Energy Efficiency in Wireless Communication

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Doctor of Philosophy

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Declaration

I certify that except where due acknowledgement has been made, the work is that of the author alone; the work has not been submitted previously, in whole or in part, to qualify for any other academic award; the content of the thesis is the result of work which has been carried out since the official commencement date of the approved research program; any editorial work, paid or unpaid, carried out by a third party is acknowledged; and, ethics procedures and guidelines have been followed. I acknowledge the support I have received for my research through the provision of an Australian Government Research Training Program Scholarship.

Nahina Islam

May 2017

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Contents

List of Figures

List of Tables

Extended Abstract

This era would probably be recognized as the information age, hence as a paramount milestone in the progress of mankind, by the future historians. One of the most significant achievements of this age is, making it possible to transmit and receive information effectively and reliably via wireless radio technology. The demand of wireless communication is increasing in a never-resting pace, imposing bigger challenge not only on service providers but also on innovators and researches to innovate out-of-the-box technologies. These challenges include faster data communication over seamless, reliable and cost effective wireless networks, utilizing the limited physical radio resources as well as considering the environmental impact caused by the increasing energy consumption. The ever-expanding wireless communication infrastructure is withdrawing higher energy than ever, raising the need for finding more efficient systems. The challenge of developing efficient wireless systems can be addressed on several levels, starting from device electronics, up to the network-level architecture and protocols. The anticipated gains of achieving such efficiency is the key feature of extending mobile devices' battery life and reducing environmental and economic impacts of wireless communication infrastructure. Therefore energy efficient designs are urgently needed from both environmental and economic aspects of wireless networks. In this research, we explore the field of energy efficiency in MAC and Physical layers of wireless networks in order to enhance the performance and reliability of future wireless networks as well as to reduce its environmental footprint.

In the first part of this research, we analyse the energy efficiency of two mostly used modulation techniques, namely MQAM and MFSK, for short range wireless transmissions, up to a few 100s of meters, and propose optimum rate adaptation to minimize the energy dissipation during transmissions. Energy consumed for transmitting the data over a distance to maintain a prescribed error probability together with the circuit energy have been considered in our work. We provide novel results for optimal rate adaptation for improved energy efficiency. Our results indicate that the energy efficiency can be significantly improved by performing optimal rate adaptation

given the radio and channel parameters, and furthermore we identify the maximum distance where optimal rate adaptation can be performed beyond which the optimum rate then becomes the same as the minimum data rate.

In the second part of this research, we propose energy efficient algorithm for cellular base stations. In cellular networks, the base stations are the most energy consuming parts, which consume approximately $60-80\%$ of the total energy. Hence control and optimization of energy consumption at base stations should be at the heart of any green radio engineering scheme. Sleep mode implementation in base stations has proven to be a very good approach for the energy efficiency of cellular BSs. Therefore, we have proposed a novel strategy for improving energy efficiency on ternary state transceivers for cellular BSs. We consider transceivers that are capable of switching between sleep, stand-by and active modes whenever required. We have modelled these ternary state transceivers as a three-state Markov model and have presented an algorithm based on Markov model to intelligently switch among the states of the transceivers based on the offered traffic whilst maintaining a prescribed minimum rate per user. We consider a typical macro BS with state changeable transceivers and our results show that it is possible to improve the energy efficiency of the BS by approximately 40% using the proposed MDP based algorithm.

In the third part of this research, we propose energy efficient algorithm for aerial base stations. Recently aerial base stations are investigated to provide wireless coverage to terrestrial radio terminals. The advantages of using aerial platforms in providing wireless coverage are many including larger coverage in remote areas, better line-of-sight conditions etc. Energy is a scarce resource for aerial base stations, hence the wise management of energy is quite beneficial for the aerial network. In this context, we study the means of reducing the total energy consumption by designing and implementing an energy efficient aerial base station. Sleep mode implementation in base stations (BSs) has proven to be a very good approach for improving the energy efficiency; therefore we propose a novel strategy for further improving energy efficiency by considering ternary state transceivers of aerial base stations. Using the three state model we propose a Markovian Decision process (MDP) based algorithm to switch between the states for improving the energy efficiency of the aerial base station. The MDP based approach intelligently switches between the states of the transceivers based on the offered traffic whilst maintaining a prescribed minimum channel rate per user. Our simulation results show that there is a around 40% gain in the energy efficiency when using our proposed MDP algorithm together with the three-state transceiver model for the base station compared to the always active mode. We have also shown the energy-delay trade-off in order to design an efficient aerial base station.

In the final part of our work, we propose a novel energy efficient handover algorithm, based on Markov decision process (MDP) for the two-tier LTE network, towards reducing power transmissions at the mobile terminal side. The proposed policy is LTE backward-compatible, as it can be employed by suitably adapting a prescribed SNR target and standard LTE measurements. Simulation results reveal that compared to the widely adopted policy based on strongest cell and another energy efficient policy, our proposed policy can greatly reduce the power consumption at the LTE mobile terminals.

Most of our works presented in this dissertation has been published in conference proceeding and some of them are currently undergoing a review process for journals. These publications will be highlighted and identified at the end of the first chapter of this dissertation.

Chapter 1

Introduction

The rapid growth in the cellular networks has increased the number of subscribers and consequently has increased the demand for cellular traffic during the past few years. Forecasts related to the enormous development of the telecommunication industry indicates that data rate per subscriber will witness a substantial increase. An undesirable consequence is the growth of the energy consumption of the networks that leads to increasing carbon dioxide (CO_2) emission worldwide along with an increase in the operational costs for operators. This aspect has triggered the requirement of more innovations in the field of energy-efficient communications. Under this circumstance, an imperative role is played by energy efficient wireless networks in promoting the minimization of global warming and its negative influence. Hence, energy efficiency has become a key issue for the cellular and wireless networks due to the huge requirement of energy for designing and operating 2G, 3G/3G+ as well as Long Term Evolution (LTE) and LTE-Advanced systems. On the other hand, the techniques related to energy efficient networks should not impact the service quality that is perceived by the customer of the network. It is a major challenge to be able to reduce the energy consumption along with the maintenance of good service quality. It is also identified in different reports that the energy consumption of cellular wireless networks' infrastructure, the internet, and wired communication networks consume up to 3% of electric energy consumption throughout the world [11] and is expected to increase rapidly in future. Researchers in [1] have presented this prediction as in

Fig.1-1 where we can see that the electricity usage in communication technology is expected to grow by more than 3 times within 3 decades. This figure also indicates that this growth can be minimized by taking proper action, this assumption is presented as best case in the figure. On the other hand, the worst case line indicates that the electricity consumption can grow upto 10 times if proper action is not taken. As an important part of information and communication technology (ICT), wireless communications are accountable for energy saving. Furthermore, mobile terminals in wireless systems requires more energy saving since the development of battery technology is much slower compared with the increasing rate of energy consumption. Therefore, pursuing high energy efficiency (EE) is the most demanding trend for the design of future wireless communications. During the past decades, much effort has been taken to enhance network throughput. Different network deployments have been well investigated to improve area spectral efficiency (ASE), such as optimization of the number of BSs in cellular networks and the placement of relay nodes in relay systems. Various resource allocation schemes have been proposed to assure quality-of-service (QoS) of each user and fairness among different users by exploiting multiuser diversity. Different advanced communication techniques, such as multiple-input multiple output (MIMO) techniques, orthogonal frequency division multiple access (OFDMA) and relay transmission, have been used extensively in wireless networks to provide high spectral efficiency (SE). However, high network throughput usually possesses a high level of energy consumption, which is sometimes not affordable for energy-limited devices or energy-aware networks. Hence, it is a very important task to investigate the approaches related to the reduction of energy consumption while achieving the requirement of throughput in such devices and networks.

Fig.1-2 shows all the network components of a typical mobile cellular network., which consists of the following three main components:

- The core network, which takes care of switching,
- Base stations, which are responsible for providing radio frequency interface, and
- Mobile terminals, which are used to make calls or to send or receive data.

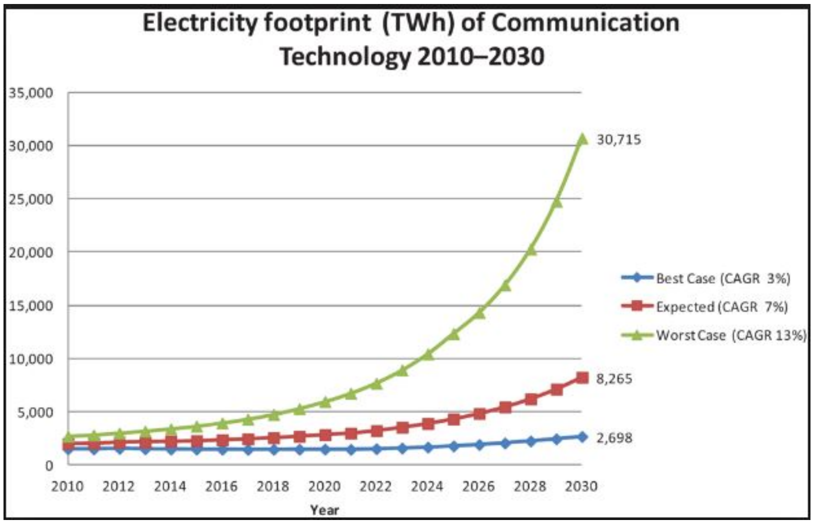

Figure 1-1: Expected Electricity footprint (TWh) of communication technology 2010-2030 [source: [1]].

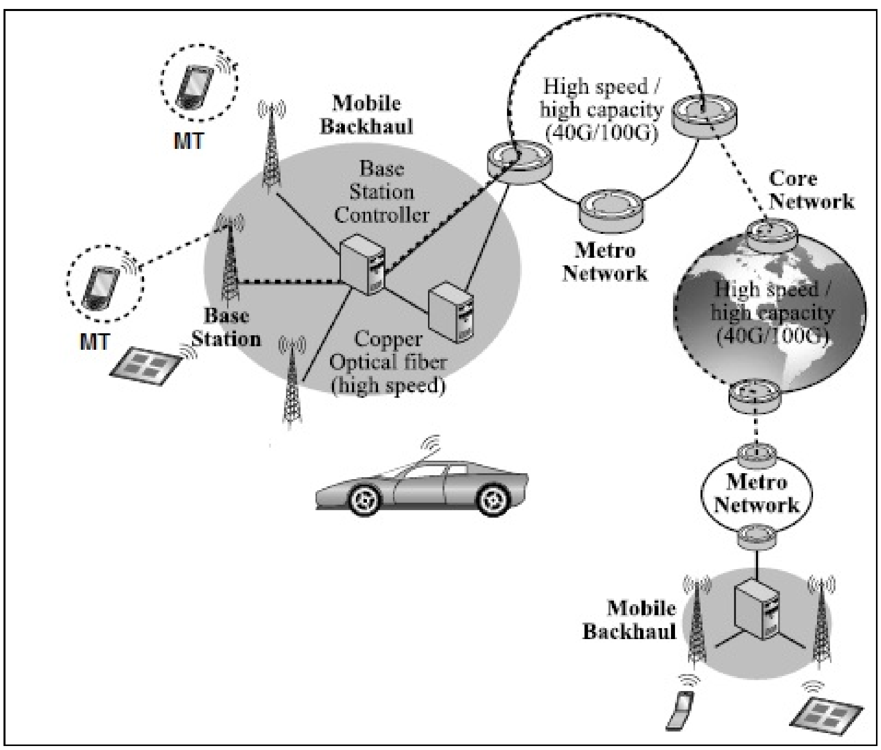

Figure 1-2: A typical wireless network [source: [2], modified].

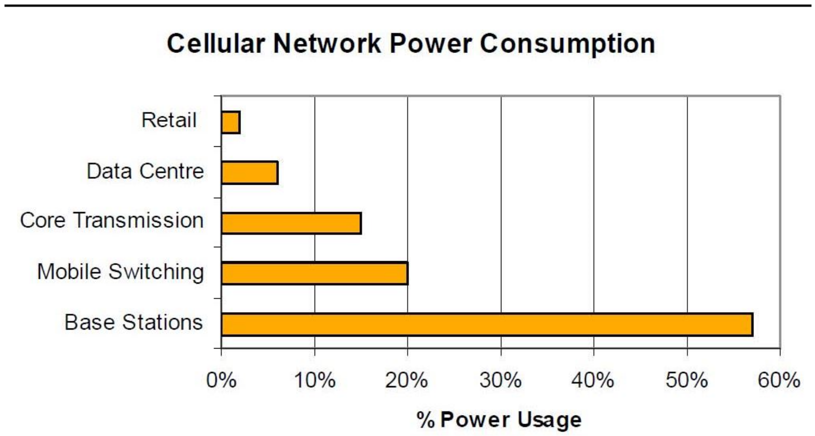

Figure 1-3: Cellular network power consumption [source: [3]] .

It is clear from Fig.1-3 that, reducing energy consumption in the BS will lead to significant improvement in energy efficiency of the network since BSs are the major source of energy consumption of wireless cellular networks. Several studies have also shown that the enegry consumption of the mobile terminal is much lower than that of the BS, making the latter a major focus of research [5].

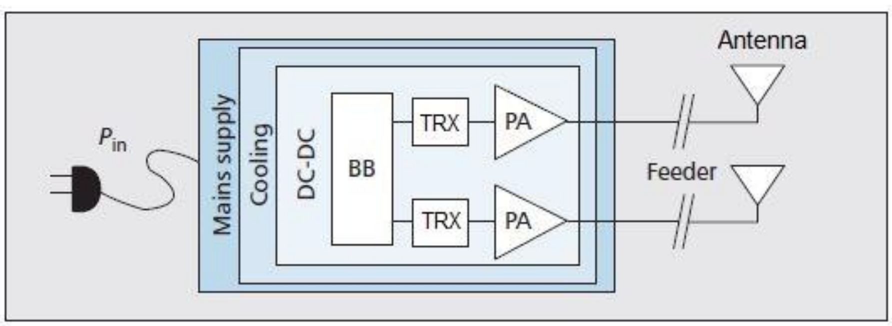

Figure 1-4: BS architecture [source: [4]]

The BS of a wireless cellular network typically consists of the following components as shown in Fig.1-4:

Radio transceivers (TRXs) TRXs transmit and receive signals to and from mobile terminals.

Power amplifiers (PAs) PAs amplify the signals from the transceiver to a power level high enough for transmission, which is typically around 510 W [5].

Antennas The antennas are responsible to radiat the signals. These antennas are typically directional to deliver the signal to the target receiver without radiating the signal into the ground or the sky.

1.1 Metrics for Energy Efficiency Measurement

An appropriate and meaningful metric plays a very important role in identifying the gain achieved by implementing energy efficient strategies in wireless cellular networks. The two most important and vasty used metrics for EE comparison are the energy consumption gain (ECG) and energy consumption rating (ECR) [12]. ECG is usually used to compare the energy consumption of two different strategies. It is defined as the ration of energy consumption of the strategy under test and that of the baseline strategy [12]. Whereas, ECR is used to measure the energy consumption per information bit that is successfully transmitted over the network. It is measured in joules per bit [12]. The EE metrics at the equipment level and the component level are fairly straightforward to define. However, the metrics at a system level or network level are more challenging to define. Moreover, EE metrics should also include the QoS requirements (such as spectral efficiency, transmission delay etc.) so that the efficiency of the strategy is correctly assessed.

1.2 Trade-offs of Energy Efficiency

Implementing the energy efficient algorithm in a communication systems involves some costs or trade-off in the network. Some of the major trade-offs of energy efficient design are presented in the following subsections.

1.2.1 Bandwidth/Power Trade Off for Reliable Communications

The two most important resource utilization metrics for a digital modulation scheme are listed below:

Power efficiency: Power efficiency relates to the ability to transmit data with a given bit/symbol error probability at a minimum received power level. The received power is usually measured in terms of the Signal to Noise Ratio (SNR), which is ratio of the received energy per bit (E_b) and the noise power spectral density (N_o). SNR is usually expressed as $\frac{E_b}{N_o}$.

Spectral efficiency: Spectral efficiency, also known as bandwidth efficiency, relates to the ability to transmit a given amount of data per unit time (second) within a minimum bandwidth. The spectral efficiency or bandwidth efficiency is usually expressed by and is presented as the ratio of the data rate and the bandwidth required for the transmission.

Authors in [5] has shown the trade-off between power efficiency and bandwidth efficiency for different modulation schemes such as M-PSK, M-FSK and M-QAM. They have also justified that, the orhtogonal frequency division multiplexing (OFDM) is a spectrally efficient transmission scheme, whereas it's high Peak-to-Average Power Ratio (PAPR) level makes it less power efficient.

Another vastly used energy efficient approach is the use of error correction coding, which increases the power efficiency of the transmission scheme at the cost of a degraded bandwidth efficiency.

1.2.2 Power Amplifier Efficiency Vs Linearity

In a wireless communication system, Power Amplifiers (PAs) are used to increase the power level of the transmit signal so that the corresponding received signal can be demodulated by the receiver under an error probability constraint. Linearity and Efficiency are the two main characteristics of PAs. The former one, linearity of the response of a PA is a very crucial factor for wireless communication, this is because the distortion of the response increases the required signal to noise ratio (SNR) to meet a certain error rate requirement and an irreducible error floor. On the other hand, efficiency of a PA is the known as the drain efficiency, which is defined as the ratio of the output RF power to the input DC power. Hence, it provides an estimation of how much DC power is converted to RF power. High efficiency of the PAs are desired to minimize the energy consumptiona and the thermal dispersion needs. PAs can be classified into variuos classes depending on the efficiency level, such as class A, B, C, etc.

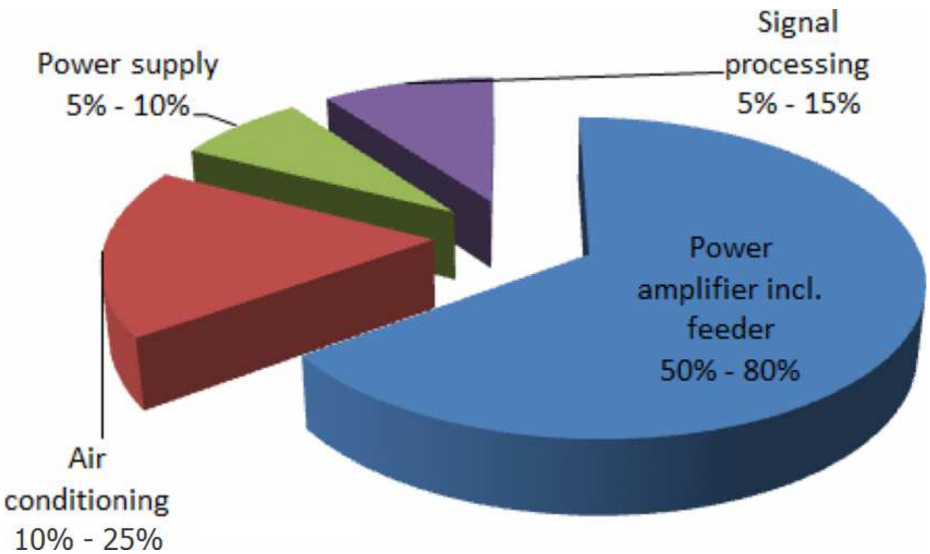

Figure 1-5: Power consumption distribution of a BS [source: [5]].

Fig.1-5 shows the power consumption distribution of a BS and depicts that PA consumes the maximum amount of power, which is around $50\% - 80\%$ of the total energy consumption of the BS [5]. Therefore highly efficient PAs are very important for green communication. However, high linearity and high efficiency are two conflicting requirements of PAs. In fact, no device or system can provide linearity in terms of constant gain if they are powered by a limited power supply. Therefore, in order to get linearity of a PA, there must be a direct relationship between the supplied power and the output power. On the other hand, in order to be power efficient the PA should use a limited amount of power even when a high output power is required. Modulation schemes like M-ary frequency shift keying (MFSK) and M-ary phase shift keying (MPSK) are less sensitive to PA nonlinearities with respect to quadrature amplitude modulation (QAM) modulation, although they are less spectrally efficient. This is the main reason behind using a combination of amplitude and phase modulation in modern broadband standards. Moreover, we can use a pre-distorter in order to enhance the bit error rate performance of non-linear PA, which increases the complexity of the transmitter though.

1.3 Different Protocol Layer Approaches Towards Energy Efficiency

Wireless networks are bounded by limited resources like: bandwidth, power, time, complexity, battery life, energy, capacity etc. Therefore efficient utilization of resources play very important role in designing efficient networks. In fact, the main objective of an efficient network design is to optimize the system performance in terms of:

- Energy consumption minimization
- QoS provision
- Mobility management
- Network access delay
- Security awareness.

From the literature review presented in Chapter-2 of this dissretation, we find many cases where a trade-off exists between some of the above mentioned criteria, for example energy-QoS trade-off, energy-delay etc.

Energy efficiency of a wireless network can be reached over different protocol layers since different protocols exploit the source of energy consumption in different ways, such as by power amplifiers, mixers, processors, registers, filters etc. Many pioneering works as presented in Chapter-2 have proposed many energy efficient appraoches for wireless communication considering both active mode and idle mode. Following a hybrid protocol architecture based on the Internet and the IEEE 802 architectures, we can list some major energy saving algorithms located at different protocol layers.

1.3.1 Physical Layer

At the physical layer, the energy consumption can be minimized by adapting the basic error-correction schemes and the modulation techniques according to the channel conditions and application requirements. Many approaches have been proposed in literature (as presented in Chapter-2) to dynamically change the transmission power in wireless networks. However, not many of them considered the battery lifetime of the mobile terminals. Most of these research work aim to offer good signal to interference and noise ratio (SINR) or maximize cell capacities. Another important aspect considered by the researchers is the drain efficiency of the power amplifier, which depends on the class of the amplifier. The drain efficiency of PA can be increased by increasing the level of nonlinearities introduced by the power amplifier. Therefore appropriate modulation schemes need to be identified which are insensitive to nonlinearities of PAs.

1.3.2 MAC Layer

In the medium access (MAC) layer, energy efficient strategies can be implemented by utilizing power saving mode under low traffic condition. These power management protocols manage the trade-off between performance and the energy consumption by determining when to switch between active mode and idle (or sleep) mode. The energy consumption due to channel access or contention resolution depends on the particular MAC protocol. For instance, in IEEE 802.11, the transmitter transmits a Ready To Send (RTS) message to inform the receiver of the senders intentions [13], the receiver then replies with a Clear To Send (CTS) message to inform the transmitter about the availability of the channel at the receiver end. The energy consumed for contention resolution includes the transmission and reception of the two messages. Moreover, the nodes may spend some time waiting until the RTS can be sent and so consume energy while listening to the channel.

1.3.3 Network Layer

At the network layer, overhead and signaling are minimzed by intelligent routing protocols, they also ensure the use of minimum energy consuming routes. Furthermore, the network layer in the wireless mobile networks has the functionality of routing under mobility constraints. Hence energy efficient routing is the prime focus of researchers in ad hoc networks.

1.3.4 Transport Layer

At the transport layer, the energy consumption and bandwidth utilization may increase due to the increased number of packet retransmissions probably because of the wireless link errors. Many researchers have proposed various schemes to alleviate the effects of non congestion-related losses on TCP performance over wireless networks. There are three basic protocols which are used to reduce retransmissions [13]:

- Link layer protocols
- Split connection protocols
- End-to-end protocols

1.3.5 Application Layer

At application layer, schemes can be proposed to reduce energy consumption by reducing the amount of data to be sent. Also more energy is consumed in the processing and transmission of multimedia applications such as video transmission. Power consumption can be reduced by reducing the effective bit rate of video transmissions, which allows the utilization of light weight video encoding and decoding techniques.

However, reducing the video bit rate will increase the processing, which is an important trade-off that should be considered while proposing energy efficient strategies in the application layer.

1.3.6 Cross Layer Approaches

The traditional layered approach is based on a layered protocol architecture which allows spliting any complex problem of network design into smaller sections, which are easy-to-solve. However this approach only provides suboptimal solution to the system performance improvements as it does not efficiently exploit available resources and consequently leads to a local performance optimization. On the contrary, the cross-layer approach optimize each protocol layer by considering the knowledge of parameters and features of the other protocol layers. Hence, better resource utilization and trade-offs solution are provided by the cross-layer design approach compared to the layered approach. However, this better performance is achieved at the cost of a more complex design beacause all of the protocols need to adapt to the changes and modifications made on one protocol. Although, industries and academics are exerting their full efforts for maximizing the energy efficiency in different layers of wireless networks, but still there are some unsolved challenges (mainly in physical layer and MAC layer) that require more attention. In this dissertation, we will mainly focus on EE techniques in physical and MAC layers.

1.4 Initiatives Taken by GreenTouch

GreenTouch is a the global consortium dedicated to improve the energy efficiency of data and communications networks. GreenTouch is supported by Alcatel Lucent and other Telco giants (such as: AT&T, Bell Labs, China Mobile, Samsung, Huawei, Freescale, CEA-LETI, INRIA (The National Institute for Research in Computer Science and Control), IMEC (Interuniversitair Micro-Elektronica Centrum), France Telecom Orange Labs, Swisscom, Portugal Telecom, and the University of Melbournes Institute for a Broadband-Enabled Society (IBES) etc.). According to

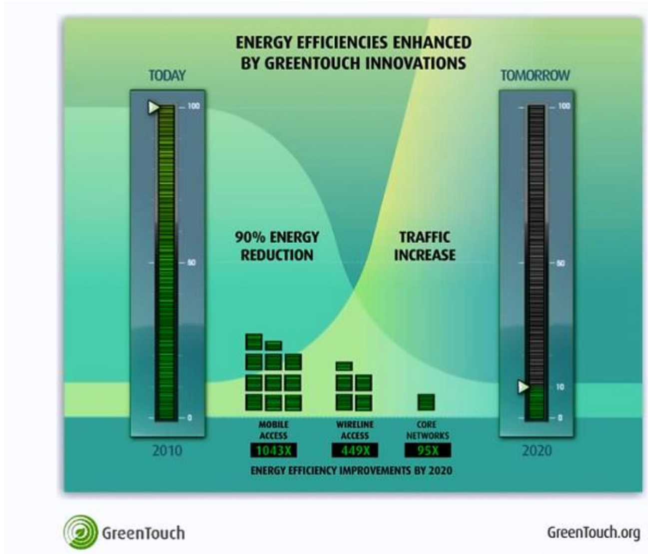

Figure 1-6: Greentouchs' anticipation about energy efficiency improvement by 2020 [source: [6]].

them, the net energy consumption in overall networks could be reduced up to 90% by 2020 [6] as shown in Fig.1-6. Greentouch believes that standardization and regulation will enable strong cooperation between operators to enable a more effective spectrum usage and avoid the costs for a four-fold deployment by 2020. Under such scenario, it is assumed that all traffic is served by a single physical infrastructure. For the 2010 reference scenario, conventional 3-sectorized macro BSs operating with 10MHz bandwidth and 2x43dBm transmit power per sector was applied. In 2020, the authors anticipated a technical evolution to 20MHz and to 8 MIMO remote radio head (RRH) antennas with 8x40dBm per sector. A heterogeneous deployment with additional small cells (HetNet scenario) where required by capacity demand will be applied by them. In [14], the authors used small cells with two omnidirectional MIMO antennas with 2x27dBm transmit power. GreenTouch has focused on the following points as the reason for increased energy efficiency in 2020 [6]. Firstly, the LTE system in the 2010 reference scenario is strongly over-dimensioned and provides a capacity that is by far above the demand for the year 2010. Additionally, the power consumption is only partially dependent on load, but dominated by the BS offset power. In order to avoid redundant coverage by four networks, operator network sharing can be applied. It is expected that the typical resource utilization in 2020 is around 25%, when all traffic is served by a single physical infrastructure. This reduces the number of BSs and results in nearly four times less energy consumption. Secondly, due to developments in the hardware and hardware management, the BSs in 2020 will operate at 2.3-fold less power per BS even at the higher load of 2020 (308W at 25% load) compared to 2010 (712W at 0.1% load). Further savings come from micro sleeps (20% overall saving) and from the use of HetNets in DU (10% overall saving) [6]. The Large Scale Antenna System (LSAS) project [14] research the use of a large number of service antennas at the base station for increased spectral efficiency and increased energy efficiency. Beyond the improvements in radiated energy efficiency, the evaluation of total system energy efficiency, including the per-antenna overhead and the computational complexity and resulting energy consumption. The energy efficiency gains achieved from these technologies are part of their ongoing research projects and it is expected to be quantified in future updates of the Green Meter research study. As MIMO is out of our research interest, this paper will be read to get some idea about the algorithm for energy efficiency. The above mentioned researches depict that optimized energy-efficient design (including network deployment, transmission scheme and resource management) could significantly reduce the energy consumption of the entire network. Nevertheless, current research results are still quite preliminary and many challenges remain unsolved.

1.5 Rationale for The Research

As already mentioned, energy consumption is growing at an incredible rate with the rapid and radical evolution of ICT. The mobile operators are already among the top energy consumers and energy consumption of mobile networks is growing much faster than ICT on the whole [15]. Furthermore, because of the mass deployment of 3G systems in developing countries (like China and India) and later 4G systems in the developed countries, energy consumption in mobile communications will increase day by day if no effective actions are taken.

There are two main important factors that motivated this research. Firstly, energy consumption in wireless communications is increasing mostly due to exponential network growth, especially with the explosion of wireless data traffic. This trend could adversely affect the energy efficiency of ICT networks and associated smart technologies. The second motivation is the urgent need to meet the global challenge of reducing greenhouse gas emissions. Every industry must play its part and ICT, at the forefront of technology, can be a leader here. In order to significantly reduce the energy consumption of todays wireless communications, some radical new approaches are needed. Recent research works have identified a gap between rapid network growth rates and historical equipment efficiency improvements - a gap that promises to increase over the decades ahead. Technologies in use today, even considering best-case projected energy efficiency improvements, are not expected to be sufficient to check the rate of energy consumption over the long term. The vision of our research is to create energy efficient wireless communication networks and technologies that enable a sustainable technique, which will dramatically improve their energy efficiency for the benefit of the ICT sector and the entire world.

1.6 Energy Efficiency in Device Level

In recent years, advanced signal processing techniques and wireless radio devices have boosted the implementation of many applications of wireless communication. The promising ubiquitous computing system has been envisioned by the technological developments in digital signal processing, microelectronics, wireless communication and networking, sensing material and Wireless Sensor Network (WSN). Low power wireless communications based sensing and computing devices are the main part of the WSN technology. These devices are called sensor nodes which are usually powered by the finite energy of a non-rechargeable battery. WSN is a quickly growing technology that has attracted well-deserved attention of the academic and industrial researchers and in the global business market. The advanced hardware technologies allow more signal processing functionality to be integrated into a single chip. Coin sized fully functional wireless node are becoming very demanding and popular among industires and researchers, in which all the application interfaces, such as, a radio frequency (RF) transceiver, analog-to-digital (A/D) and digital-to-analog (D/A) converters, baseband processors etc. are integrated within it. Such wireless nodes are usually power by small batteries. The replacement of these batteries is very difficult and expensive, even for some cases not possible. Therefore, energy consumption minimization is a very crucial design aspect for a WSN. Most of the pioneering work [16–21] related to energy-constrained communication has focused on minimizing the transmission energy of the network. The emphasis on minimizing transmission energy is reasonable in the traditional wireless link where the transmission distance is large (100 m), therefore the transmission energy is dominant in the total energy consumption. However, the nodes are densely distributed in many recently proposed wireless ad hoc networks (such as sensor networks), and the average distance between the nodes is usually below 10 m. For these circumstances, the circuit energy consumption along the signal path becomes comparable to or even dominates the transmission energy in the total energy consumption. Hence we summarize the following unsolved challenges in this area:

- The overall energy consumption including both transmission and circuit energy consumption needs to be considered in order to find the optimal transmission scheme.

- An optimal mechanism is needed to reduce energy consumption under QOS constraint.

On the other hand, rate adaptation (RA) is a popular mechanism to improve the performance of wireless sensor networks [22–24]. RA is used to optimize the various modulation and coding based physical-layer configuration depending on time varying channel conditions. The traditional goal of RA is to achieve effective throughput and high goodput. We have done extensive literature review on the above mentioned topics as presented in Chapter-2 of this thesis and have identified the following literature gaps which need more attention from the researchers.

Literature Gap

- Very few work considers transmission energy as well as circuit energy.
- Rate adaptation has been rarely used to minimize energy consumption in device level.
- Appropriate modulation techniques should be determined for various range of application.

In this thesis, we focus on the above mentioned literature gap and have formulated research question-1 accordingly, as mentioned in the research question section of this chapter. In our work presented in Chapter-3, the energy consumption associated with both the transmitting path and the receiving path, i.e., the total energy required to convey a given number of bits to the receiver for reliable detection, is investigated. Assuming all nodes transmit and receive about the same amount of data, minimizing the energy consumption along both the transmitting path and the receiving path at the same time is more appropriate than minimizing them separately.

1.7 Energy Efficiency in BSs

The dense deployment of base stations (BSs), which is necessary to satisfy the high demand of traffic, is causing enormous energy consumption with more challenging operational cost. Therefore all stockholders of wireless market possess keen interest for making improvement in energy efficiency at the network level and are putting a large research effort for finding innovative solutions. Most of the pioneering works have shown that mobile networks have a strong potential for energy savings. Most of the works done in literature, have emphasized on reducing energy consumption at the user end, so that the battery life of mobile terminals can be increased [25]. However, it has been reported in many studies that, state of the art BSs, also known as eNodeBs in LTE networks, are the major source of energy consumption, consuming approximately $60 - 80\%$ of the total energy of a cellular network [26]. Fig.1-3 [3] also shows that BSs are the major source of energy consumption of a wireless network. This is mainly because of the always-active operation of current systems. This always-active mode offers full-time coverage but fails to adapt energy consumption to traffic load variations. Therefore designing energy efficient BSs has become the most important issue for any green communication networks. Hence, operators, vendors and researchers are collaborating to propose innovative technologies and algorithms to improve energy efficiency in the BSs. Researchers in many different papers have proposed various distinctive approaches to reduce energy consumptions in BSs [27] which can be summed up in the categories as shown in Fig.1-7.

The first two approaches from the above list involves architectural changes as well as the cost of purchasing, replacing, and installing new equipments. These costs also include the expenditure involved in manpower, transportation as well as associated energy and direct cost. On contrary, rest of the three approaches that are applicable on the operating protocols of the system are less expensive and easily implementable as they do not require changes to current network architecture. In this thesis we limit our research scope to the last challenge area from the above list, where we identify literature gaps and formulate our research questions accordingly.

1.7.1 Sleep Mode Techniques in The Base Station

As discussed above, as sleep mode implementation in the BS neither require upgrade of equipments nor any hardware replacement so they incur low implementation cost, hence is much preferable energy efficient approach by the operators and vendors. The total power consumption of a BS is composed of fixed power consumption, which does not depend on the traffic load and traffic dependent power consumption, which varies with the traffic variation. As presented in paper [4], the fixed part, including air conditioning and power supply, consumes around one fourth of total energy consumption,

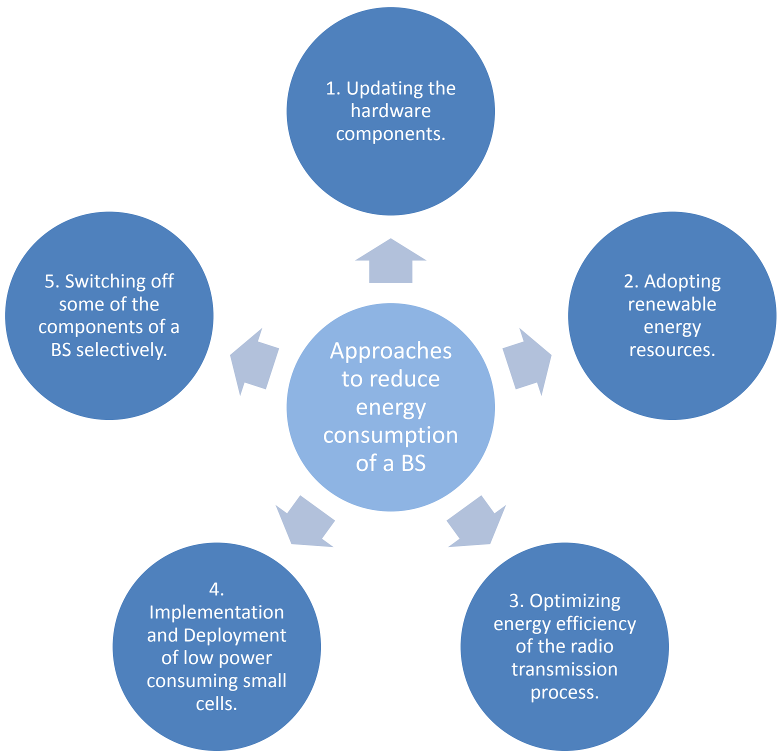

Figure 1-7: Approaches for BS energy saving

which is wasted when there is no traffic to be served by the BS. This unnecessary energy consumptions can be avoided by adopting sleep mode mechanisms in the BSs. The sleep mode approaches generally involve switching off the entire BS or certain elements including but not limited to power amplifiers, cooling equipment or the signal processing unit [28] in low traffic condition. As already mentioned BSs are the highest energy consuming part in the cellular networks. Moreover, dense deployments of BSs lead to small coverage area and more random traffic patterns for individual BS, which make sleep mode operations more desirable. The following challenges in implementing sleep mode in BSs have been identified in these studies which need more attention from the researchers:

- Implementing sleep mode might have negative impact on QoS in the network because of decreasing coverage and capacity.

- The time needed to activate the sleeping BS causes delay in providing service, which causes degradation in service and may cause call drops as well.

- BS cooperation is necessary to avoid outage events when the some of the BSs are put in sleep mode.

- Hardware components, which remain active during sleep mode, should be characterized by a very limited power consumption to avoid energy wastage.

- Current 3GPP standard constrains continuous transmission of pilot channels to guarantee coverage [29].

In order to address the above challenge, some significant works have been dedicated to reduce the energy consumption of the BSs by implementing sleep modes in the past few years [9, 30–44]. The main idea of these works is to find the minimum transmission power which ensures QoS in terms of coverage and capacity. J. Peng et. al. in [30] proposed an energy saving approach by switching off some macro BSs under downlink coverage and uplink power constraints. They considered the users' power constraints to formulate a BS energy consumption minimization problem. they also determined the optimal proportion of sleep macro BSs and transmission power of active macro BSs and their results showed significant reduction in BSs' energy consumption while guaranteeing the downlink coverage and user power consumption performance. Saker et al. [34] presented an energy-efficient system selection scheme by spliting the mobile traffic between 2G and 3G systems optimally, which can reduce around 10% of total energy consumption while satisfying QoS requirements. Then they implemented a sleep mode for either 2G or 3G systems. Their results showed that a significant amount of energy can be saved during low or medium traffic condition without degrading the QoS. Another study conducted by the the same group of researchers as presented in [38], proposed a generic framework for applying sleep mode to the BSs of mobile cellular networks. Their work was divided in two schemes, firstly they proposed a dynamic scheme where BSs are put to sleep or waken up based on the instantaneous number of users in the cell. The second scheme is a semi-static one where the BSs stay in a particular mode for a certain period of time (tens of minutes or even for hours) in order to minimize frequent transition between the sleep and active mode. These authors also discussed practical issues for sleep mode implementation in BSs in another paper [37]. In this work they proposed a guard period and a hysteresis time between active and sleep mode, in order to to avoid call blocking when the resources are being activated and to reduce frequent mode transition. Their simulation results showed that both guard period and hysteresis time provide better QoS but reduce the gain in energy efficiency. Also their guard period and hysteresis time do not adapt varying traffic condition, therefore is less suitable for practical implementation. We should also consider the delay caused by the wake up time from sleep mode. The deep sleep mode consumes almost zero power, however can cause significant delay in service due to wake up time from sleep mode, whereas stand-by mode is a lighter sleep mode, where a resource consumes little power but wakes up very quickly. This stand-by mode can be achieved by switching off only the most power consuming part of the BS, such as the power amplifier. We have reviewed more similar works from literature and have presented them in Chapter-2. In the light of these literature reviews, we identify the following literature gaps in this area which are the main focus of our research:

- Lack of an sleep mode algorithm which fulfills QOS requirement as well as reduces wake up delay.

- Lack of sleep mode scheme offering sleep mode and stand-by mode together in order to reduce energy consumption as well as wake up delay.

Our work presented in Chapter-4, fills the performance gap presented above.

1.8 Energy Efficiency in Aerial Networks

Aerial networks have recently become very popular as key enablers for rapid deployable wireless networks where coverage is provided by on-board radio heads. The quick deployment of the aerial platforms such as helikites, drones or airships, with respect to terrestrial infrastructure, make them suitable candidates in tackling a number of different challenges including, increased coverage in remote areas, better line-of-sight (LoS) conditions and resilience to unexpected disastrous situations. Facebook Aquila Drone [45] is a good examples of ongoing AeBS projects, which propose a novel solution for providing internet access from the sky by using the AeBSs. Aerial networks can also be deployed by the telecom operators in remote areas as temporary solution of patching coverage gaps [46]. The Google Loon [47] experiment is an ambitious project intended to provide network coverage to rural and remote areas. A major advantage of the aerial base stations over static terrestrial base stations is that they can change their positions to serve the dynamic network of users optimally. An AeBS can be efficiently integrated into terrestrial cellular wireless networks to either serve the ground users directly or relay traffic to the terrestrial network [48], [49]. Fig.1-8 provides a good overview of how aerial networks co-exists with terrestrial cellular infrastructure.

Although there has been increased interest in this topic, research is still at its nascent stage and there are quite a number of challenges that need more research attention:

- Energy efficient AeBS design

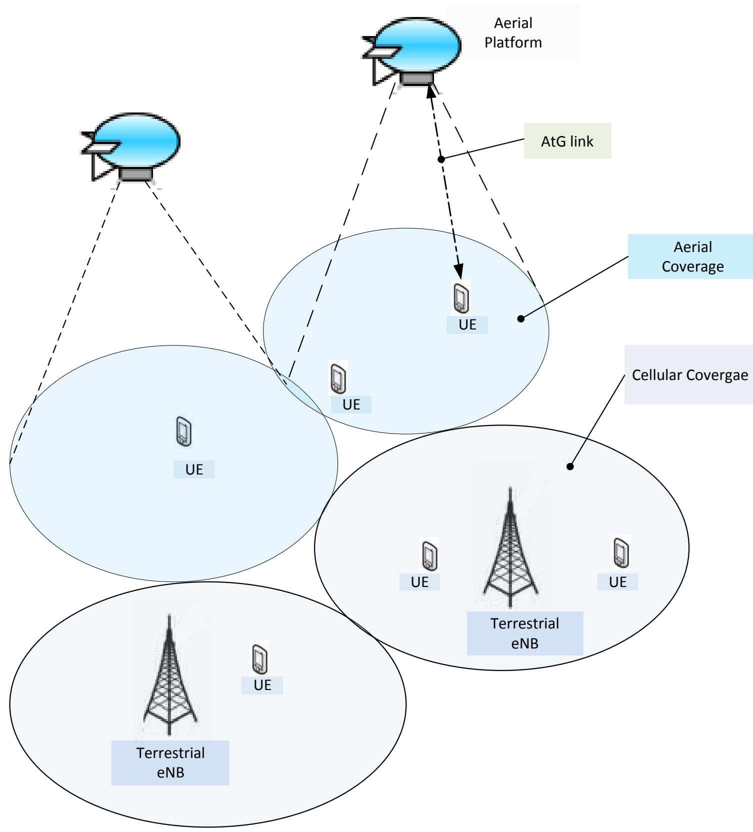

Figure 1-8: Aerial network supporting terrestrial cellular coverage.

- Optimal altitude for placement of an aerial platform
- Aerial channel modeling etc.

In order to address these challanges, some pioneering work has been found in literature. In the the European Commission project ABSOLUTE [50], a hybrid satellite-UAV ground network is developed using AeBSs to address public safety and capacity enhancement based on LTE communication systems. The main objective of the ABSOLUTE project is to design and validate an innovative holistic network architecture ensuring dependable communication services based on the rapid deployment, flexibility, scalability, resilience and provision of inter-operable broadband services. Although, significant amount of work on design and implementation of AeBS networks is found in literature, very few of these works focus on the energy efficient design of aerial base stations. We provide detail literature review on aerial base station in the next chapter, where our study finds that the energy efficiency of aerial platforms, particularly on AeBSs is not sufficiently addressed. Energy is a scarce resource for aerial base stations, hence energy-efficient operation of such networks is important given that the entire network infrastructure, including the battery-operated ground terminals, exhibits requirements to operate under power-constrained situations. Therefore, the wise management of energy is quite beneficial for the network lifetime. In this context, we study the means of reducing the total energy consumption by designing and implementing an energy efficient AeBS, where our research is focused to fill the following literature gaps:

- Lack of an sleep mode algorithm which fulfills QOS requirement as well as reduces wake up delay of an AeBS.
- Lack of a reinforcement learning algorithm to design an energy efficient and delay aware AeBS.
- Lack of low power consumption scheme offering sleep mode and stand-by mode together in order to reduce energy consumption as well as wake up delay.

1.9 Energy Efficiency in Small Cell Network

A wide range of heterogeneous deployments are supported by LTE or LTE-A, that mainly includes femtocells, picocells, and relay, with aim of extending coverage of the network, increasing the capacity of the system and reducing transmit power. Fig.1-9 depicts an example of an environment where small cells like micro, pico and femto cells co-exist in the coverage area of macrocell. Such small cells play a critical role in adopting LTE-A by bringing access network near to user in a cost-effective way. Femtocells, also known as, Home eNBs, are low-cost, short-range, user-deployed cellular access points. Femtocells interconnect standard User Equipment (UE) to the mobile operator network via the broadband access backhaul of the end user. Though normally few users are supported by femtocells, they have the functionality of regular

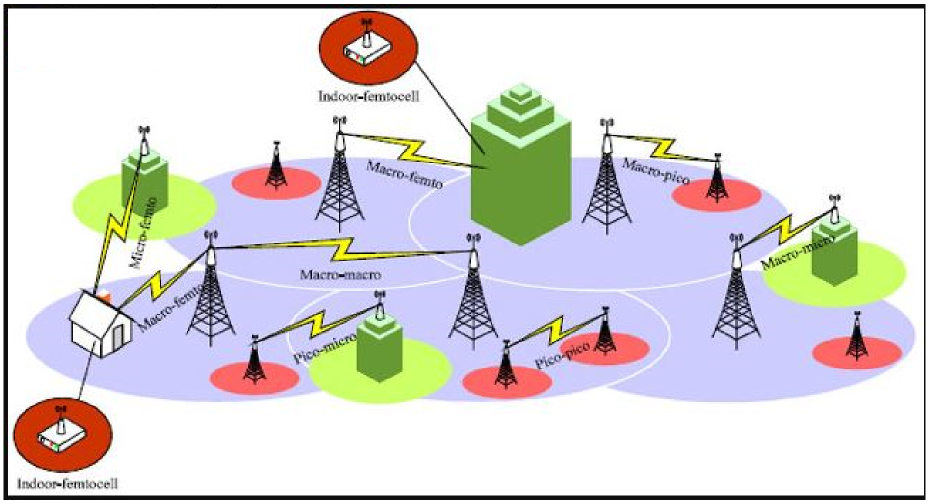

Figure 1-9: A typical heterogeneous network with macro, micro, pico and femto cells [source: [7], modified].

base stations operating in licensed band of the mobile operator. Femtocells substantially enhance the user-perceived Quality of Service and greatly improve the energy saving potential for the network nodes at the cost of employing more sophisticated interference and mobility management procedures. The requirement of advanced interference and mobility management has arisen from unplanned femtocell deployment, denser network layout, short femtocell radius and employment of access control. The unplanned deployment pattern results in increased Radio-Frequency (RF) interference at the LTE-A network nodes and complicated mobility management procedure. On the other hand, the denser network layout and the short femtocell radius increase the number of handovers (HOs) in the system and enlarge the number of candidate cells, compromising seamless connectivity and increasing the network signaling load. Additionally, access control may severely degrade Signal to Interference plus Noise Ratio (SINR) under certain interference scenarios, for instance, when an LTE-A user is not a member of a Closed Subscriber Group (CSG) femtocell in proximity. Even though femtocell deployment comprises several technical challenges, but still they significantly reduce the energy expenditure for both the UEs and the LTE-A network. As mentioned in [51], the transmit power of both the mobile terminals and the cellular stations can be reduced by four to eight orders of magnitude by deploying femtocells.

Self-optimization is another feature of femtocell that leads to further energy savings. Therefore we can say that, even though femtocell deployment enhances the EE at the access network nodes, but the actual EE gain strongly depends on: **the interference management** and **the mobility management algorithm.**

Our research focuses on the mobility management issue in the two-tier macrocell-femtocell network.

1.9.1 Mobility Management Issue in Femtocell Networks

Mobility Management (MM) is one of the most challenging issues in the femtocell networks, mainly because of the dense network layout, unplanned deployment and the short cell radii. The main challenges of MM support are posed during the phases of cell identification, access control, cell search, cell selection, handover (HO) decision, and HO execution. Cell identification is very cumbersome because of the dense and unplanned reuse of the same physical cell identifiers (PCI) within small areas, which is also known as the PCI confusion problem [52]. The access control part has three different aspects, which makes the MM more complicated. The first aspect is, the mobile terminals (MTs) has to be aware of the femtocells they can access. Then the femtocell stations should enable the identification of the access type they support. Finally the membership status of the MTs should be validated by a trusted network entity before accessing the femtocells. Cell search should also be reassessed in the context of femtocells because the dense and unplanned deployment hampers network-controlled cell search procedures. additionally, the short cell radii may increase the required energy consumption and delay overhead. Another critical issue in large-scale deployments of femtocells is the cell selection, which is mainly because of the random tracking area size. After selecting the candidate cells to HO in the femtocell network, more sophisticated HO decision algorithms are required to improve the QoS and Signal to Interference plus Noise Ratio performance in the presence of user mobility and cross-tier interference. Moreover, to reduce the delay and signaling overhead of the HO execution to or from femtocells more network architectural and procedural enhancements are needed. We opt to focus our research on the HO decision phase, which is considered to be the most important phase of MM and needs more research attention. We identify the literature gaps in this area and formulate our research direction accordingly.

1.9.2 Handover Decision

In a co-existing macro-femto cell network, a HO procedure includes all of the decision making and signaling procedures, which are required for a seamless transfer of the ongoing connection of a certain UE from its current serving cell to a candidate cell. This decision making part is referred to as the HO decision phase and the signaling part is referred to as the HO execution phase. In the heterogenous networks, the HO decision phase is performed at the serving cell and is based on signal quality measurements provided by the UE [53]. HO decision is very crucial as it aims to offload highly congested macrocells and to enhance the received signal quality at the mobile UEs. Its impact is even more prominent in the presence of femtocells, because of the denser network layout and the fast varying radio environment. Current literature depicts reports on various HO decision algorithms for the two-tier macrocell-femtocell network [25, 52–70, 70–74]. Most of these algorithms make the HO decision to/from femtocell based on signal strength [53, 65, 66], UE speed [60], [75], or traffic-type criteria [70]. However in most of these pioneering works, the impact of the HO algorithms on the energy consumption, HO delay, interference, system capacity and network signaling are not investigated. Note that, the most important feature of implementing femtocells is not only to offload the high congested traffic of macrocell but also to reduce energy consumption at the BS end as well as at UE end. To this extent, along with the received signal strength (RSS) at the UEs, the HO decision phase needs to consider the following challenges as well:

- Select a proper target cell so that the transmit power of UE reduces
- The delay occurred during the handover process which may interrupt the seamless connectivity
- The divergent interference levels at the cell sites

- The uneven power transmissions of the macrocell and femtocell stations

- The increased sensitiveness on user mobility

In this thesis we limit our research scope to the first two challenge areas, where we identify literature gaps and formulate our research questions accordingly. We have done an extensive literature review on the HO algorithm in heterogenous networks (networks with co-existing macro BS and femto BSs) and have presented them in Chapter-2 of this dissertation. Based on these literature review we have identified the following literature gaps and have proposed novel algorithms fill these gaps.

- Lack of an HO algorithm to select a suitable candidate cell which will also improve the energy efficiency of the network.

- Lack of an learning algorithm which would intelligently decide when to perform Handover while maintaining seamless connection.

Our research presented in Chapter-5 proposed an algorithm to address the above mentioned challenges and literature gaps.

1.10 Research Questions and Contribution

1.10.1 Research Questions

Based on the above mentioned unsolved challenges and literature gaps we formulate the following research questions, which address energy efficiency in layer-1 and layer-2 of wireless networks, considering-

- the devices of a wireless network,

- the BS,

- the access network.

Research question 1 (RQ1): How can we optimize energy in uplink transmission with rate adaptation using circuit level energy consumption model?

How can we use rate adaptation to minimize total energy consumption, including both transmission energy and circuit energy, under QOS constraint.

Research question 2 (RQ2): How sleep mode implementation in BSs can improve energy efficiency whilst maintaining QOS requirement as well as minimizing wake-up time delay?

Sleep mode implementation in BSs is a well known approach for reducing energy consumption, however it degrades the QOS of the network by decreasing the coverage and capacity of the network. Also some calls may get blocked while activating the sleeping BSs. Therefore some delay aware sleep mode strategies are needed which will fulfill the QOS requirement as well.

Research question 3 (RQ3): How to implement an intelligent learning algorithm to increase energy efficiency of aerial base stations?

Energy is a scarce resource for AeBSs, therefore energy efficient algorithm is much needed for aerial networks. An intelligent learning algorithm needs to be proposed which will control the mode transition behaviour of the AeBSs based on some parameters (such as delay, QOS requirement etc.).

Research question 4 (RQ4): How can we take handover decision intelligently to improve energy efficiency in LTE heterogeneous networks?
An intelligent HO algorithm for heterogeneous network needs to be proposed which will take optimal HO decision based on some parameters (such as energy efficiency, delay, QoS requirement etc.).

1.10.2 Contribution

Contribution to Address RQ1

To address RQ1, we show that the total energy consumption of a point to point communication system can be minimized by optimizing the data rate for MQAM and MFSK in an AWGN channel. Here we assume that the system will have to transmit a fixed length of packet with a fixed bandwidth to meet a given bit error rate and to find the optimal parameters we use Newton-Raphson method. We find that MQAM can minimize a significant amount of energy consumption by optimizing the data rate for shorter transmission distances and MFSK can reduce energy consumption by optimizing the data rate for longer transmission distances. This contribution is presented in Chapter-3 of this dissertation.

Contribution to Address RQ2

To address RQ2, we propose a novel strategy to implement low power consumption mode in the resources (e.g. TRXs) of a BS in LTE infrastructure. We propose a novel strategy, which can put the TRXs of a BS into active mode, stand-by mode and sleep mode depending on the traffic condition and QoS requirement. We show that the BS can save a significant amount of energy in low traffic condition following our proposed 'ternary state power consumption model'. This contribution is presented in Chapter-4 of this dissertation.

Contribution to Address RQ3

To address RQ3, we propose a novel strategy to implement low power consumption mode in the transcievers of an aerial base station. We propose a novel reward function and a MDP based 'ternary state model', which can put the TRXs of an AeBS into active mode, stand-by mode and sleep mode depending on the traffic condition and QoS requirement. Furthermore, we show that the AeBS can save a significant amount (appx. 40%) of energy in low traffic condition following our proposed 'MDP based ternary state power consumption mode', which has proven to offer fair share of energy efficiency and delay. This contribution is presented in Chapter-5 of this dissertation.

Contribution to Address RQ4

To address RQ4, we propose a MDP based HO decision algorithm for the LTE-A femtocell network, which jointly considers the impact of user mobility and energy efficiency. Our main contribution to this work is to derive individual reward function of each QoS parameter used for making handover decision. The proposed algorithm finds the optimal policy by VIA to sustain service continuity and reduce the mean UE transmit power. System-level simulations shows that the proposed algorithm significantly reduces energy expenditure at the UEs compared to existing algorithms. This contribution is presented in Chapter-6 of this dissertation.

1.11 List of Publications

We have published part of our work in the following peer reviewed conference and journal papers, where some of them are going under a review process:

1. Nahina Islam, Kandeepan, S., & Scott, J. "Optimal rate adaptation for energy efficiency with MQAM and MFSK". In IEEE Wireless Personal Multimedia Communications (WPMC), on (pp. 328-334), September 2014.

2. Nahina Islam, Kandeepan, S., & Scott, J. "Energy efficiency of cellular base stations with ternary-state transceivers". In Signal Processing and Communication Systems (ICSPCS), IEEE, (pp. 1-7). December 2015.

3. Nahina Islam, Kandeepan, S., Chavez, K., Scott, J., Eltom H. "Energy Efficient and Delay Aware Ternary-State Transceivers for Aerial Base Stations", IEEE Transactions on Aerospace and Electronic Systems, 2017. (Submitted).

4. Nahina Islam, Kandeepan, S., Rasheed, T., Chavez, K. & Scott, J. "A MDP-based Energy Efficient Handover decision algorithm for LTE-Advanced Femtocell Network", to be submitted on IEEE International Symposium on Personal, Indoor and Mobile Radio Communications, 2017.

1.12 Thesis Structure

The thesis is divided into seven chapters:

- Chapter 1 provides an introduction to energy efficiency in wireless communications, opportunities, and possible applications in different layers of wireless network; followed by the novel contributions to the addressed research questions.

- Chapter-2 provides the summary of the broad literature review, including a brief theoretical introduction on the mathematical tools that are of relevant to the work of this thesis.

- Chapter-3 presents the part of the research work, where we use rate adaptation to increase energy efficiency in device level. This work addresses research question-1.

- In Chapter-4, we propose a three state model for the transceivers of a base station to increase energy efficiency of the BS. This work addresses the issue mentioned in research question-2.

- Chapter 5 presents our work, where we propose an alogorithm to apply Markov decision process on the three state transceivers of an Aerial base station. This work addresses the issue raised in research question-3.

- In Chapter 6, we propose an energy efficient handover algorithm for LTE-A heterogeneous networks. This work addresses research question-4.

- Chapter 7 provides a brief conclusion on the outcome of the work done in the prior chapters along with some potential future work; hence, concluding the overall novelty and potential of this thesis.

Chapter 2

Background and Related Work

The ever-expanding wireless communication infrastructure is withdrawing higher energy than ever, raising the need for finding more efficient systems. The design challenges of the network architectures and protocols for energy efficient wireless communications have motivated a significant amount of innovations and research in this area. In order to address this issue some new network architectures, advanced physical layer techniques and radio and network resource management schemes have been proposed in literature. Several international research projects, such as the Green Touch initiative directed by Bell Labs, which are dedicated to energy-efficient wireless communications, are being carried out to revoke the problem before it converts to a blown up issue. Nevertheless there exit some challenges which still need to be sorted out.

In this chapter, we provide broad and detail literature review on energy efficiency at different levels of wireless networks, followed by some background information on handover procedure as well as theoritical background of Markov decision process and reinforcement learning.

2.1 Energy Efficient Metric and Energy Consumption Models for Wireless Devices

One of the essential factors of the energy efficient network design is the accurate metrics for energy efficiency (EE). This is because the optimization of protocol layers depends on the EE Metrics. Existing literature have utilized several different EE metrics. The most common metric systems are definitely the bits per joule method, which is defined as the system throughput for unit-energy consumption. In [76], this metric system capacity is being analysed at the network level; its capacity increased with the number of nodes across the network. Their research let to the realization that the suitability of the large scale and the energy limited sensors as well as the ad-hoc networks are suitable mainly for the data applications that are delay-tolerant. It is noteworthy that the authors in [76] only consider the transmit power associated with data transmission rate for its energy consumption models. But the fact is that the operation costs also include more factors, than just the transmit power. Hence, when other parts of the system power consumption are taken into account then these energy-efficient schemes will not be appropriate anymore. In [8] an energy consumption model, which considered both of the transmission energy and the circuit energy consumption has been proposed and analysed. They considered the cases where a given bit error probability, the signal-to-noise-ratio (SNR) per bit requirement rises with M for M-ary quadrature amplitude modulation (MQAM) and falls with M for M-ary frequency-shift keying (MFSK). It is believed that MFSK have greater efficiency than MQAM [77], but when the power consumption of the circuit in [8] was taken into account; this was no longer true. The authors had shown that only when transmit power dominates the total power consumption, as for long-range applications, then MFSK is more energy-efficient than MQAM. On the other hand, when the circuit power dominates the total power consumption, as for short-range applications, MQAM is more energy-efficient. In [8] up to 80% of energy has been saved by optimizing the transmission time and the modulation parameters, compared to a non-optimized strategy for uncoded systems. A similar work has been extended to fading channels in [78]. It is noticeable, that the different methods for modeling the energy consumption have significant impact on the bits-per-Joule metric. Thus, a proper set up for the energy consumption model is vital. Researchers in [7], investigated energy consumption models of macrocellular and microcellular base stations. The energy consumption at the base station with no traffic load, was dubbed the 'static energy part', while in the scenario with traffic loads was dubbed 'dynamic energy part', the overall energy consumption for the base station is the sum of both of these energy parts. Although, for a macrocell base station, the energy consumption is dominated by the static part and does not significantly depend on the transmission parameters of each user. Definition of throughput also affects the accuracy of the bits-per-Joule metric. Since not all transmitted data are real information bits, hence transmitted data should not be included into the throughout. For example, the header required in different protocols, signalling information, destroyed packets, and duplicate packets all present overhead bits. In [79], energy consumption of training sequences for channel estimation in fading channels is considered; where the optimal power allocation for pilot and data symbol in terms of EE can reduce transmit power consumption by 84.5% compared with optimal power allocation scheme for maximizing the capacity.

2.2 Energy Efficiency at Device Level

Energy is a scarce resource of network nodes, particularly in remote areas or rigorous environments where recharging is very difficult or for some cases not possible. Energy consumption is dominated by the transmit power required from each node; therefore, reducing the transmit power could reduce energy consumption. However, many applications, such as search and rescue or military surveillance, require a network topology capable of withstanding sudden node/link failures. Furthermore, many algorithms, such as consensus or swarming algorithms, require highly connected networks for fast convergence to leverage the more efficient in-network information diffusion. As the transmit power decreases, the number of network links reduces, consequently decreasing network connectivity. Therefore, there is significant interest in developing topology control schemes capable of achieving a good tradeoff between the conflicting objectives of energy consumption and network connectivity. Various topology control protocols have been developed for wireless ad hoc networks to obtain energy-efficient topologies, with minimal energy consumption. That is the case of the localized minimum spanning tree (LMST) [80], and some game-based topology control schemes [81–84]. In addition to energy-efficiency, some published works [85–87] have also considered the problem of energy balancing in topology design to extend network lifetime. Topology control approaches designed to minimize other network characteristics (link price, interference, and others) were proposed in [88–90]. In [91], the mobility strategy for network coverage was controlled, while efficiently managing energy resources. However, all these works neglected the importance of network connectivity on the capability to withstand sudden node/link failures. The authors in [92], [93] have focused on constructing k-edge connected topologies by executing LMST k times, which improves the robustness of network connectivity. In [94], a specific problem of all-to-one topology control for wireless sensor networks was investigated, in which k node-disjoint paths from each node to the sink were required. Instead of using the conventional connectivity metrics (node/edge connectivity), the authors employ algebraic connectivity here, a metric that has been shown to adequately represent the robustness of network connectivity [95–97]. Some of the pioneering work in this research area has taken the transmission energy into account, and have proposed several ways to reduce the transmission energy. In [17–20] various strategies have been proposed to minimise the transmission energy, which are suitable for long range applications. In our work presented in Chapter-3, we propose a novel strategy to reduce both transmission energy and circuit energy, so that the total energy consumption is reduced. In [98] the authors have shown that optimized transmission time can reduce energy consumption for both M-ary quadrature amplitude modulation (MQAM) and M-ary frequency shift keying modulation (MFSK) techniques. Some of the other works that have presented rate adaptation for energy efficiency are given in [15, 20]. In [20] the authors analyzed MIMO based rate adaptation in an 802.11n wireless network interface card and showed the trade-off between high throughput and energy efficiency. In [15] the authors have considered real world network topologies and traffic workloads from Abilene and Intel and have developed two power management schemes to utilize sleeping mode and rate adaptation for energy efficiency. In [99] the authors proposed an energy efficient rate adaptation algorithm for WiFi based long distance links. Different from all of these pioneering works, we analyze rate adaptation for energy efficiency in the physical layer from the fundamental equations, as presented i.n Chapter-3 of this dissertation.

2.3 Energy Efficiency at Access Level

A widely acknowledged fact of the recent age is that, the cellular communication networks will have greater economic and ecological impact in near future. As a consequence, an innovative new research discipline has been formed, namely 'green cellular networks, which has drawn the attention of many researchers who are dedicated to reduce the global footprint of cellular networks. The term green is originally a nickname of dedicated efforts to reducing unnecessary green house gases (such as, CO2) emissions from industries. Another motivation and objective of 'green' approaches, particularly for the mobile operators, is to acheive more commercial benefits, by minimizing the operating cost related to energy consumption. Hence, it has become necessary to shift the attention of netwrok designers from pursuing spectral efficiency and optimal capacity to implement energy efficient strategies. Energy-efficient wireless communication is also imperative from the users' perspective,. According to the 2010 wireless smartphone customer satisfaction study presented by J. D. Power and Associates [100], the iPhone received top marks in every category except for it's battery life. The latest report [101] in China also reflects the same issue, based on the data in [101], up to 60% of the users complained that battery endurance was the greatest hurdle when using 3G services. Without a breakthrough in battery technology, the battery life of the terminal sets will be the biggest limitation for energy-hungry applications (such as, video games, mobile P2P, interactive video, video monitors, streaming multimedia, mobile TV, 3D services, and video sharing). Therefore with the explosive growth of high-data rate applications in wireless networks, EE in wireless communications has recently drawn increasing attention from the research community. Several international research projects dedicated to energy-efficient wireless communications are being carried out.

There are various distinctive approaches to reduce energy consumptions in a mobile cellular network. Approaches found in the pioneering works can be broadly classified into the following five categories.

- Improving energy efficiency of hardware components.
- Turning off the network components selectively.
- Optimizing energy efficiency of the radio transmission process.
- Planning and deploying heterogeneous cells.
- Adopting renewable energy resources.

Approaches of the first category aim to improve hardware components (such as power amplifier) with more energy efficient design [7,28,78,79,98]. The performance of most components used in current cellular network architecture is unsatisfactory from the energy efficiency perspective. For example, the power amplifier consumes the largest amount of energy in a typical cellular base station (BS), where more than 80% of the input energy is dissipated as heat. Generally, the useful output power is only around 5% to 20% of the input power [102]. Studies showed that the potentially optimized ratio of output power to input power for power amplifiers (also known as power efficiency) could be as high as 70% [102]. Accordingly, substantial amount of energy savings can be achieved if more energy efficient components are adopted in the network. However, the implementation cost for these approaches is high. For example, a power amplifier module with 35% power efficiency for small cell WCDMA or LTE BSs (cover at most an area of a radius of 2 km) costs around \$75 [103]. The cost will be even higher for larger coverage or higher power efficiency. Therefore, careful consideration in both operational and economical aspects by network operators is required before decisions on hardware replacement are made. The second category covers approaches that selectively turn off some resources in the existing network architecture during non-peak traffic hours. Approaches in this category generally try to save energy by monitoring the traffic load in the network and then decide whether to turn off (or switch to sleep mode, also referred as low-power mode or deep idle mode in some literature), or turn on (or switch to active mode, ready mode or awake mode) certain elements of the network. Unnecessary energy consumptions, for example, air conditioning under-loaded BSs, can be avoided by adopting such sleep mode mechanisms. These approaches generally involve switching certain elements including but not limited to power amplifiers, transceivers, signal processing unit, cooling equipment, the entire BS, or the whole network back and forth between the sleep mode and the active mode [28]. Most often, sleep mode techniques aim to save energy by selectively turning off BSs during off-peak hours. As presented in Chapter-1, BSs consume the highest proportion of energy in cellular networks. On the other hand, dense BSs deployments lead to small coverage area and more random traffic patterns for individual BS, which make sleep mode operations more desirable. Given the constraint that some components (e.g., a minimum number of BSs) must always stay on to support the basic operation of the network, as well as the execution of the switch operation depends on the fluctuations in traffic profile, the reported energy saving is not as high as that of component-based approaches. Also, while it is good to save energy, BS sleeping might negatively impact Quality of Service (QoS) in the network because of decreasing capacity, unless specific remedial solutions are adopted concurrently [104], [105]. Nonetheless, because sleep mode techniques are based on current architecture, they have the advantage of being easier to test and implement as no replacement of hardware is required and the performance can be evaluated by computer simulation. The third category focuses on the radio transmission process. Approaches for this category work on the physical or MAC layer. Advanced techniques including MIMO technique, cognitive radio transmission, cooperative relaying, channel coding and resource allocation for signaling have been studied to improve energy efficiency of telecommunication networks. A variety of approaches have been proposed to efficiently utilize resources in time, frequency and spatial domains to achieve energy saving. Similar to approaches based on sleep mode, this type of approaches generally does not require upgrade of hardware components in the system. However, trade-offs between energy efficiency and other performance metrics of the network are probably inevitable. Moreover, measuring errors due to complicated uncertainty issues such as interference and noise have not yet been well investigated. Based on information theory, four fundamental trade−offs related to energy efficiency on wireless networks have been acknowledged, namely spectrum efficiencyenergy efficiency, deployment efficiency−energy efficiency, bandwidth−power and delaypower efficiency [106]. The fourth category tackles the energy efficiency issue by deploying small cells, like micro cells, pico cells and femto cells, in the cellular network [107]. These smaller cells serve small coverage areas with low energy-consuming cellular BSs [25, 52, 61, 62, 66, 72, 75, 107–114] which usually support plug-and-play feature and are affordable for user-deployment. Such heterogeneous deployment reduces energy consumption in the network by shortening the propagation distance between nodes in the network and utilizing higher frequency bands to support higher data rates, in contrast to conventional homogeneous macro cell deployment. However, the major drawback of these approaches is that, these additional small cells add more radio interferences as compared to conventional homogeneous macro cell networks, which might adversely affect the quality of service. Furthermore, the deployment of too many small cells may reverse the trend of saving energy because of extra embodied energy consumed by newly deployed cells as well as because of the overhead introduced in transmission. Therefore, the quantity and location of the small cells needs to be carefully optimized in order to reduce total energy consumption. Some research outcomes have also shown that, integrating heterogeneous network deployment with sleep mode schemes has proved to be very good approach to achieve significant gain in terms of energy saving [115–117].

The last category of the above mentioned list includes approaches that adopt renewable energy resources. Renewable resources such as hydro, wind and solar power stand out for their sustainability and environmental friendliness [118, 119] compared to widely used energy resources (such as hydrocarbon which produces greenhouse gases). Some telecom operators have implemented solar power operated cellular BSs in underdeveloped countries such as Bangladesh and Nigeria, where roads are in poor and unsafe condition, hence delivering traditional energy resources for off grid BSs (such as, diesel) cannot be guaranteed [120, 121]. Another popular approach is the energy harvesting techniques, where available energy is exploited from such renewable resources to complement existing electric operated infrastructure. This energy harvesting approach would probably be the long-term environmental solution for the mobile cellular network industry, especially for the particular areas without mature network infrastructure. However, it is technically challenging to preserve fault tolerance and data security without any service interruption while service migrates from the obsolete electric-operated BSs to the new energy harvesting BSs.

Generally speaking, green cellular network is a relatively new area of research, where the main aim is to make cellular networks greener by reducing total power consumption through various approaches described above. It was estimated that ICT roughly accounted for about 10% of global electricity consumption and up to 4% of global carbon dioxide emissions (around 1 billion tons, approximately equal to that of aviation industry and one fourth of emission by cars worldwide) as of early 2013 [122]. ICTs share in global carbon emissions is expected to grow every year, and become double by the year 2020 [29]. Furthermore, the prevalence of smart phones and tablets accessing cellular network remarkably contributes to the increasing energy consumption. Smart phones were introduced around the year of 2000. However, it was the success of mobile operating systems such as iOS, Android and Windows Phone about a decade later that finally helped them take over traditional feature phones. Tablet computers became popular almost at the same time, marked by the release of the iPad by Apple Inc. With the help of higher data transmission rate in 3G and 4G (and 5G in the future) cellular networks, smart phones and tablets enable users to perform much more tasks than ever before using cellular networks, including, but not limited to, streaming videos, downloading and reading e-books etc. As a consequence, the number of mobile subscribers are expected to increase from 4.5 billion (in 2012) to 7.6 billion by 2020; and the amount of data traffic requested by each subscriber are expected to increase from 10 GB (on average) per subscriber in 2012 to 82 GB per subscriber by 2020 [123]. Also, more dynamic and bursty mobile data and video traffic are dominating the mobile voice in cellular networks. All of these factors lead to significant increase in energy consumption. Manner et al. [124] showed that, an LTE network consumes about 60 times more energy as compared to a 2G network in order to provide the same level of coverage. The pioneering works anticipate that, more BSs, data centers and other network equipments are required to support the ever-growing mobile traffic. Since BSs consume more than half of the total energy in a typical cellular network, therefore the increase in the number of BSs has a significant impact in overall energy consumption. Researchers in [27] have shown that the number of BSs has approximately doubled from 2007 to 2012 worldwide, and this number reached more than 4 million by 2015. When cellular networks need to be extended to remote areas, off-grid BSs need to be deployed because of the unavailability of electrical grids in those areas. Off-grid BSs cost ten times more to run in comparison to their on-grid counterparts, since they generally depend on fuel, which is a costly and unreliable power source [125]. On the other hand, hydrocarbon energy, one of primary conventional energy resources that provides 85% of primary energy usage in the United States and releases large amounts of greenhouse gases when combusted, is proved not sustainable and expected to be exhausted in the near future [126].

2.3.1 Energy Efficiency in User Equipment

There have been significant improvements during the last two decades in carbon footprint per mobile subscriber. In the early 1990s, an average mobile subscriber would be responsible for 100 kg of carbon dioxide emissions per year. This figure had been reduced to one quarter, namely 25 kg per subscriber by the mid-2000s. However, the total amount of carbon footprint is still rising despite of the reduction in footprint per subscriber [127] since the number of mobile subscribers has dramatically increased. Meanwhile, the increasing number of subscribers also causes total data volume of wireless networks to increase approximately by a factor of ten every five years, which is associated with 16% to 20% increase in energy consumption [12]. The energy consumption in a cellphone, including battery chargers and user equipment (UE, which are the mobile devices used by end users),vhad been reduced from 32Whvper day in the early 1990s to 0.83 Wh per day in 2008, with a saving of more than 97%. This achievement in energy saving in UE has made the energy consumption negligible as compared to that in BSs. Nowadays, the main motivation for further improving energy efficiency in cellphones is not ecological or economic impacts, but longer battery life and thus better user experience [128–130]. For example, extensive research has been carried out on energy efficiency of data and power consuming applications such as social networking and multimedia streaming, to improve battery life of UE [130]. A comprehensive survey of energy efficient techniques on UE can be found in [27].

As mentioned earlier, energy efficiency in cellular networks and communication has been studied widely in literature [9, 10, 16, 26, 30–44, 131–141]. Some research papers [10, 30–39, 131, 132] have proposed different algorithms to implement sleep mode in the LTE BSs. MDP has been used as an effective approach for sleep mode implementation [9, 10, 30–44, 131, 132] for green communication. In [10], the authors proposed an MDP based optimal controller that associates to each traffic condition an activation/deactivation policy that maximizes a multiple objective function of the QoS and improve energy efficiency. Other papers such as [138], [139] consider a single user and use a Markov chain technique to evaluate the energy savings due to the sleep mode mechanism of a single user terminal. The authors in [139] take correlated packet arrivals into account to evaluate an MDP based sleep mode mechanism. Authors in [140] consider a similar setting of one user and one station and show how to derive the optimal sleep policy numerically by formalizing the problem as a Semi-MDP. Authors in [142] proposed a novel scheme for the sleep scheduling based on decentralized partially observable MPD (Dec-POMDP). However almost all of the above mentioned papers have proposed sleep mode of the BS in low traffic condition and the BS will be in active mode for rest of the time. The BS consumes zero power in sleep mode and requires some significant time to wake up. We can call this model as

'2-state model'. Authors in paper [9,10,30–39,132] have shown that this 2-state power consumption model can reduce energy consumption of the whole network. However, the problem is that, the BS takes significant time to wake up from sleep mode, which may cause call drop to new users. This wake up time can range from tens of seconds to couple of minutes for small cell and up to $10-15$ mins for macro cell [16]. This is clearly a constraint for an energy efficient system. To our best knowledge, very few of the previous works have implemented the stand-by mode. The authors in paper [135] proposed the low power consumption mode, which consumes small amount of power but wakes up within negligible time; their power consumption model is similar to what we propose as stand-by mode in our work presented in Chapter-4 and Chapter-5.

2.4 Energy-efficient radio resource management in Access Network

Radio resource management involves strategies and algorithms for controlling parameters such as transmit power, user allocation, data rates, handover criteria etc. in a way such that the limited radio-frequency spectrum resources and radio network infrastructure can be utilized as efficiently as possible. Energy-efficient radio resource management is one of the effective ways to reduce energy consumption of wireless systems. Most current network dimensioning is peak-load oriented to satisfy the users QoS requirements. In fact the daily traffic loads at BSs vary widely over time and space. Because of this, a large amount of power wastage occurs when the traffic load is low. This issue was already recognized by both vendors and operators and actions were taken. For instance, Alcatel-Lucent announced that a new feature of their software upgrades, dynamic power save (DPS), bring up to 27% energy saving for BSs deployed by China Mobile [15]. OPERA-Net project [143] proposed energy-saving solutions through cell-size breathing and sleep modes based on the traffic loads. Optimal power-saving schemes using cell switch-off under a trapezoidal traffic pattern and a measured traffic pattern are analysed in [28], proven that a $25-30\%$ energy saving is possible by simply switching off the active cells during the periods when traffic is low. However, no studied regarding the effect of the switch-off state on coverage. In [144], a traffic-aware BS mode (active or sleeping) switching algorithm, based on a blocking probability requirement, is introduced. To avoid frequent BS mode switching, a minimum mode holding time is suggested. It is shown that the effect of changing holding time over a specified range have little performance change on either energy saving or blocking probability [144]. In [145], demonstrates that energy saving will increase with the BS density and the variance-to-mean ratio of the traffic load. Energy saving should not only exploit the traffic load variations, but also the diversity of the QoS requirements. The trade-off between energy consumption and delay on the Internet has been extensively studied [15]. In the case of cellular network, little research has been done due to the limited service types (mainly voice communications) were available in the early systems (1G, 2G systems). However, the evolution of cellular systems and the popularity of smart phones, more and more diverse applications will appear on cellular networks. The ability to differentiate real time services and delay tolerant services is beneficial, since it is essential for scaling the energy consumption with the traffic type. Recently, some researchers have exploited the service latency of applications to reduce the energy consumption in cellular networks [15]. In [146] Energy efficiency in fading channels in the presence of Quality of Service (QoS) constraints has been studied. Effective capacity, which provides the maximum arrival rate that a wireless channel can sustain while satisfying statistical QoS constraints, is considered. Spectral efficiencybit energy tradeoff is analyzed in the low-power and wideband regimes by employing the effective capacity formulation, rather than the Shannon capacity. Based on the research, energy requirements under QoS constraints are identified. In low-power regime, minimum bit energy required under QoS constraints; same as that attained when there are no such limitations. The minimum bit energy and wideband slope expressions were obtained. The required bit energy levels are found to be strictly greater than those achieved when Shannon capacity is considered in this regime. Overall, a characterization of the energy-bandwidth-delay tradeoff is provided. Energy-efficient radio resource management can provide significant energy savings [15], but several important issues are still exposed: The collaboration between neighbouring cells should be further studied since the cell mode switching changes the coverage and handoff issues. The effect of these changes on EE should be evaluated. When the diversity of QoS requirements for different applications is exploited, a more general and practical QoS requirement model, as well as the fairness issues between users, should be considered. For example, since both the channel condition and the traffic flow are time-varying in wireless networks, it is possible that a traffic flow has a higher transmission priority according to its QoS requirement, but the corresponding channel condition is bad. Thus, we should balance the EE gain based on the diversity of QoS requirements and the QoS requirements themselves.

2.5 Implementation of Pico or Femto Cells to increase Energy Efficiency of cellular networks

Now-a-days Network operators are deploying Picocells and femtocells in the cellular network to provide energy efficient and cost-effective services. Femto cellular base stations, which are commonly known as Femto cells, are usually installed by the end user to increase indoor coverage. Femto cells reduce energy consumption by bringing receivers closer to the transmitter; hence by reducing transmit power, the penetration loss and path loss significantly. On the other hand Picocells provide localized coverage. Picocells are mostly used in densely populated areas such as airport terminals, train stations and shopping centres. Picocells and femtocells are usually installed within buildings for better indoor coverage. Both picocells and femtocells decreases the distance between the receiver and the transmitters, hence the penetration loss and path loss get reduced; as a consequence energy efficiency increases. In [102] the authors showed that 60% of total energy consumption for high-data rate user demand can be reduced by deploying picocells in urban areas. The use of femto cells in the existing macrocell network has been proved to be energy efficient due to the smaller path loss and lower transmit power. In [108] the authors have proposed a user activity detection strategy which detects the availability of active users. Hence the femtocellular BS can turn off its radio transmission and associated processing during the time when there is no active call available. As a result energy consumption reduces during the off-peak hour. The authors in [109] have proposed a new Wireless-over-Cable architecture for femtocells to offer an energy efficient solution. In [107] the authors have given a detailed description of femto cellular network design. The authors stressed that the femto cellular networks must be dealt with proper synchronization and interference management issues. Otherwise there will be more signalling overhead and consequently more energy consumption. They have also pointed out some more realistic challenges and potential researches to implement these femtocellular networks. Hence, a realistic approach to design energy-efficient femtocellular networks is still an unsolved issue.

The above mentioned researches depict that optimized energy-efficient design (including network deployment, transmission scheme and resource management) could significantly reduce the energy consumption of the entire communication network. Nevertheless, current research results are still quite preliminary and many challenges remain unsolved.

2.6 Energy Efficiency in Aerial Base Station

In the recent years, aerial networks have gained a wide popularity as key enablers for rapid deployment of wireless networks where coverage is provided by on-board radio heads [36, 4450] [50, 135, 147]. One of the main reason of this popularity is the remarkable advancement in microelectronics within the last couple of decades, which has allowed the reduction of size and weight of wireless communication equipments. Moreover, newer technologies and optical fibers have made it possible to separate remote radio head (RRH) and baseband unit (BBU), thus have reduced the weight of the equipments carried by tethered aerial platform. This has given huge opportunities to researchers and industry to propose and implement aerial communication networks in which aerial platforms carrying wireless communication equipments can be deployed to provide wireless coverage to terrestrial nodes. These aerial communication networks have shown great ability in tackling a number of different challenges including, increased coverage in remote areas, better line-of-sight (LoS) conditions and resilience to certain disasters. Different use cases have been envisioned for such networks including public safety, massive temporary events, Internet connectivity in emerging economies, etc. Although there has been increased interest in the aerial network technology, research is still at its nascent stage and there are quite a number of challenges such as designing energy efficient aerial base station, optimal altitude for placement of an aerial platform, aerial channel modeling, etc. that need to be addressed before we can see aerial communication networks in action. Some research projects have started to investigate the means of providing wireless connectivity using aerial platforms. Project CAPANINA [147] studied mechanically and electronically steerable antennas to deliver broadband wireless access using high-altitude platforms. FP7-funded ABSOLUTE project aimed to design and implement LTEA aerial base-stations using low-altitude platforms (LAPs) to provide wireless coverage and capacity to public-safety organizations in the aftermath of a large-scale disaster [50], [135]. Several companies including Google and Facebook have launched initiatives to explore opportunities to provide Internet connectivity to emerging economies using aerial platforms. One of the imporptant criteria is to select an appropriate technology to be used in aerial networks since performance of the aerial network greatly depends on these technologies. A number of different technologies such as LTE, WiFi, WiMAX, etc. can be used in conjunction with aerial networks. The authors in [148] and [149] have evaluated the performance of LTE aerial base-stations for public-safety communications. In [150], the authors have investigated the feasibility of deploying WiFi-enabled high-altitude platforms (HAPs) to provision multimedia broadcast/multimedia multicast services. The authors in [151] have studied the utilization of balloons in combination with IEEE 802.11 technology to build an ad-hoc network. In [152], the comparison of the coverage offered by unmanned aerial vehicles (UAVs) with well-known terrestrial channel models has been studied. The authors in [153] have evaluated the performance of LTE in terrestrial networks. System-level performance of LTE-V2X network has been analysed in [154]. The authors in [155] have evaluated the delay performance of LTE networks in various traffic patterns and radio propagation environments. A decentralized multitarget tracking system for cooperative Unmanned Aerial Vehicles (UAVs) with limited sensing resources is presented in [156]. The proposed system distributively incorporates a clustering algorithm, an optimal sensor manager, and an optimal path planner. Authors in [157] presented an analytical framework to estimate the performance of an aerial platform utilising Air-to-Ground channel model. This analytic framework allows rapid optimisation of the key parameters influencing aerial platforms such as the altitude and power, given a certain set of constraints or QoS requirements and thus, facilitates the rapid and optimum deployment of AeBS by just knowing the underlying urban statistics. In [158], the performance of UAVs acting as relays for ground-based nodes in a hierarchical wireless network is investigated. They derived a closed-form expression for the optimal UAV heading that achieves the highest overall data rate in the multi-user uplink system. They also developed an adaptive handoff algorithm to dynamically adjust the UAV-AP (access point) assignments in order to improve network performance. After studying all of these pioneering work, we have found that the energy efficiency of aerial platforms, particularly on aerial base stations is not sufficiently addressed. Energy is a scarce resource for aerial base stations, hence energy-efficient operation of such networks is important given that the entire network infrastructure, including the battery-operated ground terminals, exhibits requirements to operate under power-constrained situations. Therefore, the wise management of energy is quite beneficial for the network lifetime. In this context, we study the means of reducing the total energy consumption by designing and implementing an energy efficient AeBS as presented in Chapter-5 of this dissertation.

2.7 Fundamentals in Markov Decision Process

Each day people make a number of decisions that have both immediate and long term consequences. Decisions cannot be made in isolation. Todays decision impacts on tomorrow and tomorrows decisions impact on the following days. By not accounting for the relationship between present and future decisions, and present and future outcomes, a good overall performance might not be achieved. For example, in a long race, the decision to sprint at the beginning might deplete energy reserves quickly and result in a poor finish. MDP, also referred to as stochastic dynamic programs or stochastic control problems, are models for sequential decision making when outcomes are uncertain. Probability theory states that a Markov Model is defined as a stochastic model that is used to model randomly changing systems where the assumption of future states depend only on the current state and not on the events that occurred before it is held valid. There are different types of Markov model (MM): Markov Chains and Hidden Markov Models (HMMs) [159]. HMMs are models where the states are only partially observable. Observations are related to the state of the system, but they are typically insufficient to accurately determine the state. This means that the user enters the current state which is not completely tangible with the expected state. An extension to such HMMs is the inclusion of actions performed at each state that leads to the next possible state with a reward. Such cases are known as Markov Decision Processes (MDPs). However, the extension of an HMM leads to a Partially Observable Markov Decision Process (POMDP) due to the states consisting of partial information. At each time interval, the agent gets to make some observations that depend on the state. The agent only has access to the history of observations and previous actions when making a decision. It cannot directly observe the current state, hence unable to acquire complete information regarding the current state. The MDP model consists of decision epochs, states, actions, rewards, and transition probabilities. Choosing an action in a state generates a reward and determines the state at the next decision epoch through a transition probability function. Policies or strategies are prescriptions as to which action to choose under any eventuality at

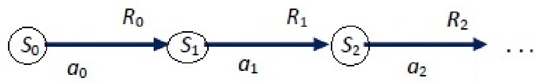

Figure 2-1: States, Action and Reward of a MDP

every future decision epoch. Decision makers seek policies that are optimal in some sense. The following example gives us a clear idea on how MDP can be helpfull in taking a decision.

Example [159]: An agent (or robot) exists in a certain environment. The environment consists of states, and the agent moves between states in this environment. Based on the current state information the agent decides which state to move to next. Depending on the agents action, the environment returns new state information and some reward. The goal in this problem is to maximize the agents reward. The above interaction between the agent and the environment can also be shown as Fig.2-1.

Here, the agent starts at state S_0 and initially executes action a_0. This gets the agent reward R_0 and takes him to state S_1. At state S_1, he executes action a_1, which gets him reward R_1 and takes him to state S_2 and so on. This environment obeys the Markov property, i.e., everything in the past can be summed up in the current state; or, in other words, the future depends only on the current state. It is also assumed that the environment has a finite number of states and that the goal of the MDP is to find an optimal way to act in this environment. MDPs are powerful modelling tools that allow controlling a Markov chain by creating optimal policies that dictate what action to take as a response to the current state [159]. MDPs have been successfully applied in a diverse range of industries, from revenue management to a variety of real life systems including inventory management. A wide range of computer, manufacturing, and communications systems can also be modeled using the MDP. Moreover, MDP models have been applied to a number of equipment maintenance and replacement problems [159]. The key ingredients of the MDP are the followings [159]:

2.7.1 Decision Epochs

Decisions are made at points of time referred to as decision epochs. Let T denote the set of decision epochs. In discrete time problems, decisions are made at all decision epochs and the time is divided into periods or stages. The set of decision epochs is denoted by $T = 1, 2, ..., M$.

2.7.2 State and Action Sets

At each decision epoch, the system occupies a state. The set of possible system states is denoted by S. If, at some decision epoch, the decision maker observes the system in state $s \in S$, he may choose action a from the set of allowable actions A.

2.7.3 Reward and State Transition Probability

As a result of choosing action $a \in A$, in state s at decision epoch t,

- the decision maker receives a reward, $R_t(s, a)$ and
- the system state at the next decision epoch is determined by the probability distribution $P[s'|s, a]$, where $s' \in S$ denotes the next state.

2.7.4 Decision Rules and Policies

A decision rule prescribes a procedure for action selection in each state at a specified decision epoch. This decision rule is said to be Markovian (memoryless), when it depends on previous system states and actions only through the current state of the system, and deterministic, when it chooses an action with certainty. Deterministic Markovian decision rules are functions δ_t, which specify the action choice when the system occupies state s at decision epoch t. A policy $\pi = (\delta_1, \delta_2, ..., \delta_M)$ is a sequence of decision rules to be used at all decision epochs, where M is the total number of decision epochs. It provides the decision maker with a prescription for action selection under any possible future system state or history. A policy is called stationary if $\delta_t = \delta$ for all $t \in T$.

2.7.5 Optimal Policy

Since the aim of MDP is to maximize the expected total reward $V(s)$ for all $s \in S$, the following optimality equation can be defined by considering a discount factor λ.

$$V(s) = max_{a \in A}\{R(s,a) + \sum_{s' \in S} \lambda Pr[s'|s,a]V(s')\} \tag{2.1}$$

The solutions of the optimality equations correspond to the maximum expected total reward $V(s)$ for all states and the MDP optimal policy. Note that the MDP optimal policy indicates the decision as to which option to choose from, given that the current state is s. There are various algorithms that are available to solve the optimization problem given in Eq.2.1. Examples include the Value Iteration Algorithm (VIA), Policy Iteration Algorithm (PIA), and Linear Programming (LP) [159]. The VIA is an iterative procedure that calculates the expected reward of each state using the rewards of the neighbouring states until the reward calculated on two successive iterations are close enough to each other. The PIA picks an initial policy, usually by taking rewards on states and computing a policy according to the maximum expected reward principle. Then it iteratively performs the following two steps: value determination, which calculates the reward of each state given the current policy; and policy improvement, which updates the current policy if any improvement is possible. The algorithm terminates when the policy stabilizes [159]. If the state space and action space are finite, the LP formulation could also be used to find the optimal policy. LP is a technique for the optimization of an objective, and is subject to linear inequality constraint. However, in our research we solve this optimization problem by the VIA, as the PIA and LP is not suitable for large state spaces.

2.8 Handover

In the heterogeneous wireless environment, a mobile user is able to enjoy an uninteruppted service using the mobile device while moving from the coverage area of one BS to another BS. This process is called a handover, by which a mobile terminal keeps

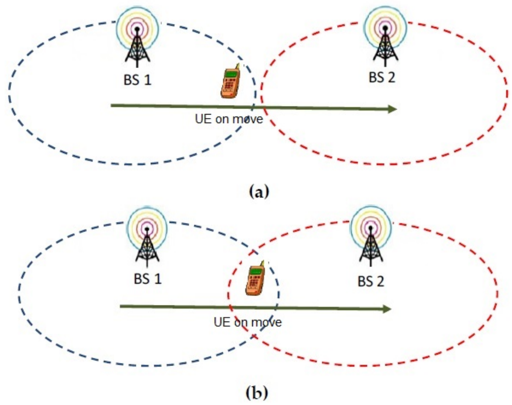

Figure 2-2: Horizontal handover. (a) Hard handover; (b) Soft handover

its connection active as it migrates from the coverage of one network access point to another [160]. Handovers are called to be seamless if the handover is transparent to the user of the available network [161]. A seamless handover is defines as a handover scheme that maintains the connectivity of all applications on the mobile device when the handover occurs [162].

2.8.1 Different types of handover

Based on different factors used in the handover decision process, handovers can be classified in various ways.

Horizontal Handover

Horizontal handover occurs when the mobile station moves from one base station to another base station within the same technology. Horizontal handover is also called an intra-technology handover, such as the handover between base stations of the UMTS, where mobile nodes move from one base station to another base station. An example of horizontal handover is illustrated in Fig. 2-2. A horizontal handover can be classified as a hard or soft handover, depending on connectivity during the handover.

Hard Handover

In a hard handover, the mobile node first has to disconnect from the current network before connecting to the new network. In other words, using hard handoff, a mobile node is allowed to maintain a connection with only one base station at any given time as illustrated in Fig.2-2(a).

Soft Handover

In the concept of soft handover, the mobile node can select the new network before disconnection from the current network. So, in soft handover the mobile node is connected to two networks at the same time, as illustrated in Figure Fig.2-2(b). Soft handovers are possible in situations where the mobile node is moving between cells that are operating on the same frequency.

Vertical Handover

Vertical handover means the handover between different wireless technologies, such as a handover between the UMTS and WLAN. This is also called an inter-technologies handover. Vertical handover can be classified into two types: upward handover and downward handover depending on data rate changes.

Upward Handover

Moving of a mobile node from a small network cell with a high data rate to a big network cell with a low data rate is called upward handover. Although the small network has a high data rate, the mobile node has to move into a large network with low data rate when leaving the transmission range of the existing small network.

Downward Handover

In downward handover, the mobile node moves from a large network cell with a low data rate to a small network cell with a high data rates. In downward handover, the mobile node discovers the available network, selects the one that provides the highest data rates and then decides to execute the handover. As it is a disadvantage to remain connected to the low data rate network when a high data rate network is available, the handover optimizes the overall network performance.

2.8.2 Related work on handover in femtocell networks

Conventional handover schemes do not assure an optimal management of the handover procedures over the HetNets and the handoff from Macrocell to femtocell is still an open issue. UEs need to select the appropriate target femtocell among many candidates by taking into account the interference level, UE speed and the available resources of the target cell. Power consumption is one of the most important problems affecting new generation systems. In fact, most of energy consumption of the telecommunication networks is caused by the base stations. Since there are several femtocells within a macrocell area, the femtocell deployment increases the energy consumption. The 3GPP TS 36.927 (release 10) [163] identifies as potential solutions for energy saving (ES) three alternatives: (i) the totally switch-off of the base stations when there are not users, (ii) the trigger of the ES procedures in case of light traffic, and (iii) the use of the femtocells in idle mode. Ashraf et al. in [108] proposed to improve the energy efficiency of femtocells via the user activity detection. The proposed procedure allows the femtocell to switch-off the radio transmissions in presence of no active calls involved. This method, however, does not foresees an effective procedure to reduce the ping-pong effect. Therefore, the total power consumption increases if idle femtocells makes the wrong decision to wake up in order to execute an unnecessary handover. In [164] a scheme for unnecessary handover minimization is presented. Authors proposed a Call Admission Control (CAC) technique to improve the handover process under particular conditions. Three parameters are taken into account: (i) the Received Signal Strength (RSS), (ii) the time in which a Mobile Station (MS) maintains the minimum required signal level, and (iii) the Signal-to-Interference Noise Ratio (SINR). The handover requests are triggered if the SINR from the femtocell is greater than the SINR from the macro and if the RSS from the femtocell is greater than a given threshold. In [165] authors proposed a new handover algorithm based on the UEs speed and the QoS requirements. They consider a dense femtocell scenario where users with high mobility cross the femtocell coverage in a short time. Under these conditions, the authors consider that users with high speed do not need to make a handover, in particular when they support non-real- time services. Three different environments are analyzed: (i) low mobile state (from 0 to 15 km/h), (ii) medium mobile state (from 15 to 30 km/h) and (iii) high mobile state (above 30 km/h). In addition, they consider real-time and non-real-time traffics in the simulation campaigns for the evaluation of the proposed algorithm. Differently from [165], an handover decision policy based on mobility prediction is proposed in [166] by considering as maximum speed 10 Km/h. A reactive and proactive handover strategy is also proposed to mitigate the frequent and unnecessary handover. In [167] the authors proposed a new handover procedure between macrocell and femtocell based on the use of the UEs residence time in a cell and by exploiting two different thresholds for the serving and the target cell, respectively. Authors demonstrated that such an approach allows to reduces the number of unnecessary handovers. In [168] authors developed a green handover protocol in two-tier OFDMA networks (macrocell and femtocell). This is mainly based on the prediction of the dwell time (t_{dwell}) and average expected transmission time ($t_{expected}$) of the UE. The algorithm consists of three phases: (i) free spectrum configuration, (ii) transmission time estimation, and (iii) green handover decision. In order to improve the energy efficiency of the network, the handover framework proposed in [168] wake-up periodically the BSs from the idle mode. In this way, they have a timely response to the network changes. Even though HO decision making is challenging in the LTE-A femtocell network, only a few reports are engaged with the matter [25, 75, 113, 114]. Assuming a single femtocell single macrocell network layout, the algorithm in [113] uses a combined Received Signal Strength (RSS) metric to choose between the macrocell and the femtocell service. The algorithm in [75] accounts for the UE speed to avoid inbound mobility to femtocells for medium to high speed users. The authors in [114] perform mobility prediction to estimate the cell residence time of the user and reduce the number of unnecessary HO events in the system. The policy in [25] uses standard measurements to reduce the mean UE transmit power in the two-tier LTE femtocell network. In [169] the algorithm is based on the MDP formulation with the objective of maximizing the expected total reward of a connection. A link reward function is used to model the QoS of the mobile connection. A signalling cost function is used to model the switching and rerouting operations when a vertical handoff occurs. This work aims at illustrating the tradeoff between these two important aspects in the vertical handoff decision. In [170], a vertical handoff decision algorithm for 4G wireless networks has been proposed. The problem is formulated as a constrained Markov decision process (CMDP). In Chapter-6 of this dissertation, we develope an energy efficient handover algorithm for heterogeneous network. To our best knowledge, Markov decision Process (MDP) has never been used to develop an energy efficient hand over decision algorithm in LTE network. Thus the novelty of our work is in developing a MDP based energy efficient hand over (HO) decision algorithm for LTE network with small cells.

Chapter 3

Optimization of Rate Adaptation for Energy Efficiency with MQAM and MFSK

3.1 Introduction

Energy efficiency in wireless communications has become one of the most attractive issues in recent years. Since, these wireless devices are operated by the batteries, therefore the maximum number of bits that can be sent are controlled by the finite battery energy. Consequently, reduction in energy consumption has become a very pivotal design aspect. Most of the pioneering work in this research area have proposed several ways to reduce the transmission energy by considering the transmission energy only. In [17–20], various strategies have been proposed to minimise the transmission energy, which are suitable for long range applications. In this work presented in this chapter, we propose a novel strategy to reduce both transmission energy and circuit energy, so that the total energy consumption can be reduced.

The energy consumption of the circuit has potential impact over the total energy consumption in wireless communication, specially, for the ad-hoc networks having dense located nodes, like sensor networks and this consumption is mostly equal and sometimes also dominates the transmission energy. This work considers consumption of both circuit energy and transmission energy, at the sides of transmitter as well as receiver. Rest of this chapter refers to the energy consumption term, which indicates the consumption of total energy that includes both the circuit energy and transmission energy.

In [8] the authors have shown that the energy consumption for both M-ary quadrature amplitude modulation (MQAM) and M-ary frequency shift keying modulation (MFSK) techniques can be reduced by optimizing transmission time. This chapter contains the extension of this work towards rate adaptation analysis for optimal energy consumption and provide novel results showing the relationship between the distance between the transmitter and receiver and the optimal rate for which maximum energy efficiency could be achieved. We have explicitly analyzed and found that optimization of the data rate R_b or optimum constellation size can reduce energy consumption for the given symbol rate under an AWGN (additive white Gaussian noise) channel. Rate adaptation has been used by some of the pioneering works [22–24] for energy efficiency. The authors in [22], analyzed MIMO based rate adaptation in an 802.11n wireless network interface card and showed the trade-off between high throughput and energy efficiency. In [23], the authors have considered real-world network topologies and traffic workloads from Abilene and Intel and have developed two power management schemes to utilize sleep mode and rate adaptation for energy efficiency. In [24] the authors proposed a rate adaptation algorithm for energy efficiency for WiFi based long distance links. Our work analyzes rate adaptation for energy efficiency in the physical layer of an wireless network utilizing the fundamental equations.

As per system constrain, peak power constrain and rate constrain are taken into account and lower and higher boundary of data rate are defined consequently. Then an equation is derived for total energy consumption from the probability of error bound approximation for each of the modulation schemes. These equations show that the energy consumption is a function of data rate and distance for a particular Bandwidth. As a consequence, significant amount of energy can be reduced by taking the maximum bandwidth and optimizing the data rate for a constant bit error rate (BER).

3.2 System Model

Fig.3-1 shows our considered communication link which connects the wireless transmitter with a receiver. An assumption is made that a Digital to Analog Converter (DAC) in the transmitter side converts baseband signal to analog signal, which is followed by a low pass filter. The mixer will then modulate this output signal by the carrier signal, which is produced by the local oscillator. This signal is then amplified by a Power Amplifier (PA), before it is released into the wireless channel. At the receiver side, the received RF signal will be filtered and amplified first by filter and then by a Low Noise Amplifier (LNA), followed by being down converted by a mixer. Finally the received signal goes through to an intermediate frequency amplifier (IFA) and an analog to digital converter (ADC).

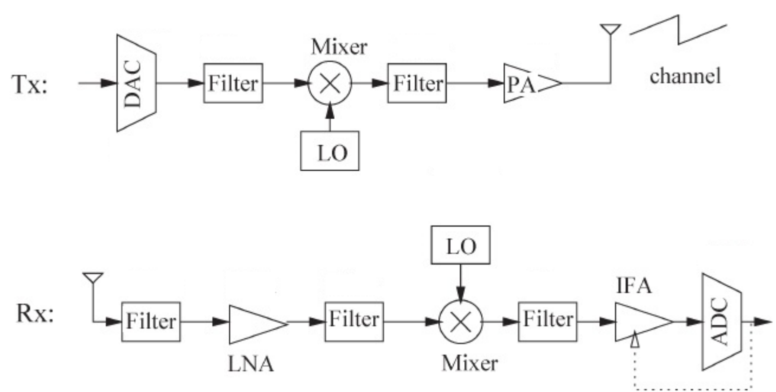

Figure 3-1: Circuit blocks in the transceiver and the receiver

The energy consumed by all of the above mentioned circuit blocks are considered in our work. However the energy consumption of the basic signal processing units (i.e sampling, coding, digital modulation, pulse shaping etc) are neglected for the sake of the simplicity of the calculations. Cirtuit blocks from the transmitter side as well as the receiver sides are assumed to work in three different modes, namely:

- **Active mode**: When a data needs to be conveyed from transmitter to receiver.

- **Sleep mode**: When there is no data available to be transmitted.

- **Transient mode**: Transition from sleep mode to active mode.

As a result, a significant amount of energy can be saved during the sleep mode.

We assume that, when the data is taken as measurements by each sensor or each node of the sensor network, then firstly, the measurement is converted into bits of L number. After that the total L bits will be transmitted towards the central processor and the node will get back to the sleep mode, after completion of the transmission. This entire work is completed within a deadline (T) and with a minimum data rate (R_{bmin}). Therefore, the time and data rate needed only for the transmission of the L bits are defined as $T_{on} \leq T$ and $R_b \geq R_{bmin}$ respectively. If no more data is available to be sent after finishing this transmission, then all of the circuit blocks are turned off to be in sleep mode. In our work, the optimization of R_b is done towards optimal rate adaptation for minimizing the energy consumption. It should be mentioned here that, the start-up time of the frequency synthesizer is to be considered during sleep to active mode transition, since it is not negligible compared to the start-up time of the other circuit blocks. Therefore the power consumed by the frequency synthesizer (P_{syn}) needs to be included in the power consumption during the transient mode (P_{tr}). Hence the total energy consumption will be the combination of transmit energy($P_t T_{on}$), power amplifier energy ($P_{amp} T_{on}$), circuit energy ($P_c T_{on}$) and transient energy $P_{tr} T_{on}$. If we substitute $R_b = \frac{L}{T_{on}}$ and $P_{tr} = 2P_{syn}$ then we can derive the following equation for the total energy consumption:

$$E_a = \frac{(1+\alpha)P_t + P_c}{R_b} + \frac{2P_{syn}T_{tr}}{L} \tag{3.1}$$

Here P_t denotes the transmit power, T_{tr} denotes the transient mode duration which is equal to the frequency synthesizer settling time, P_{syn} denotes the frequency synthesizer power consumption and P_c denotes the total circuit power consumption. Here, P_c consists of the power consumed at the transmitter side as well as the receiver side. The circuit power consumed at the transmitter side consists of the mixer power consumption P_{mix}, frequency synthesizer power consumption P_{syn}, active filter power consumption P_{filt} and the DAC power consumption P_{DAC}. On the other hand, the power consumed at the receiver side consists of the the mixer power consumption P_{mix}, the frequency synthesizer power consumption P_{syn}, the LNA power consumption P_{LNA}, the active filter power consumption P_{filr}, the IFA power consumption P_{IFA}, and the ADC power consumption P_{ADC}. It is noteworthy to mention that, we include the power consumption of the power amplifier P_{amp} separately since it is a function of the transmit power. The power consumption of the PA is given by, $P_{amp} = \alpha P_t$, where $\alpha = \frac{\zeta}{\eta} - 1$, η is the drain efficiency and ζ is the peak to average power ratio.

Hence, for a given distance (d) between the transmitter and the receiver, pathloss exponent k and a link margin of M_l, the required transmit power levels for MQAM and MFSK is given in Eq.3.2 respectively, where we consider a constant bit error probability (P_b) at the receiver end [8].

$$P_{t-MQAM} = \frac{4}{3} N_f \sigma^2 (2^b - 1) \ln\left(\frac{4(1 - 2^{\frac{-b}{2}})}{bP_b}\right) G_d B \tag{3.2}$$
$$P_{t-MFSK} = 4 N_f \sigma^2 \ln\left(\frac{2^{b-2}}{P_b}\right) G_d \frac{2B}{2^b}$$

here, N_f is the receiver Noise Figure, σ^2 is the double sided noise power spectral density, $G_d = G_l d^k M_l$ and G_l is the gain factor at $d = 1$m which is defined by system parameters such as the carrier frequency and antenna gains. Considering a realistic scenario, we impose a constraint on the maximum transmitter power (P_{max}) associated with the communications circuit of the handset, which is given by,

$$\text{Peak Power Constraint} : 0 \leq (1 + \alpha) P_t + P_{ct} \leq P_{max} \tag{3.3}$$

We also impose a minimum data rate constraint of R_{bmin} based on the technology standard. On the other hand, the power constraint in Eq.3.3 also poses a maximum allowable data rate, hence gives us a lower and an upper bounds for the achievable data rate as presented in Eq.3.4:

$$\text{Rate Constraint} : R_{bmin} \leq R_b \leq R_{bmax} \tag{3.4}$$

We find the optimal data rate in the following section for both MQAM and MFSK, based on the transceiver model and the constraints presented in this section. Note that we do not explicitly provide a value for P_{max} in our work but rather leave it open since it depends on the circuit design and the electrical power budget.

3.3 Energy Consumption for MQAM

As mentioned before, the system is expected to transmit L bits with a deadline of T seconds in order to meet a given bit error probability P_b and a total bandwidth of B. Let us denote b as the number of bits per symbol for the MQAM modulation, which is given by $b = \log_2 M$. Then the total number of MQAM symbols required for the transmission is $L_s = \frac{L}{b}$. It can also be written as, $L_s = \frac{T_{on}}{T_s}$, where T_s is the period of the symbol. We can find a relationship between the constellation size and the transmission time from the above mentioned equations, as $b = \frac{LT_s}{T_{on}}$. The data rate is of course given by the fundamental relationship $R_b = \frac{L}{T_{on}}$ or alternatively as $R_b = \frac{b}{T_s}$. Based on the above definitions and using (3.1) and (3.2), a closed form expression for the total energy consumption E_a for MQAM can be derived, given by:

$$\begin{aligned} E_a = {} & (1+\alpha)\frac{4}{3}N_f\sigma^2\frac{(2^b-1)}{b}\ln\left(\frac{4(1-2^{\frac{-b}{2}})}{bP_b}\right)Gd \\ & + \frac{P_c}{bB} + \frac{2P_{syn}T_{tr}}{L} \end{aligned} \tag{3.5}$$

In order to simlate our proposed algorithm, we use the values provided in Table. 3.1. We consider a class A power amplifier for MQAM, which gives us the drain efficiency, $\eta = 0.35$. For MQAM $\zeta = 3\left(\frac{\sqrt{M}-1}{\sqrt{M}+1}\right)$, where $M = 2^b$. Using the data provided in Table3.1 we calculate $b_{min} = \frac{L}{BT} = 2$ and $R_{bmin} = \frac{b}{T_s} = bB = 20k$ for MQAM. From the fundamental equation of data rate we know that, $R_b = \frac{b}{T_s}$, where

Table 3.1: Parameters used for the system analysis for MQAM and MFSK, directly adopted from [8]

fc=2.5 GHz	k=3.5
B=10 kHz	P_{mix} = 30.3 mW
P_{LNA}=20mW	T_{tr}=5us
T=100ms(MQAM) and T=1.07s(MFSK)	N_f=10 dB
$\eta = 0.35$(MQAM) and $\eta = 0.75$(MFSK)	$\sigma^2 = \frac{N_0}{2} = -174$dBm/Hz
L=2000 bits, G_l=30 dB	P_{syn} = 50 mW
P_{IFA}=3 mW	$P_{filt} = P_{filr}$=2.5mW
$M_l = 40dB$	$P_b = 10^{-3}$
$R_{bmin} = 20k$(MQAM)	$R_{bmin} = 1869$(MFSK)
$P_{ADC} = 6.7e^{-3}$	$P_{DAC} = 1.54e^{-2}$(MQAM)

T_s is symbol period. If we consider square pulses then $T_s = \frac{1}{B}$ and hence $R_b = bB$. Therefore we can write the expression of total energy consumption for MQAM in terms of the data rate R_b as in the following equation:

$$E_a = \frac{(1+\alpha)\frac{4}{3}N_f\sigma^2\left(2^{\frac{R_b}{B}}-1\right)\ln\left(\frac{4\left(1-2^{\frac{R_b}{2B}}\right)}{\frac{R_b}{B}P_b}\right)G_dB}{R_b} + \frac{Pc}{R_b} + \frac{2P_{syn}T_{tr}}{L} \tag{3.6}$$

Fig. 3-2 shows the relationship between the energy consumption, E_a and data rate,R_b.

From Fig.3-2 we can see that, a minimum point exists on the energy consumption curves for some distances, which indicates the existance of optimal data rate for minimum energy consumption. For instance, for $d = 5m$, a significant amount of energy can be saved by using optimal data rate $\frac{R_b}{R_{bmin}} = 5$, rather than using $\frac{R_b}{R_{bmin}} = 1$.

3.3.1 Optimal Data Rate for MQAM

Fig.3-2 clearly shows that, there exists an optimal data rate for which the energy consumption is minimum upto a certain distance between the transmitter and the reciever. In order to find this optimal data rate for a particular distance, we have to

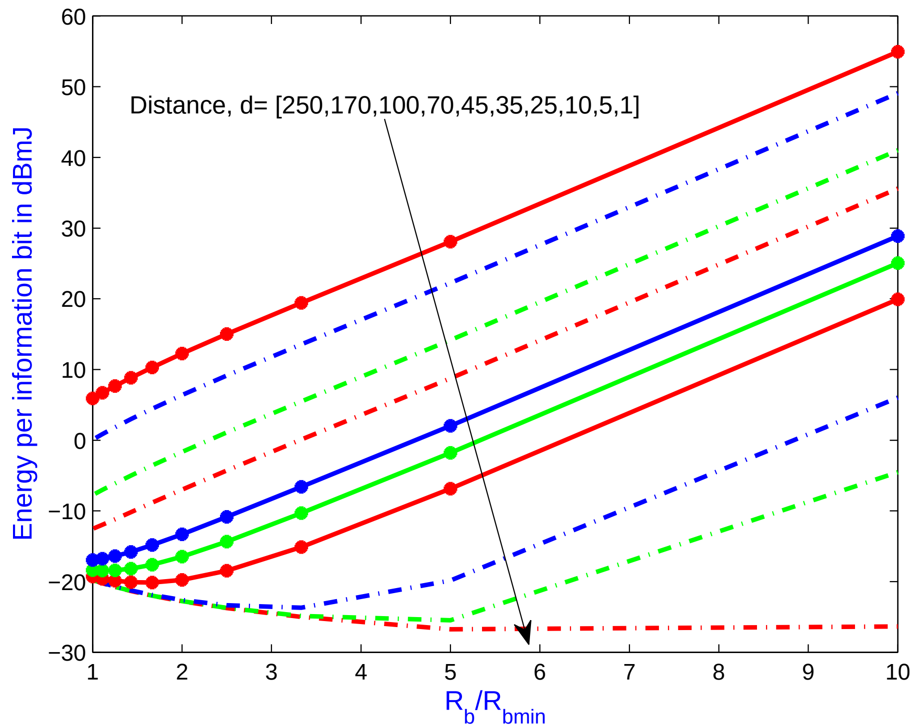

Figure 3-2: Total energy consumption for MQAM vs optimized data rate for different transmission distances,d(m)

find out the R_b for which the first derivative of E_a with respect to R_b will become zero. In other words, we have to find out the root of $\frac{dE_a}{dR_b}$ for each particular distances. We have applied the Newton-Raphson method to find these roots.

Newton-Raphson Method As per the Newton-Raphson method [171], x_{n+1} is an updated estimate of the root of the function $f(x_n)$ after n iterations, as shown in eqn(3.7):

$$x_{n+1} = x_n - \frac{f(x_n)}{f'(x_n)} \tag{3.7}$$

After a few iterations of the above mentioned equation we are able to find the root of $f(x_n) = 0$. We have applied the same method to find the root of $\frac{dE_a}{dR_b}$. This root will be the value of R_b for which we will have the minimum energy consumption for particular distance, d. The expression for $\frac{dE_a}{dR_b}$ is given below.

$$
\begin{aligned}
\frac{dE_a}{dR_b} = & \frac{2^{\frac{R_b}{B}} K_1 d^k \ln\left(\frac{-B\frac{4}{2^{\frac{R_b}{2B}}-4}}{P_b R_b}\right)}{R_b} - \frac{P_c}{R_b^2} \\
& - \frac{K_2 d^k \ln\left(-B\frac{4}{2^{\frac{Rb}{2B}}-4} P_b R_b\right)\left(2^{\frac{R_b}{B}}-1\right)}{R_b^2} \\
& - \frac{K_3 d^k \left(2^{\frac{R_b}{B}}-1\right)\frac{B\left(\frac{4}{2^{\frac{R_b}{2B}}-4}\right)}{P_b R_b^2} + \frac{2}{\left(2^{\frac{R_b}{2B}}\right) R_b} K_4}{\left(\frac{4}{2^{\frac{R_b}{2B}}-4}\right)}
\end{aligned}
\tag{3.8}
$$

where, $K_4 = \frac{\ln 2}{P_b}$. $K_1 = G_l M_l N_f \sigma^2 \ln(2)\left(\frac{4a}{3}+\frac{4}{3}\right)$, $K_2 = B G_l M_l N_f d^k \left(\frac{4a}{3}+\frac{4}{3}\right)\sigma^2$, $K_3 = G_l M_l N_f P_b \sigma^2 \left(\frac{4a}{3}+\frac{4}{3}\right)$.

After applying the Newton-Raphson method, we find the optimal data rate $R_b = 8.1727$ for $d = 1$m; $R_b = 4.5508$ for d = 5m; $R_b = 1.33$ for d = 30m and $R_b = 0.3015$ for d = 100m. These results are plotted in Fig.3-4. As R_b defines the constellation size for a fixed Bandwidth so we have to find an integer value of optimal data rate,R_{bopt}. Therefore we have to find the nearest integer which will give us minimum energy consumption as shown in Table 3.2. For example, for $d = 1$m R_b is 7.9491, so we took the two nearest integers to this value (7 and 8) and found energy consumption for each of them as -27.9870 dBmJ and -27.9450 dBmJ respectively. As $R_b = 7$ gave us the minimum energy so we choose $R_{bopt} = 7$ for d=1m. Thus we defined that particular R_b as the optimal data rate, $R_b opt$. On the other hand, the data rate is related to bit per symbol (b) by the expression, $b = \frac{R_b}{B}$. Hence optimization of bit per symbol can also reduce energy consumption.

3.3.2 Optimization Range for MQAM

It is evident from Eq.3.5 that the transmission energy is dependent on the transmission distance d whereas the circuit energy consumption is independent of d. Hence energy can be minimised by optimizing the data rate only when the circuit energy

Table 3.2: Finding the Optimal data rate for MQAM

$Distance$	$R_b/R_{b_{min}}$	$R_{b_{floor}}$	$E_a for R_{b_{floor}}$	$R_{b_{Ceil}}$	$E_a for R_{b_{Ceil}}$	$Selected\ R_b\ for\ minimum\ Energy$
1	7.9491	7	-27.9870	8	-27.9450	7
5	4.3469	4	-24.7752	5	-23.6941	4
10	2.9552	2	-22.0347	3	-22.0892	3
15	2.2286	2	-20.3035	3	-18.4045	2
30	1.2087	1	-15.3076	2	-12.9579	1
35	1.0279	1	-13.7114	2	-10.8640	1
40	0.8860	-	-	-	-	$lessthanRbmin$

consumption dominates or is equal to the transmission energy. With increasing distance the transmission energy starts dominating the circuit energy as the transmission energy increases with d. Therefore there should be a maximum distance beyond which energy saving is no longer possible by optimizing the modulation parameters (i.e. R_b or b).This maximum distance will make the derivative of E_a relative to R_b equal to zero at the minimum data rate. For the above example, $d = 35$m is the threshold, where $\frac{dE_a}{dR_b} = 0$ at the point $\frac{R_b}{R_{bmin}} = 1$. Beyond this distance no more energy saving is possible by doing rate adaptation for MQAM for the above mentioned numerical example.

3.4 Energy Consumption for MFSK

Let us now consider the whole scenario for MFSK. If we denote b_1 as the bit per symbol for MFSK, then the number of orthogonal carriers will be, $M = 2^b_1$. The data rate can defined as $R_{b1} = \frac{b_1}{T_s}$ regardless of the modulation technique. The total bandwidth for MFSK is $B = \frac{2^b_1}{2T_s}$ as in [77], given carrier separation is $\frac{1}{2T_s}$. Therefore, bandwidth efficiency, $B_e = \frac{R_{b1}}{B} = \frac{2b_1}{2^b_1}$. Bandwidth efficiency can also be defined as, $B_e = \frac{L}{BT_{on}}$ for any modulation technique. Hence, we can derive the relationship between b_1 and transmission time as $\frac{2b_1}{2^b_1} = \frac{L}{BT_{on}}$. Now Data rate R_{b1} is also defined as $R_{b1} = \frac{L}{T_{on}}$. Therefore, the relationship between bit per symbol and Data rate for MFSK is $R_{b1} = \frac{2b_1 B}{2^b_1}$. We have considered non-coherent MFSK as it is mostly used in most of the practical receivers. The authors in [78] have derived the expression for total energy consumption from the general equation of probability of error P_b for MFSK as in the following Eq.3.9:

$$E_a = \frac{(1+\alpha)4N_f\sigma^2\ln(\frac{2^{b_1-2}}{P_b})G_d}{b_1} + \frac{P_c 2^b}{2b_1 B} + \frac{2P_{syn}T_{tr}}{L} \tag{3.9}$$

where $\alpha = \frac{1}{\eta} - 1$. We simulate these equations using the same parameters provided in Table3.1. Note that the DAC and the mixer are not considered for the MFSK transmitter model [8]. Moreover, for MFSK we have used class B or higher class power amplifier for which $\eta = 0.75$ is used. As MFSK is not bandwidth efficient so it needs more time to transmit the same number of bits compared to MQAM for a given bandwidth. Therefore the maximum delay is increased to $T = 1.07s$ and consequently the maximum bit per symbol has become $b_{max} = 6$. The optimal modulation parameters (constellation size and data rate) for MFSK are found in the following section, in order to minimize energy consumption for a given bit error rate (BER).

3.4.1 Optimal Constellation Size for MFSK

The relation expressed in Eq.(3.9) can be better understood by plot E_a vs b_1 for MFSK as in Fig.3-2; which shows that for shorter distances, the enegry consumption decreases with b, however start increasing after certain b. Whereas, for longer distances, this energy consumption decreases with increasing b.

Fig.3-3 depicts that, for $d = 1$ m, about 80% of the energy consumption can be reduced by using optimal bit per symbol (b_{opt})=2 when compared to using $b_1 = b_{max}$. If we apply the Newton-Raphson method as Eq.3.7 then we can find the root of $\frac{dE_a}{db_1}$, which provides us the value of b_1 for which we will have minimum energy for a particular distance. As a result of applying the Newton-Raphson method we find optimal bit per symbol, $b_1 = 3.3935$ for d=100m; $b_1 = 1.5464$ for d=30m; and $b_1 = 1.4429$ for d=5m. These values of b_1 give us minimum energy for certain distances. The value of b_1 must be an integer, that is why these optimal b_1 values are then

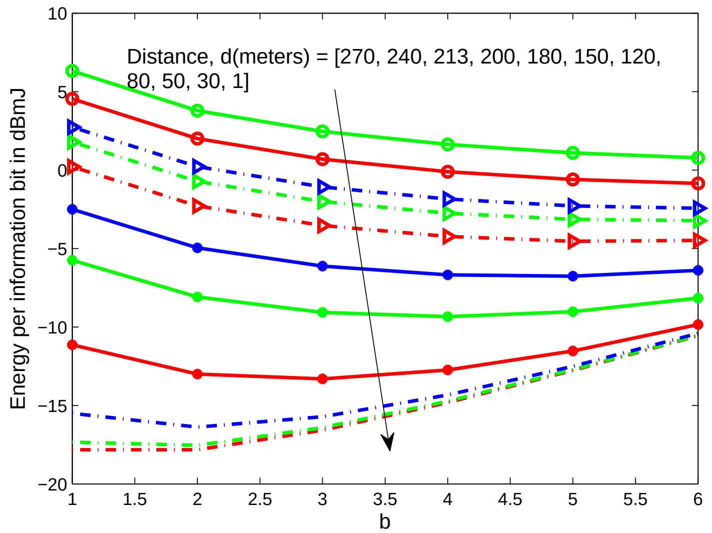

Figure 3-3: Total energy consumption for MFSK Vs Constellation size for different transmission distances

approximated by upper and lower integers (as shown in table3.3) to find the optimal constellation size for minimum energy consumption. For example, b_1=1.5464 for d=30m, the lower and upper integer of 1.5465 is 1 and 2. Therefore we calculate the energy for b_1=1 and b_1=2 and we find the energy as −17.3397 dBmJ and −17.5487 dBmJ respectively. As b_1=2 gives us less energy consumption than $b_1 = 1$ so we choose the optimal bit per symbol, b_1 as 2 for d=30.

Using the same approach we find the optimal bit per symbol for all of the distances. The expression of $\frac{dE_a}{db_1}$ is used in Newton-Raphson method for finding optimal constellation size for MFSK as shown below in Eq.3.10:

$$\frac{dE_a}{db_1} = -\frac{k_1 2_1^b}{b_1^2} + \frac{k_1 2_1^b \ln 2}{b_1} + \frac{k_2 d^k}{b_1} + \frac{k_3 d^k \ln\left(\frac{2^{(b_1-2)}}{P_b}\right)}{b_1^2} \tag{3.10}$$

here $k_1 = \frac{P_c}{2B}$; $k_2 = G_l M_l N_f \sigma^2 \ln 2(4a+4)$ and $k_3 = G_l L M_l N_f \sigma^2 (4a+4)$

Table 3.3: Finding the Optimal constellation size and data rate for MFSK

$Distance$	b	b_{floor}	$R_{b_{floor}}$	$E_a\ for\ R_{b_{floor}}$	b_{Ceil}	Rb_{Ceil}	$Ea\ for\ R_{b_{Ceil}}$	$selected\ b\ and\ R_b$
1	1.4427	1	5	-17.8251	2	6	-17.8252	b=2; R_bopt=6
5	1.4429	1	5	-17.8242	2	6	-17.8246	b=2; R_bopt=6
10	1.4451	1	5	-17.8142	2	6	-17.8191	b=2; R_bopt=6
15	1.4525	1	5	-17.7800	2	6	-17.8000	b=2; R_bopt=6
30	1.5465	1	5	-17.3397	2	6	-17.5487	b=2; R_bopt=6
35	1.6127	1	5	-17.0231	2	6	-17.3612	b=2; R_bopt=6
39	1.6798	1	5	-16.6983	2	6	-17.1632	b=2; R_bopt=6
40	1.6984	1	5	-16.6073	2	6	-17.1067	b=2; R_bopt=6
45	1.8021	1	5	-16.0967	2	6	-16.7814	b=2; R_bopt=6
50	1.9212	1	5	-15.5032	2	6	-16.3861	b=2; R_bopt=6
60	2.1929	2	5	-15.4106	3	6	-15.0863	b=2; R_bopt=5
75	2.6424	2	4	-13.6358	3	5	-13.8034	b=3; R_bopt=5
90	3.0983	3	3	-12.2765	4	4	-11.9759	b=3; R_bopt=3
105	3.5373	3	3	-10.6645	4	4	-10.6944	b=4; R_bopt=4
120	3.9513	3	2	-9.0717	4	3	-9.3428	b=4; R_bopt=3
135	4.3389	4	2	-7.9900	5	3	-7.9076	b=4; R_bopt=2
150	4.7009	4	1	-6.6760	5	2	-6.7664	b=4; R_bopt=1
165	5.0395	5	1	-5.6381	6	2	-5.4414	b=5; R_bopt=1
195	5.6551	5	1	-3.4876	6	2	-3.5389	b=6; R_bopt=2
205	5.8443	5	1	-2.8104	6	2	-2.9196	b=6; R_bopt=2
210	5.9362	5	1	-2.4797	6	2	-2.6143	b=6; R_bopt=2
213	5.9905	5	1	-2.2838	6	2	-2.4326	b=2; R_bopt=2
215	6.0263	6	0	-2.3122	7	1	-2.1511	NA as b>bmax and Rb<Rbmin
225	6.2017	6	0	-1.7179	7	1	-1.6212	NA as b>bmax and Rb<Rbmin
240	6.4533	6	0	-0.8532	7	1	-0.8370	NA as b>bmax and Rb<Rbmin
255	6.6922	6	0	-0.0216	7	1	-0.0701	NA as b>bmax and Rb<Rbmin

3.4.2 Optimal Data Rate for MFSK

We can find the relation between total energy consumption with data rate by using the relationship between R_{b1} and b_1 (bit per symbol). The optimal data rate for minimum energy consumption can be found from the optimal bit per symbol as derived in the above mentioned section. We use the equation $R_{b1} = \frac{2b_1 B}{2_1^b}$ to find out this optimal data rate for MFSK and as a result we find R_{bopt1} =6, 5, 3, 2, 1, 1 for d=10, 60, 90, 135, 150 and 210 meters respectively.

3.4.3 Optimization range for MFSK

Similar to MQAM, in MFSK as well, there exists a maximum distance, d above which there is no energy savings possible by optimizing modulation parameters. To find this threshold, we find the value of d for which the derivative of E_a relative to b_1 for the maximum value of b_1 becomes zero. For the specific set of parameters in Table3.1, $d = 213m$ is the threshold, where $\frac{dE_a}{db_1} = 0$ at $b_1 = b_{max}$ for MFSK.

3.5 Comparison of Optimal Data Rate for MQAM and MFSK

In the following Fig.3-4 we have compared the optimal data rate for MQAM and MFSK. In Fig.3-4 region I is the desired region where the data rate is greater than or

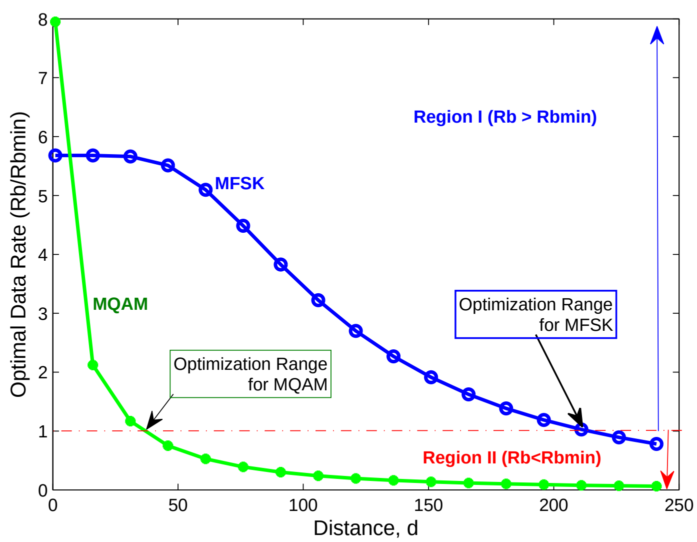

Figure 3-4: Optimal data rate vs distance for both MQAM and MFSK

equal to R_{bmin} and region II is the unaccepted region where the data rate is less than R_{bmin}. In this figure it is evident that, for MQAM, rate adaptation can be used to reduce energy consumption for shorter distances between transmitter and receiver for a given BER, packet size and bandwidth. Whereas for MFSK, rate adaptation can result in energy efficiency for longer distance between transmitter and receiver for a given BER, packet size and bandwidth. Hence it can be said that rate adaptation is a good approach to save energy for short range applications using MQAM, whereas MFSK is suitable for long range applications.

3.6 Parametric Effects on the Optimal Rate for Energy Efficiency

This section analyzes the effect of varying bandwidth and pathloss exponent on the optimal data rate for energy efficiency for both MQAM and MFSK techniques.

3.6.1 Effect of Varying Path loss exponent

We calculate optimal data rate for different path-loss exponent by keeping the other system parameters constant and show the result in Fig.3-5, which shows that the optimal data rate and optimization range decreases with increasing path loss exponent for both MQAM and MFSK. Therefore if we need to use the system for longer distances or if we require higher data rate then we should select lower value for path loss exponent.

3.6.2 Effect of Varying Bandwidth

In this section, the total energy consumption of MQAM for different bandwidth (BW) has been observed for a particular distance between transmitter and receiver as presented in Fig.3-6. The total energy consumption of MFSK is also analyzed for different bandwidth (BW) for a particular distance between transmitter and receiver, and the results are presented in Fig.3-7. Finally, the optimal data rate for different Bandwidth is shown in Fig.3-8 with respect to distance, for both MQAM and MFSK. Note that, only the curves for the operational region (where R_b is greater than R_{bmin}) are shown in Fig.3-8. From these figures, we can see that, larger bandwidth gives us higher optimal data rate and longer optimization range for both MQAM and MFSK, this is

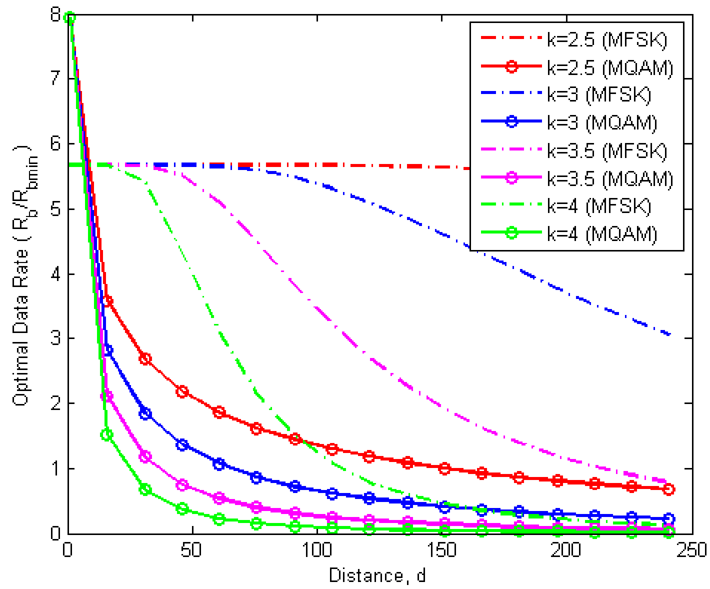

Figure 3-5: Optimal data rate vs distance for both MQAM and MFSK for different path loss exponent(k)

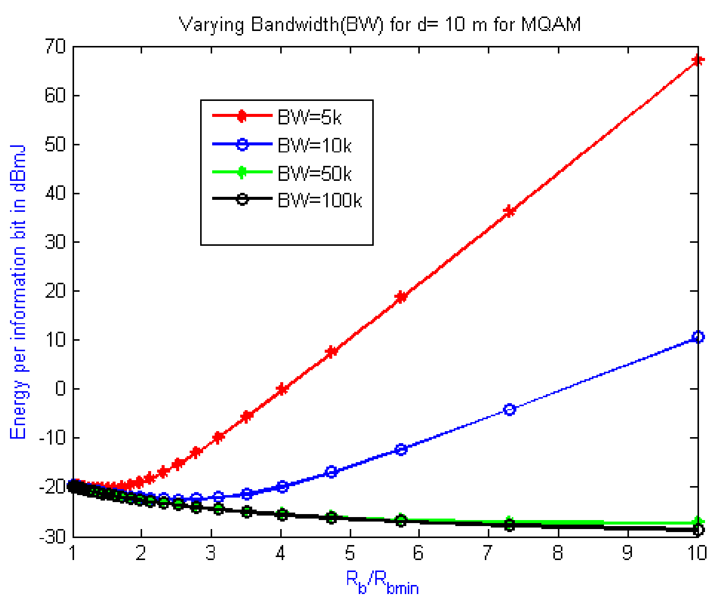

Figure 3-6: Total energy consumption for MQAM Vs optimized data rate for different bandwidth for a particular transmission distance

because optimal data rate and optimization range both are monotonically increasing function of bandwidth. Therefore for a system design we should select the maximum bandwidth for a particular distance and for a given bit error rate. As a consequence the maximum energy efficiency can be achieved by selecting larger optimal data rate for longer transmission distances.

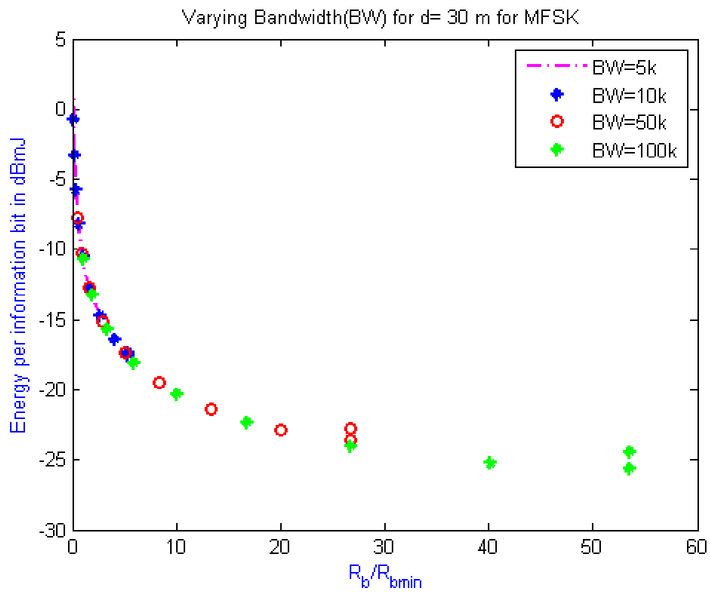

Figure 3-7: Total energy consumption for MFSK Vs optimized data rate for different bandwidth for a particular transmission distance

3.7 Summary of Contribution and Conclusion

In this chapter, we have shown that the total energy consumption of a point to point communication system can be minimized by optimizing the data rate for MQAM and MFSK in an AWGN channel. Here we assume that the system transmits a fixed length of packet with a fixed bandwidth to meet a given bit error rate. In order to find the optimal parameters we have used Newton-Raphson method. Our simulation results show that MQAM can minimize a significant amount of energy consumption by optimizing the data rate for shorter transmission distances; whereas MFSK can reduce energy consumption by optimizing the data rate for longer transmission distances. These results from our work can be directly used for an entire network for every transceiver node such that a greater energy efficiency could be obtained globally.

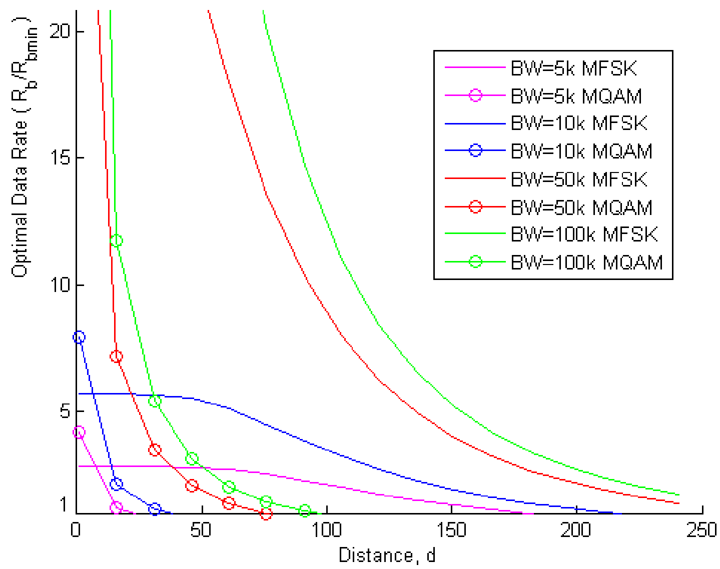

Figure 3-8: Optimal data rate vs distance for both MQAM and MFSK for different Bandwidth(BW)

Chapter 4

Energy Efficiency of Cellular Base Stations with Ternary-State Transceivers

4.1 Introduction

The ever-growing expansion of the cellular networks and the number of subscribers has increased the demand for cellular traffic. These mushrooming of networks have pushed the limits of energy consumption in wireless networks, which in return are having severe impact on the industrys overall carbon footprint. A massive expansion of network infrastructure is triggered by these rapid growth of mobile data traffic. As a consequence, the energy consumption in wireless communication is increasing dramatically [133]. As a result, the urgent need of energy efficient designs is increasing from both economic and environmental aspects. The base stations (BS), which are also known as eNodeBs, are the most energy consuming parts of a cellular network, consuming approximately $60 - 80\%$ of the total energy [26] consumption. Hence control and optimization of energy consumption at the base stations are the main focus of any green communication scheme. Most of the pioneering works on green communication are dedicated to the reduction of the transmit power of the base stations; where the main idea is to optimize transmission power ensuring Quality of service in terms of capacity and coverage [134, 142, 172]. However, the problem with these approaches is ignoring the significant part of energy consumption which exists even for low traffic condition; therefore these schemes alone are insufficient to reduce the energy consumption of wireless networks. The main reason behind this is the load-independent components of the energy consumption, which makes low load resources totally inefficient in terms of energy. In order to address these issues of energy consumption in wireless communication, we propose a novel strategy to reduce the base station energy consumption ensuring a good quality of service. One of the encouraging fact about our research work presented in this chapter is that, the base stations in dense urban areas are deployed very close to each other, as a result their coverage area overlaps with each other. This coverage overlapping provides an excellent opportunity to put some of the base stations into sleep mode in low traffic condition without degrading the quality of service (QOS) requirement. As a consequence, the energy consumption of the base station and the total network reduces significantly on low traffic condition. In this chapter, we propose a novel strategy of controlling BS sleep mode and wake up mode under quality of service (QOS) constraint.

4.2 Related Work and Novelty of our Proposed Model

Energy efficiency in wireless networks and communication has been studied elaborately in literature [10, 27, 30, 31, 34–44, 132, 134, 136, 173]. One of the mostly appreciated approach is implementing low power consumption mode in the base stations, which has been proposed in some research papers [10, 27, 30, 31, 34–38, 40–44, 132, 134, 136] for reducing energy consumption in wireless communication. The authors in paper [10] has proposed a Markov decision based optimal controller that associates to each traffic an activation/deactivation policy that maximizes a multiple objective function of the QOS and the energy consumption.

The authors in [39] proposed an approach to reduce energy consumption in mobile networks by introducing discontinuous transmission on the base station side. In some of the pioneering works [10, 30, 31, 42, 43, 69], markov decision process (MDP) has been used as an effective approach for sleep mode implementation for green communications. However, the majority of such studies have proposed either deep sleep mode or the stand-by mode for the inactive base station under low traffic condition and the base station will be in active mode for rest of the time, we refere to this model as '2-state power consumption model'. A base station consumes ideally zero power in deep sleep mode and requires some significant time to wake up from sleep mode, which introduces latency in the service due to the time needed to wake up. Whereas the stand-by mode require less time to wake up, however consumes some energy inspite of being in inactive mode. The authors in paper [10, 30, 31, 34, 36–38] has shown that this 2-state (either deep sleep or stand-by sleep) power consumption model can reduce energy consumption of the whole network with compromising quality of service or introducing latency in the service. In order to mitigate this problem, depending on quality of service (QOS) requirements and the traffic condition, we propose an energy efficient '3-state power consumption model' for the transceivers used within a base station by implementing all of these three modes, namely Active mode, Stand-by mode, Sleep mode, on the transceivers(TRXs) in order to reduce energy consumption as well as wake up delay. We have explained the operation and transition procedure of these modes in the following sections. Our simulation results depict that a significant amount of energy can be saved in low traffic condition as a result of applying this 3-state model , while we can also fulfil the quality of service requirement in terms of data rate and can avoid delay. Another novelty point of our work is that we proposed the sleep mode for the transceivers (TRXs) within a base station, whereas the above mentioned papers have implemented the sleep mode in the entire base station itself. We keep one of the TRXs always active in order to assure the coverage of the base station at all time, which is a significant novelty of our work.

4.3 Network Model

Let us assume that we have a base station with N number of TRXs. We adopt the architecture of a BS as proposed by the researchers from Fujitsu company [131] as shown in Fig.4-1. We assume that all of the N TRXs needs to be in active mode in the peak hour when the traffic condition is high. We assume equal distribution of BW among the TRXs, hence if the total bandwidth of the BS is BW_T then each of the TRX will be able to offer a bandwidth of $\frac{BW_T}{N}$ to the users. When all the TRXs are active ,then the BS can support maximum number of users for a given arrival rate and death rate of calls within its coverage area, provided that all the users get satisfactory data rate. We periodically monitor the number of active users within the coverage area after some certain duration, dt. Then we determined the required signal to noise ratio (SNR) per user by link budget calculation, consequently the required bandwidth for all of the active users using Shannon's capacity formula for a minimum target data rate and hence we determined the required number of active, stand-by and sleeping TRXs.

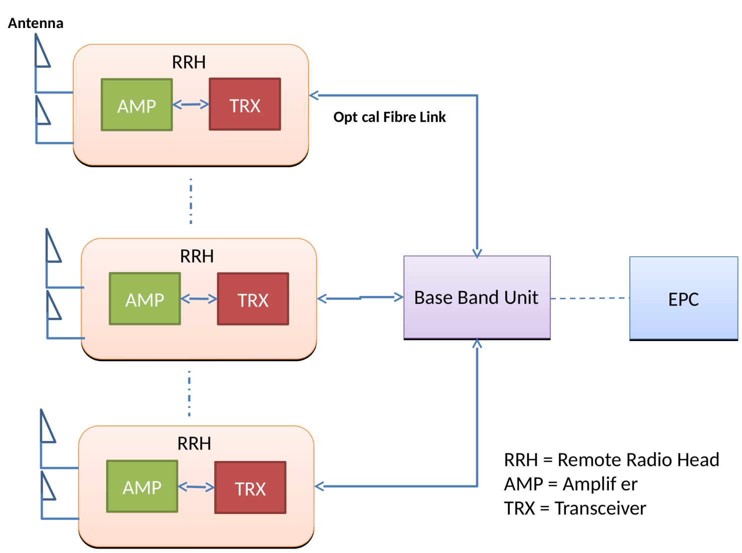

Figure 4-1: Radio Architecture of a BS

Traffic Model We adopt a traffic model where the users arrive according to a Poisson process in the coverage area of the BS with a certain arrival rate, λ and death rate, μ.

Propagation Channel Model We consider the log-normal shadowing model with a pathloss exponent, α and a shadowing variance, σ^2 under an AWGN channel. The received signal to noise ratio (SNR) per user is determined by a link budget calculation using Eq.4.1, where P_{out} is the transmit power of the BS; PL is the pathloss; G_t and G_r are the transmit and receive antenna gains respectively; X is log-normal shadowing and P_n is the noise power. Eq.4.2 is used to find the pathloss PL, where d_0 is a reference distance, f_c is the carrier frequency, c is the speed of light and d is the distance between the BS and the user. The values of d_0 and c are constant and are provided in Table.4.1.

$$SNR_{perUser}(dB) = P_{out} + G_t + G_r - PL - X - P_n \tag{4.1}$$

$$PL = 20log(\frac{4\pi d_0 f_c}{c}) + 10\alpha log(\frac{d}{d_0}) \tag{4.2}$$

4.4 Three state Markov Model for a Transceiver

Accroding to our proposed three state model, all of the N number of TRXs of a base station needs to be active during peak hour, hence can provide the required data rate to all the active users during high traffic condition. During the low traffic condition, our algorithm determines the required number (N_{act}) of active transceivers to provide the acceptable QOS in terms of data rate to all of the active users. At the same time we let one ($N_{std} = 1$) of the transceivers to stay in standby mode so that it can be activated with minimum delay when required. Please note that, $N_{std} = 0$ when all of the TRXs are active during peak traffic demand. The rest of the transceivers are kept in sleep mode i.e. $N_{slp} = N_{max} - N_{act} - N_{std}$ in order to reduce energy consumption. As per our proposed model, when the number of active transceivers need to be increased due to higher date rate requirement, then the stand-by transceiver goes to the active mode and one of the sleeping transceivers goes into stand-by mode. On the other hand, when the traffic demand decreases, then the stand-by TRX goes back to sleep mode, and one of the active TRX goes into stand-by mode. We also ensure that one of the TRXs is always there in stand-by mode (unless $N_{max} = N_{act}$). The transition of all these three states can be represented as a three-state Markov model [159]. Fig.4-2 represents the markov model for one TRX, where the states of the TRX are represented by S_0, S_1 and S_2 when it is in sleep, stand-by or active mode respectively. Pr_{ij} represents the transition probability between states S_i and S_j, where i=(1,2,3) and j=(i-1, i, i+1).

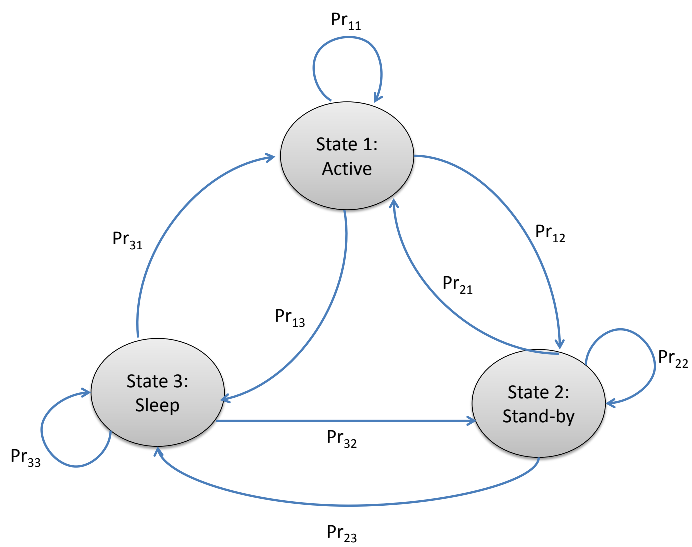

Figure 4-2: Proposed Three-state Markov Model for a Transceiver

4.4.1 Markovian Model for the Base Station

In this section we develop the Markov model for the base station. Having N number of TRXs in the base station and the states of the TRXs are represented by S_0, S_1 and S_2 when it is in sleep, stand-by or active mode respectively, the 1st state of the BS can be represented as, $\pi_1 = [S_2\ S_1\ S_0\ S_0\ S_0\ .\ .\ .\ .\ .\ .\ .\ S_0]$ where one of the TRXs is in active mode (i.e. denoted by state S_2), one of the TRXs is in stand-by mode (i.e.

denoted by state S_1) and rest of the TRXs are in sleep mode (denoted by state S_0). Similarly the 2nd State of the BS, $\pi_2 = [S_2\ S_2\ S_1\ S_0\ S_0\ .\ .\ .\ .\ .\ .\ .\ S_0]$, 3rd State of the BS, π_3= $[S_2\ S_2\ S_2\ S_1\ S_0\ .\ .\ .\ .\ .\ .\ .\ S_0]$, ... (N-1)th State of the BS, $\pi_{(N-1)}$ = $[S_2\ S_2\ S_2\ S_2\ S_2\ .\ .\ .\ .\ .\ .\ .\ S_1]$ and Nth State of the BS, $\pi_N = [S_2\ S_2\ S_2\ S_2\ S_2\ .\ .\ .\ .\ .\ .\ .\ S_2]$. Therefore the Markov chain for the base station can be shown as in Fig.4-3. For the BS Markov model as depicted in the figure Pr_{ij}^{BS} are the transition probabilities between the BS states π_i and π_j, where i=(1,2..N) and j=(i-1, i, i+1).

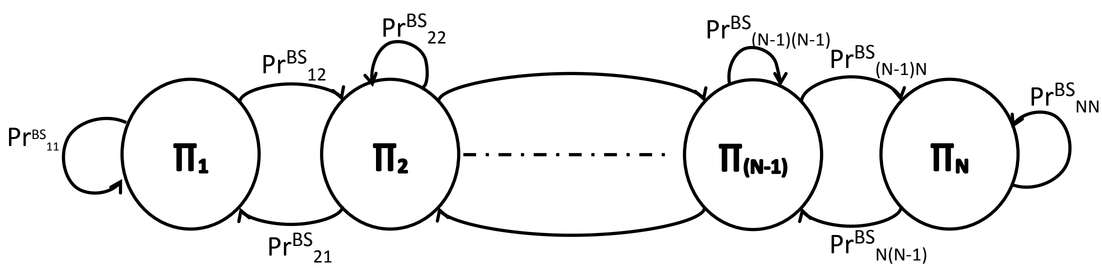

Figure 4-3: Markov Model for the Base Station

4.5 Power Consumption Model

The total power consumed in the BS depends on the number of active, standby and sleeping transceivers. The following power consumption model presented in Eq.4.3, which is derived from the paper [4] and [9] can be used to determine the total power consumption of the entire BS.

$$P = N_{act}(P_o + dPP_{out}) + N_{std}P_{std} + N_{slp}P_{slp} \tag{4.3}$$

where N_{act}, N_{std} and N_{slp} are the number of TRXs in active mode, stand-by mode and sleep mode respectively; P_{out} is the output power or transmit power; dP is the slope of load-dependent power consumption; P_o and P_{std} are the power consumption at minimum non-zero load and in stand-by mode respectively. Please note that the TRXs in sleep mode consume zero power. Table 4.1 shows the reference values of all these variables for a macro base station [4]. Some researchers from Ericson company have reported that a transceiver consumes approximately $10W$ power in stand-by mode and takes approximately $30us$ to go into the active mode [39], on the contrary, it consumes zero power in sleep mode, however takes approximately $10s$ to wake up [39]. In order to find the total energy consumption of the BS we applied trapezoidal numerical integration [171] on the Power consumption curve. It is worth mentioning that if we do not apply any sleep or standby mode to the transceivers, in other word if we consider that all the transceivers are always active regardless of the traffic requirement then the power consumption model become as Eq.4.4 where N is the total available transceivers in the eNodeB and N_{tx} =number of transmitting transceivers.

$$P = N\,P_o + N_{tx}\,dP\,P_{out} \tag{4.4}$$

Two-State Power Consumption Model In order to compare with our proposed three-state model, we are describing the two-state model here. In the 'two-state power consumption model' [30–32,39,131], some of the transceivers in the BS consumes some power even when there is no active user at all. Here the authors have proposed a micro sleep mode or standby mode for some of the transceivers of the BS in low traffic condition and rest of the transceivers of the BS will be in active mode. Hence they have not proposed any 'complete sleep mode' in the system, thus the BS consumes some power even when there is no active user at all. This model can be expressed as the following power consumption equation Eq.4.5.

$$P = N_{act}(P_o + dPP_{out}) + N_{std}P_{std} \tag{4.5}$$

4.6 Energy Saving Algorithm for the Base Station using Three-State Model

We propose the following algorithm as in Fig.4-3 to determine the required number of active, stand-by and sleeping TRX to assure the required quality of service (QOS in terms of required data rate and BW) for all of the active users and hence we switch the state (i.e. active or stand-by or sleep mode) of the transceivers as per requirement. As mentioned earlier,the total available bandwidth of the BS is assumed to be BW_T and there are N TRXs in the BS. Therefore each of the TRXs will be able to offer a BW of $b_1 = \frac{BW_T}{N}$ to the users since we are assuming equal distribution of the BW among the TRXs. As per our algorithm, we monitor the number of active users in every particular duration, dt. The quality of serive is ensured by guaranteeing a minimum target data rate (R_t) per user. Then we use the above mentioned propagation model and traffic model to determine the total required BW for all of the active users during that particular time duration (dt) and accordingly we activated the required number of TRXs denoted as N_{act}. Moreover, we always put one of the transceivers in stand-by mode ($N_{std} = 1$ unless all of the TRXs are in active mode) in order to avoid the delay needed to wake up from sleep mode to become active. We put rest of the TRXs in sleep mode i.e. $N_{slp} = N - N_{act} - N_{std}$ in order to reduce energy conusmption, since they are not required to provide service. If the required bandwidth become less than $(b_1 - a)$ then we activate only one TRX as one TRX can offer upto b_1 BW, here a is an integer which is a small fraction of b_1. Please note that we have allocated only $(b_1 - a)$ to one TRX, though its max capacity is b_1, that is because we want to avoid the drop off or delay in serving a new user which might arrive during this time. If the total required bandwidth goes above $(b_1 - a)$ then we immediately activated the stand-by TRX and switch one of the sleeping TRXs to stand-by mode. On the other hand, when the BW requirement decreases, then one of the active TRXs goes back to sleep mode, provided that one of the TRXs is always there in stand-by mode (unless $N = N_{act}$). Following the same procedure, we can change the states of all of the transceivers as per the total BW requirement. The bandwidth allocation for all of the N TRXs are shown in algorithm 1.

Algorithm 1 Algorithm to calculate required number of active, stand-by and sleep mode TRXs

Set the total number of transceiver, N, Set another variable $n = 1$
Set minimum target data rate, C
Calculate $SNR_{perUser}$ using above mentioned propagation model
required minimum $BW_{perUser} = \frac{C}{log_2(1+SNR_{perUser})}$
Total required minimum $BW_T = \sum(BW_{perUser})$
Check in every dt duration
while $1 \leq n \leq N$ **do**
  if $((n-1)b_1 - a) < BW \leq (nb_1 - a)$ **then**
    $N_{act} = n$
  else
    $n = n + 1$
  end if
end while
while $N_{act} \neq N$ **do**
  $N_{std} = 1$
  $N_{sleep} = (N - N_{act} - N_{std})$
end while

4.7 Expected Energy Consumption for the Ternary State Markov Model

In this section, the convergence of the proposed three state Markov model for the transceivers is being analysed. A well known property of a Markov process is that, it follows the following formula [159] of convergence,

$$V_{ss} = P^m V_i \tag{4.6}$$

or equivalently

$$V_{ss} = PV_{ss} \tag{4.7}$$

where, V_i is the initial state vector; P is the Transition probability matrix; V_{ss} is the steady state matrix and m is the number of iteration. Therefore, firstly we determine the state transition probabilities for each of the transceivers. Then from the initial state matrix the steady state matrix for each of the transceivers is determined for our proposed three state model. These steady state matrices assure the convergence of our three state Markov model as they follow the Eq.4.7. We use the steady state vectors of each transceivers to find the total energy consumption using the following Eq. 4.8.

$$E_{expected} = \sum_{i=1}^{N} V_{ss}^{i} E_s \tag{4.8}$$

Here, N=number of transceivers, V_{ss}^{i} is the steady state vector for i^{th} transceiver and $E_s = [E_{active}, E_{stand-by}, E_{sleep}]$ is the three state energy consumption vector. Here E_{active}, $E_{stand-by}$ and E_{sleep} are the energy consumption of one transceiver if it is in active, stand-by or sleep mode respectively for the entire time. We use Eq.4.8 to determine the expected energy and the results are provided in the simulation result section.

4.8 Simulation Results

We use the parameters provided in Table 4.1 to simulate our proposed algorithm using Matlab simulation. We use the traffic model as mentioned in the network model section to determine the total number of users in the coverage area of the base station under the above mentioned propagation channel environment. In order to implement the traffic model in the simulation, we generate some random number of users for a time index (t_1), in the next time index (t_2) some of these users terminate their calls and rest of them continue with their calls; these numbers depend on the birth rate and death rate. We use the same birth rate to add some new users at time instant (t_2). Hence users are generated and terminated at each time index ($t_1, t_2, t_3, ...t_n$) until we reach the end of our total simulation time. We compare our work with the case where all of the TRXs are always active regardless of the traffic condition, which is refered as 'All TRX active' model; as well as with the model proposed by Frenger et.

al. in [39] where all of the inactive TRXs are kept in stand-by mode, which is refered as 'Frengers 2-state mode' model. Fig.4-4 shows the power consumption of a BS for 'All TRX active' model, 'Frengers 2-state model' and for our 'Proposed 3-state model' (where we are implementing active, stand-by and sleep mode on the TRXs). It clearly shows that our proposed model offers a significant amount of power saving than two state model and 'all TRX active' model in low traffic condition. The reason is, in our proposed model some of the TRXs are in active mode, one of them is in stand-by mode and rest of them are in sleep mode; whereas, in the 2-state model none of the TRXs stay in stand-by mode (they are either in stand-by mode or in active mode, hence consume more power). As one may expect, the power consumption is highest for the 'all TRX active' mode at all time. Therefore, the TRXs in sleep mode consume less power as per our proposed model, as a result the total power consumption of the BS decreases. Also, as expected, the power consumption is the same for two state and three state models in higher traffic condition, as almost all of the TRXs have to be in active mode in order to support the load. Therefore our proposed model has been proved to be a power efficient model in low traffic condition. In order to find the total energy consumption of the BS we apply trapezoidal numerical integration [171] on the power consumption curve and find the energy consumption to be $4.13MJ$ for all active mode, $3.5MJ$ for Frengers 2-state mode and $3.2MJ$ for prposed 3-state mode model when there are maximum number of users is 40 in the coverage area. Hence our proposed '3-state model' proved to be the most energy efficient model compared to the others.

Table 4.1: BS parameters for the power consumption model (adopted from [9] and [10])

BS range, L = $2.5km$	carrier frequency, $f_c = 1800MHz$	Path loss Exponent, $\alpha = 2.5$
Transmit power = $40W$	Antenna Gain = $10dB$ and $2dB$	$BW_T = 6MHz$
Shadowing Mean = 0	Variance = 1	Total TRXs, $N = 3$
$\lambda = 0.01$	$\mu = 0.005$	$P_{max} = 40W$
BW per TRX = $2MHz$	$P_o = 185W$	
$dP = 4.7$	$P_{std} = 150W$	$P_{slp} = 0W$
$dt = 2sec$	$b_1 = 2MHz$	$a = 0.2MHz$

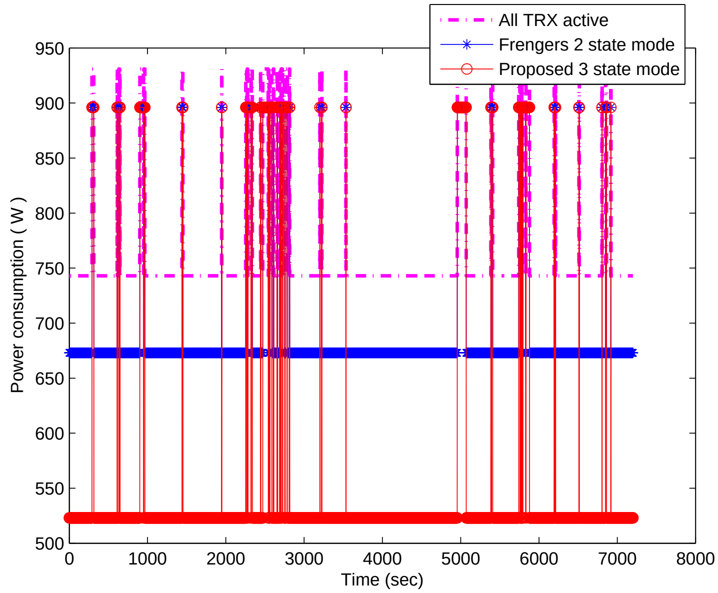

Figure 4-4: Power consumption of the Base Station (BS)

In order to verify the convergence of the Markov model, we found the steady state vectors as $[1, 0, 0]$, $[0.9889, 0.0111, 0]$ and $[0.0186, 0.9703, 0.0111]$ for transceiver 1, 2 and 3 respectively for the given set of data provided in Table.4.1, where the observation period was 1 hours. When we used Eq.4.8 to find the expected total energy for a base station with 3 transceivers we found it to be $E_{expected} = 3.2247MJ$. we compared this energy consumption with the calculated energy consumption from Eq.4.3, which is $E_{calculated} = 3.2245MJ$ for our proposed three state model and found that both of the results are close to each other.

4.8.1 effect of varying different parameters

We observe the effect of varying the user arrival rate or birth rate on the energy consumption and the results are shown in Fig.4-5 and Fig.4-6 for two different death rates. These figures depict that the energy consumption for both 2-state and 3-state mode increases with the increase of birth rate, however they get saturated after a certain limit. as expected the 3-state mode consumed less energy than the other two modes. We simulate the results for two different death rates (0.005 and 0.01) and find that the energy consumption starts increasing after higher birth rate for the later one. We also find that, the simulated energy consumption for the ternary state Markov model matches with the expected energy consumption calculated from Eq.4.3.

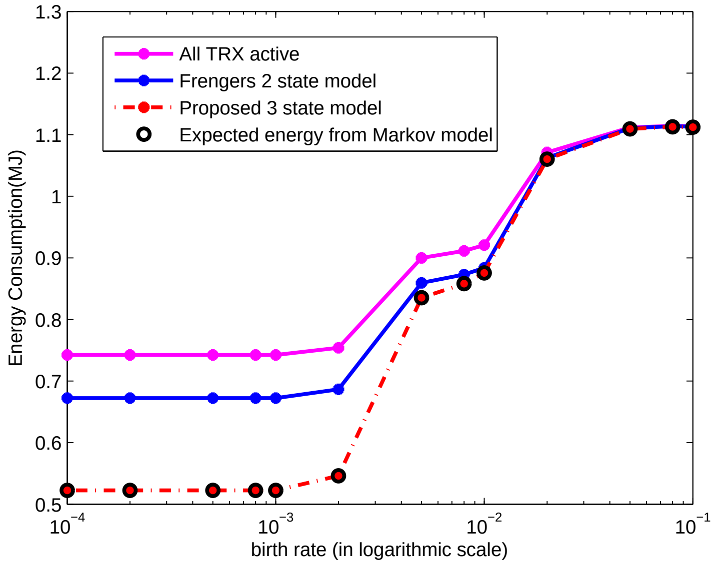

Figure 4-5: Effect of Varying Birth Rate for Fixed Death Rate = 0.005

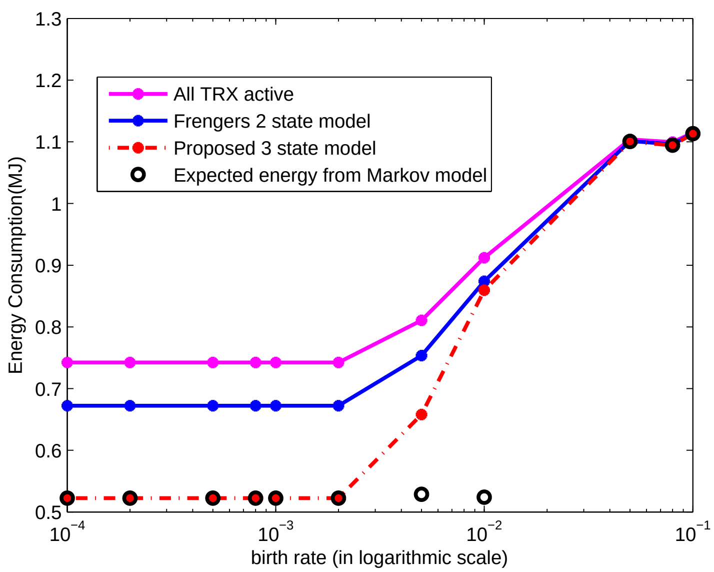

Figure 4-6: Effect of Varying Birth Rate for Fixed Death Rate = 0.01

Now we vary the range of the BS as in Fig4-7 and found that the energy consumption increases with the range but gets saturated after a certain period. Note that different ranges of BSs represent different types of BS (Pico, Femto, Micro, Macro etc). Therefore our proposed model is the most energy efficient model for any type of BSs. Finally we investigate the effect of varying target data rate as shown in Fig.4-8 and find that energy consumption increases with the increase of target data rate and reaches at saturation after certain time (for our case after 500$kbps$). In all of these cases, our proposed '3-state model' is the most energy efficient one compared to '2-state model' and 'all TRX active' model.

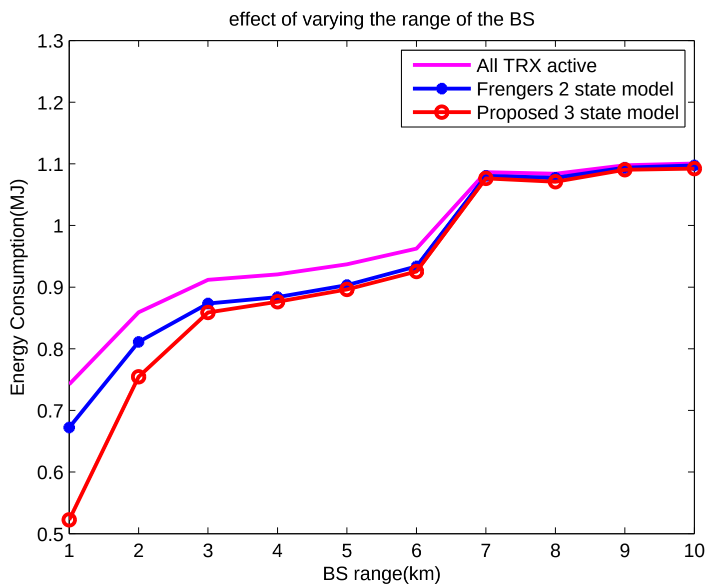

Figure 4-7: Effect of Varying BS Range

4.9 Summary of Contribution and Conclusion

In our work presented in this chapter, we proposed a novel strategy to implement low power consumption mode in the transceivers of a base station in LTE infrastructure. We propose an algorithm with 'ternary state Markov model' which can put the transceivers of a BS into active mode, stand-by mode and sleep mode depending on the traffic condition and QOS requirement. Hence we have shown that the BS can save a significant amount of energy in low traffic condition following our proposed

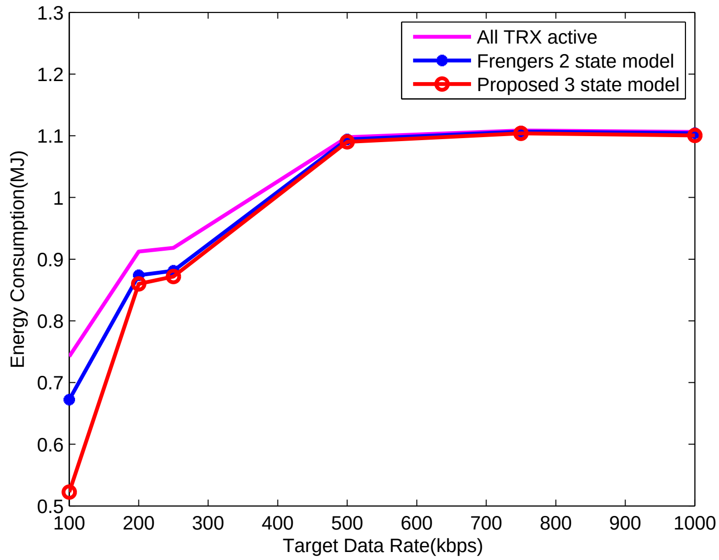

Figure 4-8: Effect of Varying Target Data Rate

'ternary state power consumption mode', which proved to be more energy efficient compared to the conventional 'two-state power consumption mode'.

Chapter 5

Energy Efficient and Delay Aware Ternary-State Transceivers for Aerial Base Stations

5.1 Introduction

Aerial base stations (AeBSs), which are the unmanned aerial vehicles mounted base stations, provide a promising solution to complement the capacity and coverage of terrestrial cellular systems, especially in some special situations when the terrestrial base stations are not enough to provide coverage and capacity. With significant progress in the drone technology, like increased payload capacity, longer average flight time, better power management techniques, and the capability to harvest solar energy, aerial base stations can serve a multitude of purposes such as surveillance, localization and communication, making them a flexible solution to augment and enhance the capabilities of the current terrestrial cellular systems. Aerial platforms are categorized according to their altitude capability as follows:

High altitude platforms (HAPs): Where platforms operate above the stratosphere (ranging from 17 km to 22 km) [174].

Low altitude platforms (LAPs): Where platforms operate in the troposphere.

(ranging from a few dozens to a few thousands meters) [50].

Our research is focused on LAPs, which provide coverage for smaller region compared to HAPs . A LAP can be operated at elevations between a few dozens to a few thousands meters depending on multiple factors such as the different types of antennas, aircraft, radio technologies, available payload power and type of the intended relief missions. The quick deployment of the unmanned aerial vehicles (UAVs) such as helikites, drones or airships, with respect to terrestrial infrastructure, make them suitable candidates in tackling a number of different challenges including, increased coverage in remote areas, better line-of-sight (LoS) conditions and resilience to unexpected disastrous situations. Facebook Aquila Drone [45] is a good examples of ongoing AeBS projects, which propose a novel solution for providing internet access from the sky by using the AeBSs. Aerial networks can also be deployed by the telecom operators in remote areas as temporary solution of patching coverage gaps [46]. The Google Loon [47] experiment is an ambitious project intended to provide network coverage to rural and remote areas. A major advantage of the aerial base stations over static terrestrial base stations is that they can change their positions to serve the dynamic network of users optimally. An AeBS can be efficiently integrated into terrestrial cellular wireless networks to either serve the ground users directly or relay traffic to the terrestrial network [48], [49]. Fig.5-1 provides a good overview of how aerial networks co-exists with terrestrial cellular infrastructure.

Although there has been increased interest in this topic, research is still at its nascent stage and there are quite a number of challenges such as energy efficient AeBS design, optimal altitude for placement of an aerial platform, aerial channel modeling, etc. that need to be addressed before we can see aerial communication networks in action. In order to address these challanges, some pioneering work has been found in literature. In the the European Commission project ABSOLUTE [50], a hybrid satellite-UAV ground network is developed using AeBSs to address public safety and capacity enhancement based on LTE communication systems. The main objective of the ABSOLUTE project is to design and validate an innovative

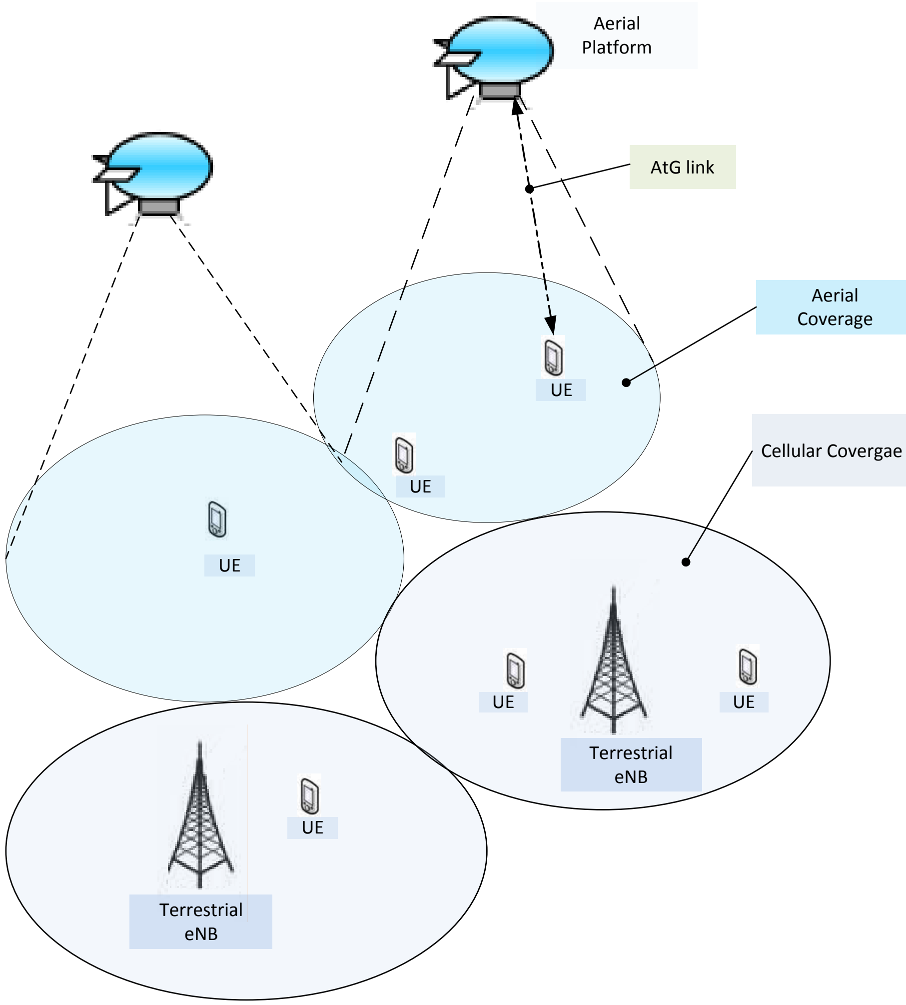

Figure 5-1: Aerial network supporting terrestrial cellular coverage.

holistic network architecture ensuring dependable communication services based on the rapid deployment, flexibility, scalability, resilience and provision of inter-operable broadband services. We provide detail literature review in the next section, where our study finds that the energy efficiency of aerial platforms, particularly on AeBSs is not sufficiently addressed.

Energy is a scarce resource for aerial base stations, hence energy-efficient operation of such networks is important given that the entire network infrastructure, including the battery-operated ground terminals, exhibits requirements to operate under power-constrained situations. Therefore, wise management of energy is quite beneficial for the network lifetime. In this context, we study the means of reducing the total energy consumption by designing and implementing an energy efficient AeBS. One of the effective approaches of increasing energy efficiency is switching off the network resources that are not necessary to guarantee the target QoS for the offered traffic. In this scenario, a minimal or zero power consumption mode of a resource can play a very crucial role if the aim is to increase energy efficiency of the network. Thus, network resources such as frequency carriers, power amplifiers or transceivers (TRXs) can be turned off or put in low power consumption mode to reduce the total energy consumption when these resources are not needed. However, we must also consider the delay caused by the required wake up time from sleep mode. The deep sleep mode consumes ideally zero power, but it can cause a significant delay in service due to the wake up time from sleep mode; whereas in a lighter sleep mode (also known as stand-by mode) a resource consumes little power but wakes up very quickly. Our proposed model provides a good trade–off between energy efficiency and wake-up delay, while ensuring user-perceived QoS. In our work presented in this chapter, we implement low and zero power consumption modes on the transceivers (TRXs) of a AeBS, without having to switch off the complete cell site. We also ensure that at least one TRX is active at all times so that the network provides the coverage to the region all the time. We propose three different power consumption modes for the transceivers (TRXs) of a AeBS and a novel MDP based algorithm to control these modes of the TRXs of an AeBS under a QoS constraint.

5.2 Related Work

Energy efficiency in wireless networks and communication systems has been studied widely in the literature [10, 27, 30, 31, 34–44, 132, 134, 136, 173]. However, very limited works in the literaure has focused on the energy efficiency of AeBSs. Most of the work on aerial platforms [156], [157], [158] have focosued on multitarget tracking system, air-to-ground channel modeling, their performance as relay etc. In [140], the authors analyzed the effectiveness of implementing cooperative relay to improve the energy efficiency of the terrestrial terminals while communicating with the LAP platforms deployed for emergency recovery operations. Autors in [139] have proposed a real-time adaptive transmission strategy for dynamically selecting the direct and cooperative links based on the channel conditions for improved energy efficiency. They showed that the cooperation between mobile terrestrial terminals on the ground could improve the energy efficiency in the uplink depending on the temporal behavior of the terrestrial and the aerial uplink channels. The design and evaluation of an adaptive cooperative scheme is proposed in [135] with the aim of extending the survivability and improving energy efficiency of the battery operated aerial-terrestrial communication links. Some research papers [10, 27, 30, 31, 34–38, 40–44, 132, 134, 136] have proposed different algorithms to implement sleep mode in the LTE base stations (BSs). The authors in [39] proposed an approach to reduce energy consumption in mobile networks by introducing discontinuous transmission on the base station side. In some of the pioneering works [10, 30, 31, 42, 43, 69], MDP has been used as an effective approach for sleep mode implementation for green communications. In [10], the authors proposed an MDP based optimal controller that associates to an activation/deactivation policy that maximizes a multiple objective function of the QoS and improves energy efficiency. They showed that their algorithm saves more than 25% of energy needed to run the network over a typical day. Other papers such as [42], [43] consider a single user and use a Markov chain technique to evaluate the energy savings due to the sleep mode mechanism of a single user terminal. The authors in [43] take correlated packet arrivals into account to evaluate an MDP based sleep mode mechanism. Authors in [44] consider a similar setting of one user and one station and show how to derive the optimal sleep policy numerically by formalizing the problem as a Semi-MDP. The authors in [132] proposed a novel scheme for the sleep scheduling based on a decentralized partially observable MDP (Dec-POMDP). However almost all of the above mentioned papers have proposed sleep mode for the BS in low traffic conditions and the BS will be in active mode for the rest of the time. We refer to this model as a '2-state model'.The authors in papers [10, 42–44, 132] have shown that this 2-state power consumption model can reduce energy consumption of the whole network significantly. However, the problem is that the BS takes significant time to wake up from sleep mode, which may cause a call drop to the new users. This wake up time can range from tens of seconds to a couple of minutes for small cells and up to 10-15 mins for a macro cell [41]. This is clearly a significant performance constraint for an energy efficient system. The authors in paper [39] proposed a low power consumption mode, which consumes some small amount of power but wakes up within negligible time. Their power consumption model is similar to what we propose as stand-by mode. Unlike the approaches published in the literature so far, we propose a MDP based algorithm on the transceivers of a AeBS so that they can intelligently switch among three different modes, thereby offering even greater energy savings without significantly compromising QOS.

Novelty of our work: As already presented in some pioneering works [10, 27, 30, 31, 34–38, 40–44, 132, 134, 136], switching off a TRX within a BS is a very good approach to reduce energy consumption during low traffic conditions, however each sleeping TRX takes significant amount of time to wake up and become fully operable. As a consequence, some users may experience a delay in accessing the network and some calls might be dropped as well. In order to overcome the problem of call dropping due to the wake up delay, we propose an energy efficient '3-state MDP model' for the TRXs within a BS. We propose three different modes, namely 'Active mode', 'Stand-by mode' and 'Sleep mode' for the TRXs of a BS. The TRXs are switched between the three modes, depending on the traffic condition and QoS requirements. The mode transition behaviour of the TRXs was presented as a Markov model in our previous work as in [175]. In our work, we utilize this Markov model to find the optimal policy in terms of energy efficiency using the Markov decision process (MDP). We have also shown the energy-delay trade–off in order to design an efficient base station. We have differentiated the stand-by mode from the sleep mode by defining that a TRX in stand-by mode consumes some small amount of energy but takes negligible time to return to the active mode; whereas a TRX in sleep mode does not consume any energy but takes more time to wake up. Hence sleep mode gives us the advantage of power saving, whereas stand-by mode allows us to avoid the wake up delay. The hardware and software setups for these low power consumption and zero power consumption modes have already been proposed in the literature [41] and [39], but this is the first time to author's knowledge that both sleep and stand–by modes have been employed to reduce energy consumption of a AeBS. Another novelty of our work is in defining a reward function for the Markov decision process (MDP), which helps us to get an optimal policy for selecting a particular mode for each TRX. As a result of applying the proposed 3-state MDP model, we find that a significant amount of energy can be saved under low traffic conditions while still fulfilling the QoS requirement in terms of data rate and call drop out performance. We also ensure that at least one of the TRXs is always active so that the coverage is always preserved.

5.3 Network Model

The global network architecture of an aerial-terrestrial network is shown in Fig. 5-2, which depicts a communication environment managed by a aerial base station, which are linked to multiple terrestrial UEs and supported by an evolved packet core (EPC) backhaul links. An aerial base station platform may constitute the deployment of one or more aerial devices depending on the particular requirement for a communications system to support the required services. These aerial devices carry communication payload (4G LTE) with the backhaul links supported by satellite communication (DVB-S2/RCS uplink broadcast) [135]. The first responders in the terrestrial segment are equipped with multi-radio mobile terminals (UE), with radio technologies such as LTE/WiMAX to communicate with the Aerial BS and WiFi/WPAN (IEEE 802.15.4) to communicate with the ground terminals.

We consider a cell served by one aerial BS, which is equipped with N number of TRXs. In our proposed model we are implementing low and zero power consumption modes on the TRXs of the aerial BS. We have adopted the architecture of a BS as described in [131], which is shown in the RF front end of Fig.5-3. From this figure we can see that a BS has several remote radio heads (RRH), which consist of an amplifier (AMP) and a TRX. The proposed algorithm is managed in the algorithm

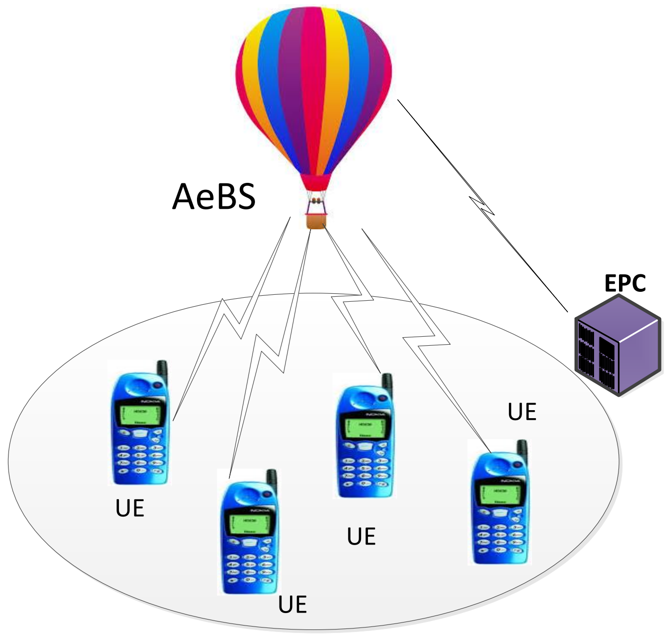

Figure 5-2: Aerial Network Architecture.

management unit, which is included in the base band unit of the BS as shown in Fig.5-3. The Mobility Management Entity (MME) unit of the Evolved Packet Core (EPC) also has some contribution in the algorithm, as the MME can inform the BS if any new user is approaching the cell and if any handover is about to happen. Thus, the MME can help the BS to update the total number of active users. Hence the centralized management unit is included in the MME.

Traffic Model: We adopt a traffic model where the users arrive according to a Poisson process in the coverage area of the BS with a certain arrival rate, u_λ and death rate, u_μ. Here we include all the users originating calls in the cell as well as the users being handed over from other cells.

Propagation Channel Model: The radio channel in aerial networks is different from that of the traditional terrestrial networks. In terrestrial networks, the transmitted signal travels through the urban or suburban environment, therefore the signal

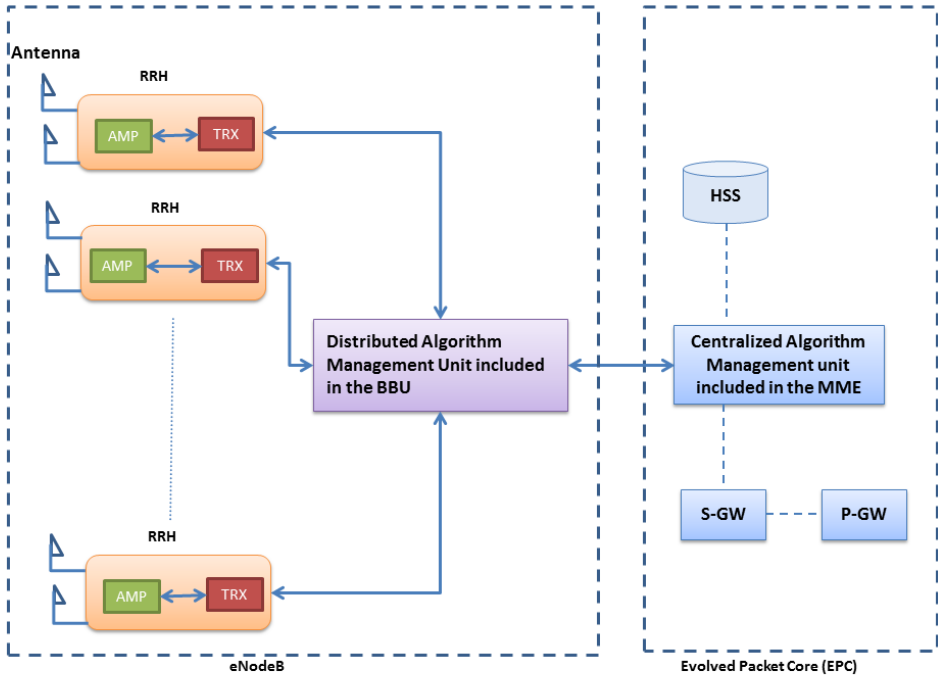

Figure 5-3: LTE-Radio Architecture [Remote Radio Head (RRH), Amplifier (AMP), Transceiver (TRX), Home Subscriber Server (HSS), Mobility Management Entity (MME), Serving Gateway (S-GW), Packet Data Network Gateway (P-GW), Base Band Unit (BBU)].

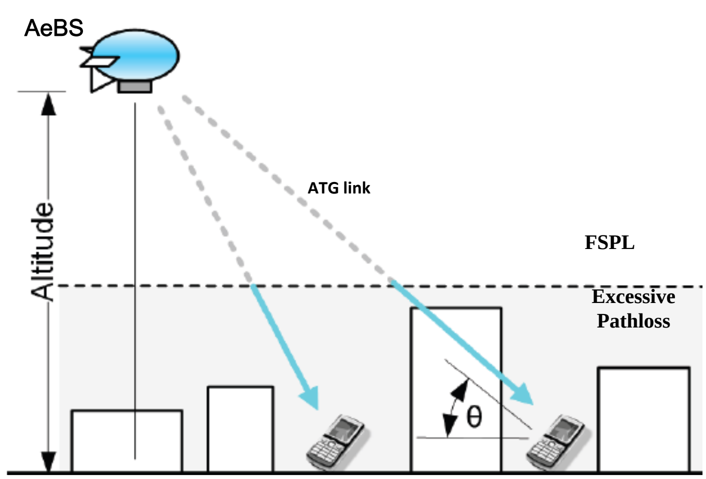

Figure 5-4: ATG propagation model between an AeBS and UEs.

decays as a function of distance. Usually, the pathloss of a terrestrial network is modeled as a log-distance model and includes path-loss exponent in the estimaton. On the other hand, in aerial networks, the transmitted signal travels through free space before reaching the urban or suburban environment where it undergoes scattering. An air-to-ground (AtG) channel model for an aerial network was proposed in [176] and [148] which depends on the height of the AeBS and the elevation angle seen from the UE located at ground as shown in Fig.5-4. In our work, we adopt this AtG channel model as described subsequently. According to [176] and [148], the path loss is is given by Eq.5.1:

$$\mathrm{PL} = \mathrm{FSPL} + \eta \tag{5.1}$$

Here η is the excessive pathloss which is estimated using the model described in section-V of [176] for 2000 MHz frequency; FSPL is the free space pathloss, which can be calculated from Eq.5.2:

$$\mathrm{FSPL} = 20\mathrm{log}(\frac{\Delta h}{\mathrm{sin}\theta_n}) + 20\mathrm{log}(f_{MHz}) - 27.55 \tag{5.2}$$

where $\frac{\Delta h}{\mathrm{sin}\theta_n}$ is the distance (d) between the AeBS and the UE, and f_{MHz} is the system centre frequency in MHZ; $\Delta h = h_{AeBS} - h_{UE}$; h_{AeBS} is the altitude of the AeBS and h_{UE} is the height of the UE; θ_n is the elevation angle measured in degree, which represents as the angle at which the AeBS is seen from the UE's location.

Furthermore, we assume that the UEs have slow movement on the ground, and therefore the channel is not varying over time, at least over several transmissions. The propagation effect on the terrestrial side due to various obstacles is modeled by a random shadowing component X on top of the mean pathloss PL [177]. In particular, we adopt the log-normal shadowing model for $X(dB)$ as described later in this section. The received signal to noise ratio (SNR) per user is given by a link budget calculation using Eq.5.3:

$$SNR(dB) = \P_{out} + G_t + G_r - \mathrm{PL} + X - P_n \tag{5.3}$$

Table 5.1: Required time for a TRX to become active(Hence approximate delay experienced by a new user)

TRX become active	Required time
From active mode	0 sec (delay group-1)
From stand-by mode	30 μsec (delay group-2)
From sleep mode	50 sec (delay group-3)

where $\P_{out}$ is the transmit power of the BS in dB; G_t and G_r are the transmit and receive antenna gains in dBi respectively; P_n is the noise power in dB and X is log-normal shadowing in dB, given by a gaussian random variable with mean 0 and standard variation σ [177]. Then Shannon's capacity formula [177] is used to determine the required bandwidth for all of the active users for a minimum target data rate, as shown in Eq.5.4:

$$BW_{\text{req}} = \frac{R_t}{\log_2(1 + snr)} \tag{5.4}$$

where R_t is the target data rate and snr is signal to noise ratio in linear value.

5.4 Markov Modeling of Transceivers and the Base Station

We consider an aerial BS with N number of TRXs. In low traffic condition we need only few of the TRXs to be active to provide satisfactory service, hence it gives us the opportunity to put rest of the TRXs in in–active mode, where they are non-operational, and consume less power. However, each TRX needs some significant time to wake up from sleep mode, which causes a delay in providing service to the new users. Table. 5.1 outlines the delay required for a TRX to remain in active mode, or switch to active from either stand-by or sleep mode.

Therefore in order to design an energy efficient ,as well as delay aware BS, we propose a three state model for the TRXs of an aerial BS. These states can be defined as follows:

1. **Active Mode:** In active mode the TRX is in fully operational mode and consumes maximum power of all states.

2. **Stand-by Mode:** In stand-by mode, the TRX is in low power consumption non-operational mode, where it consumes a small amount of power but requires negligible wake-up time to go back to the active mode. Researchers from Ericson [39] have reported that a cell consumes approximately $10W$ power in stand-by mode and takes approximately $30\mu s$ to go into the active mode.

3. **Sleep Mode:** In sleep mode, the TRX is totally switched off so that it consumes almost zero power, however takes longer time to wake up. The authors in [41] have reported that small cells can take tens of seconds to couple of minutes to wake up from sleep mode, where a macro BS takes $10 - 15$ minutes to wake up from sleep mode. Note that there is some non-zero ultra–low power consumption during sleep mode, however this ultra–low power consumption is assumed to be negligible compared to the power consumed in active mode. Hence sleep mode is treated as zero power consumption mode in this work.

5.4.1 Motivation of using three different modes

The well known advantage of implementing sleep mode in base staions is the reduction in energy consumption. However, the main cost of implementing sleep mode in a TRX is the switching delay since it takes at least $40 - 60$ seconds [40] to switch into fully operational mode. On the contrary, any TRX in stand-by mode consumes considerable power, but it takes negligible time (around $30\mu s$) to switch to operational mode. Therefore we utilize both of the modes so that we can have the power saving advantage from sleep mode and reduce activation delay by utilizing stand-by mode. Fig. 5-5 graphically depicts the time and energy required to switch between active mode and sleep mode. The energy gain for being in sleep mode equals $(\P_{act} - \P_{slp})t_{slp}$, where $\P_{act}$ and $\P_{slp}$ represent the power consumption in active and sleep mode, respectively, and t_{slp} is the duration of the time spent in sleep mode. It is clearly shown in the figure that a TRX needs quite a long time ($t_{slp-act}$) to wake up from sleep

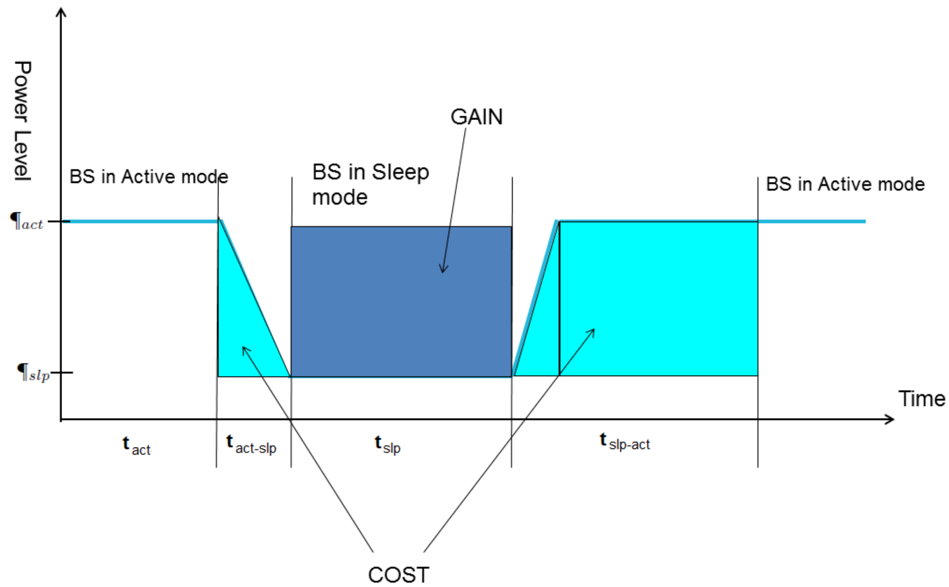

Figure 5-5: Graphical representation of energy saving and energy wasting due to activating BS from sleep mode.

mode and become active. This wake up delay issue of sleep mode was highlighted on Fig.6 of paper [40], where Gomez *et. al* showed that, a resource element takes approximately 5*sec* to shut down (switch to sleep mode), and approximately 60*sec* to switch on (switch to active mode). In a power limited aerial base station, switching delay significantly limits the base station's ability to meet the QOS requirements. However, wake-up delay can be minimised by adding an intermediate stand-by mode to the sleep mode. This additional state model gains the energy efficiency by utilizing sleep mode, as well as the reduced wake-up delay from stand-by mode.

5.4.2 Markov Model for a Transceiver

As per our proposed model, TRX-1 is a single state transceiver since is always active to preserve the coverage and TRX-2 is only capable of switching between active and stand-by mode. The state transition model for TRX-1 is presented in Fig.5-6-a, while the two state transition model for TRX-2 is presented in Fig.5-6-b. The remaining TRXs follow a three state transition model following traffic load, and QoS

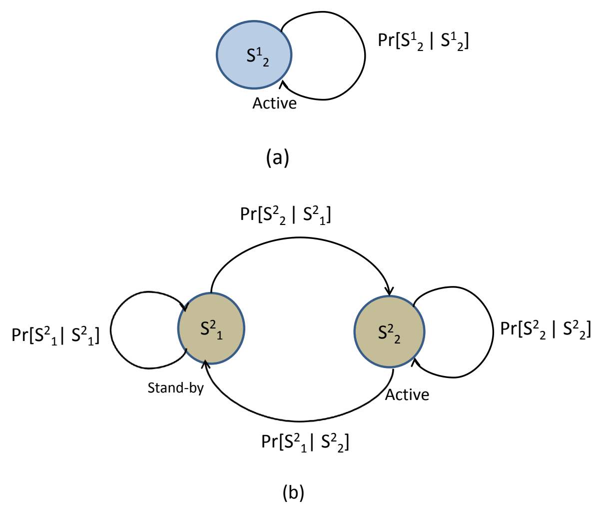

Figure 5-6: State Transition Model for (a)TRX-1 and (b)TRX-2.

requirements. The proposed three state transition model can be represented as a stochastic three-state Markov model [178] as in Fig.5-7. S_0^n, S_1^n, and S_2^n represent the three possible states of the n^{th} TRX at sleep mode, stand-by and active mode respectively; while a_0^{n-1}, a_1^{n-1} and a_2^{n-1} represent the base station's action to put the $(n-1)^{th}$ TRX in sleep, stand-by and active mode respectively, where $3 \leq n \leq N$. The possible transition model at each time instant(t) is presented by the probability $Pr[S_q^n(t+1)|S_j^n(t), a_l^{n-1}(t)]$; where $q, j, l \in 0, 1, 2$ represent the indexes of state and action receptively, $S(t)$ represents current state and $S(t+1)$ represents the next state after taking action $a(t)$ at time instant (t). In Fig.5-6, Fig.5-7 and the remaining sections of this chapter, we ignore the time index in the transition probabilities for the sake of simplicity.

5.4.3 Markov Model for the Base Station

Based on the states of the TRXs as defined in the previous section, we can further define the states of the aerial BS, which would the the combinations of the different states of all the TRXs as described in this section.

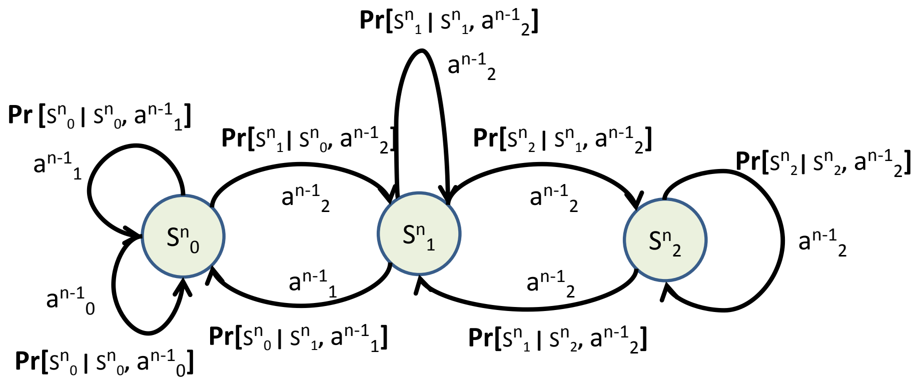

Figure 5-7: Proposed Three-state Markov Model for n^{th} Transceiver where $3 \leq n \leq N$.

States of the BS: Based on the states S_j^n of the TXS, where $n = 1, 2, 3, ..., N$ and $j \in \{0, 1, 2\}$, the 1^{st} state of the BS is given by, $\Pi_1 = [S_2^1\ S_1^2\ S_0^3\ S_0^4\ S_0^5\ .\ .\ .\ .\ .\ .\ .\ .\ S_0^N]$ where the first TRX is in active mode, the second TRX is in stand-by mode and rest of the TRXs are in sleep mode. Similarly the second state of the BS is given by, $\Pi_2 = [S_2^1\ S_2^2\ S_1^3\ S_0^4\ S_0^5\ .\ .\ .\ .\ .\ .\ .\ .\ S_0^N]$, and the N^{th} state of the BS is given by, $\Pi_N = [S_2^1\ S_2^2\ S_2^3\ S_2^4\ S_2^5\ .\ .\ .\ .\ .\ .\ .\ .\ S_2^N]$. Hence, the state space of the BS is given by, $\Pi = \Pi_1 \times \Pi_2 \times ..... \times \Pi_N$, where $\times$ represents the cartesian product.

5.5 MDP based Algorithm for the Aerial Base Station

In this section, we present our algorithm of applying the three different modes on the TRXs of an AeBS. According to our proposed model, we change the states of the TRXs one at a time therefore it is sufficient that we only perform our decision policy on the 3^{rd} TRX if it is on sleep mode, or the m^{th} TRX which is on stand-by mode, where $3 \leq m \leq N$. This way we only need to run a decision making strategy (the MDP solution) only on the chosen TRX as mentioned above for finding the optimal policy for the entire aerial BS. We use value iteration algorithm (VIA) [159] to solve the MDP and find the optimal policy to estimate state transition sequence for m^{th} TRX based on the reward function as explained in the following subsection. Additionally, the optimal policy decides the optimal action and hence the state transition sequence for $(m-1)^{th}$ TRX. Thus the transition probability for the m^{th} and $(m-1)^{th}$ TRX is calculated based on forward algorithm [159] using these state transition sequences of the particular TRXs. The detail of the MDP and VIA is provided in the following subsection. The rest $(N-m)$ TRXs are kept in sleep mode if the optmail policy decides to keep the m^{th} TRX in stand-by mode. However, if the optimal policy decides to switch the m^{th} TRX to active mode then the $(m+1)^{th}$ TRX will become stand-by, keeping the remaining TRXs in sleep mode.

Fig.5-8 depicts different states of TRXs of an AeBS for different traffic condition, which is a result of applying our porposed algorithm for a sample traffic condition over a certain period of time considering an AeBS with 5 TRXs. The figure shows the state transition sequence of each TRX for varying traffic condition.

5.5.1 MDP Algorithm

In this section, we define action, reward function and transition probability to formulate the MDP based algorithm of the aerial base station. Afterward, value iteration algorithm (VIA) is used to obtain the optimal policy to solve the MDP.

Action: If we apply the Markov decision policy on the n^{th} TRX, then action $a_0^{(n-1)}$, $a_1^{(n-1)}$ and $a_2^{(n-1)}$ represent the action of keeping or transitioning $(n-1)^{th}$ TRX into sleep, stand-by and active mode respectively. Hence the action for the aerial BS is, $\zeta = a_k^{(n-1)}$, where $k = 0, 1, 2$.

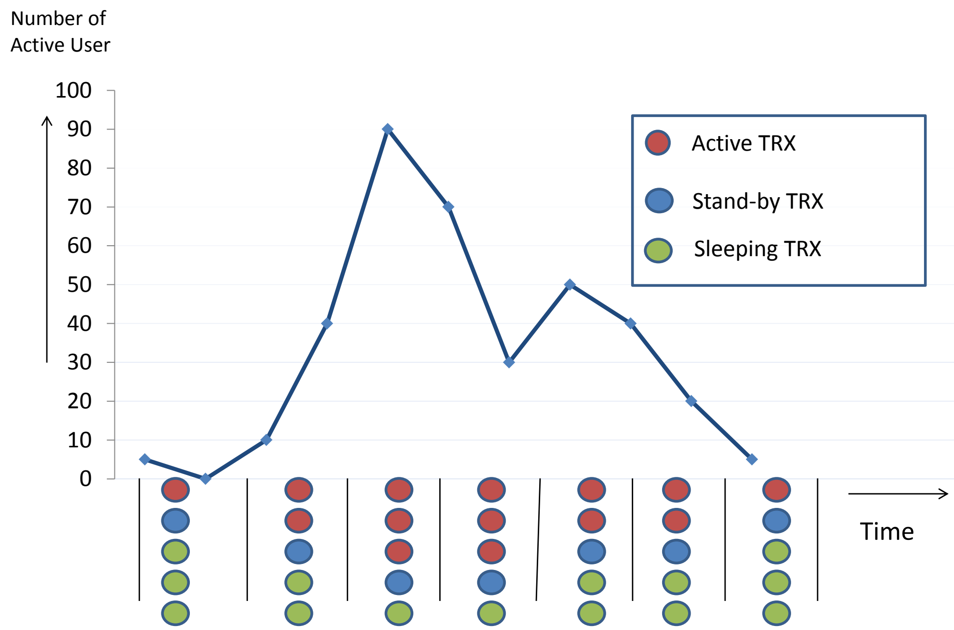

Figure 5-8: State transition for the TRXs for a sample traffic

Reward: The reward function for a state Π_i and action ζ is defined as Eq.5.5, where $i = 1, 2...N$

$$R(\Pi_i, \zeta) = 1 - \text{Energy Conumption} \tag{5.5}$$

On the other hand, energy consumption of the AeBS is proportional to the number of active TRXs (n_{act}) as Energy consumption $= \frac{N_{act}}{N}$ and The number of active TRXs is proportional to the total required bandwidth to provide satisfactory QOS. Hence the reward function can be represented as Eq.5.6

$$R(\Pi_i, \zeta) = 1 - \frac{b_\zeta - b_{min}}{b_{max} - b_{min}} \tag{5.6}$$

Where, b_ζ is the total required bandwidth to provide satisfactory QOS for a certain action ζ, b_{max} and b_{min} are the maximum available bandwidth and minimum bandwidth that can be offered by the AeBS respectively.

Transition Probability: The transition probability between the states of the transceivers is learned using forward algorithm [159] based on optimal policy. To be more precise, the transition probabilities for the n^{th} and $(n-1)^{th}$ TRXs are calculated based on forward algorithm [159] using state transition sequences of the n^{th} and $(n-1)^{th}$ TRXs, these state transition sequences are obtained from the optimal action taken by the optimal policy when MDP is applied to the n^{th} TRX. For simulation purpose, the state transition probabilities for the transceivers for a particular set of simulation parameters are presented in the simulation results section.

Value Iteration Algorithm: If we denote $V(\Pi_i)$ as the maximum expected total reward for an initial state Π_i and next state Π_{i+1} then the optimality equation is given by Eq.5.7 as follows:

$$V(\Pi_i) = \max_{\zeta_m \in \zeta}\{R(\Pi_i, \zeta_m) + \sum_{\Pi_{i+1} \in \Pi} \lambda Pr[\Pi_{i+1}|\Pi_i, \zeta_m]V(\Pi_{i+1})\}$$

Here, $R(\Pi_i, \zeta_m)$ is the reward function for a state $\Pi_i \in \Pi$ and action ζ_m as explained in Eq.5.6; $Pr[\Pi_{i+1}|\Pi_i, \zeta_m]$ is the transition probability between current state $\Pi_i \in \Pi$ and future state $\Pi_{i+1} \in \Pi$ for an action $\zeta_m \in \zeta$; ζ is the set of all possible actions, Π is the set of all possible states and λ is the discount factor. The solution of the optimality equation correspond to the maximum expected total reward $V(\Pi_i)$ and the MDP optimal policy $\phi(\Pi_i)$. This MDP optimal policy $\phi(\Pi_i)$ indicates the decision of allocating a certain mode to a particular transceiver. As explained in Algorithm.2, VIA [159] is used to solve this optimization problem, where λ is the discount factor. In this algorithm, we initialize the future value of the optimal policy to be zero at step 1. Then step 1 to step 4 is repreated to update this value function until we get the optimal policy, for which we get the maximum reward. Step 3 and 4 are done to ensure the convergence of the algorithm.

We assume equal distribution of bandwidth (BW) among the TRXs, hence each of the TRXs is able to offer a bandwidth of $\frac{BW_T}{N}$ to the users, where the total bandwidth

Algorithm 2 Value Iteration Algorithm

1: Set $V^0(\Pi_{i+1}) = 0$ for each state Π_i. Set a variable, $k = 0$.
2: For each state Π_i, compute $V^{k+1}(\Pi_i)$ by $V^{k+1}(\Pi_i) = \max_{\zeta_m \in \zeta}\{R(\Pi_i, \zeta_m) + \sum_{\Pi_{i+1}\in\Pi} \lambda \Pr[\Pi_{i+1}|\Pi_i, \zeta_m]\, V(\Pi_{i+1})\}$
3: $\delta = \max(V^{k+1}(\Pi_i) - V^k(\Pi_i))$
4: If $\delta < \frac{1-\lambda}{2\lambda}$, go to step 5. otherwise increase k by 1 and return to step 2.
5: Output a stationary optimal policy, ϕ, such that $\phi(\Pi_i) = \arg\max_{\zeta_m\in\zeta}\{R(\Pi_i, \zeta_m) + \sum_{\Pi_{i+1}\in\Pi} \lambda \Pr[\Pi_{i+1}|\Pi_i, \zeta_m]\, V(\Pi_{i+1})\}$ and stop

of the BS is BW_T. When all the TRXs are active, then the BS can support the maximum number of users by offering them the satisfactory QoS (in terms of data rate) for a given call arrival rate and death rate within its coverage area. Our proposed model is more effective in low traffic condition when some of the TRXs can be put to low power consumption mode without degrading the QoS. We first start by monitoring the number of active users in the coverage area and then calculate the total required bandwidth using the above mentioned propagation model at each decision epoch. After that, we calculate the reward using this required bandwidth and determine the transition probabilities as mentioned above. Finally, VIA is used to determine how many TRXs (N_{act}) are required to be in active, stand-by and in sleep mode during that decision epoch. Note that we always keep one of the TRXs in stand-by mode (unless all of the TRXs needs to be active) ($N_{std} = 1$) so that the new users experience minimal delay in accessing the network. The entire algorithm is presented in the flow diagram in Fig.5-9.

5.6 Power Consumption Model

The total power consumed in the AeBS depends on the number of active, standby and sleeping TRXs. The following power consumption model presented in Eq. 5.7 is used to determine the total power consumption of a AeBS for our proposed 3-state model, it is derived from the papers [4] and [9].

$$\P_{3-state} = N_{act}(\P_o + d\P \cdot \P_{out}) + N_{std} \cdot \P_{std} + N_{slp} \cdot \P_{slp} \tag{5.7}$$

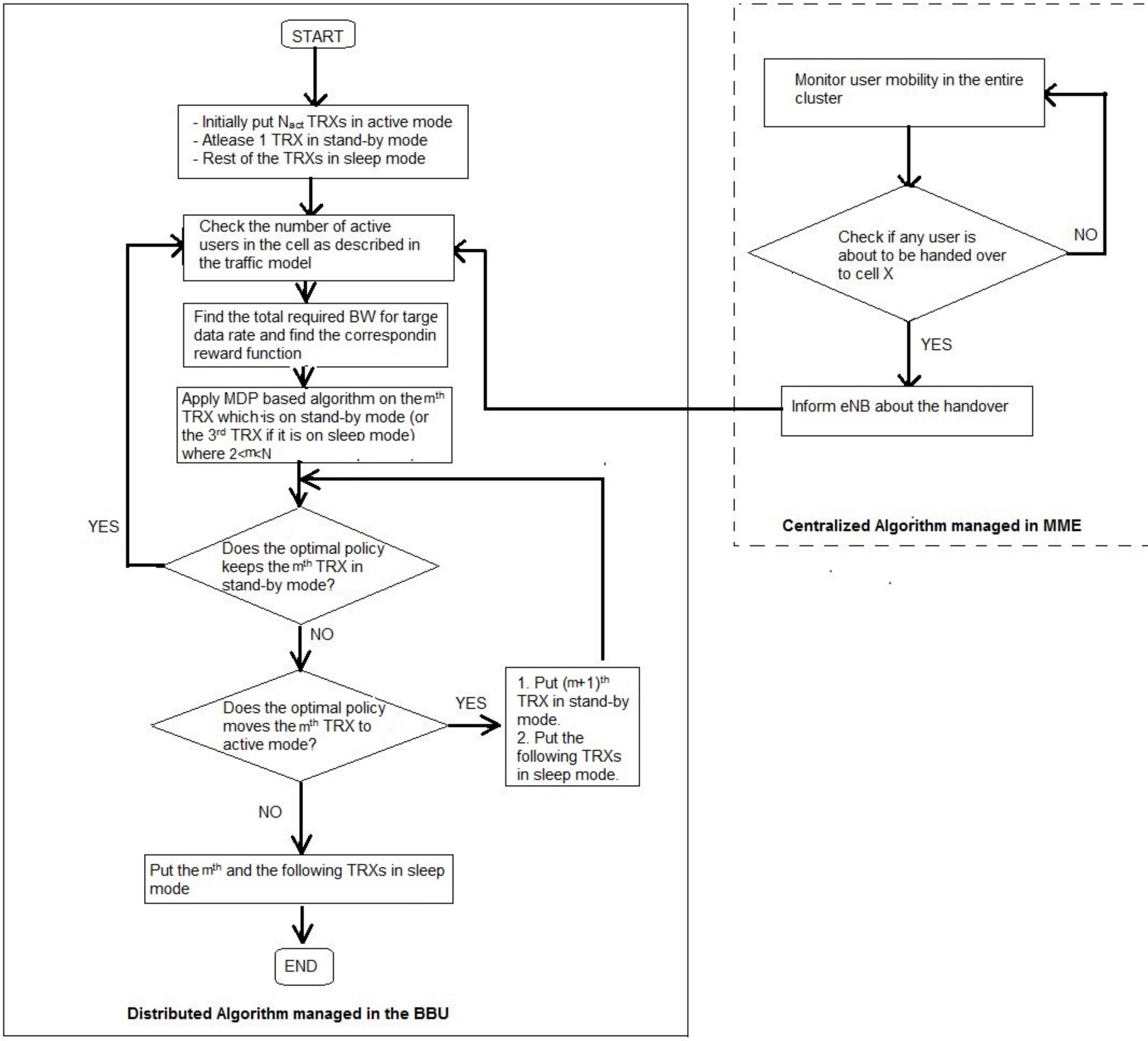

Figure 5-9: Flow chart of the algorithm.

where N_{act}, N_{std} and N_{slp} denote the number of TRXs in active mode, stand-by mode and sleep mode respectively; $\P_{out}$ is the output power or transmit power; $d\P$ is the slope of load-dependent power consumption which is represented as a linear transmission power dependence factor in [9]; $\P_o$ and $\P_{std}$ are the power consumption at minimum non-zero load and in stand-by mode respectively. Please note that the TRXs in sleep mode ideally consume zero power. The reference values of all these variables for an AeBS [4] is shown in Table .5.2. In order to find the total energy conusmption of the AeBS, we apply trapezoidal numerical integration [171] on the power consumption curve of the AeBS. For the 'All TRX active' mode we do not apply any sleep or standby mode to the TRXs, hence we consider that all of the TRXs are always active regardless of the traffic requirement. The power consumption model for this mode is given in Eq. 5.8 where N is the total available TRXs in the eNodeB and N_{tx} is the number of transmitting TRXs which is equivalent to N_{act} in Eq.5.7.

$$\P_{all-TRX-active} = N \cdot \P_o + N_{tx} \cdot d\P \cdot \P_{out} \tag{5.8}$$

Two-State Power Consumption Model: In the 'two-state model', as proposed by most of the pioneering work [10, 27, 30, 31, 34–38, 40–44, 132, 134, 136], all of the inactive TRXs are kept in either stand-by mode or in sleep mode. This model can be expressed as the following power consumption model as in Eq. 5.9, where N_{low} the number of TRXs either in stand-by mode or in sleep mode. We have compared our proposed model with two different 'two-state models', namely 'Frenger 2 state (active-standby) model' where $N_{low} = N_{std}$ and 'Combes MDP based 2 state (active-sleep) model' where $N_{low} = N_{slp}$.

$$\P_{2-state} = N_{act}(\P_o + d\P \cdot \P_{out}) + N_{low} \cdot \P_{std} \tag{5.9}$$

5.7 Simulation Results

We use Matlab simulation to get the simulation results presented in this section. We use the traffic model as mentioned in the network model section to determine the total

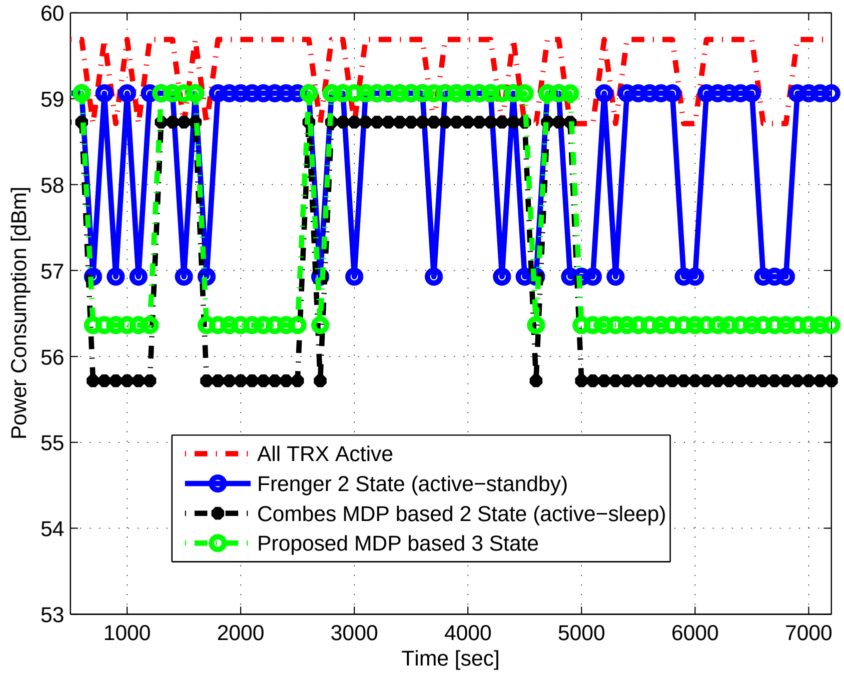

Figure 5-10: Power consumption of the AeBS for different models.

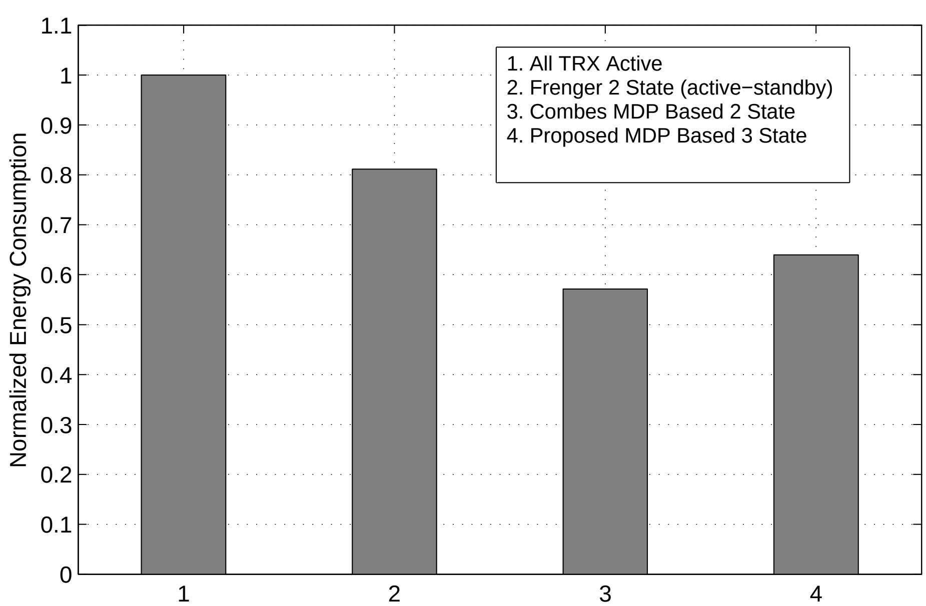

Figure 5-11: Energy consumption of different models normalized with respect to 'All TRX Active' model.

Table 5.2: Parameters used in the simulation

Parameters	**Values**
Altitude of AeBS, h	200 m
Carrier frequency, f_c	2000 MHz
AeBS Transmit Power	40 W
Shadowing Mean	0
Variance, σ^2	7
Total number of TRXs, N	3
Antenna Gain	10 dB and 2 dB
User arrival rate, u_λ	0.01
User death rate, u_μ	0.005
$\P_{max}$	40 W
Minimum data rate R_t	300 kbps
Discount factor, λ	0.975
$d\P$	4.7
$\P_{std}$	10 W
$\P_{slp}$	0 W
BW_T	6 MHz
b_{max}	6 MHz
b_{min}	2 MHz
BW per TRX	2 MHz
dt	2 sec

number of users in the coverage area of the AeBS at each decision epoch under the above mentioned propagation channel environment. The value iteration algorithm is used to solve the optimal policy, which determines the particular mode (active, stand-by and sleep) for each TRXs during every decision epoch. Finally the above mentioned power consumption model is used to find the total power consumption of the base station for different models. The total observation period is 2 hour and the simulation parameters are given in Table. 5.2. For the set of parameters provided in Table. 5.2, we find the transition probability matrix for the second TRX (TRX2) as the eq.5.10 and the transition probabilities for the third transceiver(TRX3) are shown in Fig.5-13.

$$Pr_{TRX2} = \begin{bmatrix} 0.9842 & 0.0158 & 0 \\ 0.0044 & 0.9956 & 0 \\ 0 & 0 & 0 \end{bmatrix} \tag{5.10}$$

For the third TRX, the transition probabilities among all of the three states for

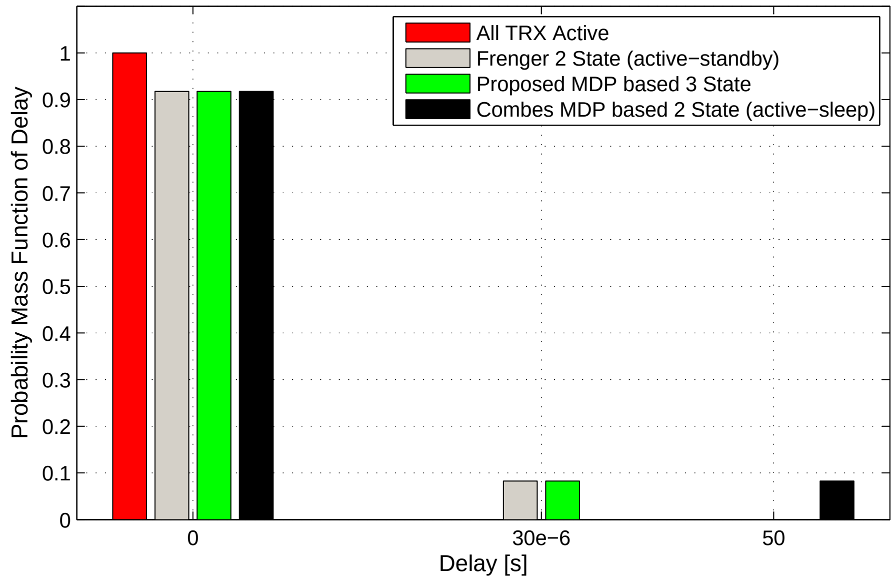

Figure 5-12: Percentage of users experiencing delay.

certain actions are presented in Fig.5-13. In this figure, S_0, S_1 and S_2 represents the states of the transceiver (TRX3) at sleep mode, stand-by and active mode respectively; and a_1^2 and a_2^2 represent the action of TRX2 becoming or remaining at stand-by and active mode respectively.

Fig.5-10 compares the power consumption of an AeBS for always active TRXs referred as 'All TRX Active'; 2-state model proposed in [39] referred as 'Frenger 2 state (active-standby) model'; MDP based 2-state model [10] referred as 'Combes MDP based 2 state (active-sleep) model'; and our proposed 3-state MDP model referred as 'proposed MDP based 3 state model'. These models can be defined as below:

- **All TRX Active**: According to this model, all of the TRXs of the AeBS are always active.

- **Frenger 2 State (active-standby) Model**: According to this model, the TRXs are capable of switching between active mode and stand-by mode depending on the traffic load [39].

- **Combes MDP based 2 State (active-sleep) Model**: According to this

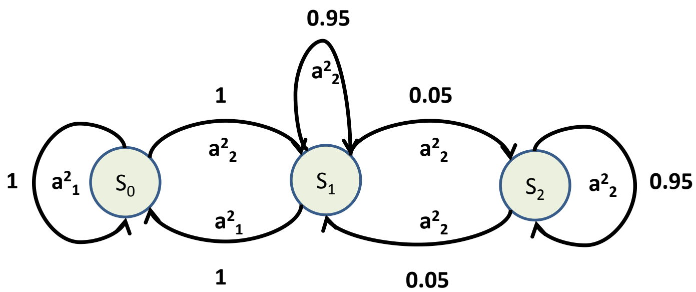

Figure 5-13: Three-state Markov Model for TRX3 with the transition probabilities calculated using the parameters provided in Table. 5.2.

model, the TRXs are capable of switching between active mode and sleep mode depending on the traffic load [10].

- **Proposed MDP based 3 State Model**: According to this model, the TRXs are capable of switching among active mode, stand-by mode and sleep mode depending on the traffic load.

Fig.5-10 clearly shows that using the proposed MDP model, we can save a significant amount of power than 'All TRX active' and 'Frenger 2 state model' in low traffic condition. This is because, as per our proposed model, some of the TRXs are in active mode, one of them is in stand-by mode and rest of them are in sleep mode; whereas in 'Frenger 2 state model' all of the unused TRXs are in stand-by mode. On the other hand, the 'Combes MDP model' put all of the unused TRXs in sleep mode only, which results in less power consumption compared to our proposed model but causes more wake up delay. This wake up delay can cause some call drops for the new users who would need to wait for a sleeping TRX to wake up and provide service. In order to see the delay performance of the above mentioned four different models we generate Fig.5-12, which shows the percentage of the total users experiencing delay (from delay group defined in Table. 5.1) in receiving service within the observation period for the four different models. As expected, all the users in 'All TRX active' model will experience no delay (delay group-1) at all because all of the TRXs are always active for this mode. On the other hand, 'Frenger 2 state model' uses stand-by mode and 'our proposed model' uses standby and sleep mode, therefore few (around 12%) of the users experience approximately 30 μsec (delay group-2) of delay for both of these models. On the contrary, these users (around 12%) experience a higher delay which is appx. 40sec (delay group-3) of delay in the 'Combes MDP model' as this model implements only sleep mode for the unused TRXs. From these results we can say that although the users experince small amount of delay in our proposed model as a consequence of applying stand-by and sleep mode in the unused TRXs; but this disadvantage is outweighed by the benefits of reduced energy consumption. However, as expected, the power consumption is the same for the two states and three states models in higher traffic condition, as almost all of the TRXs needs to be active in order to support the load. Therefore, our proposed model offers a fair share of energy efficiency and delay in low traffic condition.

The bar chart shown in Fig.5-11 compares the energy consumption between all the models and shows that the MDP based three state model can reduce approximately 40% energy consumption compared to the enerrgy consumption of the 'All TRX active' model. Note that the energy consumption of this figure has been normalized by the energy consumption of 'All TRX active' mode. We have applied trapezoidal numerical integration [171] on the power consumption curves in order to find the total energy consumption of the BS.

5.7.1 Steady state analysis and expected energy consumption of the aerial base station

If we consider an aerial base station with three transceivers, then there would be three possible states for the AeBS:

- **State-1:** 1 TRX active, 1 TRX stand-by and 1 TRX in sleep mode.
- **State-2:** 2 TRXs active, 1 TRX stand-by and 0 TRX in sleep mode.
- **State-3:** 3 TRXs active, 0 TRX stand-by and 0 TRX in sleep mode.

The transition probabilities between these states are found from the state transition probabilities of the TRXs.

For instance, the transition probability between state-1 and state-2 is as follows:

$$P_{12} = Pr_{22}^{1} Pr_{12}^{2} Pr_{01}^{3} \tag{5.11}$$

Where, Pr_{22}^{1}, Pr_{12}^{2} and Pr_{01}^{3} are the probability of transition between active-active for TRX-1, probability of transition between standby-active for TRX-2 and probability of transition between sleep-standby for TRX-3 respectively. Following the similar steps we find the state transition probability matrix for the entire BS as presented in Eq.5.12.

$$\begin{bmatrix} 0.9956 & 0.0044 & 0 \\ 0.0168 & 0.93 & 0.05 \\ 0 & 0.03 & 0.97 \end{bmatrix} \tag{5.12}$$

As the state transition process of the TRXs and AeBS follow a MDP model, therefore they converge at the steady state, when the current state become same as the future state. Hence if the state vectors of the AeBS is $[\Pi_1 \Pi_2 \Pi_3]$ at steady state, then it must follow the following conditions as in Eq.5.13 and Eq.5.14:

$$\begin{bmatrix} \Pi_1 & \Pi_2 & \Pi_3 \end{bmatrix} \cdot \begin{bmatrix} P_{11} & P_{12} & P_{13} \\ P_{21} & P_{22} & P_{23} \\ P_{31} & P_{32} & P_{33} \end{bmatrix} = \begin{bmatrix} \Pi_1 & \Pi_2 & \Pi_3 \end{bmatrix} \tag{5.13}$$

$$\Pi_1 + \Pi_2 + \Pi_3 = 1 \tag{5.14}$$

By solving Eq.5.13 and Eq.5.14 we find the values for the state vectors of the AeBS as Eq.5.15:

$$\begin{bmatrix}\Pi_1 & \Pi_2 & \Pi_3\end{bmatrix} = \begin{bmatrix}0.75 & 0.09 & 0.16\end{bmatrix} \tag{5.15}$$

Once we get the state probability vector for the AeBS, then we can find the expected energy consumption of the entire BS from Eq.5.16:

$$E[\chi] = \sum_{i=1}^{N} Pr[\Pi_i]\chi_i \tag{5.16}$$

Here N is the total number of states of the BS, $Pr[\Pi_i]$ is the probability of being in i_{th} state of the BS which is found from the state vector, and χ_i is the energy consumption at that particular state. Using the given set of parameters provided in Table. 5.2 for a BS consisting three transceivers, we find the expected energy consumption as $0.40996MJ$ which is close to the calculated energy consumption ($0.407018MJ$) of the BS with three state transceivers using MDP model. Therefore our expected energy consumption provides pretty close estimation to our calculated energy consumption for proposed MDP based three state model.

5.7.2 Effect of the Parametric Variation

In this section, we vary the different parameters and show their effect on the energy consumption of the aerial BS. At first, we vary the altitude of the AeBS in Fig.5-14 and find that the energy consumption increases with the altitude of the AeBS, however become almost constant after a certain altitude (above 900 meters) for the given set of parameters; this is because, all of the TRXs need to active in order provide satisfactory service above that particular altitude. These results depict that our proposed model consumes less energy than 'All TRX active' model and 'Frenger 2 state (active-standby) model', however consumes little more energy than 'Combes MDP based 2 state (active-sleep) model'. Fig.5-15 shows the expected delay experienced by the users, from where we can see that 'Combes MDP based 2 state

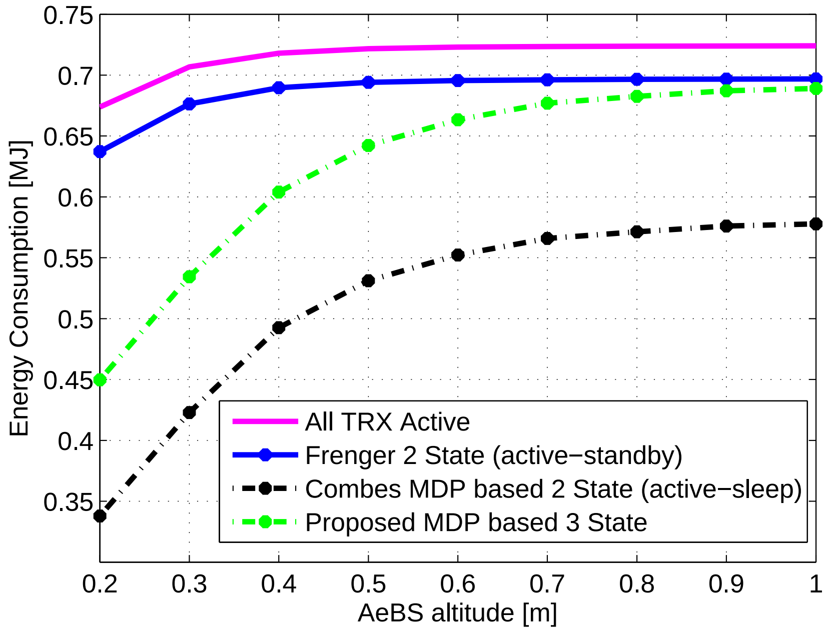

Figure 5-14: Effect of varying the altitude of the AeBS on energy consumption.

(active-sleep) model' offers more delay than 'Proposed 3 state model','Frenger 2 state (active-standby) model' and 'All TRX active' model. The delay decreases with the AeBS altitude since higher altitude requires more TRXs to be active, hence put less TRXs in sleep/stand-by mode, and consequently reduces the required delay to wake up.

We also observe the effect of different shadowing variance on the energy consumption and expected delay and the results are shown in Fig.5-16 and Fig5-17. These figures depict that the energy consumption and the delay of the AeBS almost remain same for various shadowing variance, this is because the signal travels in free space for most of the time and is rarely affected by shadowing in the path between the AeBS and the UE. Finally, the effect of varying minimum acceptable data rate on the energy consumption is shown in Fig. 5-18, we find that the energy consumption increases with target data rate, This is because more active TRXs are needed to support the increased target data rate, hence the energy consumption increases. Fig5-19 shows the expected delay experienced by the users for different target data rate, which shows that increasing the target data rate decreases the delay after certain

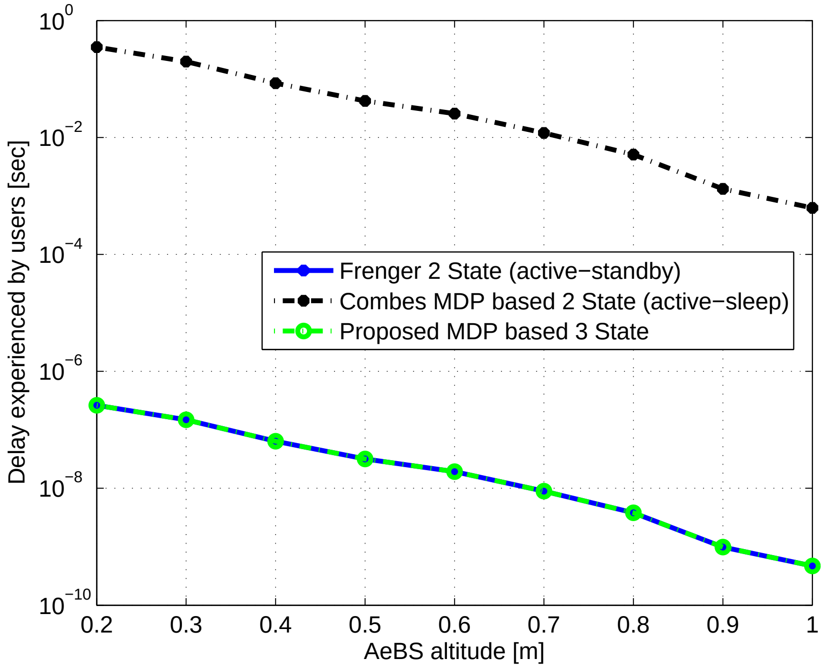

Figure 5-15: Delay experienced by users vs Altitude of the AeBS.

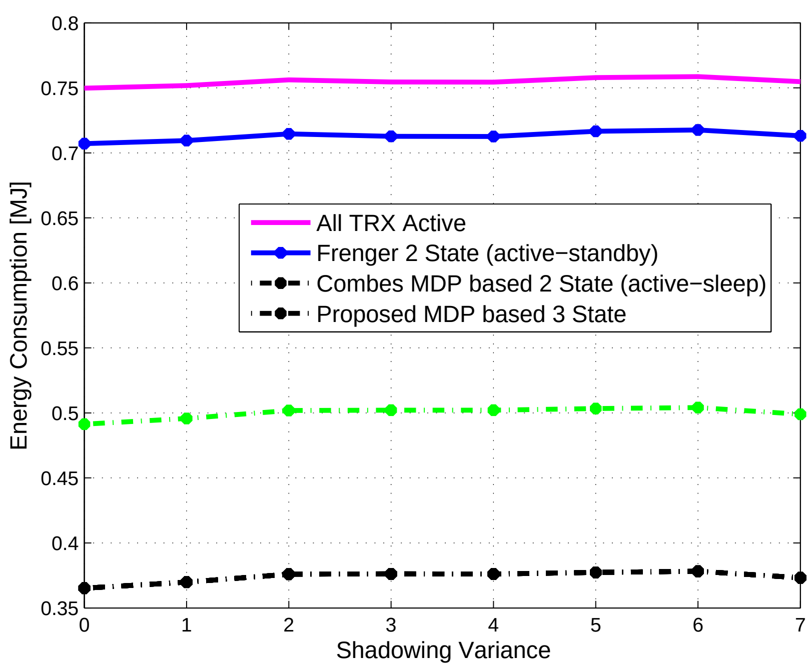

Figure 5-16: Effect of varying variance of shadowing on energy consumption.

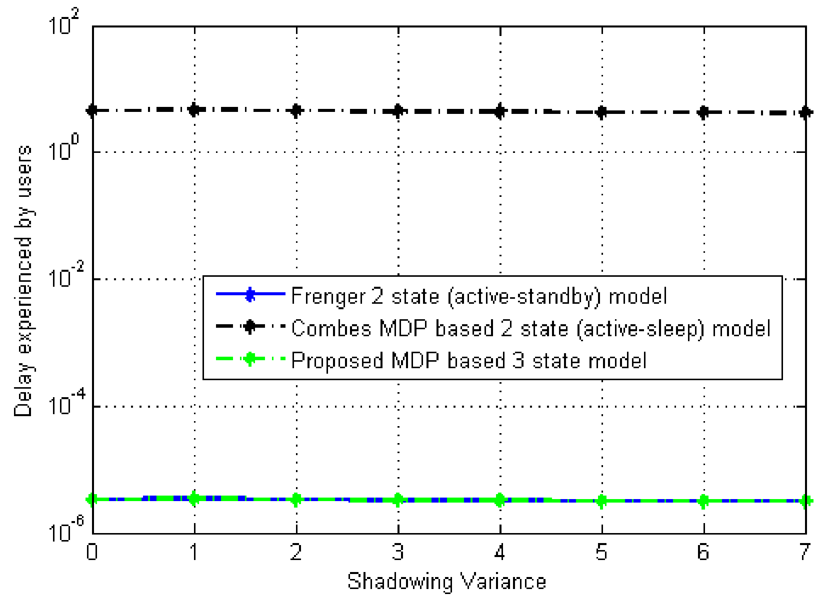

Figure 5-17: Delay experienced by users vs Shadowing varianvce.

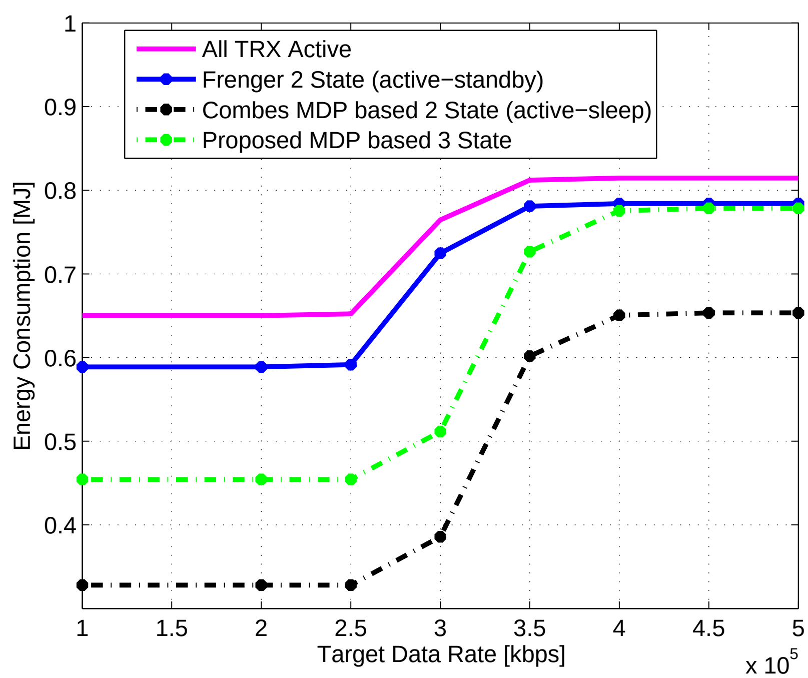

Figure 5-18: Effect of varying target data rate on energy consumption.

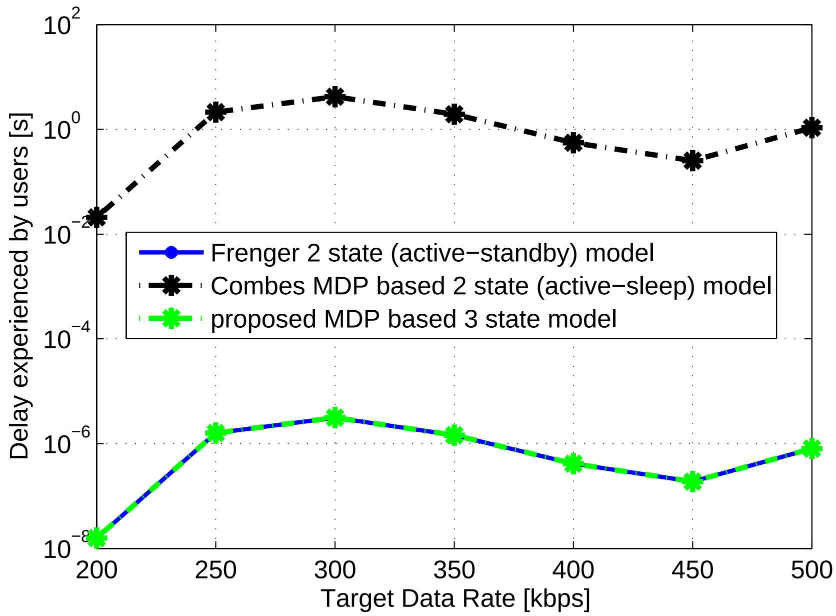

Figure 5-19: Delay experienced by users vs data rate.

point, that is because higher data rate put less TRXs in sleep/stand-by mode, hence reduces the required delay to wake up. All of these figures depict that 'Combes MDP based 2 state (active-sleep) model' offers higher delay than 'Proposed 3 state model', 'Frenger 2 state (active-standby) model' and 'All TRX active model'. All of these results again show that, our proposed model is an efficient model which reduces not only energy consumption but also call dropping caused by wake-up delay.

5.8 Summary of Contribution and Conclusion

In this chapter, we have proposed a novel strategy to improve the energy efficiency of aerial base stations using the Markov Decision process. The proposed method considers a three-state transceiver model with active, sleep and standby modes where the states are adopted between each other based on the MDP based algorithm. In the MDP based approach we have proposed a novel reward function, which helps us to find the optimal policy to improve the energy efficiency depending on the traffic condition and QoS requirement. Our results indicate that the AeBS can save a significant amount (appx. 40%)of energy in low traffic condition, where delay experienced by the user due to wake-up time of sleeping transceivers is very small. Therefore, the proposed model has proven to offer fair share of energy efficiency and delay for an aerial base station.

Chapter 6

A MDP-based Energy Efficient Handover decision Algorithm for LTE-Advanced Heterogeneous network cell Network

6.1 Introduction

Over the past few years, wireless connectivity at anywhere and anytime has gradually become a reality and has resulted in remarkably increased mobile traffic. Mobile data traffic from prevailing smart terminals, multimedia-intensive social applications, video streaming, and cloud services are expected to grow at a compound annual growth rate of 61% before 2018, and is expected to outgrow the capabilities of the current 4G (fourth generation) and Long Term Evolution (LTE) infrastructure by 2020 [61]. Release 10 of the 3rd Generation Partnership Project (3GPP) for the Long Term Evolution (LTE) system, namely LTE-Advanced (LTE-A), describes a wide range of technical improvements for the LTE system, which includes but not limited to, advanced multi-antenna techniques, carrier aggregation, relaying and enhanced support for heterogeneous deployments [71], [179]. Support of smallcells is an integral part of the LTE-A system since it plays a vital role for its wide adoption in a broad scale. Femtocells are low-cost and low-power cellular access points which incorporate the functionality of a regular base station, however support fewer users compared to macrocells. Femtocells operate in the mobile operators licensed spectrum [52]. These smallcells are capable of enhancing the Quality of Service (QoS) perceived by the users and can improve the energy efficiency for the network nodes. Existing reports of wireless networks are aticipating that within the next few years, the number of deployed smallcells will surpass that of macrocells by up to six times [72]. To this extent, the smooth integration of smallcells into the macro-cellular network layout is critically important for heterogenous LTE-A networks. However, many technical challenges arises with implementation of smallcells, including but not limited to the areas of energy efficiency [112] and handover (HO) decision making [25,70,73–75,112–114,169,178–181]. Energy saving is essential in the presence of smallcells, because of the vastly overlapping cell coverage and the dense network layout. However more sophisticated HO decision making is required in the presence of LTE-A smallcells to sustain a low HO probability without sacrificing the smallcell utilization opportunities. Existing literature includes various energy saving approaches for the LTE-A smallcell network which mainly focus on the reduction of the energy expenditure at the cells [112]. Different from existing energy saving approaches, in this chapter we focus on reducing the energy-expenditure at the User Equipment (UE). To this extend, we propose a Markov decision process (MDP) based energy efficient HO decision making algorithm, an approach which has not been thoroughly investigated in the literature.

Even though HO decision making is challenging in the LTE-A smallcell network, only a few reports are engaged with the matter [25,53,54,69,75,113,114,169,170]. Assuming a single-smallcell single-macrocell network layout, the algorithm in [113] uses a combined Received Signal Strength (RSS) metric to choose between the macrocell and the smallcell service. The algorithm in [75] accounts for the UE speed to avoid inbound mobility to smallcells for medium to high speed users. The authors in [114] perform mobility prediction to estimate the cell residence time of the user and reduce the number of unnecessary handovers in the system. The policy in [25] uses standard measurements to reduce the mean UE transmit power in the two-tier LTE smallcell network. Authors in [53] has proposed an algorithm based on the received signal strength (RSS) and wireless transmission loss in hierarchical cell networks, which considers the discrepancy in transmit power between macrocell and smallcell base stations. The article [169] presents an algorithm which is based on the MDP formulation with the objective of maximizing the expected total reward of a connection. They use a link reward function to model the QoS of the mobile connection and a signaling cost function to model the switching and rerouting operations when a vertical handoff occurs. In [170], a vertical handoff decision algorithm for 4G wireless networks has been proposed were the problem is formulated as a constrained Markov decision process (CMDP). In article [69] handover decision algorithm considering data arrival, handover delay and signaling cost has been proposed based on Markov decision processes. Their expected total reward seeks a balance between transmission latency and handover signaling overhead, under dynamic traffic arrivals. To our best knowledge, Markov decision Process(MDP) has never been used to develop an energy efficient and delay aware HO decision algorithm in LTE networks. Hence the novelty of our work is in developing a MDP based hand over (HO) decision algorithm for LTE network which not only reduces energy consumption, but also reduces handover latency. Also the main contribution of our work is in formulating a novel reward function for finding the optimal policy to reduce energy consumption and handover delay.

6.2 System Model

We consider a LTE-Advance network consisting a cell with one macro Base station (BS) and few small BSs as shown in Fig.6-1. Macro BS is referred to as evolved Node B (eNB), while small BS as Home eNB (HeNB). We are assuming that the small BSs are co-located in the coverage region of a macro BS. The small BSs are assumed to work in OSG (open subscriber group) mode. Let us assume that there are X number of users in the coverage area of the macro BS. A UE (u_1) moves along the road and passes through a series coverage areas of small BSs; also note that the macro BS is always available. We focus our analysis on the HO decision phase for the

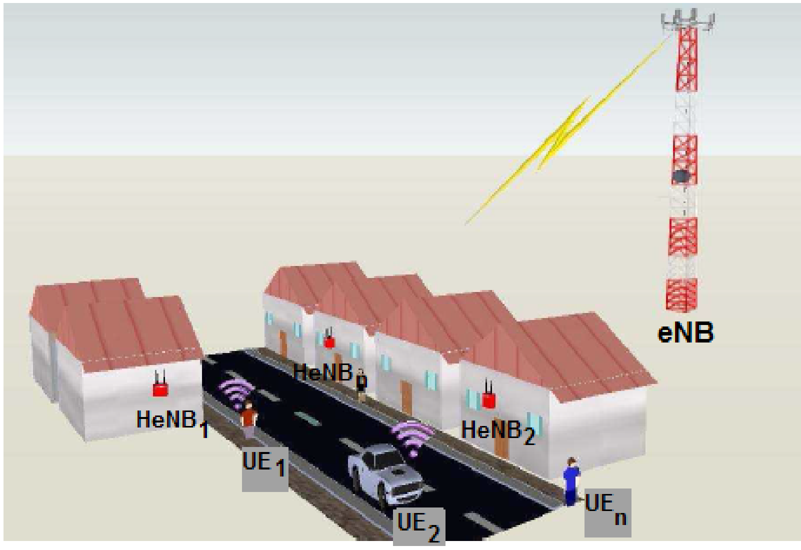

Figure 6-1: Network diagram with Macro BS(eNB) and small BS

user u_1, which is served by macro BS (c_M) and is in the proximity (candidate and accessible) of the small BS (c_f). The user is suppose to have a prescribed mean signal to interference and noise ratio ($SINR$) target, denoted by γ_t to support its ongoing services.

Let us assume that we derive all the following parameters in the context of the HO decision phase over the time interval, namely, Time To Trigger (TTT). We condister the log-distance pathloss for the macro BS as given in Eq.6.1 and that for the small BS ass given in Eq.6.2. Here R_M and R_f are the distance between the UE and the eNB and HeNB respectively, f_{cM} and f_{cf} are the carrier frequency of the eNB and HeNB respectively, n_M and n_f are the pathloss exponent of the eNB and HeNB respectively, $d_0 = 1m$ and L_w is the wall penetration loss.

$$PL_{macro}[dB] = 20\log_{10}(\frac{4\pi d_0 f_{cM}}{c}) + 10n_M\log_{10}(\frac{R_M}{d_0}) \tag{6.1}$$

$$PL_{small}[dB] = 20\log_{10}(\frac{4\pi d_0 f_{cf}}{c}) + 10n_F\log_{10}(\frac{R_f}{d_0}) + L_w \tag{6.2}$$

For a target uplink $SINR$ (γ_t) (dB) we can calculate the uplink transmit power of user u_1 as given by Eq.6.3 and Eq.6.4 for macro and small base station (BS) respectively, where P_n is the noise power in linear scale; I_M is the interference power at the macro BS in linear scale; I_f is the interference power at the small BS in linear scale and G_M, G_{UE} and G_F are the antenna gain of the macro BS, UE and Femto BS in dB respectively; and X_M, X_f are the log-normal shadowing components in dB values, which are Guassian distributed with zero mean and variance σ_M^2 and σ_f^2 for macro and small BS respectively.

$$P_{UE-Macro}[dBm] = \gamma_t - G_M - G_{UE} + PL_{macro} + 10\log_{10}(P_n + I_M) + X_M \tag{6.3}$$

$$P_{UE-Femto}[dBm] = \gamma_t - G_F - G_{UE} + PL_{small} + 10\log_{10}(P_n + I_f) + X_f \tag{6.4}$$

Eq.6.3 and Eq.6.4 can be used to estimate the mean power consumption of user u_1 if we assume the transmit power to be the primary contributor to the UE power consumption. We use the UE transmit power for the small BS ($P_{UE-Femto}$) and macro BS ($P_{UE-Macro}$) and handover delay to formulate the reward funcion in MDP in order to take the handover decision.

In order to solve the above equations the UE needs the information from the eNB and HeNB about their transmit power, antenna gain, longitude and latitude coordinates for both the eNB and HeNB in order to estimate the distance. We obtain these information from the synchronization information [182]. Please note that the eNB and HeNB positioning information needs to be sent just once, which is in the beginning of the synchronization as the location of eNB and HeNB are fixed. Thus this process is not much energy consuming. We are also assuming that the UE has indoor and outdoor localization via its GPS. This localization procedure is out of the scope of this work, the readers can refer to the paper [183] for more information on the localization. This total information gathering procedure may be completed in few bytes only. Hence the energy needed to be spent in this process (E_{sync}) can be calculated as the following Eq.6.5, where P_{tx} is the transmit power, B_{sync} is data needed to receive information and b is the total data rate. Therefore the total energy saved in our algorithm = (Energy saved - Energy spent in synchronization).

$$E_{sync} = \frac{P_{tx} * B_{sync}}{b} \tag{6.5}$$

6.3 Markov Decision Process (MDP) Model formulation

MDP, also known as stochastic dynamic programs, is a commonly used model for sequential decision making for stochastic problems with uncertain outcomes. An MDP model mainly consists of five elements: decision epochs, states, actions, transition probabilities and rewards. Choosing an action from the action set in a current state generates a reward. This reward, along with the transition probability, determines the state at the next decision epoch. Policies and strategies are prescriptions of which action to choose under any eventuality at every future decision epoch.

In this section, we explain how the handover decision problem in a heterogenous network can be formulated as an MDP and how value iteration algorithm (VIA) solves the MDP problem to obtain the optimal policy of selecting the appropriate candidate BS at each decision epoch.

Decision Epochs: The decision epoch is defined as a sequence of time $T = 1, 2, ..., Q$ which represents the time of succesive decision as shown in Fig.6-2.

State: In the proposed handoff decision algorithm, the state is defined as the target base station that the UE is going to be connected with. Hence the state sapce is presented as Eq.6.6:

$$S \in \{Macro, Femto\} \tag{6.6}$$

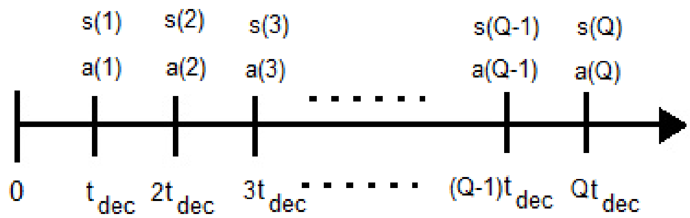

Figure 6-2: Timing diagram of an Markov decision process

Action: For our proposed model, the action represents the selection of the appropriate target base station that the UE is going to connect with at a particular decision epoch based on the reward function. The reward function is defined in the next paragraph. Based on the action chosen by the policy, the UE may stay connected to the current serving base station or choose another target base station in order to reduce energy consumption and handover delay. Hence, the action (A) is defined as selecting the appropriate candidate BS and is represented as $A \in \{a_{mm}, a_{mf}, a_{fm}, a_{ff}\}$, where a_{mm} represents the action of staying with the macro BS, a_{mf} represents the action of switching from macro BS to small BS, a_{fm} represents the action of switching from small to macro BS and a_{ff} represents the action of staying with small BS.

Our proposed model can be represented as Fig.6-3, where Pr_{mm}, Pr_{mf}, Pr_{fm} and Pr_{ff} represents the transition probability between macro-macro, macro-small, small-macro and small-small respectively.

Reward: For a state $s \in S$ and selected action $a \in A$, the reward function $R(s,a)$ is defined as Eq.6.7,

$$R(s,a) = w_p f_p(s,a) + w_d f_d(s,a) \tag{6.7}$$

Where $f_p(s,a)$ and $f_d(s,a)$ are the power consumption reward function and delay reward function respectively; w_p and w_d are the respective weight factors where $w_p + w_d = 1$. The power consumption and delay reward functions are defined as Eq.6.8 and Eq.6.9:

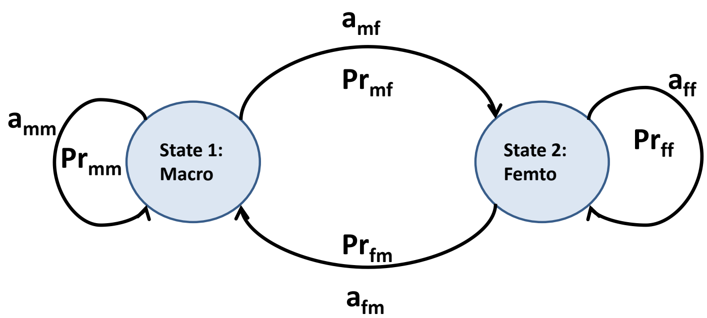

Figure 6-3: Proposed markov model

$$f_p(s,a) = \frac{p_{max} - p_a}{p_{max} - p_{min}} \tag{6.8}$$

$$f_d(s,a) = \frac{d_{max} - d_a}{d_{max} - d_{min}} \tag{6.9}$$

where p_a and d_a are the UE power consumption and handover delay of the BS selected by action a respectively; p_{max} is the maximum transmit power of the UE, d_{max} is the maximum tolerable time delay to transfer a call to the new BS, p_{min} is the minimum transmit power required to meet the QOS, and d_{min} is zero.

Transition Probability: For a current state is $s \in S$ and the chosen action is $a \in A$, the probability that the next state would be $s' \in S$ is denoted as transition probability $Pr[s'|s,a]$. We determine the percentage of coverage area [177] for each base station in order to calculate transition probability. It is noteworthy that, some locations within the coverage area of the BS will be below the desired received signal strength threshold due to random effects of shadowing. Hence the percentage of the coverage area gives us a good estimation of the transition probability. We start by calculating the radius of the cells from link budget calculation for a mean received signal strength (γ). If $R_p(r)$ is the received signal at the UE located at r radial distance from the BS, then the probability that this received signal exceeds the threshold γ is represented by the following eqaution Eq.6.10, where n is the pathloss exponent:

$$\begin{aligned} Pr(R_p(r) > \gamma) &= Q\left(\frac{\gamma - R_p(r)}{\sigma}\right) \\ &= \frac{1}{2} - \frac{1}{2}erf(\frac{\gamma - R_p(r)}{\sigma\sqrt{2}}) \\ &= \frac{1}{2} - \frac{1}{2}erf(\frac{\gamma - [P_t - (PL(d_0) + 10nlog(\frac{r}{d_0}))]}{\sigma\sqrt{2}}) \end{aligned} \tag{6.10}$$

Where $Q(.)$ is the Gaussian tail integral function and $erf(.)$ is the Gaussian error function. In order to determine the path loss as referenced to the cell boundary (where $r = R$), we refer to the following equation Eq.6.11

$$PL(r) = 10nlog(\frac{R}{d_0}) + 10nlog(\frac{r}{R}) + PL(d_0) \tag{6.11}$$

Therefore Eq.6.10 may be expressed as Eq.6.12

$$Pr(R_p(r) > \gamma) = \frac{1}{2} - \frac{1}{2}erf(\frac{\gamma - [P_t - (PL(d_0) + 10nlog(\frac{R}{d_0}) + 10nlog(\frac{r}{R}))]}{\sigma\sqrt{2}}) \tag{6.12}$$

If we let $a = \frac{\gamma - P_t + PL(d_0) + 10n\,log(\frac{R}{d_0})}{\sigma\sqrt{2}}$ and $b = \frac{10n\,log\,e}{\sigma\sqrt{2}}$, then the percentage of coverage area with a received signal greater than or equal to γ is expressed as Eq.6.13

$$U(\gamma) = \frac{1}{2} - \frac{1}{R^2}\int_0^R r\,erf(a + b\,ln\frac{r}{R})\,dr \tag{6.13}$$

By substituting $t = a + b\,ln\frac{r}{R}$ in Eq.6.13 we get,

$$U(\gamma) = \frac{1}{2}(1 - erf(a) + exp(\frac{1 - 2ab}{b^2})[1 - erf(\frac{1 - ab}{b})]) \tag{6.14}$$

Hence for a given value of n and σ, Eq.6.12 and Eq.6.14 can be used to determine the probability that the received signal strength will be greater than the threshold and the percentage of coverage area that would receive coverage above the threhold received signal respectively. Then from the percentage coverage area of macro BS (A_m) and the percentage coverage area of small BS (A_f), we can find the transition probabilities between different cells. For instance, the probability of staying with macro BS, $Pr_{mm} = \frac{A_m - A_f}{A_m}$; the transition probability between macro-small BS, $Pr_{mf} = \frac{A_f}{A_m}$; the transition probability between small-macro BS, $Pr_{fm} = \frac{A_m - A_f}{A_m}$; and the probability of staying with small BS, $Pr_{ff} = \frac{A_f}{A_m}$.

Optimality Equations and Value Iteration Algorithm: Let us now denote $V(s)$ as the maximum expected total reward for an initial state s, then the optimality equations are given by Eq. 6.15 as follows:

$$V(s) = max_{a \in A}\{R(s,a) + \sum_{s' \in S} \lambda Pr[s'|s,a]V(s')\} \tag{6.15}$$

The solution of the optimality equation correspond to the maximum expected total reward $V(s)$ and the MDP optimal policy $\pi(s)$. This MDP optimal policy $\pi(s)$ indicates the decision of selecting the appropriate candidate cell. Value iteration algorithm (VIA) [159] is used to solve this optimization problem. The VIA is shown in algorithm 3 where ζ is an error function.

Algorithm 3 Value Iteration Algorithm (VIA)

1: Set $V^0(s') = 0$ for each state s. Specify $\zeta > 0$, and set $k = 0$.
2: For each state s, compute $V^{k+1}(s)$ by
    $V^{k+1}(s) = max_{a \in A}\{R(s,a) + \sum_{s' \in S} \lambda Pr[s'|s,a]V^k(s')\}$
3: $\delta = max(V^{k+1}(s) - V^k(s))$
4: If $\delta < \zeta \frac{1-\lambda}{2\lambda}$, go to step 5.
    otherwise increase k by 1 and return to step 2.
5: Output a stationary optimal policy, π, such that
    $\pi(s) = argmax_{a \in A}\{R(s,a) + \sum_{s' \in S} \lambda Pr[s'|s,a]V^{k+1}(s')\}$
    and stop

6.3.1 Handover decision process

The handover decision process involves three main phases: 1) Base station discovery; 2) Base station analysis; and 3) Base station selection for the handoff execution.

- **Base station Discovery:** During the Base station(BS) discovery phase, the user equipment determines which BS is available for handover. In our proposed method the advertised information from the candidate BS is the required transmit power of UE for target BS and delay needed to be connected to the target BS. Please note that the transmit power is determined from a target $SINR$, which ensures that the service meets the QOS requirement. The traffic loads in the BS may also change with time and therefore the BSs are monitored after a particular period of time,TTT. We refer to this time as decision epochs as mentioned earlier. At each decision epoch the UE determines its state based on the maximum reward function for the candidate BS.

- **Base Station Analysis:** In this stage, the expected total reward and transition probability for all of the target BSs are determined using the above mentioned equations.

- **Base Station Selection:** Finally by executing all the steps of VIA, we get the optimal policy for handoff execution. A candidate BS which has highest corresponding value of the total expected reward (TER) is selected as the best BS to handoff. Therefore for our environment we can select the small BS if $TER_{small} > TER_{Macro}$. Fig.6-4 shows a sample sequence of states and actions taken by optimal policy for providing maximum expected reward, over a sample time period. According to this sample policy, at first the UE will be connected to the macro BS (state S_1), then will take action $a_m f$ and will handover to the small BS (state S_2). At the next decision epoch the optimal policy will take action $a_f f$ and let the UE stay at state S_2 followed by taking action a_{fm} and switching to state S_1 at the following decision epoch.

Our proposed HO decision process is illustrated in fig.6-5.

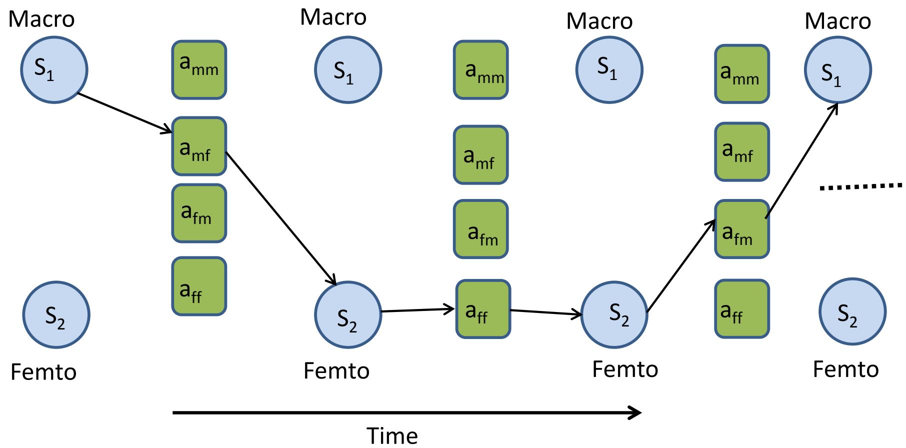

Figure 6-4: A sample of states and actions taken by optimal policy

6.3.2 Avoiding Ping Pong effect

We might face a problem while executing handover, namely Ping-pong effect, where the UE can jump between the macro and small BSs very frequently. In order to get rid of this problem we introduce hysteresis time dT. Therefore if a BS offers maximum expected reward for a time not less than the hysteresis time dT, only then the UE would be handed over to it. That way we can avoid the frequent occurance of handover.

6.4 Performance analysis of the proposed model

This section evaluates the performance of the proposed algorithm. For the simulation purpose, we consider a macro BS with certain coverage region, two small BSs are located within this region. A certain user u_1 is moving linearly from eNB to HeNB with speed v_s. There are some other active users as well, who causes interference.

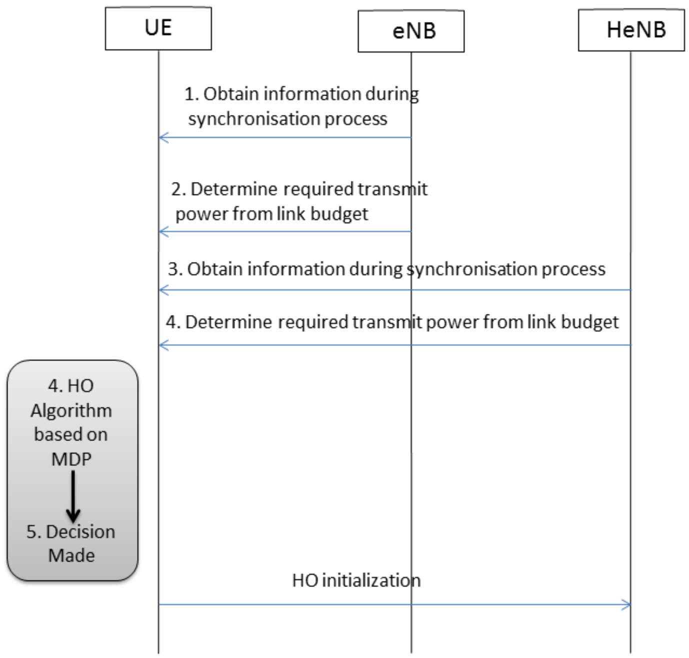

Figure 6-5: Signal flow of the proposed Handover algorithm

Table 6.1: System-level simulation model and parameters for the Macro BS and the Femto BS

Parameter	eNB (macrocells)	HeNB (smallcells)
Carrier Frequency	$2000MHz$	$2020MHz$
Channel Bandwidth	$20MHz$	$20MHz$
RS transmit power	$43dBm$	$23dBm$
Cell coverage	$500m$	$50m$
Log-normal shadowing variance	8	4
path loss exponent	3.5	2.8
Interference Power	-80 dBm	-90 dBm

Table 6.2: Other parameters for simulation

Mean UL SINR target,$\gamma_t = 10dB$	Noise power $= -145$ dBm
Overall simulation time =1000 sec	ζ for the VIA $= 10^{-3}$
User speed $= 10km/h$	discount factor, λ for the VIA $= 0.975$

Fig.6-6 presents a sample scenario used in the simulation, where we have one Macro BS and two femto BSs and a user can originate a call from any random location

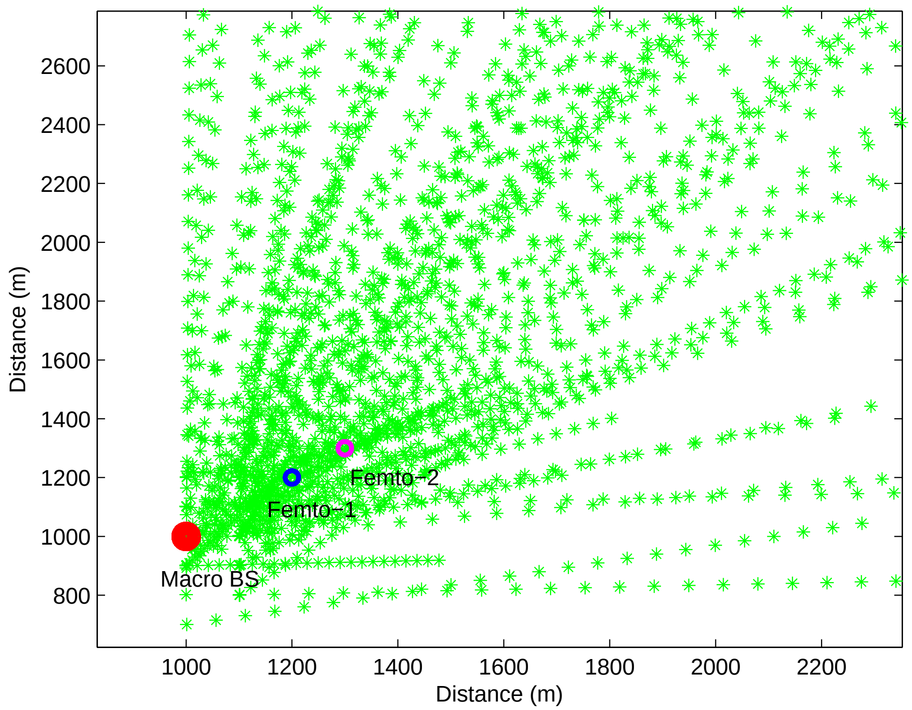

Figure 6-6: A sample scenario used for simulation

(x_0, y_0) and move onto any random direction. We have run the simulation for 5000 times and averaged the results over 5000 realizations of the scenario. We have used fixed interference power for the sake of simplicity. We assume that each handover is successful and there is no call drop. Transmission links experience log-normal shadowing with mean zero and variance σ_m^2 and σ_f^2 for eNB and HeNB, respectively. We use MDP algorithm to decide if the UE should handover to any other candidate BS other than its serving BS, so that the UE consumes less power and fulfill the QOS requirement. In order to find the transition probability we have considered the ratio of the percentage coverage area of eNB and HeNB. With the cell coverage values provided in table.6.1 and table.6.2 we find the transition probability of macro-macro,$Pr_{mm} = 0.9$; macro-small, $Pr_{mf} = 0.1$; small-small, $Pr_{ff} = 0.1$ and small-macro, $Pr_{fm} = 0.9$. For the handover delays, we assume that they are uniformly selected from the set $20ms$, $40ms$, $60ms$, $80ms$. According to the proposed algorithm, value iteration algorithm solve the MDP and will provide optimal policy on which BS to select at each decision epoch. By following the decision provided by optimal policy, thus by choosing the BS with maximum expected reward we can assure maximum energy efficiency and minimum delay, while satisfying the QOS requirement.

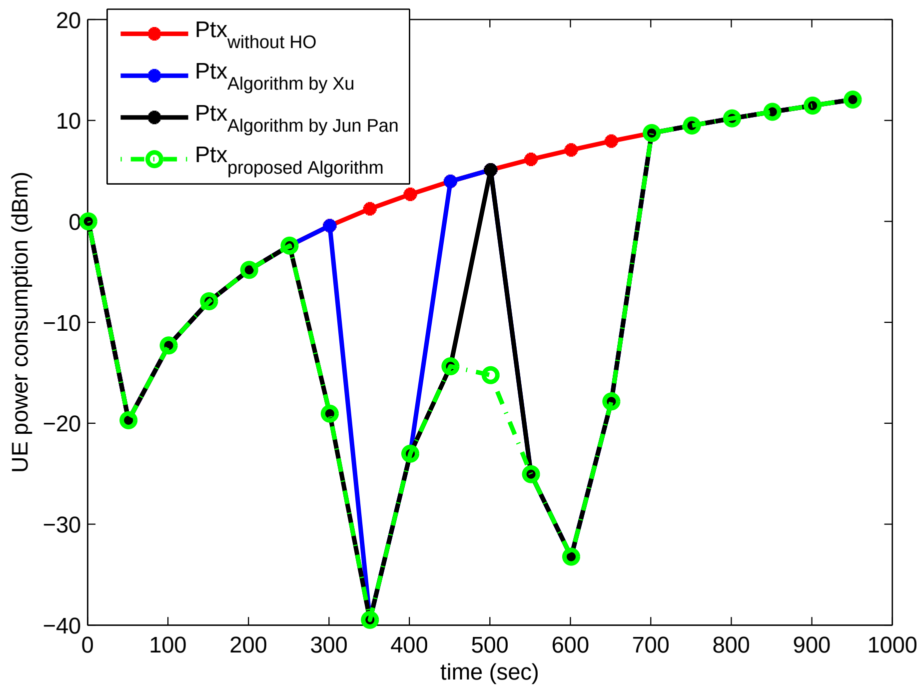

Figure 6-7: UE power consumption comparison for different algorithm

We compare our result with two other handover algorithms proposed by P. Xu et. al. in [53] and J. Pan et. al. in [69], we refer to these models as 'Algorithm by Xu' and 'Algorithm by Jun Pan' respectively. P. Xu proposed a handover algorithm based on the received signal strength (RSS) and wireless transmission loss as in presented [53]; whereas J. Pan proposed a MDP based handover algorithm considering handover delay, data arrival and signaling cost as their decision factors as presented in [69]. Also we compare our proposed model with the case with no HO at all. Fig.6-7 shows the UE power consumption for our proposed handover algorithm and that of the above mentioned algorithms, which depicts that our algorithm consumes the minimum amount of power among all of the other algorithms. This is because, according to our optimal policy the UE stays connected to the small cell for which its power

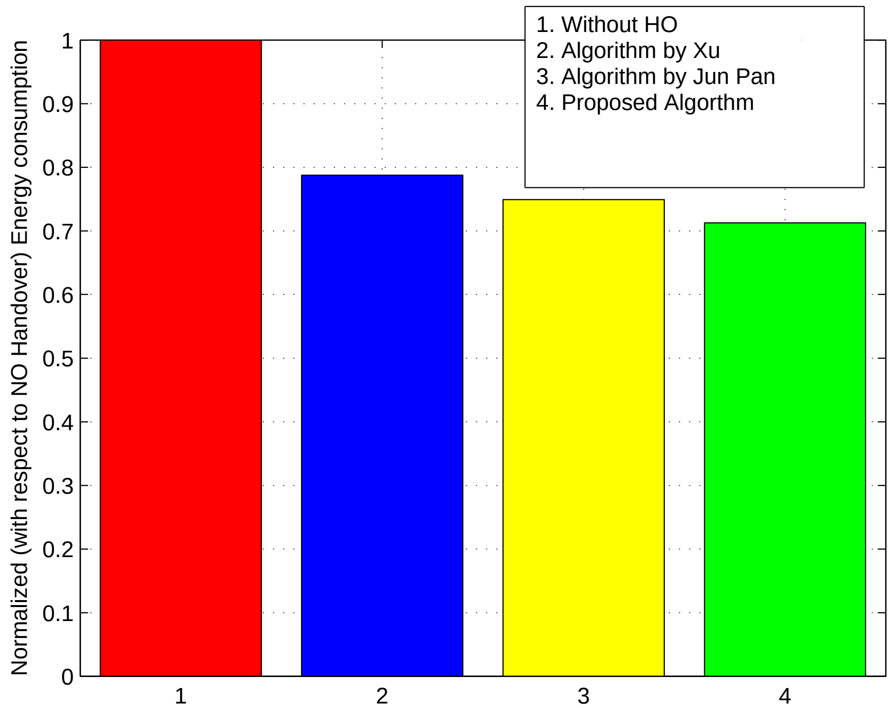

Figure 6-8: Normalized energy consumption (normalized with respect to 'No HO algorithm')

consumption is the lowest and avoids frequent handover in order to reduce delay in providing service. Fig.6-8 and Fig.6-9 shows the energy consumption and handover delay for the four different models, from where we can see that our proposed model consumes minimum energy among all of the other algorithms, as well as offers lowest handover delay among all of the algorithm. It is evident from the figures that our proposed handover (HO) decision algorithm is the power efficient (consequently energy efficient) model as well as offers less handover delay.

In Fig.6-10, we observe the effect of different weight factors (used in the reward function) on the energy consumption. As expected, our proposed model is no longer a power efficient model when the power weight factor is very less less. Hence, the power weight factor should be selected as more than 0.5 for an energy efficient HO algorithm.

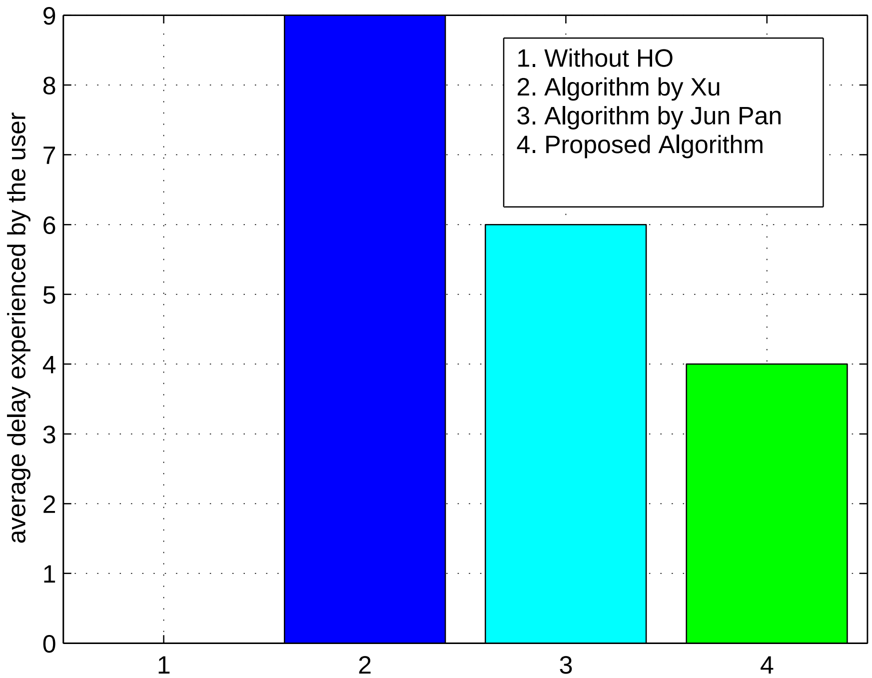

Figure 6-9: Average handover delay experienced by the user

6.5 Summary of Contribution and Conclusion

In this chapter, we proposed a Markov Decision Process based handover decision algorithm for the LTE-A heterogeneous (macro-small) network, which jointly considers the impact of user mobility and energy efficiency. Our main contribution to this work is to derive individual reward function of each QoS parameter used for making energy efficient handover decision. The proposed algorithm finds the optimal policy by VIA to sustain service continuity and reduce the mean UE transmit power. System-level simulations showed that the proposed algorithm significantly reduces energy expenditure at the UEs and latency introduced by handover procedure compared to existing algorithms.

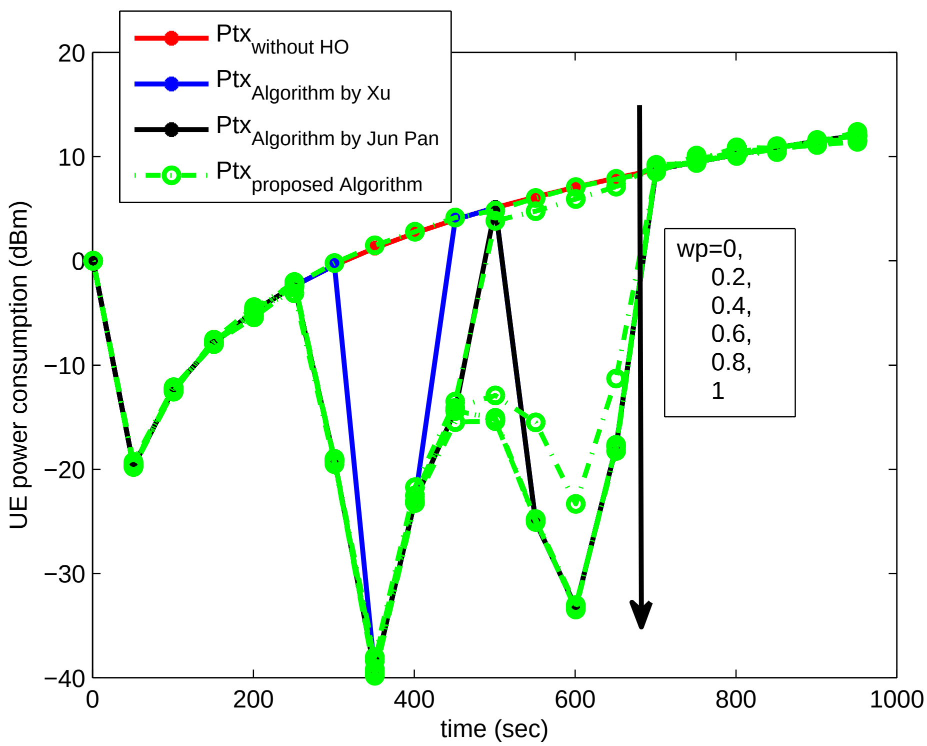

Figure 6-10: Power consumption for variable weight factor

Chapter 7

Conclusion and Future Research Paradigms

In this research, we explore the field of energy efficiency in MAC and Physical layers of wireless netorks in order to enhance the performance and reliability of future wireless networks as well as to reduce its environmental footprint. The research questions and the relevant contributions of this thesis are addressed individually in chapters 3-6. The four research questions are based on energy efficient approaches for different layers of wireless networks, which cover some gaps found in existing literature.

While addressing **research question-1**, we have shown that the total energy consumption of a point to point communication system can be minimized by optimizing the data rate for MQAM and MFSK in an AWGN channel. Here we assume that the system transmits a fixed length of packet with a fixed bandwidth to meet a given bit error rate. In order to find the optimal parameters we have used Newton-Raphson method. Our simulation results show that MQAM can minimize a significant amount of energy consumption by optimizing the data rate for shorter transmission distances; whereas MFSK can reduce energy consumption by optimizing the data rate for longer transmission distances. These results from our work can be directly used for an entire network for every transceiver node such that a greater energy efficiency could be obtained globally. The **future work** related to RQ-1 may correspond to implementing the rate adaptation strategy at the network level and perform link level simulations using the results obtained in this work.

While addressing **research question-2**, we propose a novel strategy to implement low power consumption mode in the transceivers of a cellular base station in LTE infrastructure. We propose an algorithm with 'ternary state Markov model' which can put the transceivers of a BS into active mode, stand-by mode and sleep mode depending on the traffic condition and QOS requirement. Hence we have shown that the BS can save a significant amount of energy in low traffic condition following our proposed 'ternary state power consumption mode', which proved to be more energy efficient compared to the conventional 'two-state power consumption mode'. The **future work** related to RQ-2 may focus on implementing an optimal controller to organize these mode transitions and also on implementing this strategy into Heterogeneous network.

While addressing **research question-3**, we propose a novel strategy to improve the energy efficiency of aerial base stations using the Markov Decision process. The proposed method considers a three-state transceiver model with active, sleep and standby modes where the states are adopted between each other based on the MDP based algorithm. In the MDP based approach, we have proposed a novel reward function, which helps us to find the optimal policy to improve the energy efficiency depending on the traffic condition and QoS requirement. Our results indicate that the AeBS can save a significant amount (appx. 40%) of energy in low traffic condition, where delay experienced by the user due to wake-up time of sleeping transceivers is very small. Therefore, the proposed model has proven to offer fair share of energy efficiency and delay.

The **future work** related to RQ-3 may focus on experimenting the proposed method on a three state prototype transceiver base station in house and comparing the simulation based study. Moreover, a stochastic geometry based energy efficiency analysis may to be done as part of the future work.

While addressing **research question-4**, we propose a Markov Decision Process based handover decision algorithm for the LTE-A heterogeneous (macro-femto) network, which jointly considers the impact of user mobility and energy efficiency. Our main contribution to this paper is to derive individual reward function of each QoS parameter used for making handover decision. The proposed algorithm finds the optimal policy by VIA to sustain service continuity and reduce the mean UE transmit power. System-level simulations showed that the proposed algorithm significantly reduces energy expenditure at the UEs and latency introduced by handover procedure compared to existing algorithms. The **future work** related to RQ-4 may focus on implementing the MDP based HO decision algorithm to reduce the energy consumption at the base station end.

Throughout this research, we relied on verifying the analytic results and formulas against computer simulations using Matlab simulations. We also presented practical numerical examples to reflect the usefulness of the presented methodologies. The majority of the work presented in this dissertation was published in-part or as a whole in peer-reviewed conference proceedings or otherwise currently undergoing a peer review process for journal publications. These publications has been highlighted and identified towards the end of the first chapter.

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