.2: The SNR-CQI map table.

CQI	SNR	CQI	SNR	CQI	SNR
1	-6.93	6	2.69	11	12.28
2	-5.14	7	4.69	12	14.17
3	-3.18	8	6.52	13	15.88
4	-1.25	9	8.57	14	17.81
5	0.76	10	10.36	15	19.82

of BSs or environmental conditions. In Figure. 4.2, the summary of mobile edge tasks is presented.

When all base stations are informed about the threshold value which is obtained in the previous step by the MEC; each base station employs the power allocation algorithm presented in Algorithm 2 that is based on the received CQI feedback from its UEs. BSs compare CQI measurements of user-specific reference signals [108] with the threshold value (line 5) to increase or decrease the power allocation to each RB individually per transmit time interval (1 ms).

In the basic power allocation model where power is allocated to each UE homogeneously, UEs located at the edges experience a high amount of interference from neighboring base stations. The amount of power allocated to UEs located at the cell-center has to be reduced to overcome the interference effect over UEs located at the edges in the PA algorithm.

Each base station independently monitors the feedback from active UEs. When the amount of received CQI value is higher than the threshold, the BS will reduce the power (P) continuously until it makes sure the allocated power is higher than the minimum possible transmission power (P_{min}) and the new received CQI value is still equal or higher than the threshold (lines 15-18). To enhance the network throughput, BSs need to allocate more power to the UEs located at the edges in comparison with other UEs. Therefore, if the amount of received feedback from a UE is less than the threshold, BSs will consider it as the edge UE. In this case, BSs need to amplify the allocated power for 1% (Δ) until they make sure the new CQI feedback is higher than

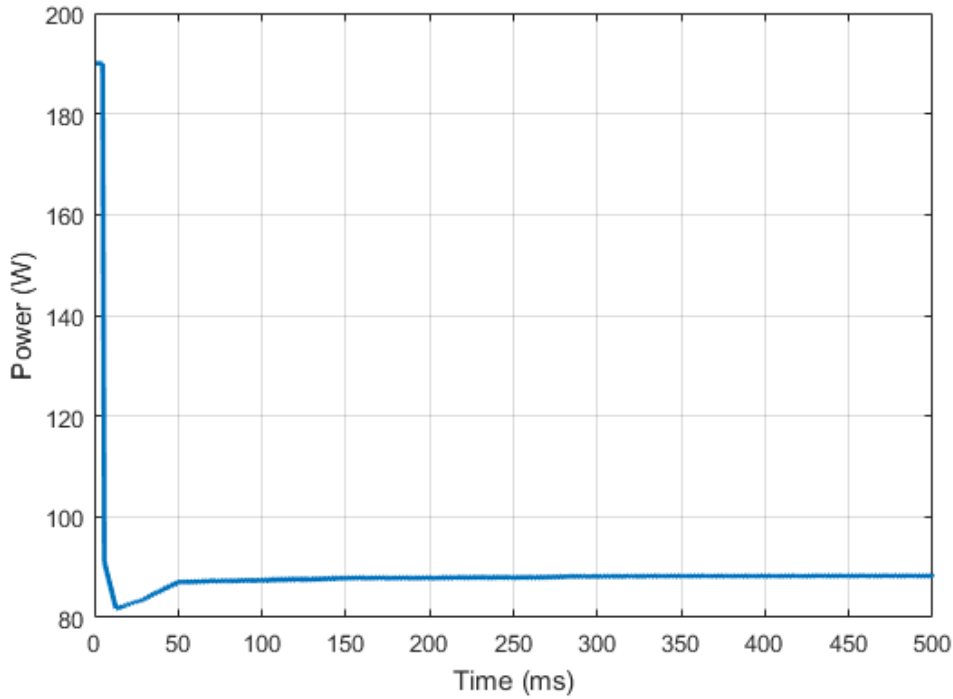


Figure 4.4: The effect of applying fluctuation reduction over the PA algorithm.

the threshold and the amount of allocated power is still below the maximum transmission power (P_{max}) (lines 6-9). By choosing a larger (Δ) value, the precision of the PA algorithm can reduce, but the algorithm will converge faster. BSs periodically communicate with MECs to adapt their transmission powers by any changes happen in the network condition. To decrease the convergence time in our algorithm because mainly large portion of UEs are located close to the BSs; at first, we reduce the power to the half then we run the algorithm to decrease the power adaptively based on UEs conditions (line 13). To reduce the fluctuation during power allocation, BSs maintain the history of last 10 power allocation to their associated UEs. In case, the amount of power allocated to a UE after power reduction for about (Δ) is not lower than the average of power which have been allocated to the UE in the last 10 time slots (P_{avg}) (line 12), BSs will allocate the same power as the previous step. In Figure. 4.4, we present the effect of applying fluctuation reduction (FR) over the proposed algorithm. As we can see, the overall power consumption in the network will converge after 50 *ms* and by applying FR over our algorithm; the power fluctuation is reduced.

Algorithm 2: The power adaptation algorithm.

```
1 Receive the threshold value from MEC
2 for All available RBs do
3    $P_{max} \leftarrow P_{max} = \frac{\text{Sector Maximum Downlink Power}}{\text{Number of Available RBs}}$ 
4    $P_{min} \leftarrow$  minimum applicable power per RB
5   if  $CQI \leq T_{CQI}$  then
6     while  $P \leq P_{max}$  and  $CQI < \text{Threshold}$  do
7        $P \leftarrow P + \Delta$ 
8        $CQI \leftarrow$  Request for a new CQI feedback
9     end
10  end
11  if  $CQI \geq T_{CQI}$  then
12    if  $P - \Delta \leq P_{avg}$  then
13       $P \leftarrow \frac{P}{2}$ 
14       $CQI \leftarrow$  Request for a new CQI feedback
15      while  $P \leq P_{min}$  and  $CQI < \text{Threshold}$  do
16         $P \leftarrow P - \Delta$ 
17         $CQI \leftarrow$  Request for a new CQI feedback
18      end
19    end
20  end
21 end
```

CHAPTER 5

RESULTS AND DISCUSSION

For the evaluation, we use the Vienna-LTE simulator which is a system level simulator to implement the downlink channel model and the network environment of a multi-user OFDMA system such as LTE [109]. In this simulator, collisions on the random-access channel and other parameters such as noise, interference, shadowing, fading, antenna size, BSs height, number of transceivers, angle of antennas, handover, channel model, traffic model, walking model are considered based on real-life LTE networks and applied in the proposed algorithm. We modified the power allocation model and developed our scheduling module in this simulator.

5.1 Simulation Models and Parameters

The scheduling algorithm is implemented for sparse and dense small cell scenarios to show its capabilities in dynamic networks. We simulate two different network scenarios:

- Sparse network: where the density of BSs varies between 5 to 20 BS/km², and 100 UEs are uniform randomly distributed in the region of interest.
- Dense network: the density of BSs varies between 20 to 100 BS/km², and 1000 UEs are uniform randomly distributed in the region of interest.

To provide a fair comparison among the BDPA algorithm, the LP-WUR [27] and the C-ICIC [28] are described in Section IV.D.1 and IV.D.2, respectively, we employed different types of bursty traffic loads in our simulation which are modeled based on

real-life LTE networks [1]. Simulation parameters and traffic models are summarized in Table 5.1 and Table 5.2, respectively.

Table 5.1: Simulation parameters and their values.

Parameters	Value	Ref
Frequency	2.14 GHz	[110]
K	6910 KM^{-1}	[104]
γ	4	[104]
N_0	$10^{-15.82}$	[104]
Subcarrier Frequency	15 kHz	[110]
Macro BSs Max Power	10 W	[110]
Small BSs Max Power	100 mW	[27]
Small BSs Sleep Power	15 mW	[27]
LP-WUR Power	$10 \mu\text{W}$	[27]
Transmission Time Interval	1 ms	
Simulation Area	$2000 \text{ m} \times 2000 \text{ m}$	
RRH Antenna Gain	Omni-directional	[111]
Path Loss Model	$128.1 + 37.6 \log_{10}^R$, R in km	[110]
Noise Power Spectral Density	-174 dBm/Hz	[110]
Receiver Noise Figure	9 dB	[110]
Density of BSs (BS/km ²)	5,10,15,20,35,50,75,100	
Active UEs	20,50,100,1000	
UE Speed	5,20,40 km/h	
Feedback	CQI	[111]
Feedback Delay	3 TTI	
Scheduler	Proportional Fair	
Number of Monte-Carlo Runs	30	
Simulation Length	100 TTI	

Table 5.2: Traffic types in OFDMA-based networks [1].

Traffic Type	Transmission Category	Traffic Load
FTP	Best effort	10%
HTTP	Interactive	20%
Video Stream	Streaming	20%
VoIP	Real-time	30%
Gaming	Interactive & real-time	20%

5.2 Vienna Simulator, Implementation Details

Vienna LTE system level simulator consists of different modules including antennas, channel models, network generation, schedulers, traffic models, walking models and etc. Each BS includes three sectors and in each sector, small cells are implemented. UEs and BSs are distributed uniform randomly in the region of interest. A wide variety of schedulers exist in this simulator such as best CQI, proportional fair, round robin, and max-min. All of these schedulers will be invoked through *lteScheduler.m* file. To make the BDPA algorithm applicable over different scheduling models, we implement our algorithm in the scheduler coordinator (*lteScheduler.m*) under the power allocation module. We also modify the traffic and the mobility models for different scenarios as explained in the sequel.

5.3 What's happening at MEC?

Our main aim is reducing the amount of energy consumption in the network by gathering information at the MEC to apply the BDPA algorithm. In MEC, by considering the density of BSs, the appropriate T_{SINR} and T_{CQI} values which can be used as the threshold value to maintain minimum throughput and coverage requirements in the network, needs to be obtained through (4.3).

In Figure. 5.1, the probability of coverage for various SINR thresholds is presented. We also examine three different BS densities (10, 50, 100 BS/km²) to show how

T_{SINR} can be changed under various conditions. As we can see, when the BS density is low (10 BS/km²), if we set T_{SINR} at -10 dB the probability of coverage will be around 57%. However, by increasing the density of BSs to 50 BS/km² and 100 BS/km², the probability of coverage will be boosted up to 98% and 100%, respectively. By evaluating Figure. 5.1 we can find out if BS density is very low, we may face with too much coverage holes which can degrade the QoS in the network. Moreover, by increasing the density of BSs the amount of received interference will also increase, but this improvement will be negligible when the BS density reaches to its optimum level. Therefore, we need to adapt density of BSs to the network condition to enhance QoS and prevent resource wastage in the network.

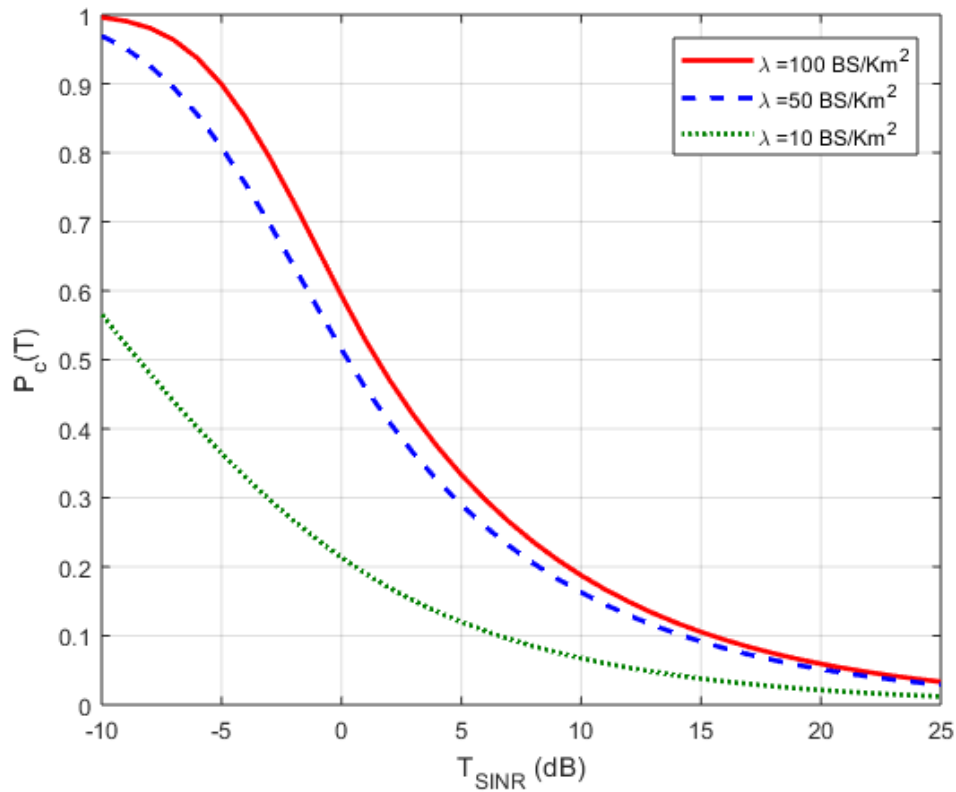


Figure 5.1: The probability of coverage for different SINR thresholds.

The SNIR threshold (T_{SINR}), which is found at the edge cloud will be used by the BDA algorithm and by employing the snapshot of the network condition, it has to be mapped to a CQI value since BSs characterize the channels' quality by using 4-bit CQI values. Therefore, by evaluating BLER in the network, the SINR value which

is obtained from the previous step can be mapped to its corresponding CQI level (Figure. 4.3) to achieve (T_{CQI}) which will be forwarded to BSs to be used in the PA algorithm. Therefore, the BDPA algorithm will be invoked to optimize the network resources when the corresponding information is received through MECs.

5.4 Validation of the BDPA Algorithm

We validate the BDPA algorithm in this section and compare it with the a sleep scheduling technique that we call as the LP-WUR technique which employs low-power wake-up receivers [27]. We also compare our results with a cooperative interference inter-cell control (C-ICIC) model which jointly allocates power and resource among UEs to enhance energy consumption and network throughput [28]. In the LP-WUR, density of BSs are adapted based on UEs request, while in the C-ICIC energy consumption will be optimized by collaboration of neighbor BSs with each other. Therefore, we can compare the effect optimizing energy consumption based on UEs request or collaboration of neighbor cells with a MEC based architecture (BDPA) in this thesis. We present its details in the sequel. We evaluate throughput, spectral efficiency, energy efficiency, and the impact of mobility and user density on the performance of the BDPA algorithm in this section.

5.5 LP-WUR Sleep Scheduling Technique

By equipping senders and receivers with wake-up receivers, an on-demand energy-efficient UE-controlled sleep scheduler is presented in [27] that we call as LP-WUR technique. For comparing the BDPA performance we implemented the LP-WUR technique in the Vienna simulator as well. Due to a low amount of power consumption in wake-up radio modules ($10 \mu\text{W}$ approximately), they can be always in the active mode to listen to channels. Therefore, the wake-up radio can trigger a BSs for transmission whenever a wake-up signal is successfully received and small cells can go to the sleep mode when the transmission is terminated. To implement LP-WUR, we trace communications among UEs and BSs and we examine energy consumption, throughput and spectral efficiency for this algorithm, whenever a packet is exchanged

between UEs and BSs.

5.6 Cooperative ICIC (C-ICIC) Technique

In this model, authors introduced C-ICIC technique which can enhance the received SINR and exploits communication channel by reducing the inter-cell interference (ICI) effect between adjacent BSs [28]. In the C-ICIC, UEs are classified into a bad radio (BR) group if they are negatively affected due to the ICI (by considering the amount of received wideband CQI feedback), while the rest of UEs will be classified as a good radio (GR). In the C-ICIC, satisfaction functions for UES, cells, sectors are defined. Then, resource blocks and power allocation are based on the satisfaction functions. C- ICIC is a distributed technique facilitating cooperation among adjacent cells.

5.7 Monte-Carlo Simulation Results

In this section, we present the quality of service, spectral efficiency, energy consumption results. We further evaluate the impact of user density and mobility.

5.8 Quality of Service (QoS)

As it is explained previously, QoS can be maintained when the minimum required throughput in each small cell (R_{ij}^*) can be satisfied. In this work, for increasing the system efficiency with respect to our opponents (LP-WUR and C-ICIC), we defined R_{ij}^* as the mean throughput which can be achieved in in LP-WUR and C-ICIC. In Figure. 5.2 and Figure. 5.3, we compare the mean throughput of the BDPA algorithm with the LP-WUR and the C-ICIC techniques in sparse and dense network scenarios, respectively. Throughput can be affected by increasing density of UEs and BSs in the network, due to higher transmission rates in the network. As we can see, when BS density is low (Figure. 5.2) the maximum achievable throughput by the BDPA, the LP-WUR and the C-ICIC algorithms are around 10 Mbps, 8.5 Mbps and 9 Mbps,

respectively. These values are boosted up to 15 *Mbps* and 11 *Mbps* when BS density is increased (Figure. 5.3). In both scenarios, we can achieve a higher network throughput in different conditions by employing the BDPA algorithm. Because, in the BPDA algorithm by considering the capacity of each cell and reducing the number of active BSs, the total amount of interference received by UEs will be reduced which increases channel quality and improves the overall network throughput. Moreover, unlike the C-ICIC, the BDPA by employing MEC in its architecture can have a higher perspective over the network which can maintain network coverage and adapt BSs density while transmission power is reduced. With the power adaptation feature of the BDPA algorithm, the received SINR for UEs located at the cell borders will be enhanced that improves the network throughput compared to the LP-WUR and the C-ICIC technique. The proposed algorithm can provide a larger network throughput in dense networks and can enhance QoS up to 26% in comparison to the LP-WUR and the C-ICIC techniques.

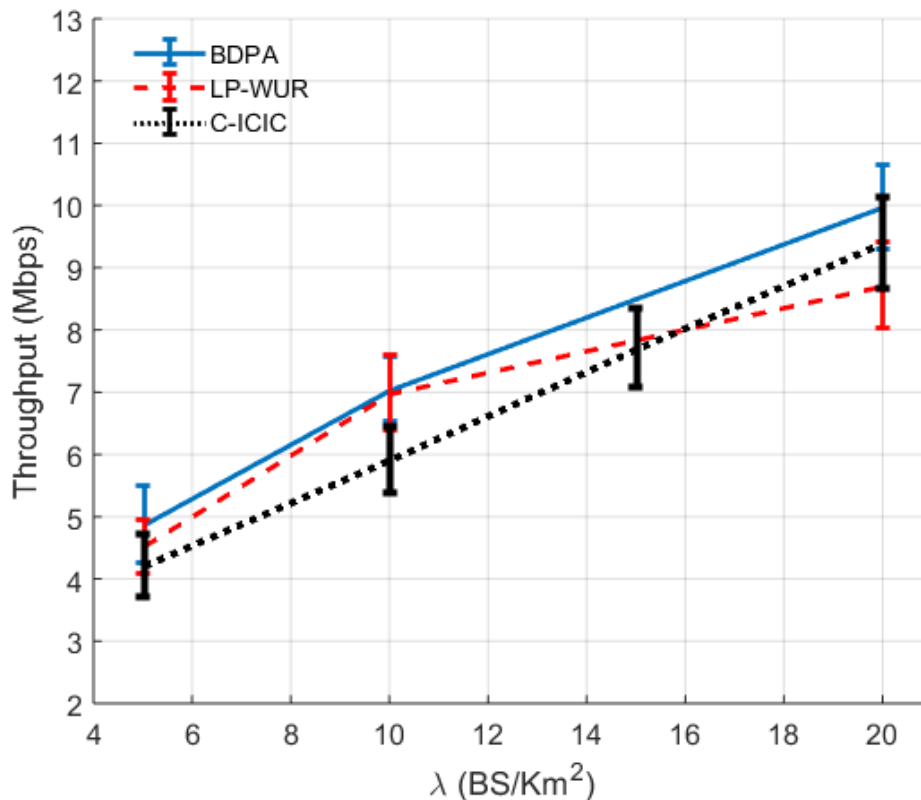


Figure 5.2: The effect of applying the BDPA algorithm on network throughput in a sparse network with 100 UEs for different BS densities.

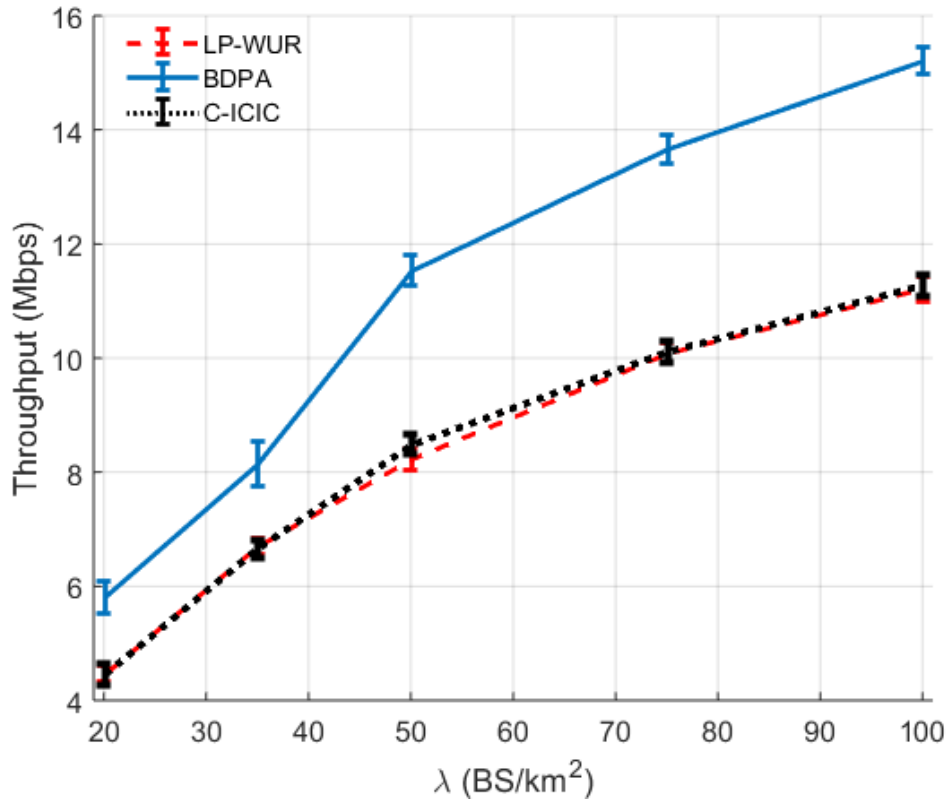


Figure 5.3: The effect of applying the BDPA algorithm on network throughput in a dense network with 1000 UEs for different BS densities.

5.9 Spectral Efficiency

We present the effect of applying the BDPA algorithm on the spectral efficiency in Figure. 5.4 and Figure. 5.5. Spectral efficiency can be enhanced by using a high order MCS which is possible when the interference in the network is low and the network has enough capacity to handle the traffic load. In both cases (sparse and dense) the spectral efficiency will reduce by increasing BS density due to the high amount of interference. The highest spectral efficiency in a sparse network for the BDPA, the LP-WUR and the C-ICIC are when BS density is 5 BS/km² (Figure. 5.4) and it is about 11 *bps/Hz*, 9 *bps/Hz* and 8.9 *bps/Hz*, respectively. Additionally, in the dense network (1000 UEs) the highest spectral efficiency for the BDPA, the LP-WUR and the C-ICIC can be achieved is when BS density is 20 BS/km² and it is about to 35 *bps/Hz*, 27 *bps/Hz* and 28 *bps/Hz*, respectively. Due to the larger number of deactivated

BSs by the BDPA algorithm (which can reduce the interference in the network), the average spectral efficiency per cell can be enhanced by 30%. The BDPA algorithm, by adapting density of BSs and distributing their load to other cells, can use resources more efficiently in comparison to the LP-WUR and the C-ICIC techniques. Although BSs are only activated whenever UEs request in the LP-WUR technique, they can be activated with even a single UE request. Therefore, the LP-WUR technique cannot use resources efficiently and spectral efficiency will always be lower than that of the BDPA algorithm. The C-ICIC adjusts transmit power in two levels based on UEs class (BR and GR) while in the BDPA, power can be adjusted at different levels based UEs condition which can distribute power among UEs more efficiently. Therefore, the BDPA can provide higher throughput and spectral efficiency with respect to the C-ICIC.

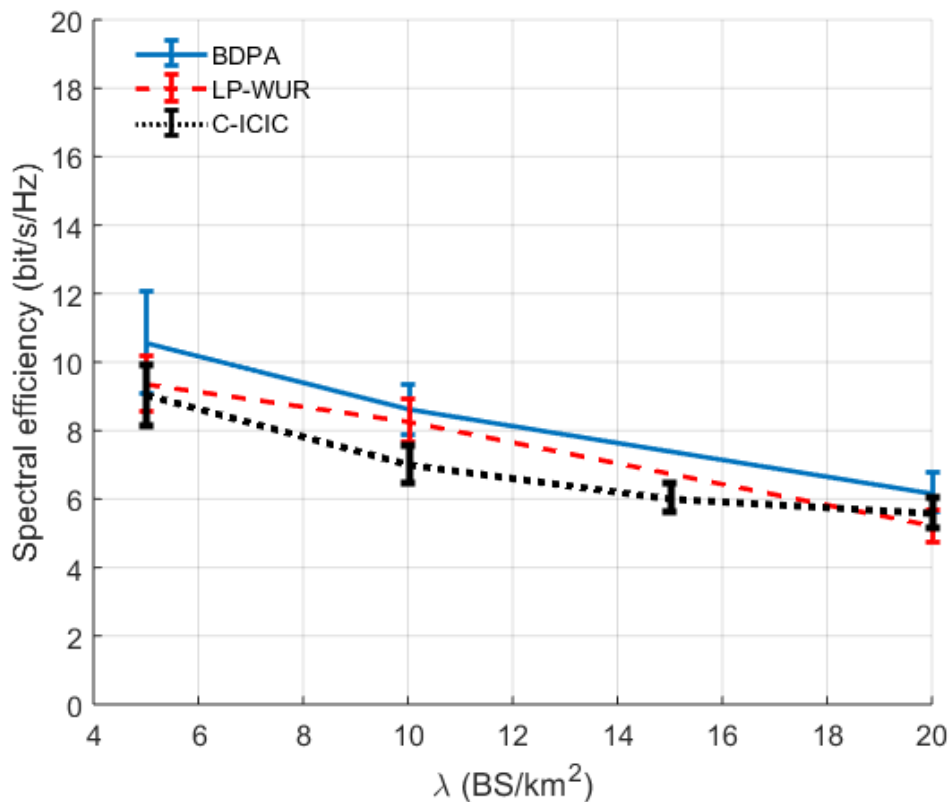


Figure 5.4: The effect of applying the BDPA algorithm in a sparse network with 100 UEs on spectral efficiency for different BSs' densities.

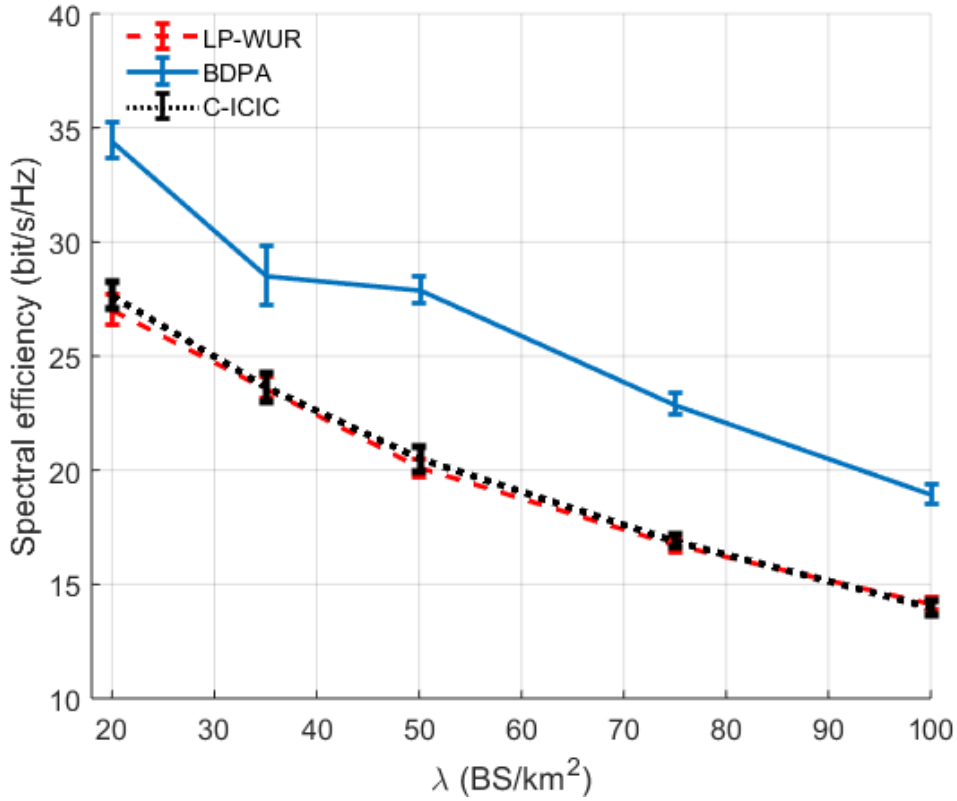


Figure 5.5: The effect of applying the BDPA algorithm in a dense network with 1000 UEs on spectral efficiency for for different BSs' densities.

5.10 Energy Consumption

To evaluate the energy efficiency of the BDPA algorithm, we analyze the amount of energy consumption for different numbers of UEs and BSs in Figure. 5.6 and Figure. 5.7. As it is shown, by increasing BS density the amount of energy consumption in both scenarios will increase. When the network is sparse (Figure. 5.6) and BS density is 20 BS/km², the BDPA, LP-WUR and C-ICIC algorithms consume almost same amount of power for about 12000 W; while, the overall power consumption in the dense scenario (Figure. 5.7) will increase up to 13400 W, 14100 W and 13600 W, respectively when BS density is 100 BS/km². In all cases, the highest amount of energy is conserved in the BDPA algorithm due to the low number of active BSs during each transmission in comparison with [27] and [28]. As we can see in these figures, by adapting MCS in the network based on our power adaptation model and

offloading BSs, we can always achieve less energy consumption in comparison to the LP-WUR and the C-ICIC techniques. The BDPA algorithm can conserve a higher amount of energy in dense networks and can save up to 5% more energy with respect to the LP-WUR technique which means 3 kW per second or 98.55 Tera-Watt per year. The amount of energy conservation will be larger in ultra-dense networks.

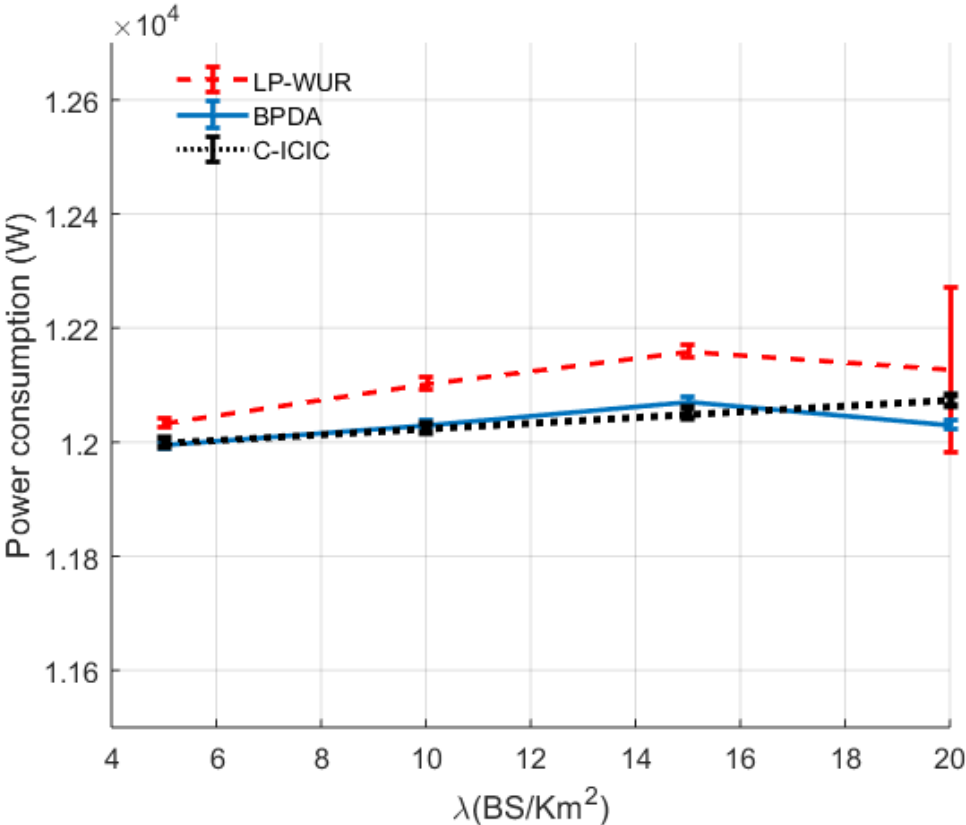


Figure 5.6: The effect of applying the BDPA algorithm on energy consumption in a sparse network with 100 UEs and bursty traffic for different BSs' densities.

Moreover, in the LP-WUR technique, when we have a continuous traffic load all BSs need to be in the active mode to provide service for their associated UEs. However, in the BDPA algorithm, network resources will be used in an efficient manner by offloading the traffic of low-load BSs to neighboring cells and deactivating them to conserve more energy. As we can see in Figure. 5.8, the proposed algorithm can conserve up to 12% more energy when the traffic load is high.

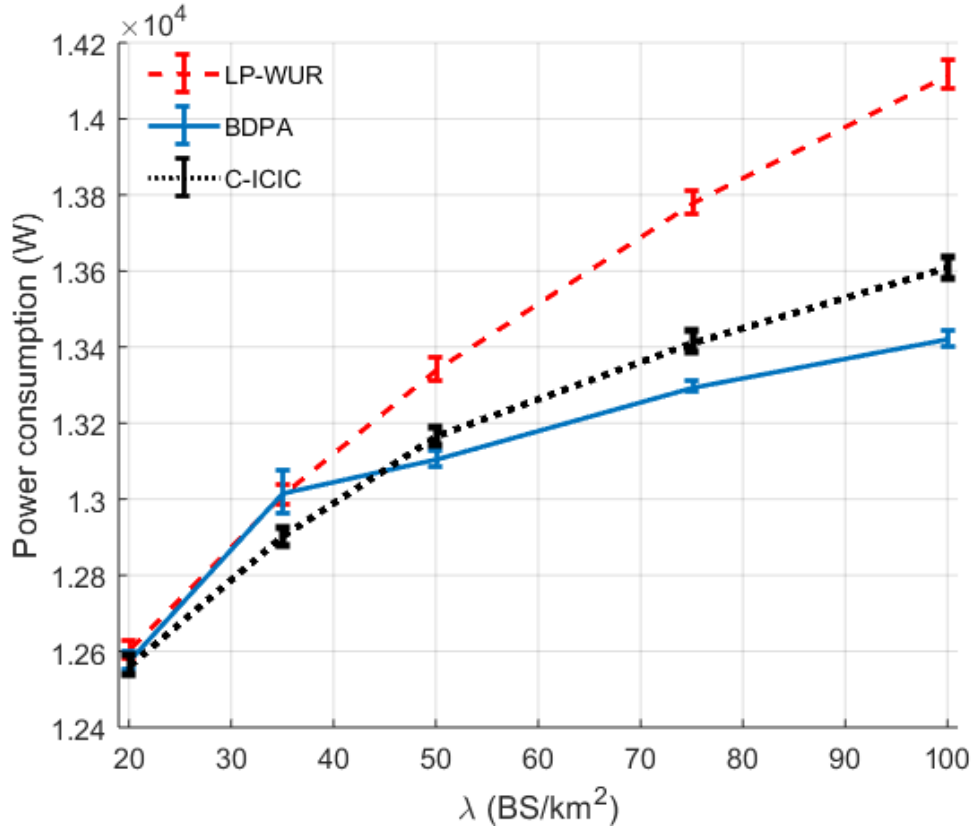


Figure 5.7: The effect of applying the BDPA algorithm on energy consumption in a dense network with 1000 UEs and bursty traffic for different BSs' densities.

5.11 User Density

In dynamic networks, in addition of variation in density of BSs, UE density will also vary in a day. By keeping the density of BSs constant ($50 \text{ BS}/\text{km}^2$), we evaluate the effect of UE density on throughput, spectral efficiency and power consumption in Figure. 5.9, Figure. 5.10 and Figure. 5.11, respectively. As we can see, in all of these cases, the BDPA algorithm can achieve higher performance in comparison to the LP-WUR and the C-ICIC techniques. When the density of UEs are low, they have almost the same performance. As we can see, by increasing UE population, the BDPA algorithm produces better results. In the BDPA algorithm, to satisfy UE constraints such as throughput, when UE density is low and based on the UEs locations we may need to keep more BSs in the active mode in comparison to the LP-WUR and the C-ICIC technique. However, by increasing UEs' density the amount of data transmission will

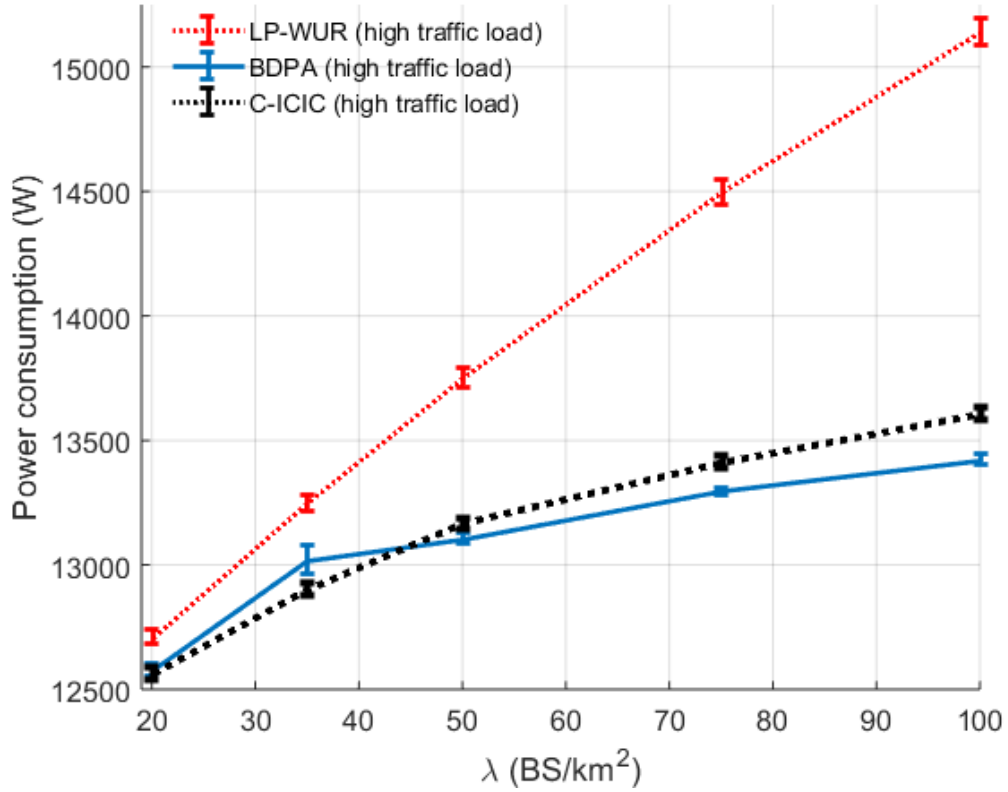


Figure 5.8: The effect of applying the BDPA algorithm on energy consumption in a dense network when traffic load is high for different BS density.

also increase, and LP-WUR needs to turn on and off BSs more frequently. At this point, the BDPA can be more efficient by distributing load among cells and deactivating redundant BSs. Moreover, in BDPA by enhancing $SINR$ (4.2), we can enhance the received interference by UEs more accurately with respect to the C-ICIC. Therefore, the overall throughput and spectral efficiency will be enhanced while the energy consumption can be maintained in comparison with the C-ICIC.

5.12 Mobility

To provide a real-life condition in our simulation, the mobility of UEs for different speeds are also considered. The density of UEs and density of BSs are 100 and 20 BS/km^2 , respectively and we evaluate 3 different speeds for UEs (5 km/h , 20 km/h and 40 km/h) to simulate pedestrians, cyclists and drivers in our analysis. As

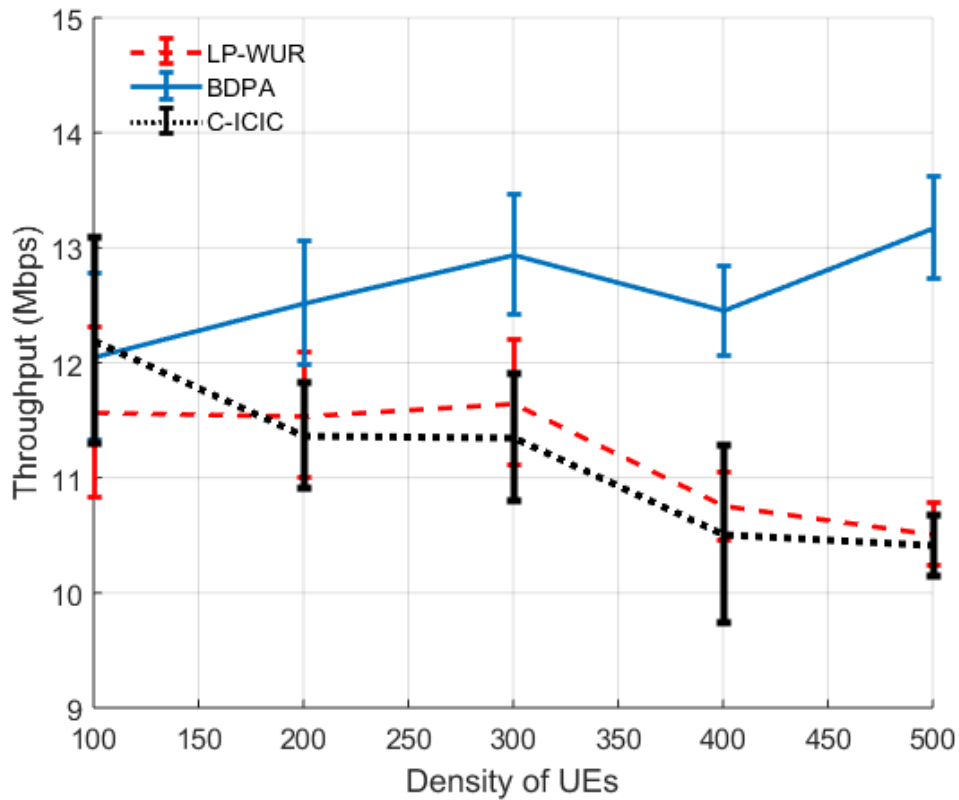


Figure 5.9: The effect of applying the BDPA algorithm on network throughput when density of BSs is fixed at $50 \text{ BS}/\text{km}^2$ and UEs' density is varied between 100 to 500.

it is shown in Figure. 5.12, the proposed algorithm can achieve a higher network throughput in all cases compared to the LP-WUR and the C-ICIC techniques. The main reason that BDPA can perform better is equipping BDPA with MEC and providing higher perspective over network state in comparison with the LP-WUR and the C-ICIC techniques. Therefore, the BDPA algorithm can predict faster and more accurate when a BS needs to be turned off or vice versa.

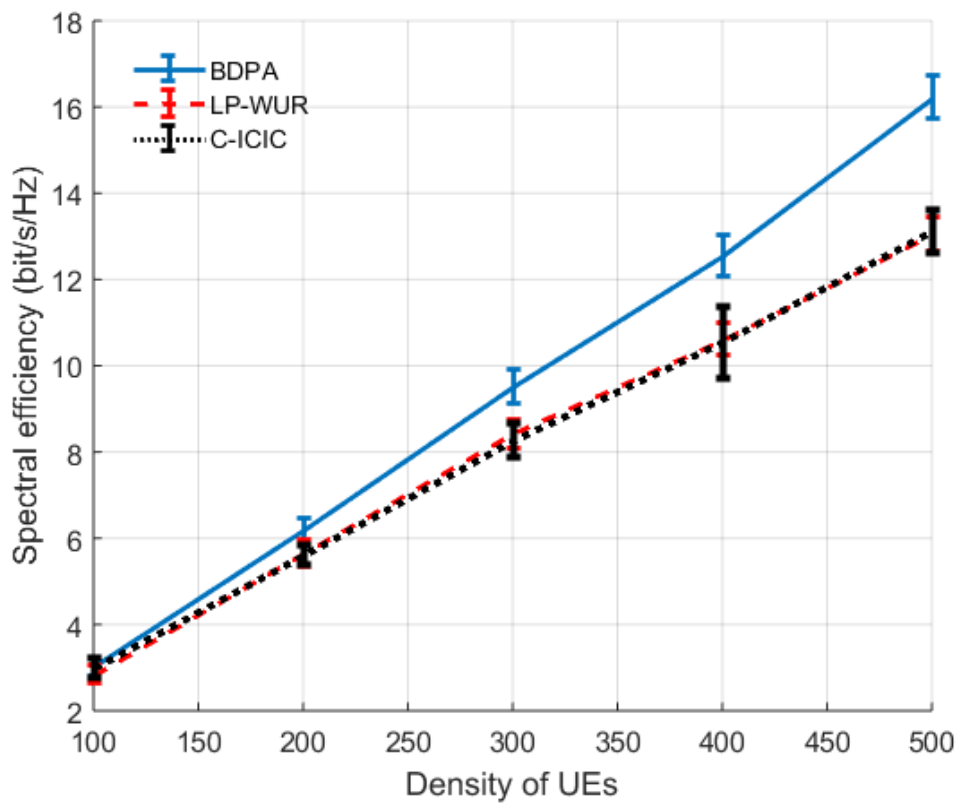


Figure 5.10: The effect of applying the BDPA algorithm on spectral efficiency when density of BSs is fixed at $50 \text{ BS}/\text{km}^2$ and UEs' density is varied between 100 to 500.

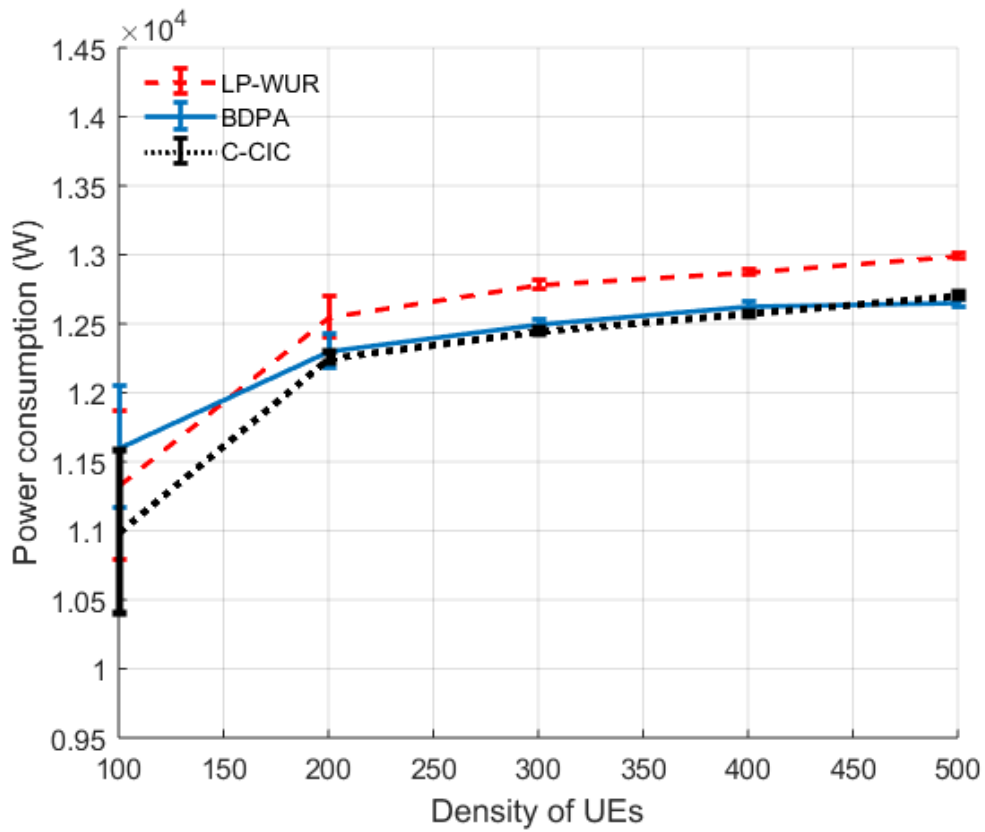


Figure 5.11: The effect of applying the BDPA algorithm on power consumption when density of BSs is fixed at $50 \text{ BS}/\text{km}^2$ and UEs' density is varied between 100 to 500.

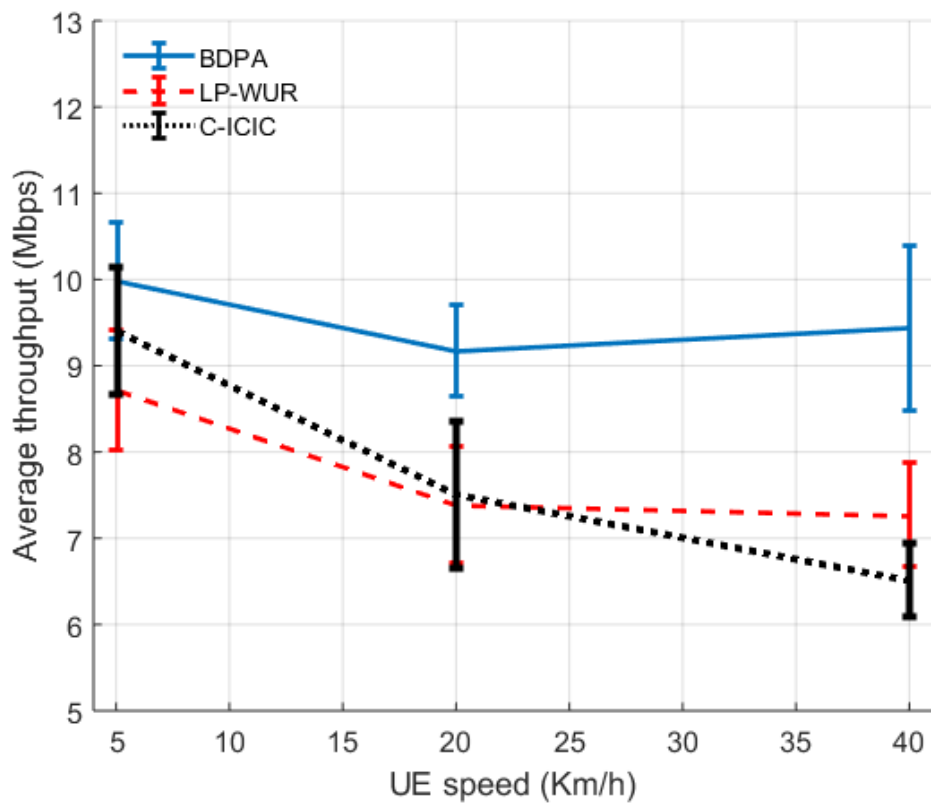


Figure 5.12: The effect of applying proposed algorithm on network throughput in a sparse network with 100 UEs for varied velocities.

CHAPTER 6

CONCLUSION AND FUTURE WORK

6.1 Conclusion

With the invent of mobile BSs such as drone cells, not only the user's devices but also the elements in the infrastructure of the network has also become mobile introducing many novel and not-addressed challenges. A flexible and density-adaptive mobile communications architecture is required. However, there is a big research gap between the state of the art and the ambition of achieving a self-organized, adaptive and flexible networking architecture. The existing architectures have severe limitations and shortages to be able to address the presented paradigm changes. We stress in this thesis that density-aware and –adaptive networking is crucial in future networks by presenting a qualitative and quantitative analysis of the impact of density on network performance. In this thesis, we proposed a density-aware, energy-efficient and spectrum-efficient sleep scheduling technique by applying two heuristic algorithms to conserve energy and enhance the quality of service including users' throughput and satisfying the required network coverage simultaneously in a heterogeneous network. Base station density is adapted by considering cell capacities and by balancing traffic load among cells. We prevent coverage holes and enhance network throughput by applying a cell-zooming technique and improving signal-to-interference-plus-noise ratio for users located at cells borders. We provide higher processing power and higher perspective over the network state in comparison to individual base stations by equipping the network with multi-access edge cloud. The proposed model is examined with a system level simulator to provide reliable results. All in all, we find out future networks can become smarter and more efficient if we consider BS density in our models and adapt it to the network condition.

6.2 Future Work

We experience a major paradigm shift in mobile networks. The infrastructure of cellular networks becomes mobile as it is densified by using mobile and nomadic small cells to increase coverage and capacity. Furthermore, the innovative approaches such as green operation through sleep scheduling, user-controlled small cells, and end-to-end slicing will make the network highly dynamic and density of dynamic networks may vary in time and space from sparse to dense or vice versa. Therefore, providing density adaptive solutions in different scenarios such as tactile operations, mobility management, interference management, distributed and collaborative caching models, etc. is necessary for future wireless networks. This work can be extended by providing a multi-objective model with considering its lower bound in order to achieve close-to-optimum solutions. Furthermore, the effect of the mobility of base stations by considering dynamic interference models and evaluation of heterogeneous networks over the network performance can be evaluated in future work. Moreover, in the next generation of mobile network, dynamic downlink and uplink symbol allocation for asymmetry traffic will be supported and it is called as flexible time division duplex (TDD). Although this feature can provide a highly flexible air interface for the 5G network, it can cause inter-cell cross-link interference as well. Therefore, providing a flexible interference management model for flexible TDD and including its effect in the future optimization models will be vital.

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CURRICULUM VITAE

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EDUCATION

Middle East Technical University, Turkey *Feb 2014 - Present*
PhD. Candidate, Graduate Research Assistant
Department of Computer Engineering
CGPA: 3.93

Eastern Mediterranean University, Cyprus *Feb 2011 - Sep 2013*
MSc
Department of Computer Engineering
CGPA 4.00

ACADEMIC PROJECTS AND RESEARCH EXPERIENCE

- Energy optimization and enhancing QoS in 5G networks.
- Evaluation of Terahertz band in data centers.
- Evaluation of 5G test-beds.
- Analyzing of Circuit switch models, Traffic models, Queuing networks and effective bandwidth calculation.
- Developing a desktop search engine.

- Passing Microsoft Certified Solutions Associate (MCSA) courses at Tehran Institute of Technology.
- Achieving official Certified Network Associate (CCNA) certificate (09.2013)

TECHNICAL STRENGTHS

Engineering/Math software:	MATLAB, CODE VISION, ACTIVE-HDL, PROTEUS, Glomosim, NS2, NS3, MININET, Vienna LTE, Vienna 5G
Programming Languages:	VC++, JAVA, PYTHON
LTE implementations:	srsLTE, OAI, OpenLTE, NextEPC, tinyLTE

WORK EXPERIENCE

- ULAK- *03/2019 - Present* (5G network developer)
 - Developing 5G network stack.
 - Implementing different 5G scenarios by using NS3.
 - Studying Mobile BSs and analyzing networks behaviour in 5G.
 - Optimizing MAC layer and resource allocation models in 5G.
- LNL Technology- *01/2019 - Present* (5G network developer)
 - Working with OAI, srsLTE, OpenLTE, NextEPC and other open source LTE and 5G stack implementations.
 - Working with USRP, BladeRF, ZedBoard, Xilinx zc702 and Analog Devices boards such as FMCOMMS5.
 - Developing LTE stack over ARM processors.
- TUBITAK 1001 project under the grant number 215E127 (Density-adaptive Wireless Networks (DAWN))- *05/2016 - 11/2018* (Graduate Research Assistant)
 - Evaluating the effect of BSs' density over network parameters in future networks.

- Providing density-adaptive solution for dynamic networks in order to enhance spectral efficiency and energy conservation.
- Prepared a survey paper about the BS mobility and its effect over network parameters such as bandwidth, coverage, interference and QoS in the network.
- Evaluating available testbeds in 5G networks and publish it as a book chapter.
- ANP- 05/2009 - 02/2011 (Data Center Management)
 - Working in two well-known Iranian banks data centers
 - Monitoring and evaluating server conditions
 - Completely familiar with power generators, UPS systems, and cooling systems to maintain data centers condition close to optimum level.

ACADEMIC ACHIEVEMENTS

- Tuition fee waiver scholarship by Middle East Technical University(METU) because of my high CGPA in the computer engineering department.
- Student research assistant at Middle East Technical University (METU).
- Member of WIreless Systems, Networks and Cybersecurity (WINS) Lab.
- Winning a grant for participating at ESoA-IRACON course about Large-Scale Radio Propagation in Belgium (June 2017).

PUBLICATIONS

- S.Mollahasani and E.Onur, "Density-Aware, Energy- and Spectrum-Efficient Small Cell Scheduling", IEEE Access, vol. 7, pp. 65852-65869, 2019
- S.Mollahasani and E.Onur, "Density-aware power allocation in mobile networks using edge computing," in Proc. of the 26th Signal Processing and Communications Applications Conference (SIU 2018), pp. 1-4 Izmir Turkey, 2018

- M.Çalik, S.Mollahasani and E.Onur, “Density-aware Joint Optimization of Cell Scheduling and User Association” in 16th IEEE/WCNC workshop on flexible and agile networks (Invited paper-FLEXNETS 2018)
- S.Mollahasani, A.Eroğlu, O.Yamaç and E.Onur, “Simulators, Test Beds and Prototypes of 5G mobile Networking Architectures” book chapter in Networks of the Future: Architectures, Technologies, and Implementations, CRC press, October, 2017
- S.Mollahasani and E.Onur, “Evaluation of Terahertz Channel in Data Centers” in Proc. of the IEEE/IFIP Network Operations and Management Symposium, NOMS, pp.727-730 Istanbul, Turkey, April, 2016
- S.Mollahasani and M.Salamah, “Decentralized LEACH Routing Algorithm for Wireless Sensor Networks” in 3rd global conference on computer science, software, network and engineering (COMENG 2015)