HAL
open science

Management of advanced sleep modes for energy-efficient 5G networks

Fatma Ezzahra Salem

To cite this version:

Fatma Ezzahra Salem. Management of advanced sleep modes for energy-efficient 5G networks. Networking and Internet Architecture [cs.NI]. Institut Polytechnique de Paris, 2019. English. NNT : 2019IPPAS004 . tel-02500618

HAL Id: tel-02500618

https://theses.hal.science/tel-02500618v1

Submitted on 6 Mar 2020

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

INSTITUT POLYTECHNIQUE DE PARIS

NNT : 2019IPPAS004

Thèse de doctorat

Gestion des modes de veille avancés pour des réseaux 5G économes en énergie

Thèse de doctorat de l'Institut Polytechnique de Paris
préparée à Télécom SudParis

École doctorale n°626 Institut Polytechnique de Paris (ED IP Paris)
Spécialité de doctorat : Mathématiques et Informatique

Thèse présentée et soutenue à Orange Labs, Châtillon, le 20/12/2019, par

FATMA EZZAHRA SALEM

Composition du Jury :

Guy Pujolle Professeur Emérite, Sorbonne Université - LIP6	Président
Cicek Cavdar Associate Professor, Institut Royal de Technologie (KTH)	Rapporteur
Halima Elbiaze Professeur, Université du Québec à Montréal (UQAM)	Rapporteur
Zwi Altman Ingénieur de recherche, Orange Labs	Examinateur
Laurent Lefèvre Chargé de recherche/HDR, Inria	Examinateur
Azeddine Gati Ingénieur de recherche, Orange Labs	Encadrant de thèse
Tijani Chahed Professeur, Télécom SudParis	Directeur de thèse

INSTITUT POLYTECHNIQUE DE PARIS

NNT : 2019IPPAS004

Thèse de doctorat

Management of Advanced Sleep Modes for Energy-Efficient 5G Networks

Thèse de doctorat de l'Institut Polytechnique de Paris
préparée à Télécom SudParis

École doctorale n°626 Institut Polytechnique de Paris (ED IP Paris)
Spécialité de doctorat : Mathématiques et Informatique

Thèse présentée et soutenue à Orange Labs, Châtillon, le 20/12/2019, par

FATMA EZZAHRA SALEM

Composition du Jury :

Guy Pujolle Professeur Emérite, Sorbonne Université - LIP6	Président
Cicek Cavdar Associate Professor, Institut Royal de Technologie (KTH)	Rapporteur
Halima Elbiaze Professeur, Université du Québec à Montréal (UQAM)	Rapporteur
Zwi Altman Ingénieur de recherche, Orange Labs	Examinateur
Laurent Lefèvre Chargé de recherche/HDR, Inria	Examinateur
Azeddine Gati Ingénieur de recherche, Orange Labs	Encadrant de thèse
Tijani Chahed Professeur, Télécom SudParis	Directeur de thèse

To my beloved country, my dear family, friends,
teachers and all the people I love.

Acknowledgements

"I have come to believe that a great teacher is a great artist and that there are as few as there are any other great artists. Teaching might even be the greatest of the arts since the medium is the human mind and spirit".

John Steinbeck

I would like to convey my sincere gratitude to my supervisors Tijani Chahed and Azeddine Gati for their guidance and assistance throughout this thesis. I am grateful for all the efforts that have been deployed in order to make this project successful and for all the constructive remarks and criticism that helped me improve my work and acquire a lot of knowledge.

I am also very grateful to Zwi Altman and Eitan Altman for their invaluable help and involvement during this work.

I address, likewise, my thanks to all my colleagues in Orange Labs for the welcoming and friendly environment.

My respect and gratefulness are due to all my teachers, who marked my education journey, generously assisted me, taught me to be scholarly-resourceful and provided me with immense knowledge.

I would like to thank my dear parents for being a source of love, strength, inspiration and permanent support during all my life, also my brothers and friends for their help, encouragements and lovely company.

May the members of the jury find here my deep gratitude for the honor they make to me by evaluating my thesis.

Abstract

The energy consumption of mobile networks has been an active research direction in the last decade for both environmental and economic concerns. With the tremendous growth in the traffic as well as the proliferation of devices and new services and the expansion of Machine to Machine communications, the need to reduce the energy consumption became more and more urgent and was emphasized by the expected 5G roll out.

Knowing that the radio access network is the most energy consumer in the network, particularly the base stations which consume around 80% of the mobile energy consumption, we direct our study towards this component. The energy consumption of the base stations is composed of two parts: a fixed one that does not vary with the load, and a second part which is load-dependent. Our target is to find efficient solutions enabling to reduce the fixed component. One promising solution is to put the base station, or some of its components, into *sleep mode* whenever there is no traffic to serve.

We study in this thesis an *Advanced Sleep Mode* technique enabling to shut down the base station's components in a gradual manner depending on the time needed for each of them to deactivate and reactivate again. This introduces different possible levels of sleep. Going from one level to a deeper one will help us make more energy savings as we deactivate more components but can also incur a larger delay for the users who request a service when the base station is in sleep mode. The network operator has to find efficient management solutions that can handle this tradeoff between energy consumption reduction that can be achieved by the sleep modes, and the minimization of the corresponding induced delay.

To this aim, we propose in this work management solutions based especially on learning techniques, namely Markov Decision Processes and Q-learning, which

enable us to find the optimal policy to follow depending on the priorities given to both metrics: energy consumption and delay.

Our solutions show that the energy savings can reach 90% in low traffic when priority is given to energy reduction. The more we care about delay, the more energy saving decreases, as is the case for the induced delay. We show that even when we have a strict constraint on the delay, we can still achieve high energy savings (around 50%) while the added delay by the sleep mode is negligible.

Keywords - Energy consumption, Base stations, Advanced Sleep Modes, delay, management solutions, Markov Decision Processes, Q-learning.

Résumé

La consommation énergétique des réseaux radiomobiles a été une direction de recherche très active au cours de la dernière décennie et ce, pour des raisons économiques ainsi qu'environnementales. Avec l'énorme croissance du trafic ainsi que la multiplication des équipements mobiles, des nouveaux services et des communications Machine à Machine, la nécessité de réduire la consommation énergétique est devenue de plus en plus urgente surtout avec le déploiement des réseaux 5G.

Sachant que le réseau d'accès est le plus grand consommateur dans le réseau mobile, en particulier les stations de base qui consomment environ 80% de la consommation totale, nous nous focalisons dans cette thèse sur ce composant. La consommation énergétique des stations de base est composée de deux parties: une partie fixe qui ne varie pas en fonction du trafic et une partie qui en dépend. Notre objectif est de trouver des solutions efficaces permettant de réduire la partie fixe de cette consommation. Une solution prometteuse consiste à mettre la station de base, ou certains de ses composants, en *mode veille* s'il n'y a pas de trafic à servir.

Nous étudions dans cette thèse une technique dite "modes de veille avancés" qui permet d'éteindre les composants de la station de base de manière progressive en fonction du temps nécessaire pour chacun pour se désactiver et se réactiver de nouveau. Ceci introduit différent niveaux de sommeil possibles. En allant d'un niveau à un autre plus profond nous pouvons réaliser plus d'économies d'énergie puisqu'il y a plus de composants qui sont en veille, mais nous introduisons plus d'impact sur le délai s'il y a des demandes de services qui arrivent pendant cette période de veille. L'opérateur doit trouver alors des politiques de gestion efficaces pour gérer ce compromis entre la réduction d'énergie et la minimisation de l'impact sur le délai.

Dans ce contexte, nous proposons des méthodes de gestion des modes de veille avancés basées spécifiquement sur des modèles d'apprentissage, à savoir les processus de décision Markoviens et le Q-learning, qui nous permettent de trouver la politique optimale à suivre en fonction des priorités accordées aux deux métriques: la consommation d'énergie et le délai. Nos solutions montrent que les économies d'énergie peuvent atteindre 90% dans le cas d'un faible trafic lorsque la priorité est accordée à la réduction d'énergie. Plus on augmente la contrainte imposée sur le délai, plus la réduction d'énergie diminue, et aussi l'impact sur le délai. Nos résultats montrent que même si la contrainte sur le délai est très forte, nous pouvons aussi avoir des économies d'énergie élevées (environ 50%) alors que l'impact sur le délai devient négligeable.

Mots clés - Consommation énergétique, stations de base, modes de veille avancés, délai, politique de gestion, processus de décision Markoviens, Q-learning.

Contents

Acknowledgements **iii**

Abstract **v**

Résumé **viii**

Contents **ix**

1 General Introduction **3**

2 Green Networking **7**
2.1 Need for Green communications 7
2.2 Projects for Green 10
2.3 Energy-related metrics 13
2.4 Energy-efficient levers in wireless networks 15

3 Implementation Strategies of Sleep Modes in Base Stations **21**
3.1 Related works 21
3.2 Advanced Sleep Modes (ASM) 26
3.2.1 Description 26
3.2.2 Power model 27
3.3 Lean carrier design 31
3.4 Implementation strategies for ASMs 32
3.4.1 System model 32
3.4.2 Gradual deactivation (buffering approach) 36
3.4.2.1 Description 36
3.4.2.2 Numerical investigation 36
3.5 Need for energy-delay tradeoff 43

4 Learning Models for ASM Management **45**
4.1 Reinforcement Learning (RL) framework 46
4.1.1 Agent-environment interaction in RL 46
4.1.2 Mathematical foundation 47
4.1.2.1 Markov property 47
4.1.2.2 Value functions 47
4.1.2.3 Bellman equation and optimality equations 48

4.1.3 Exploitation-exploration dilemma in RL 49
4.2 Model-based learning 49
4.2.1 Markov Decision Process (MDP) framework 49
4.2.2 Modeling ASM problem using MDPs 50
4.3 Model-free learning 62
4.3.1 Temporal-Difference (TD) formalism for ASM 62
4.3.1.1 Q-learning proposal 64
4.3.1.2 Q-learning characteristics 65
4.3.1.3 Discretizing action space 66
4.3.2 Implementation results 67
4.3.3 Simulation-based approach 69

5 General Conclusion and Perspectives 73

Publications

Conference papers

[C1] **F. E. Salem**, T. Chahed, E. Altman, A. Gati and Z. Altman, "Scalable Markov Decision Process Model for Advanced Sleep Modes Management in 5G Networks", submitted to Valuetools 2020.

[C2] **F. E. Salem**, T. Chahed, E. Altman, A. Gati and Z. Altman, "Optimal Policies of Advanced Sleep Modes for Energy-Efficient 5G networks", 2019 18th IEEE International Symposium on Network Computing and Applications (NCA), Cambridge, MA USA, 2019.

[C3] **F. E. Salem**, T. Chahed, Z. Altman and A. Gati, "Traffic-aware Advanced Sleep Modes management in 5G networks", 2019 IEEE Wireless Communications and Networking Conference (WCNC), Marrakech, 2019.

[C4] **F. E. Salem**, Z. Altman, A. Gati, T. Chahed and E. Altman, "Reinforcement learning approach for Advanced Sleep Modes management in 5G networks", 2018 IEEE 87th Vehicular Technology Conference (VTC-Fall), Chicago, 2018.

[C5] **F. E. Salem**, A. Gati, Z. Altman and T. Chahed, "Advanced Sleep Modes and Their Impact on Flow-Level Performance of 5G Networks", 2017 IEEE 86th Vehicular Technology Conference (VTC-Fall), Toronto, 2017.

Journal papers

[J1] **F. E. Salem**, T. Chahed, E. Altman, A. Gati and Z. Altman, "Learning models for Advanced Sleep Modes in 5G networks", in preparation.

[J2] A. Gati, **F. E. Salem** et al., "Key technologies to accelerate the ICT Green evolution - An operator's point of view", under submission.

Chapter 1

General Introduction

THe mobile traffic has been experiencing a drastic increase during the last years which is expected to continue due to the proliferation of smartphones and connected devices as well as the addition of new services and use cases especially in 5G systems and beyond. The traffic increase and the development of the network's architecture are directly translated into a huge increase of the energy consumption of mobile networks. Reducing it has become a key pillar for mobile operators [1] for two motivations: reducing the energy Operational Expenditures (OPEX) and building ecological and environmental-friendly networks by reducing the carbon footprint.

For this sake, many efforts in research and industry have been dedicated to design *Green Networks* that can guarantee the Quality of Service (QoS) and Quality of Experience (QoE) needed by the network operators so as to meet the expectations of their clients, while reducing the energy consumed to do so. Many projects gathering several partners were organized in the last decade and promising ideas and solutions were proposed [2] [3] [4].

In this scope, we aim through this work to contribute to this research activity by studying new solutions that can reduce the energy consumption in 5G networks. It has been validated that the base stations are the main energy consumers in the networks, with a part of 80% of the overall energy consumption of mobile network [5]. For this reason, we focus in this thesis on the energy consumption of the base stations. It is composed of a fixed part that is always present even when there is no transmission and a load-dependent part. We aim to design systems that are able to profit from the idle periods in the base stations in order to decrease the

fixed energy consumption. This can be done by putting some of the components of the base stations into a low power mode, also called *sleep mode*. By doing it in adequate manner, this feature can help us approach the ultimate target of having *"zero energy consumption at zero traffic"*. As a drawback of this feature, the users' delays can be impacted, if a user requests a service when the base station is in sleep mode, as the wake up process of the deactivated components needs some time. A compromise between the energy consumption reduction target and the preservation of an acceptable delay is thus needed. This compromise has to take into consideration the policy of the network operator regarding both metrics and the different requirements of 5G networks.

The contributions of this thesis are:

- Proposing implementation strategies of an enhanced sleep mode solution called *"Advanced Sleep Modes (ASM)"* dedicated to 5G networks. It permits to deactivate the different components of the base station in a gradual manner depending on the time needed for each of them. The solutions were integrated in a large scale network simulator enabling to compute the energy consumption based on a reference power model (IMEC power model tool) and compare it to a baseline design without any sleep mode. The simulator enables also to quantify the impact of this solution on the users' latencies. A buffering approach is proposed in order to manage the users' request that arrive during the sleep periods and different scenarios were compared.

- Studying the impact of the periodicity of the control signals on the performance tradeoffs brought by the ASMs (energy reduction versus delay). This periodicity plays a major role in the activation/deactivation of ASMs since a long period allows deeper sleep modes, thus more energy savings. The results were part of the proposals to the 3GPP discussion about the *"Lean carrier design"* that was standardized in 2017 for the 5G New Radio [6].

- Proposing a solution based on Markov Decision Process (MDP) enabling to find the optimal policy to orchestrate the different levels of sleep modes during the idle periods of the base station. A generalized framework for an idle period characterized by a hyper-exponential distribution and in which we want to derive the optimal policy on which sleep levels to use is developed.

- Proposing a simplified MDP solution that permits to reduce the complexity and cope with the memory constraints that are faced in the previous solution.

- Proposing a model-free solution based on a reinforcement learning approach (namely Q-learning algorithm) that enables to find an efficient solution that can be applied without having a full knowledge of the environment's dynamics as in the MDP case. The solution enables us to find the best durations of the different sleep mode levels during the idle periods of the base station, when following a predefined ordering: from the deepest level to the lowest one. The solution is validated numerically enabling to find the adequate policy for a generic idle period which is hyper-exponentially distributed, and using a network simulator that takes into account different values of the load and simulates a realistic File Transfer Protocol (FTP) traffic.

The remainder of this dissertation is structured as follows: Chapter 2 introduces the general context of the thesis and highlights previous projects and proposed solutions for green communications. Chapter 3 presents the state of the art regarding sleep modes in base stations and our first ASM implementation strategy. Chapter 4 presents our modelling of ASM based on learning approaches, namely MDP and Q-learning. Finally, Chapter 5 concludes the thesis and gives perspectives for future works.

Chapter 2

Green Networking

This chapter introduces the general context of the thesis which is *"Green communications"*. We firstly outline the needs behind this research direction. We then highlight the most famous projects that were organized to find solutions enabling to reduce the energy consumption of wireless networks. We present also the most used metrics enabling to assess the performances and energy-efficiency of suggested solutions. Finally, we present some promising solutions that have been studied in the literature.

2.1 Need for Green communications

The number of mobile subscriptions has been increasing significantly during the last years as can be seen in Figures 2.1 and 2.2. It is forcasted that the 5G subscriptions will reach 10 millions by the end of 2019 and 1.9 billions by the end of 2024 (for enhanced mobile broadband) [7]. Gathering all technologies (2G, 3G, 4G, 5G,...), the total mobile subscriptions are expected to reach 8.8 billions by 2024 [7].

Machine to Machine (M2M) communications are also expected to increase considerably during the next years, as illustrated in Figure 2.3. According to Cisco forecast [8], they are expected to reach 14.6 billion connections by 2022.

Such a drastic increase in mobile subscriptions, also the multiplication of M2M communications and devices, will be translated by a huge increase in data traffic

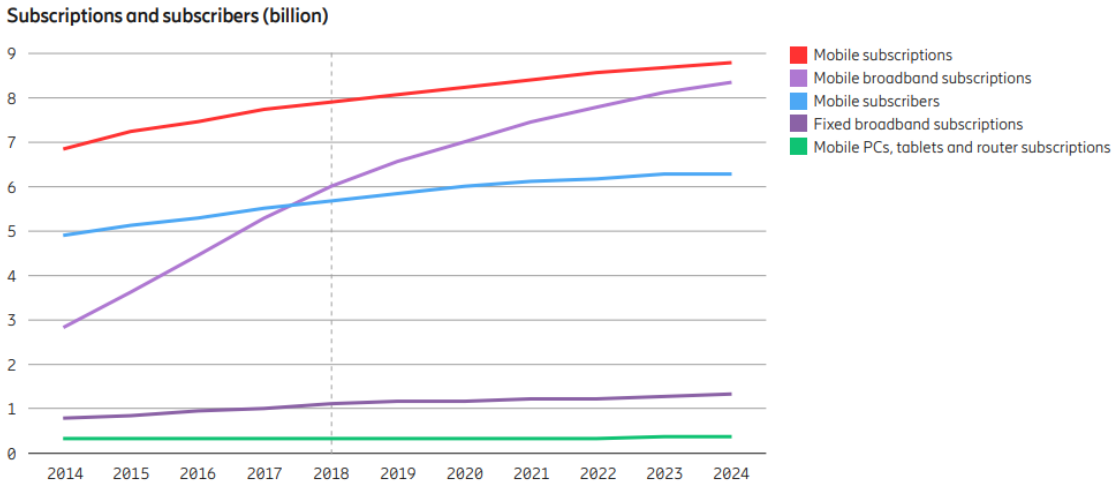

FIGURE 2.1: Evolution of number of subscriptions and subscribers [7].

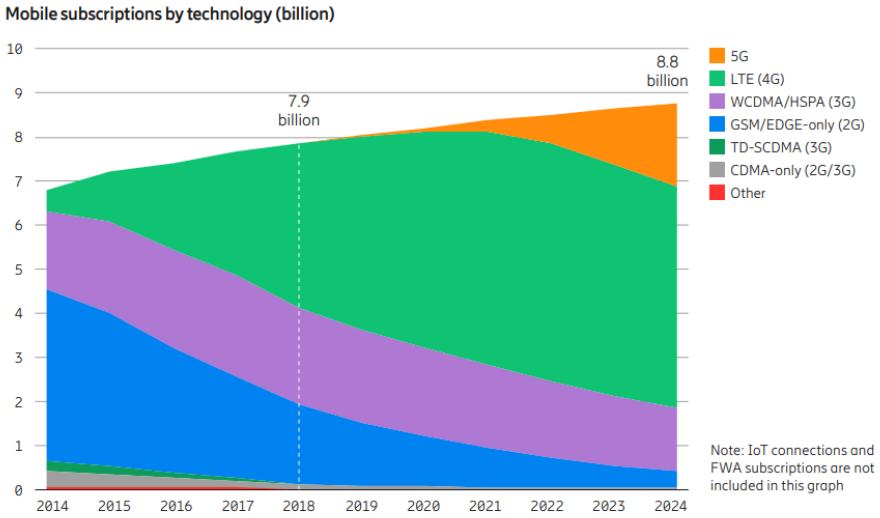

FIGURE 2.2: Evolution of mobile subscriptions by technology [7].

as shown in Figure 2.4. The global internet traffic is expected to be 150,700 GB per second in 2022 compared to 46,600 GB per second in 2017 [8].

As a consequence of this booming traffic, the power consumption in Information and Communication Technologies (ICT) is also increasing significantly, as shown in Figure 2.5.

Moreover, the ICT sector is contributing to 2% of the global CO_2 emissions which is comparable to the contribution of the aviation sector [9]. It is predicted that mobile communications will contribute to around 160 Million tons of CO_2 in 2020 [10].

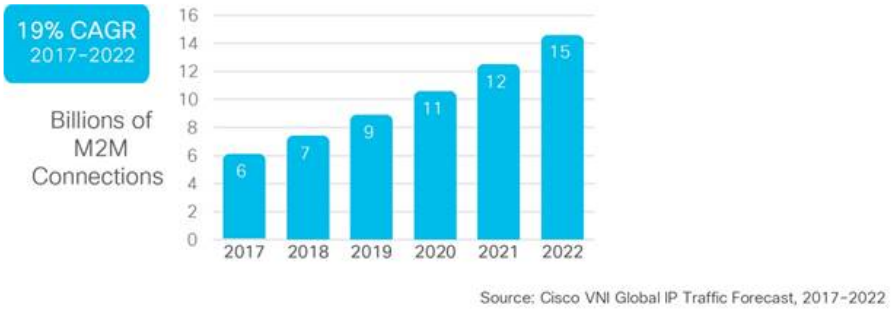

FIGURE 2.3: Evolution of the number of M2M connections [8].

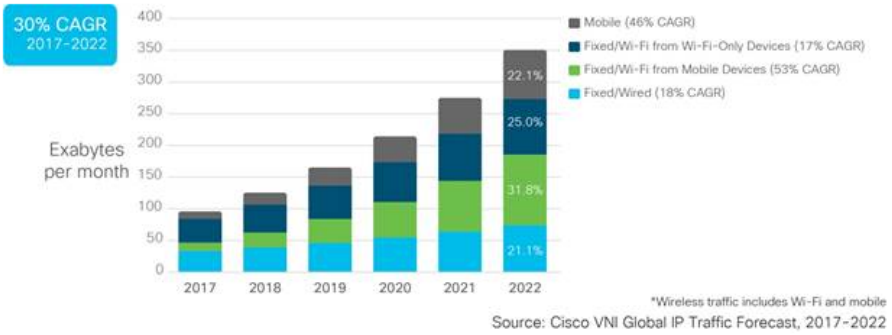

FIGURE 2.4: Global internet traffic, wired and wireless [8].

It is also estimated that ICT sector represents 3% of the global energy expenditure and that 57% of the energy consumption comes from mobile and wireless networks [10].

Motivated by the need to reduce the energy bill of mobile operators and to build ecological and sustainable networks and be able to reduce their carbon footprint, many efforts were, and are being, devoted to find efficient solutions that can reduce the energy consumption in mobile networks while satisfying the required QoS/QoE.

Since the Radio Access Network (RAN) is the main energy consumer in mobile networks [11], a new research direction named *"Green Radio"* has emerged during the last decade. Its aim is to build future wireless architectures with higher energy efficiency [11]. To achieve this target, many projects were launched and many promising techniques were proposed and discussed. The next section is dedicated to present some of them.

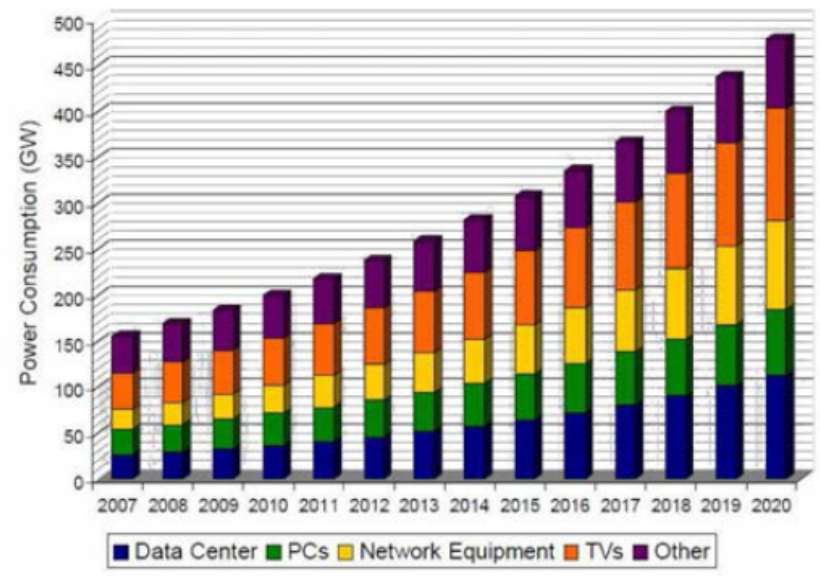

FIGURE 2.5: Power consumption evolution from 2007 to 2020, source ITU

2.2 Projects for Green

OPERA-Net

The Celtic Plus project named OPERA-Net (Optimising Power Efficiency in Mobile Radio Networks) was launched in 2008 and lasted 3 years [12]. It was composed of main European mobile operators and was extended in 2012 (OPERA-Net2 [13]). The project focused on heterogeneous broadband wireless network, mobile radio access network, link-level power efficiency, amplifiers and testbeds [14]. Its objective was to reduce the overall environmental impact of mobile radio networks, in order to contribute to fulfill European and national environmental targets [13]. Among the solutions provided by this project: delivering energy efficient optimized power amplifier transmitter hardware, proposing simple downlink power control to improve energy efficiency of LTE base station, designing so-called Smart Frame Filling algorithm to reduce active LTE base station energy consumption up to 30%, advanced cooling studies, renewable energy use policies in macro radio access networks, field trial to assess energy savings in Egypt, along with standardization contributions [13].

Green Radio

The Mobile Virtual Centre of Excellence (VCE) Green Radio project is a three-year program that was established in 2009 with the objective to achieve a hundredfold reduction in the power consumption of wireless networks compared to the baseline design and to identify appropriate architectures that can permit to do so [15] [16]. Among the achievements of the project: defining metrics and models to quantify energy consumption, defining advanced power amplifier techniques, designing energy efficient architectures and resource management strategies [17].

EARTH

Energy Aware Radio and neTwork tecHnologies (EARTH) is a European project composed of 15 partners from 10 countries, gathering the main European mobile operators and research organizations [18]. It lasted from January 2010 until June 2012 and focused on finding methods to enhance the energy efficiency of mobile broadband systems, therefore decreasing the CO_2 emissions. The main target was to increase the energy efficiency at least by half compared to the existing systems. Among the achievements of the project: energy efficient deployment strategies, energy efficient network architectures, new network management mechanisms that are adaptive to load variations with time, innovative component designs with energy efficient adaptive operating points, new radio and network resource management protocols for multi-cell cooperative networking [19].

GreenTouch

GreenTouch is an international consortium that was launched in 2010 and lasted until 2015. It was composed of leading ICT contributors including equipment providers, operators, research institutes and academic organizations.

The consortium had the mission to enhance energy efficiency by a factor of 1000 compared to the baseline of 2010 and to deliver a roadmap of architectures, specifications and solutions that, if combined in an end-to-end architecture, can allow to achieve this target [20].

As a result, the research studies concluded that it is possible to decrease the net energy consumption in end-to-end communication networks by up to 98% compared to 2010. Figure 2.6 summarizes the GreenTouch research study, called "Green Meter", regarding the potential improvements of energy efficiency, the net energy reduction and the expected traffic growth, in the mobile access, the fixed access and core network for 2020 compared to 2010.

	Energy Efficiency Improvement Factor (2020 vs. 2010 Reference Scenario)	Traffic Growth (from 2010 to 2020)	Net Energy Reduction of 2020 Relative to 2010
Mobile Access	10,000x	89x	99%
Fixed Access (Residential)	254x	8x	97%
Core Network	316x	12x	96%

FIGURE 2.6: Summary of GreenTouch "Green Meter" results

A public interactive application called "GWATT for GreenTouch" was launched. It allows to visualize the portfolio of technologies and summarizes the GreenTouch results [21]. Several white papers and deliverables are also publicly available in GreenTouch website [22]. A tool allowing to quantify the power consumption of wireless base stations was developed and is freely accessible [23].

5GrEEn

5GrEEn (Toward Green 5G Mobile Networks) project was funded by European Institute of Innovation and Technology (EIT) ICT Labs in 2013 and was composed of industrial and academic partners (Telecom Italia, KTH, AALTO University, Ericsson) [24]. The project focused on the energy efficiency aspects of 5G mobile networks [25]. Green mobile backhauling and load-adaptive massive multiple-input multiple-output (MIMO) solutions were proposed [26].

SooGreen

Service-oriented optimization of Green mobile networks (SooGreen) [27] is a European Celtic-Plus project that was launched in 2015 and lasted 3 years. Among its objectives: modeling the energy consumption of services, defining performance indicators for energy efficiency of services, defining service-specific offload techniques enabling to reduce the energy consumption, optimizing energy storage and cooling in base stations, etc [28].

Among the achievements of the project: analyzing the energy consumption per service and defining key performance indicators for service energy consumption, contributing to standardization (ETSI) regarding the assessment of energy efficiency of Cloud-RAN (CRAN) networks, proposing a virtualized CRAN (V-CRAN) architecture, designing efficient energy storage systems and smart grid deployment strategies, proposing energy efficient solutions for WIFI networks, etc [26].

2.3 Energy-related metrics

In order to be able to evaluate the energy savings and to assess the performance of new solutions with respect to a baseline scenario and be able to compare different approaches, meaningful metrics should be defined carefully.

The most popular indicator to measure the *greenness* of a network is called "Energy Efficiency (EE)" which represents the amount of information expressed in bits which is reliably transmitted per Joule of consumed energy [29]. EE is hence expressed in bits per Joule and it is considered as a key pillar for 5G networks. As expressed in the Next Generation Mobile Networks (NGMN) Alliance white paper [1], 5G should enhance EE by a factor of 2000 during the next decade. This objective can be achieved by the multiplication of traffic by 1000 on one side, and by decreasing energy consumption by half on the other side.

The EE metric links both the network's capacity to its energy consumption. This definition expresses a paradigm shift from only focusing on the amount of transmitted bits towards a particular attention to the cost needed for this transmission, which is expressed in the energy consumption term.

Many factors can affect the EE of the network, for instance: the power consumption, the radiated transmit power, the network architecture, etc. The EE for a single link can be expressed as presented in [3] as follows:

$$EE = \frac{Tf(\gamma)}{T(\mu p + P_c)} = \frac{f(\gamma)}{(\mu p + P_c)}[bits/Joule] \tag{2.1}$$

where:

- T is the duration of the observed time interval.

- f is the system benefit as a function of the SINR denoted by γ.
- $\mu = 1/\eta$, with η the efficiency of the transmit power amplifier.
- p is the radiated power.
- P_c is the static power dissipated in all other circuit blocks.

Another metric that can also be considered is the ratio between the spectral efficiency and the total power consumption which is expressed in Bit-per-Joule-Hz [30].

Some studies considered as a metric the ratio between the peak power and the maximum data throughput, expressed in Joules per bit. This metric is called Energy Consumption Rating (ECR) [16].

As a relative measure enabling to compare two different systems, one can consider the energy consumption gain of a solution compared to a baseline system, which can be written as [4]:

$$\nu = \frac{E_{baseline} - E_{test}}{E_{baseline}} \tag{2.2}$$

Another metric that can be considered is the total energy consumption. Constraints should be imposed on the required level of QoS and QoE. The problem can then be formulated as a constrained minimization problem.

Other metrics are used for data centers such as the Power Usage Efficiency (PUE) and the Data Center Efficiency (DCE) [31].

The authors in [32] present an absolute EE metric which depends on the temperature of the medium and which can be expressed as follows:

$$dB_\epsilon = 10log_{10}(\frac{Power/BitRate}{kTln(2)}) \tag{2.3}$$

where k is the Bolzmann factor.

Another metric that can be considered is the power consumed in a certain area, expressed in Watts/Km^2 [33] [34].

A detailed taxonomy of green metrics can be found in [35] where different categories of metrics are presented.

The enhancement in the energy-related metrics can affect negatively other performance metrics such as the spectral efficiency, the deployment efficiency, the delay, etc. Thus, tradeoffs between the different *conflicting* metrics should be studied carefully in order to meet the requirements specified by the network operator. Detailed tradeoffs are presented in [11]. The main objective of this thesis is to satisfy the tradeoff between energy reduction and delay.

2.4 Energy-efficient levers in wireless networks

We present in this section some of the most known energy reduction levers that were suggested in previous research studies.

Heterogeneous Networks (HetNets)

The architecture of the so-called Heterogeneous Networks (HetNets) is characterized by the deployment of different types of base stations: macro cells and small cells (femto- and pico-cells). A typical design of this architecture is shown in Figure 2.7.

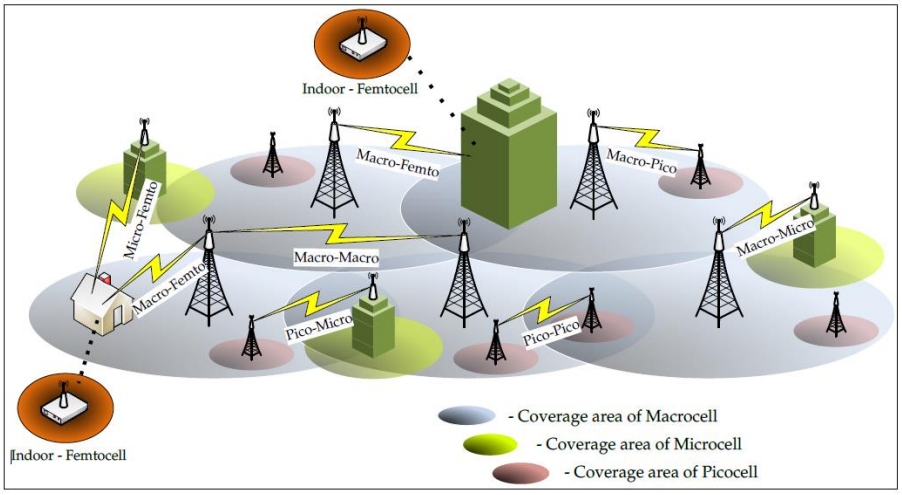

FIGURE 2.7: Typical architecture of a Heterogeneous Network [31].

Small cells can provide high data rates with decreased transmit power as the distance between the base station and the user equipment is shortened due to the densification of the network. These cells can be activated on demand which leads to a changing shape of the network as shown in Figure 2.8

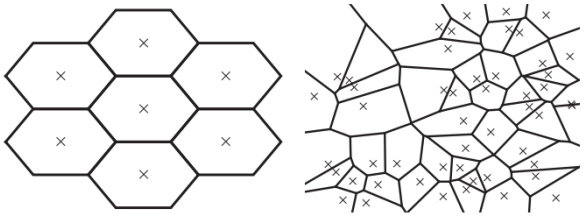

FIGURE 2.8: Network layout in a Heterogeneous Network (right-hand side) compared to a traditional one [3].

Several research studies focused on the energy efficiency of HetNets. For instance, the authors in [36] show that the deployment of small cells in the cell edge can reduce significantly the energy consumption. Also, the authors in [37] investigated the impact of the combination of macro and pico cell deployment on energy efficiency. Their results show that an energy saving of 60% can be achieved with this joint deployment in urban areas with high data rate user demand. The authors in [38] show that the area power consumption defined as $P = \frac{P_{ma}+NP_{mi}}{A}$ (where P_{ma} and P_{mi} represent respectively the average powers consumed by the macro and the micro sites, N is the number of micro sites and A is the cell size) can be decreased with the deployment of micro sites while maintaining certain area throughput target.

Cloud-RAN

The Cloud-Radio Access Networks (C-RAN) concept was proposed by China Mobile [39] and is considered as a promising new design for 5G networks. It corresponds to a shift from a distributed architecture to a centralized one where the BaseBand Unit (BBU) of multiple base stations are gathered in a common virtual pool as illustrated in Figure 2.9.

C-RAN is considered an energy-efficient architecture for many reasons:

- with the centralized architecture, the number of base stations can be reduced which allows energy savings [39].
- the virtualization of the BBU allows an energy-efficient cooling [40].
- the interference between Remote Radio Heads (RRHs) can be reduced by the use of cooperative radio technology. This allows to densify the RRHs

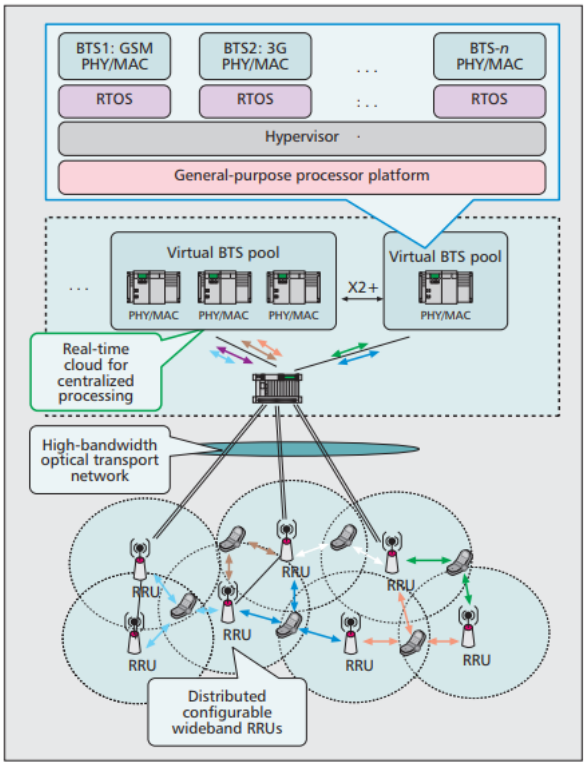

FIGURE 2.9: Architecture in C-RAN [40].

thus reduce the distance between the RRHs and user equipments. In this case, small cells can be deployed, using less transmission power which can reduce in turn the RAN power consumption [39].

Trials in 2G and 3G networks in China showed energy savings of 70% in the OPEX [40]. In [41], the authors present a cloud-assisted BBU cluster testbed, named eBase, which consists in the consolidation of isolated BBUs into a virtualized unified pool, which allows energy savings. They show that this design can reduce energy consumption by 20%, while 95% of QoS are satisfied.

Relaying and Device to Device (D2D) communications

Relays in a wireless network correspond to intermediate nodes that enable to exchange information between the base station and a mobile terminal. They are considered as an efficient technique enabling to enhance the energy efficiency of the base stations since it permits to decrease the transmission distance, which yields an increase in the data rates and a reduction in the transmission energy [16].

D2D communications refer to the case where a device can play the role of a relay node. Co-located devices can communicate wirelessly with each other without going through the base station or with limited involvement of the base station [42] [44]. Communication between nearby devices can be done using lower transmit power compared to the conventional scenario in which each device has to communicate with the base station which can be distant. This explains why D2D is considered as an energy efficient lever in 5G networks [3].

Caching

As the mobile data traffic is witnessing a tremendous increase and duplicated downloads of popular contents contribute significantly to this data tsunami [10], new approaches for data storage and delivery were considered. Local caching, which consists in bringing the contents closer to the users, has attracted much attention in the research community [43] and has been considered among the most disruptive paradigms in 5G networks [44] [45], that can be seen as a promising green solution [46].

In cellular networks using caching technique, the contents (video, audio, webpages) can be stored in nodes closer to the end users, for instance base stations, routers and other neighboring user equipments (for D2D communications). By adopting an intelligent content caching at the edge of the network, redundant transmission of the same contents can be avoided. As a consequence, energy consumption, backhaul traffic, as well as user perceived latency can be reduced.

Energy harvesting

An efficient solution to build green and environmental-friendly mobile networks is to harvest energy from the environment and convert it into electrical power [3]. This energy can be produced from different renewable natural sources such as solar and wind energy.

Another way to produce energy is to exploit the ambient radio signals present in the air. This is known under the name of Radio Frequency (RF) energy harvesting, or wireless power transfer [47] [48]. Co-channel interference signals can be used to

harvest energy, which allows to make them an efficient source of energy instead of being harmful interference [49].

Smart grids

Smart grid is an evolution of the traditional electricity grid to an advanced *smart* one that uses communication technologies in order to generate, transport and distribute electricity [2]. Among its advantages: preventing power blackout by using intelligent control algorithms [50], reducing peaks in power usage, improving reliability, security and useful life of electrical infrastructures and accelerating the adoption of distributed, renewable energy sources [51].

The smart grid can help mobile operators to optimize their energy procurement, reduce their CO_2 emissions and their energy costs [52] [53] [54].

Cell zooming

The concept of *cell zooming* was proposed in [55]. It consists in adjusting the size of the cells according to the traffic load conditions. It has been shown in [55] that this technique has the potential of decreasing the energy consumption in cellular networks.

The authors in [56] studied the impact of the size of the cell on the network's energy consumption. They showed that the optimal energy-efficient size depends on many factors such as the base station technology, the data rates and the traffic demands. They introduced a multi-layer architecture that selects the best cell size depending on the traffic demand and they showed that the energy consumption can be reduced by up to 40%. The authors in [57] proposed three cell zooming techniques and showed that 40% of energy reduction can be achieved.

Sleep strategies

An efficient solution enabling to reduce energy consumption is to put some components of the network into sleep, i.e., deactivate them, for a certain period of time that has to be well defined. Many works focused on sleep modes in base stations

as they are the main energy consumers in the network [61]. It has been shown in previous works that the power consumption of the base station is composed of two parts: a fixed part which is traffic independent, comprising the power consumption of air conditioning and power supply, and a traffic dependent part. Figure 2.10 shows the variation of the power consumption of a 4G base station as a function of the load.

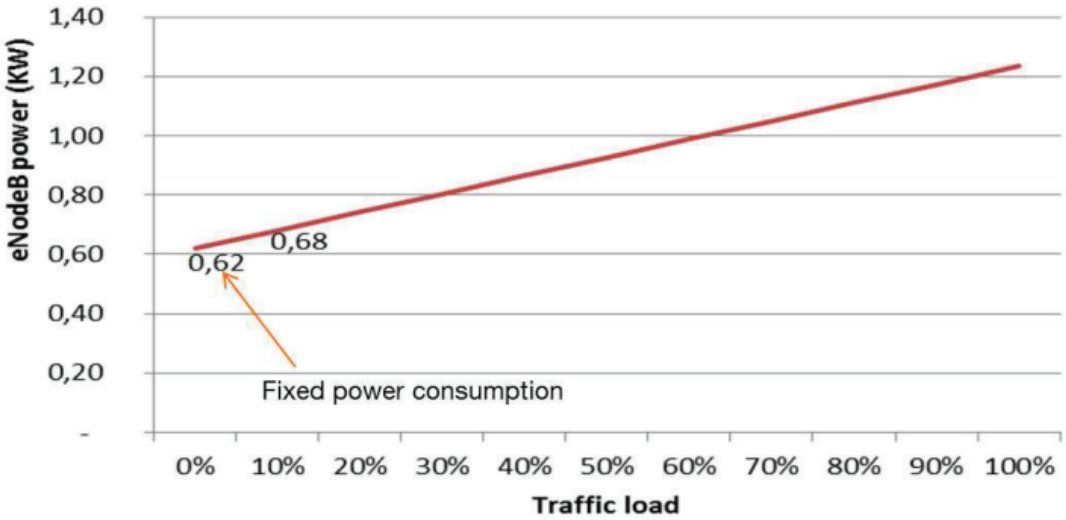

FIGURE 2.10: Power consumption variation in 4G base station as function of the load [58]

By putting the base station into sleep mode, we can reduce the fixed power consumption. This is a promising solution especially in low loads when the fixed part share is very high: for instance, it represents 91% of the total power consumption of the base station when the load is equal to 10% as can be seen is Figure 2.10 [58].

We focus in our work on this technique for the base station as will be explained in details in the next chapters. We aim to find efficient management solutions that can enable us to choose which components in the base stations to deactivate according to the traffic conditions and depending on the tradeoff between the energy reduction target and the delay induced by the sleep strategy.

Chapter 3

Implementation Strategies of Sleep Modes in Base Stations

We present in the first section of this chapter the state of the art on sleep modes in wireless base stations. We then introduce the *Advanced Sleep Mode (ASM)* feature along with the power model and tool used in our work. After that, we describe the lean carrier design that was standardized in 5G networks. We finally present our implementation strategy of ASM, describe our network simulator and give our simulation results.

3.1 Related works

It has been shown in previous studies that the traffic load varies considerably on a daily basis [59]. However, the energy consumption of the base station does not vary significantly with this traffic variation because even during the idle periods there is a fixed power that is consumed due to the cooling and load-independent factors. This can be shown in Figure 3.1 where we observe that the energy consumption variation does not scale with the traffic variation.

In order to adapt the base stations' energy consumption to traffic variation, an energy saving feature called *"sleep mode"* was proposed and consists on deactivating some cells in the network depending on the load condition [60].

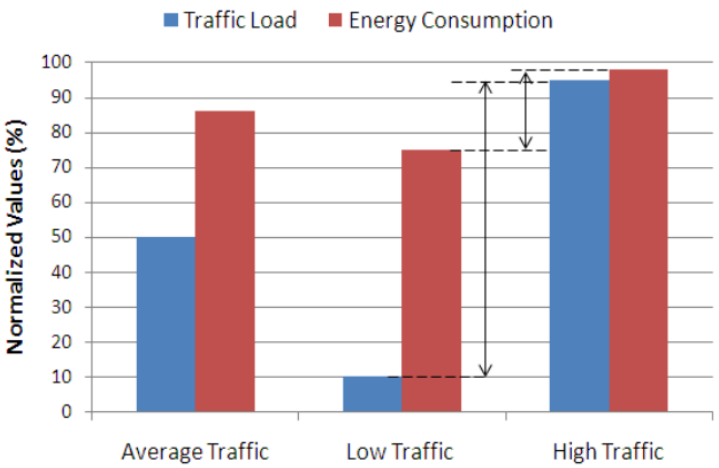

FIGURE 3.1: Variation of the energy consumption with respect to the traffic [60]

During the last decade, many studies focused on the potential benefits of this feature and investigated different scenarios of implementation and different improvements as well as the possible components of the base station in which this technique can be used (if we do not need to shut down all the components in the base station) [61]. This section is dedicated to survey some of these works.

For instance, the authors in [60] introduced the idea of *"cell size breathing"* which can be explained by the fact that the size of a cell can adapt to the traffic load variations: when the load decreases, the size of the cell will increase which can cause an overlapping between the neighboring cells. In their paper, the authors investigated the potential energy savings of exploiting cell size breathing effect to put redundant cells into sleep modes. Their results show that by adding this feature, the energy consumption can be reduced by 33% without any degradation of the network's performance, especially when optimizing the antennas' tilt.

The authors in [62] propose a sleep mode mechanism called cell Discontinuous Transmission (DTX) which consists in shutting down the radio transmitter in OFDM symbols that do not carry data nor reference symbols. In this work, the authors make the assumption that the deactivation delay to enter the sleep mode is zero and consider only one level of sleep which consumes 10W and needs a wake up time of 30 μs. The authors propose in this paper two DTX schemes:
i. Cell micro DTX which is a LTE Rel-8 compliant DTX scheme in which all the control signals: cell reference symbols (CRS), Primary and Secondary Synchronization signals (PSS and SSS), broadcast signal (PBCH) are transmitted in all

the subframes, even when there is no traffic.
ii. Enhanced cell DTX which is considered as a non LTE Rel-8 compliant scheme. In this case, only the synchronization signals and the broadcast signal are considered mandatory.

The potential energy savings with these two schemes are evaluated and compared to a baseline scenario when there is no cell DTX implemented and to an ideal case corresponding to a lower bound where it is considered that no synchronization signals nor broadcast overhead are transmitted from any cell. This latter case is considered in order to show the technology potential of cell DTX. The results of this work show that significant gains can be achieved by this mechanism: the micro DTX can reduce the energy consumption by 61% compared to the baseline case while the reductions with the enhanced DTX can reach 70% compared to the cell micro DTX and 89% compared to the baseline. Considering the ideal case, the energy savings can reach 40% compared to the enhanced DTX and 93% compared to the baseline scenario. These results are very promising and show the need to reduce the control signals in order to reduce significantly the energy consumption and use the sleep mode for longer periods. Indeed, depending on the period of the control signals and on the traffic conditions, we may have the possibility to implement deeper levels that consume less power than the cell DTX. In this paper, the authors consider that by introducing a delay which is equal to 30 μs (on the order of one half OFDM symbol), the Power Amplifier (PA) can be activated before the beginning of the transmission of a non-empty OFDM symbol. This can be done by designing properly the hardware. In this case, the cell DTX will not have an impact on the delay. However, going into deeper levels of sleep will be accompanied by an impact on the delay due to the higher activation time. A tradeoff between energy reduction and delay needs to be studied in this case.

The authors in [63] focus on a single user single antenna system in an urban macrocell environment. They propose a sleep mode mechanism which takes advantage of the concept of "blank subframes" [64] and apply it to LTE system. Their time-domain sleep mode proposal consists in selecting the optimal number of active subframes in each LTE frame in order to reduce the energy consumption by reducing the transmission of the control signals in the other subframes. When there is no user data to be transmitted within a frame, the authors consider that one subframe will be used to transmit control signals in order to ensure the communication with mobile terminals while some of the other subframes will be empty.

Thus, the optimal number of active subframes, denoted by N_{opt}, can be between 1 and 10 (as the LTE frame is composed of 10 subframes). In this paper, the authors propose a theoretical model enabling to compute the energy consumed in each frame and to derive the optimal N_{opt}. Depending on the load factor, different strategies (optimal N_{opt}) are deduced. The most profitable scenario is when the traffic load is very low (0%). In this case, the energy savings can be up to 90%. The more the load factor increases, the less energy reductions are achieved because more subframes will be activated. The authors show that when the load factor exceeds 60%, the energy savings become very low. They also show that the potential energy savings depend on the users' locations. For a load factor comprised in]0..100[, the energy reduction decreases with the user's distance.

In [65] and [66], the authors developed a framework enabling to deactivate some resources in the network depending on the traffic conditions, if the QoS is not degraded. These resources can be for example a given number of transmitters (TRX) in GSM or carriers in 3G and LTE. The activation process of these resources needs a certain duration which is considered to be around 3-5 seconds. Due to this activation delay, new arrivals will have degraded QoS and new, or handover, connections can be blocked or dropped. Also, a ping-pong effect can occur with consecutive ON/OFF oscillations in the system. To cope with these limitations, the authors introduce a guard interval to anticipate the upcoming traffic and a hysteresis time before the deactivation of the resources to be sure that the traffic is really decreasing. By tuning these parameters adequately, a tradeoff between energy reduction and QoS preservation can be found. Based on a Markovian model, the optimal control in [66] was derived using an exhaustive search of all possible policies.

In [67], Combes et al. proposed an optimal controller derived using Continuous Markov Decision Process (CTMDP). It enables to find the optimal policy for the activation/deactivation of a subset of the resources in the network based on the traffic conditions and on the tradeoff between energy consumption and QoS. This tradeoff is expressed in a cost function which is a weighted sum of the two metrics. As in [65] and [66], the authors introduced a hysteresis time to prevent the ping-pong effect. They also proposed an online controller for this sleep mode mechanism using an ϵ-greedy algorithm. Their results show that the proposed controller can adapt dynamically to daily traffic patterns and that this solution insures that QoS is always above 80% while the energy savings are more than 25%.

In [68], the authors propose an implementation strategy for a multilevel sleep mechanism which consists in shutting down gradually the base station going from the lightest levels to the deepest ones depending on the load. The base station wakes up upon the arrival of a user request. The wake up process is also gradual, going from the actual sleep level to all the lighter levels until reaching the active state. The authors evaluated the energy savings of this solution and studied the impact of signaling periodicity on the potential energy reduction. They present system level results based on both analytical and simulation approaches. They show that significant energy reductions are expected especially in low loads: they can reach up to 92%. This value decreases with the load but even at 40% of resource utilization, significant gains can be reached. They are about 15% depending on the periodicity of signaling and they saturate at a periodicity of 20 - 40 ms. However, in this work the system performance was evaluated only with regards to the energy savings.

In [69], the authors propose an implementation strategy of a similar multilevel sleep mode, applied to a 5G base station characterized by control/data plane separation. The paper presents an approach to use different levels of sleep, each characterized by its transition latency (deactivation + activation durations) and the corresponding power consumption. Based on the prediction of the vacation time of the base station using machine learning techniques applied to historical traffic pattern, an optimal strategy can be deduced to match the vacation time to the best-fitted sleep level depending on its length. The performance of this solution was investigated in terms of energy saving gain depending on the average vacation time.

Several other studies focused on the implementation of the sleep modes in small cells and in heterogeneous networks. For instance, the authors in [70] studied this feature for femtocells. The objective is to increase the number of deactivated femtocells in order to mitigate interference and enhance the energy efficiency without having a negative effect on the performance of their subscribers. The authors show that this can be done by combining hybrid access with sleep mode and power control mechanisms.

Also, the authors in [71] proposed an optimal control of the sleep mode mechanism in femtocells in heterogeneous networks. The optimal policies (derived using MDP), depend on the traffic load and the localization of the users in the cell. The authors investigated the ideal case with a complete knowledge about the positions

of the users and the traffic served by the femtocells available to the macro base station when taking the decision, and the more realistic case when the base station has partial or delayed information about the traffic localization.

The authors in [72] presented two sleep mode algorithms enabling to define the time instants in which the micro or pico base stations can be put into sleep. The performance evaluation was conducted considering different heterogeneous networks' topologies and capacity requirements. Depending on the scenario, the authors show that the energy savings can reach up to 10%.

Paper [73] focuses on sleep modes for heterogeneous networks in which data and control planes are split and independent. The results show that the sleep modes are very promising in this architecture: the energy reduction can be almost 50% compared to traditional networks and 27% compared to flexible modern deployments.

3.2 Advanced Sleep Modes (ASM)

3.2.1 Description

The feature named "Advanced Sleep Modes (ASMs)" corresponds to a gradual deactivation of the different components of the base station. Different types of sleep levels can be considered according to the transition time of each component, i.e., the time needed to shut it down then wake it up again. For instance, the PA needs only one OFDM symbol (71μs) for this transition while other components like the digital baseband need more time. This led to the classification of the different components of the base station into four categories [74]. Each of them defines a sleep mode level and comprises the components having the same transition time. These categories define the different possible levels of sleep modes that a base station can enter, and are denoted as ASM:

- SM_1: represents the shortest sleep mode which needs a transition time of 71 μs (OFDM symbol). The PA and some components of the digital baseband and the analog front-end are deactivated.

- SM_2: corresponds to a longer sleep mode which needs 1 ms as a transition time (1 sub-frame) and in which more components of the analog front-end are disabled compared to the first level.

- SM_3: the PA, all the components of the digital baseband and almost all the parts of the analog front-end (except the clock generator) are switched off. This subset of components needs 10 ms (a frame) to deactivate then wake up again.

- SM_4: corresponds to the standby mode in which the base station retains its wake-up functionalities but almost all its components are deactivated. It groups the components that need more than 1 s for the transition latency (deep sleep mode).

Going from one level of sleep mode to a deeper one allows more energy reduction since we deactivate more hardware; the base station needs however more time to reactivate them to serve the users, which may increase the latency.

Each sleep mode level is characterized by 3 different time intervals:

- **Deactivation slope:** to enter each sleep mode, there is a deactivation time needed that we can take as half of the transition time for the corresponding sleep mode.

- **Sleep length:** for each sleep mode, we consider that the minimum duration to remain in this state is equal to its transition duration, thus 71 μs for SM_1, 1 ms for SM_2, 10 ms for SM_3 and 1 s for SM_4. Once this time elapses, we decide whether to go into another sleep mode or to continue in the current sleep mode.

- **Activation slope:** the process of activating the base station from a sleep mode needs an activation period. We can consider that this period is equal to half of the transition duration (equal to the deactivation duration).

Table 3.1 summarizes the different characteristics of the ASMs:

3.2.2 Power model

- Simplified power model:

TABLE 3.1: Advanced Sleep Modes characteristics

Sleep level	Deactivation duration	Minimum sleep duration	Activation duration
SM_1	35.5 μs	71 μs	35.5 μs
SM_2	0.5 ms	1 ms	0.5 ms
SM_3	5 ms	10 ms	5 ms
SM_4	0.5 s	1 s	0.5 s

The power consumption of the base stations can be presented as shown in Figure 3.2. As indicated earlier, it is composed of two parts: a fixed one (represented by P_0 in the figure) which is mainly due to the system architecture and includes power consumption of control signals and backhaul infrastructure as well as load-independent consumption of baseband processors and a variable, load-dependent one, which depends on the transported traffic.

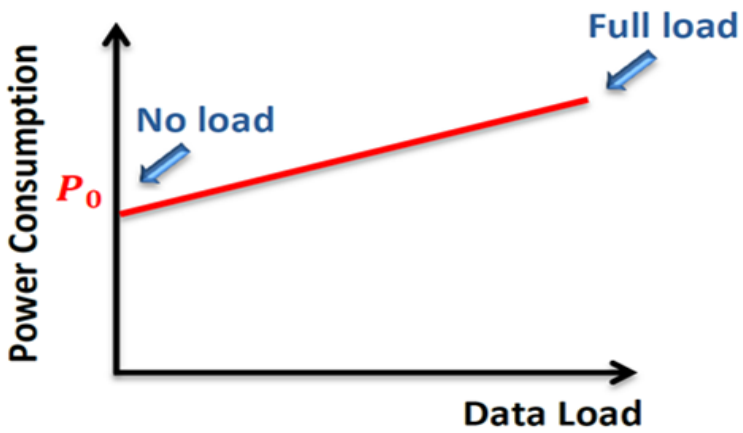

FIGURE 3.2: Power consumption model for the base stations

- Base station structure:

A typical base station architecture is depicted in Figure 3.3.

The power model assumes that the base station is composed of the following main components and sub-components:

- Power Amplifier (PA).
- Analog Front-End (FE), comprising: amplifiers and filters (analog baseband and RF), up/down-conversion mixers, frequency synthesizer and digital to analog/analog to digital converter (DAC/ADC).

TABLE 3.2: Deactivated sub-components in each sleep mode

Components	**Subcomponents**	**SM$_1$** (71μs)	**SM$_2$** (1ms)	**SM$_3$** (10ms)	**SM$_4$** (1s)
PA		X	X	X	X
Digital Baseband	Predistorsion			X	X
	BB filtering	X	X	X	X
	Up-Down sampling	X	X	X	X
	FFT/IFFT	X	X	X	X
	MIMO precoding	X	X	X	X
	Synchronization	X	X	X	X
	Channel estimation	X	X	X	X
	Equalizer computation	X	X	X	X
	Equalization	X	X	X	X
	OFDM Mod/Demod	X	X	X	X
	Mapping/Demapping	X	X	X	X
	Channel coding	X	X	X	X
Digital Control	Control				
	Backhaul				
	Network				
Analog Front End (Rx)	LNA	X	X	X	X
	LNA 2	X	X	X	X
	Frequency synthesis		X	X	X
	Mixer	X	X	X	X
	VGA	X	X	X	X
	CLK generation				X
	ADC			X	X
Analog Front End (Tx)	Modulator	X	X	X	X
	Buffer	X	X	X	X
	Frequency synthesis		X	X	X
	Feedback VCO		X	X	X
	Feedback Mixer	X	X	X	X
	CLK generation				X
	DAC		X	X	X
	Feedback DAC			X	X
Power Supply	AC/DC				
	DC/DC				
	Cooling				

- Digital Baseband (BB) comprising: baseband filtering, up/down-sampling, FFT/IFFT, digital pre-distortion, digital compensation of system non-idealities, modulation/demodulation, channel encoding/decoding, channel estimation, synchronization and processing for Multiple Input Multiple Output (MIMO) and equalization.

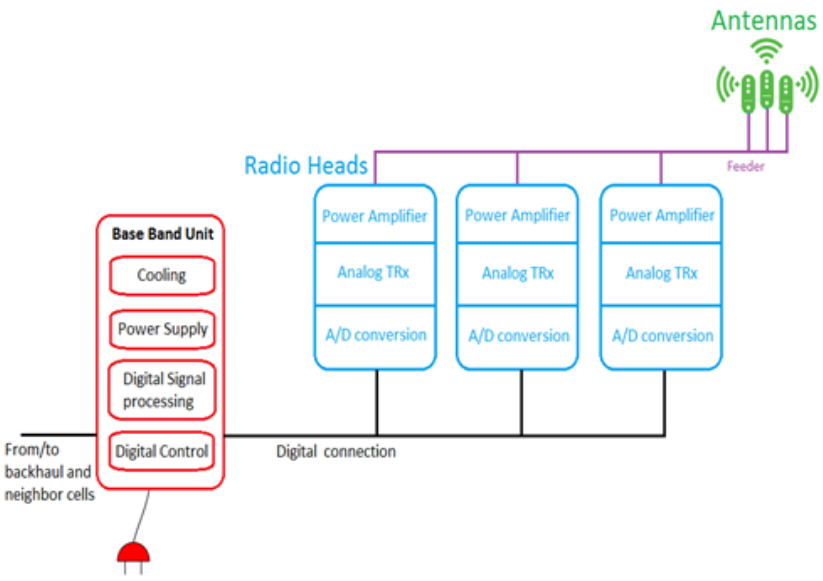

FIGURE 3.3: Base station architecture

- Digital control (DC) which contains 3 components: platform control processor, backbone serial link interface and MAC and network-layer processors.
- Power Supply (PS): AC/DC convertor, DC/DC convertors and active cooling.

A classification of the different components of the base station that are deactivated in each ASM level is given in Table 3.2.

- Mathematical model:

The power consumption of a base station can be defined as the sum of the power consumptions of its different components :

$$P_{Total} = P_{PA} + P_{FE} + P_{BB} + P_{DC} + P_{PS} \tag{3.1}$$

In the case of a multi-sector base station, this value is multiplied by the number of sectors.

The power model used in this work in called IMEC Power Model tool which is an advanced tool for quantifying the power consumption of the base stations [23]. It was funded by the GreenTouch consortium and developed by IMEC researchers [74].

The model provides three outputs:

- The total power consumption (in Watt) of the base station according to the possible configuration which depends on the different parameters chosen as inputs.
- The throughput (in Mbps) of the selected scenario.
- A split of the power consumption between the base station's components.

Among the parameters allowing to configure the base station in this power model we can find: the type of the base station, the year of deployment, the number of sectors and the number of antennas per sector, the output power, the bandwidth, etc.

3.3 Lean carrier design

The base station has to wake up periodically to send signaling bursts in order to communicate with the mobile terminals. In LTE systems, the base station transmits various control signals, such as Cell-specific Reference Signals (CRS) which are broadcasted during 4 OFDM symbols out of 14 (depending on MIMO configuration), Primary and Secondary Synchronization Signals (PSS and SSS, respectively), transmitted in the first and fifth sub-frames of the LTE radio frame, and the Physical Broadcast CHannel (PBCH) which is transmitted in the first sub-frame. Figure 3.4 illustrates the different control signals that are sent in an LTE frame. Such frequent signaling prevents the usage of ASMs other than SM_1.

A new carrier design was proposed for LTE in [75] called *Lean Carrier*. It consists in minimizing the control channel and reference signal overhead in the LTE frame. It has been shown in [76] that this type of carrier can reduce the interference, thus increases the spectral efficiency, and can also enhance the spectrum flexibility and reduce the energy consumption as less signaling will be transmitted by the base station. As presented in Section 3.1, papers [62] and [63] assessed the potential energy savings of such design combined with the sleep mode mechanism.

The same idea was discussed in 3GPP in order to define the 5G New Radio (5G NR) [76] [77] taking into consideration the energy-efficient design of the Lean Carrier. It has been agreed that the synchronisation signals sent by the base station will be grouped in blocks, named Synchronisation Signal Blocks (SSB),

and sent with a period that can be adjusted by the network operator. It can take values in the range 5, 10, 20, 40, 80 and 160 ms [6]. With these values of signaling periods, we can use deeper sleep levels than the μDTX used in 4G.

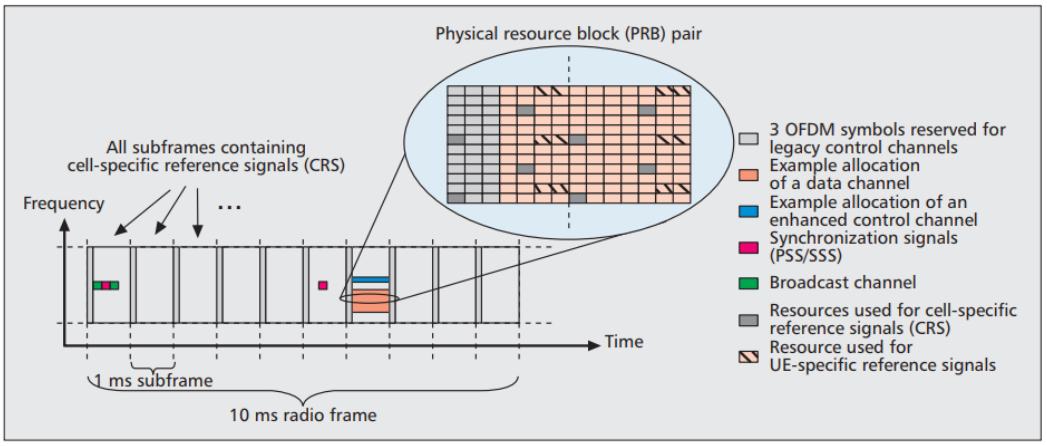

FIGURE 3.4: Control signals in LTE frame [75].

3.4 Implementation strategies for ASMs

3.4.1 System model

a. Interference model

We consider in this section a 5G network serving elastic data traffic in the downlink direction with full frequency reuse.
Let i be a user located in a given cell denoted by C_i. The interference on user i during time slot t is given by:

$$I_{i,t} = \sum_{C \neq C_i} \frac{1}{n_{C,t}} \sum_{j=1}^{n_{C,t}} P_c h_{i,j} \tag{3.2}$$

where :

- $n_{C,t}$ is the number of users in cell C during time slot t.
- P_c is the downlink transmit power of cell C.
- $h_{i,j}$ characterizes the channel gain between base station C serving user j and user i located in cell C_i.

b. Data rate model

The peak data rate for user i during time slot t is computed using Shannon formula as follows:

$$R_{i,t} = \alpha W log_2(1 + SINR_{i,t}) \tag{3.3}$$

where W represents the bandwidth, α the fraction of the bandwidth used for data transmission and $SINR_{i,t}$ the Signal to Interference plus Noise Ratio (SINR) of user i during time slot t and which is computed as follows:

$$SINR_{i,t} = \frac{P_i h_i}{I_{i,t} + N_0} \tag{3.4}$$

where N_0 is the noise variance.

We assume round-robin scheduling. Then, the average data rate for user i is computed as:

$$\bar{R}_{i,t} = \frac{1}{N_t} R_{i,t} \tag{3.5}$$

where $R_{i,t}$ is the peak data rate and N_t is the number of users scheduled during the considered time slot.

c. Energy consumption model

The energy consumption for base station k is computed as follows:

$$E_k = \sum_{i=1}^{N_e} \tau_i P_{i,k}(S_{k,\tau_i}, \mu_{k,\tau_i}, L_{k,\tau_i}, L_{k,\tau_{i-1}}) \tag{3.6}$$

where:

- N_e is the number of events. An event corresponds to any change that occurs in the network such as service request by a user, departure of a user or activation of ASM.
- τ_i is the duration between two events i and $i-1$. As the events are the same for all the base stations, τ_i does not depend on k.
- $P_{i,k}$ is the power consumption of base station k during τ_i and is computed using IMEC power model tool [23]. It depends on S_{k,τ_i}, the state of the base station during τ_i and on μ_{k,τ_i} and L_{k,τ_i}, respectively its load and its sleep

level during the time period τ_i.

The base station can be in 4 different states:
- Idle: $S_{k,\tau_i} = 0$; so its load during τ_i is $\mu_{k,\tau_i} = 0$ and in this case we can either activate or not the ASMs. If activated, the power consumption depends on L_{k,τ_i}, the sleep level during τ_i.

- ON: $S_{k,\tau_i} = 1$; two cases are possible: the base station is active to serve at least one user so that its load is $\mu_{k,\tau_i} = 1$ (assuming elastic data traffic corresponding to File Transfer Protocol (FTP) transfer) or it is only active for signaling, in this case its load is $\mu_{k,\tau_i} = 0.2$. The power consumption depends on these load values.

- Activating: $S_{k,\tau_i} = 2$; in this case the base station wakes up from a sleep mode, either to serve a buffered user or to send signaling bursts, and its power consumption during this state is the same as in the current sleep level L_{k,τ_i} from which it is awaking. At the end of this period the base station becomes active.

- Deactivating: $S_{k,\tau_i} = 3$; during this state the base station is entering a sleep mode but its power consumption is the same as in the previous state, i.e., the power in active state if the base station is entering SM_1 or the power consumption in $L_{k,\tau_{i-1}}$ (previous sleep mode level) if it is entering a deeper sleep mode (2, 3 or 4).

Finally, the total energy consumption of the whole network is:

$$EC = \sum_{k=1}^{N_{BS}} E_k \tag{3.7}$$

where N_{BS} is the number of powered base stations.

d. Load computation

The load ρ_k of base station k assuming elastic data traffic is defined as the fraction of time during which this base station is active:

$$\rho_k = \frac{1}{T} \sum_{j=1}^{N_e} \tau_j \mathbb{1}_{\{x_e(\tau_j)=1\}} \tag{3.8}$$

where :

- $T = \sum_{j=1}^{N_e} \tau_j$ is the total observation time.
- $x_e(\tau_j) = \begin{cases} 1 & \text{if } \mu_{k,\tau_i} = 1. \\ 0 & \text{otherwise.} \end{cases}$

We define the average load in the network as follows:

$$\rho_{Total} = \frac{1}{N_{BS}} \sum_{k=1}^{N_{BS}} \rho_k \tag{3.9}$$

c. Throughput and latency metrics

We consider in this work an FTP service, thus the throughput of user i is computed as follows:

$$Throughput_i = \frac{FS_i}{T_{dep,i} - T_{req,i}} \tag{3.10}$$

where FS_i is the size of the file downloaded by user i, $T_{req,i}$ is its request time and $T_{dep,i}$ is its departure time.

The mean user throughput (MUT) is the average value over the throughputs of all the users in the system:

$$MUT = \frac{1}{N} \sum_{i=1}^{N} Throughput_i \tag{3.11}$$

where N is the number of all users admitted in the network.

In order to quantify the impact of ASMs on latency, we focus on control-plane (c-plane) latency defined as the time required for user i to transit from idle state to active state [78], thus:

$$\Delta_{Latency,i} = T_{serve,i} - T_{req,i} \tag{3.12}$$

where $T_{serve,i}$ is the time when the base station starts serving user i and $T_{req,i}$ is the time when the request occurs.

This equation does not take into account the latency already present in the network, but rather corresponds to the delay added to this latency due to buffering.

3.4.2 Gradual deactivation (buffering approach)

3.4.2.1 Description

We consider in this work only users in connected mode and omit the case of initial cell selection. In a baseline scenario without ASMs, we assume that a user is always served immediately upon service request. When in sleep mode, the base station does not transmit or receive anything but listens to incoming user traffic. We propose that a connected user who requests a service (such as download of a file) during this idle period is kept in a buffer until the base station wakes up. The buffering duration depends on the depth of the sleep state: the deeper the sleep mode, the longer it takes for the base station to wake up. It also depends on the state of the base station during the idle period: when the user request of service occurs during the deactivation slope, this user will have to wait until the components corresponding to the current sleep mode finish their deactivation then wake up again. If this request occurs during the sleep period, the user has to be buffered for a duration equal to the activation delay needed to wake up from the current sleep mode. The service request can also occur while the base station is activating; in this case, the user has to wait for the remaining time for the activation to be served. Figure 3.5 illustrates these different buffering behaviors. Once the base station becomes active, it serves all its buffered users in a round-robin fashion.

In this work, a file is considered as a sequence of packets which we term as flow. We activate the ASMs only between flows of connected users. The inter-packet dynamics are not taken into account in this study. Furthermore, we consider that the activation of the ASMs in a base station does not force the users to change from connected to idle mode (otherwise they will need to wait for the next synchronization to be attached again to the base station).

3.4.2.2 Numerical investigation

a. Simulation setup

Simulations are done using an event-based simulator that we coded in Matlab. We consider an FTP service where users download a file of exponential size with mean 4 Mbits and once the download is complete they quit the network. We only

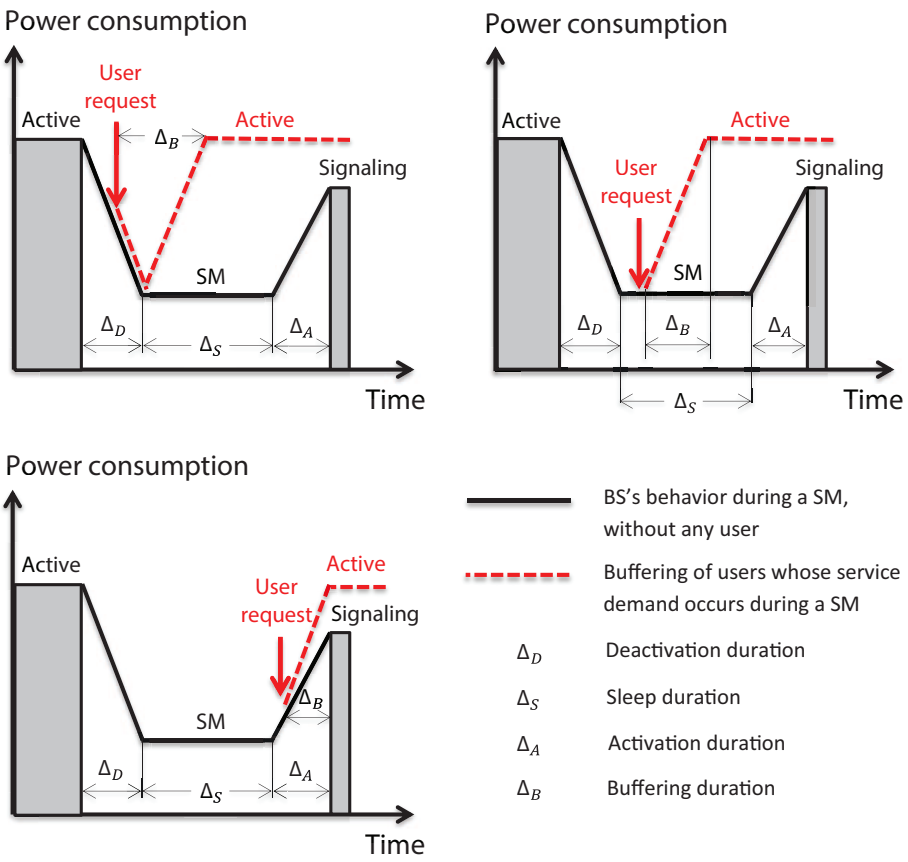

FIGURE 3.5: Buffering Approach.

simulate users in connected mode and assume that the service requests follow a Poisson process.

We model 19 sites, each comprising 3 sectors with conventional 2x2 MIMO macro base stations, 20 MHz Bandwidth, 2.6 GHz carrier Frequency, FDD, 30m antenna height, placed as in Figure 3.6. We focus on a Dense Urban case with an Inter-Site Distance ISD = 500m. No mobility is taken into account in all the simulations and we consider a Uniform distribution of users' positions in the network. Table 3.3 summarizes these different characteristics.

- Power consumption values:

Table 3.4 presents the variation of the power consumption of a single site (3 sectors) used in our configuration in transition from the active state to the deepest sleep mode and the power needed for signaling. These power values are calculated using [23].

b. Convergence analysis:

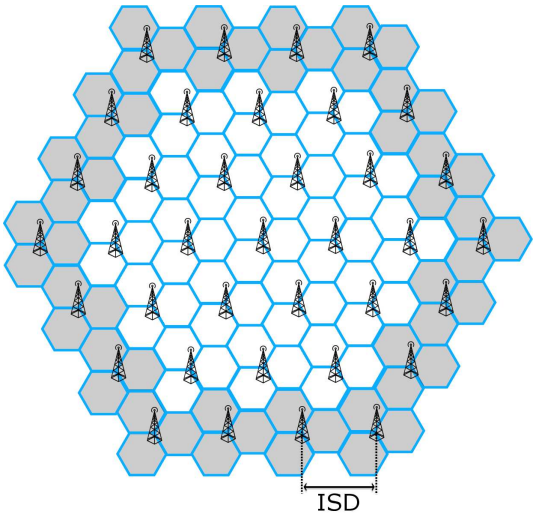

FIGURE 3.6: Coverage map of an hexagonal network deployment. (Traffic is simulated in the white sites while the grey ring comprises interfering sites).

TABLE 3.3: Simulator characteristics

Network parameters	
Number of sites	19
Macro Cell layout	hexagonal tri-sector
Antenna height	30 m
Bandwidth	20MHz
Scheduling type	Round Robin
Channel characteristics	
Thermal noise	-174 dBm/Hz
Path loss (d in km)	128.1 + 37.6 $\log_{10}(d)$ dB
Shadowing	Log-normal (6dB)
Traffic characteristics	
Service type	FTP
Average file size	4 Mbits

We run the same simulation 100 times for different simulation durations then evaluate the error rates of the mean user throughput, energy consumption and average load. The error rate ϵ_X of a set of observations X is based on its mean value E(X) and its standard deviation σ_X and is computed as: $\epsilon_X = \frac{\sigma_X}{E(X)}$.

Table 3.5 summarizes the error rates for each performance indicator. This evaluation is done using the lowest arrival rate (1user/sec/Km^2). For higher values, it is guaranteed to get lower error rates as we focus on a larger population.

TABLE 3.4: 2x2 MIMO 3-sectorized base station power consumption in 2010 technology in different states.
Radiated Power: 46 dBm, Data-related signaling: 10%, Bandwidth: 20 MHz

Active		**Idle**	**ASM**			
Full load	**Signaling**	**(0% load)**	**1**	**2**	**3**	**4**
750 W	490 W	328 W	157 W	42.9 W	28.5 W	24.3 W

As the error rate at 200 sec is acceptable and does not decrease significantly at 300 sec, which is much more greedy in terms of computation time, we fix the simulation duration to 200 sec for all scenarios.

TABLE 3.5: Error Rates

Simulation time	**20 sec**	**50 sec**	**100 sec**	**200 sec**	**300 sec**
MUT error rate	13.14%	8.15%	6.82%	**1.99%**	1.55%
Average load error rate	18.92%	11.95%	8.13%	**6.14%**	5.81%
Energy error rate	1.18%	0.53%	0.18%	**0.12%**	0.09%

We simulate several configurations:
- The first scenario corresponds to our reference scenario in which no sleep mode is used. Several periods of signaling bursts are tested: 5 ms, 10 ms, 20 ms, 40 ms, 80 ms and 100 ms and for each of them we assess the performance of the network for 14 different traffic arrival rates varying from 1 to 60 user/sec/Km^2. We assume that the signaling burst length is limited to 1 ms.
- The second scenario is an energy-efficient implementation in which we use the ASMs as described in Section 3.4.2.1. We keep the same arrival rates and signaling periods as in the first scenario and compare the performance with respect to this baseline.

c. Performance results

- Impact on energy consumption

Figure 3.7 shows the reduction of the energy consumption using ASMs with respect to the reference scenario for different signaling periods as a function of the average load in the network. We observe that we can achieve up to almost 90% of energy consumption reduction in low loads when we increase the signaling bursts' period.

For a fixed period, the reduction of the energy consumption decreases as a function of the load. This behavior is quite intuitive since for an increased load more users are admitted in the network which reduces the inactivity periods of the base station and prevents it from staying in a sleep mode.

We observe also that the more we increase the signaling period, the more we can profit from idle periods and make energy gains. These gains start to saturate from a period of 80 ms. We can reach more than 50% of energy consumption reduction for loads varying between 5% and 30%, knowing that even high loaded networks rarely exceed 30% of average load over 24 hours. This result satisfies the Next Generation Mobile Networks (NGMN) Alliance requirement to reduce the energy consumption by half [1].

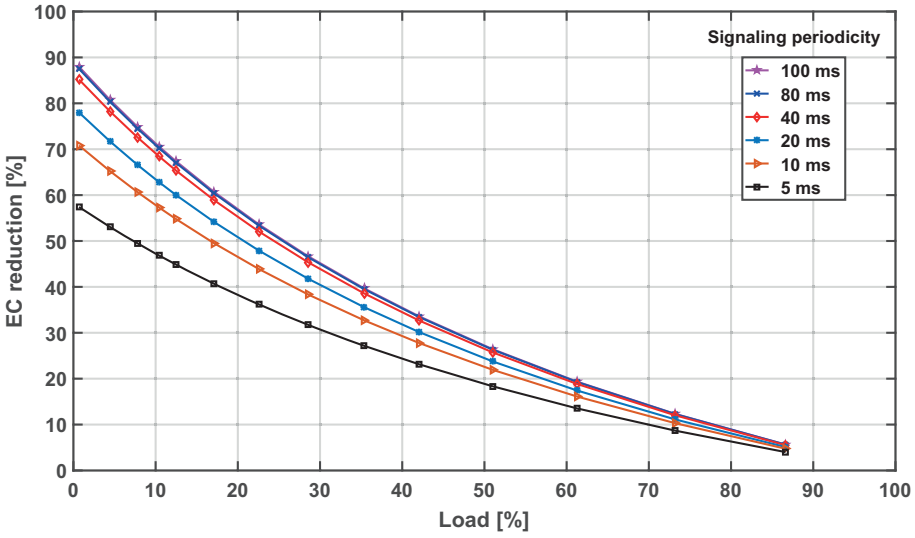

FIGURE 3.7: Energy Consumption reduction using ASMs w.r.t reference scenario.

- Impact on throughput

Along with the energy consumption decrease, ASMs are accompanied by a throughput degradation since each time the users ask to download a file during a sleep period, they have to be buffered until the base station wakes up and resumes its activity. This buffering delay causes a capacity decrease compared to the baseline scenario where all the users are served immediately. We observe in Figure 3.8 that the throughput degradation depends on the load value. The larger the load, the less users are buffered and the less degradation in mean user throughput is observed.

Figure 3.8 shows also that this degradation depends on the signaling period in the network as this period determines the sleep mode level that the base station can reach during its idle periods. We can observe two groups: for periods of 5 ms, 10 ms and 20 ms, the base stations are allowed to go into SM_1 and SM_2, hence the average users' buffering durations are the same between the 3 configurations and so is the case for the mean user throughput whose degradation is between 2% and 4% for loads between 5% and 30%. A second group corresponds to periods of 40 ms, 80 ms and 100 ms. In these cases SM_3 is also allowed which results in more buffering delays and consequently higher mean user throughput degradation which varies from around 17% to 13% for loads comprised between 5% and 30%.

It is interesting to note that when the ASMs are activated, certain users can see their throughputs increase compared to the reference scenario. This is due to the fact that other users in other interfering cells were buffered and so for these buffering durations, the conditions of the considered users were improved: less interference, so higher $SINR$ values and consequently better data rates and shorter sojourn times.

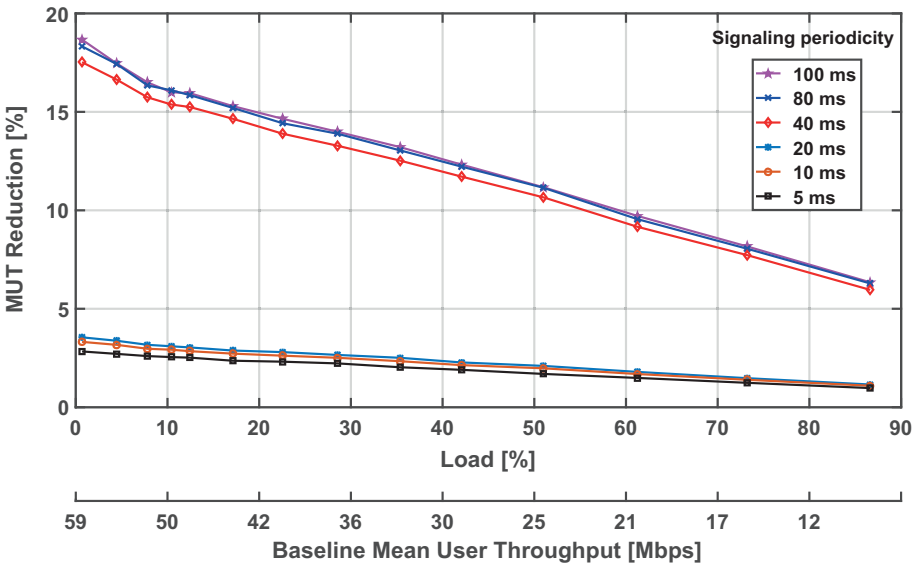

FIGURE 3.8: Degradation of the Mean User Throughput (MUT) using ASMs w.r.t reference scenario.

- Impact on latency

Figure 3.9 shows the average delay added to the baseline c-plane latencies in the different configurations as a function of the load and the signaling periods. We observe the existence of two groups similarly to Figure 3.8. This is explained by

the fact that the latency depends on the sleep mode depth. The deeper the sleep modes, the longer delays we add with respect to the baseline latency. The small variation that we can observe in the average latencies between different periods of the same group is due to the fact that for a shorter period, there is a higher probability that the user's service request occurs while the base station is active (even for signaling), consequently there is less buffering of users and hence less impact on latencies and less throughput degradation.

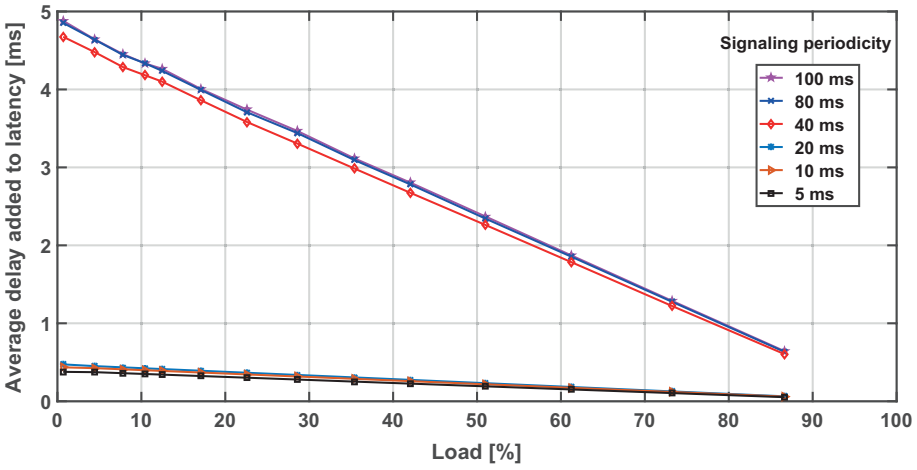

FIGURE 3.9: Average delay added to the baseline c-plane Latency due to the buffering strategy.

Figure 3.10 shows in detail these increased latencies for 3 different load values (low, average and high) with the corresponding percentage of impacted users for two configurations, each from a different group: for an average load (i.e., 30%) in the first group (upper figure), about 65% of users are not affected by the ASMs because they are not buffered, or they are slightly affected because their service request occurs during SM_1 (the values in the x-axis are rounded so very low values are presented as zero). In this case, there is no (or a very small) delay added to their baseline latencies while 35% of users have a c-plane latency increased by 1 ms. As it is a rounded value, it comprises also the users requesting a service during SM_2 so their latencies are increased only by 0.5 ms. For the same load in the second group (lower figure), 30% of service requests arrive while the base station is active (or in SM_1), so the latencies of the corresponding users are not (or slightly) affected, while the rest are buffered. About 60% of users are buffered for 5 ms because their service request occurs during SM_3. Some of the users have a latency incremented by less than 5 ms because either their request for service occurs while the base station is in SM_1, SM_2 or during the activation slope. We

also observe from Figure 3.10 that some users have a delay larger than 5ms; this happens only when the service requests by these users occur while the base station is deactivating to enter SM_3 so they have to be buffered for the rest of the time needed for deactivation then wait for the activation period (5ms).

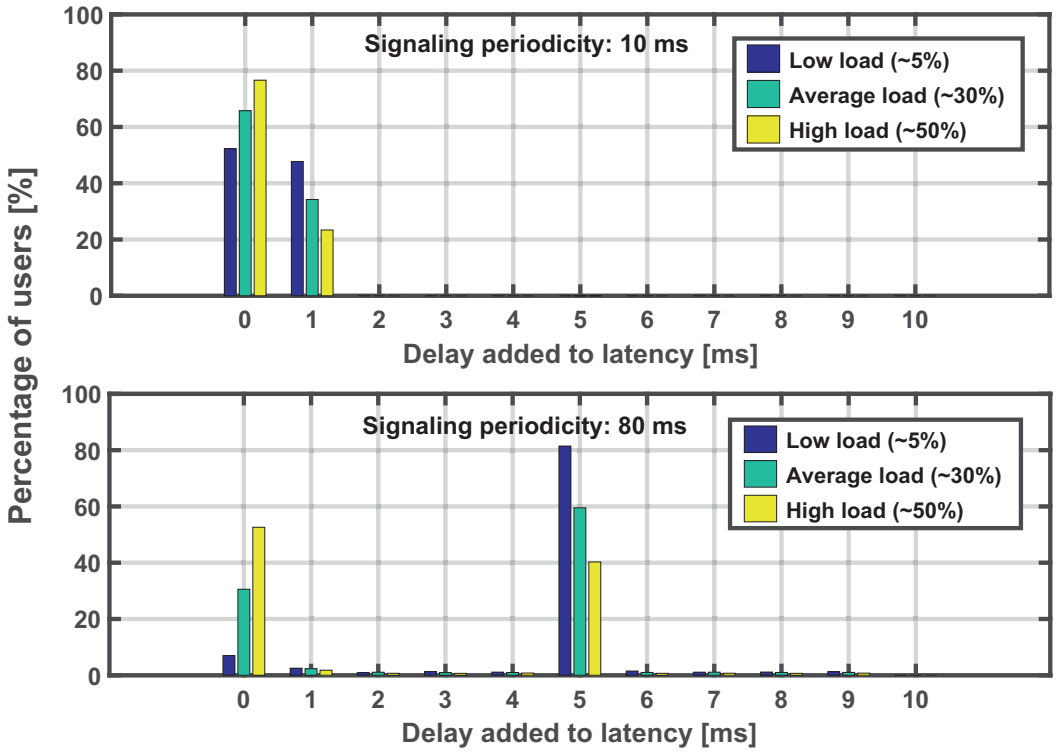

FIGURE 3.10: Average delay added to c-plane Latency.

3.5 Need for energy-delay tradeoff

We presented in this chapter a literature review of previous research activities related to sleep modes in the base stations. We also presented the ASM concept and the power model used in this work in order to compute the power consumption of base station depending on the needed configuration. Then, we developed a mechanism to implement the ASMs and to buffer the users whose service requests occur during sleep periods. The proposed approach is evaluated for different traffic loads and various periods of control signals and is compared to a reference scenario with no sleep mode so as to assess the energy consumption reduction versus throughput and latency degradations.

Our results show that ASMs can considerably decrease the energy consumption (up to around 90% for low loads) when we increase the signaling period at the

expense of users' throughput and latency degradation. For low signaling periods, an average decrease of 3% in throughput is observed with an increase in latency by less than 1 ms. For high periods, the decrease in throughput can reach 19% in low load and latencies are increased by 5 ms. Management of the different metrics tradeoff is therefore critical and should be carried out according to the operator's policies which has to orchestrate the network taking into account the different requirements of 5G use cases. Hence, we need a management system to orchestrate the ASM levels in the network.

Chapter 4

Learning Models for ASM Management

The ASM implementation can be seen as a decision making problem in which there is an interaction between an *Agent* which can be represented by the base station in our case and an *environment* which can refer to the network. The agent's target is to act optimally in its environment so as to maximize a certain outcome which can be represented in our model by the energy reduction that may be achieved by the sleep modes. This outcome has to be defined carefully according to the specificities of the environment and depending on the different constraints that can be imposed on the agent, for instance the constraint that it may have on the delay for certain use cases such as Ultra Reliable Low Latency Communications (URLLC). This problem can be formulated as a learning process in which the agent tries to find out the optimal strategy, also called *policy*, to follow depending on the different information that may be provided by the environment and according to the tradeoff between the different metrics that it is trying to optimize or satisfy.

We can have a complete knowledge about the agent-environment interaction. In this case, the transition probabilities from a given state of the environment to another one depending on the action chosen by the agent and the corresponding outcome are fully known. This can be represented by a Markov Decision Process (MDP) and can be solved using Dynamic Programming (DP) algorithms. Otherwise, the optimal policy can be deduced without considering a specific model for

this interaction. The environment's dynamics (for instance the transition probabilities and the reward functions) are not fully known in this case which corresponds to the model-free approach. It can be solved for instance by the Temporal-Difference (TD) methods.

This chapter presents the formulation and the numerical resolution of the ASM problem according to these two approaches.

4.1 Reinforcement Learning (RL) framework

4.1.1 Agent-environment interaction in RL

RL is a machine learning approach that aims to achieve an optimal goal by interacting with an environment. It consists on learning how to map situations to actions in order to optimize a numerical outcome [79]. This outcome can have a negative value, in which case it is considered as a cost or penalty to be minimized. It can also be a positive signal which can be seen in this case as a reward to maximize. This outcome signal given by the environment indicates to the decision maker entity, called also *agent* or *controller*, whether the actions he chose in a given situation, denoted also as *state*, are appropriate or should be avoided in the future. The environment evolves in time and is characterized by uncertainty. The agent has to adapt itself to this evolution and to learn continuously.

Figure 4.1 illustrates this agent-environment interaction for the RL framework. Different signals are exchanged between the two parts: at each decision point t the environment informs the agent about its state denoted by S_t. Based on it, the agent takes an action A_t which yields a reward R_t.

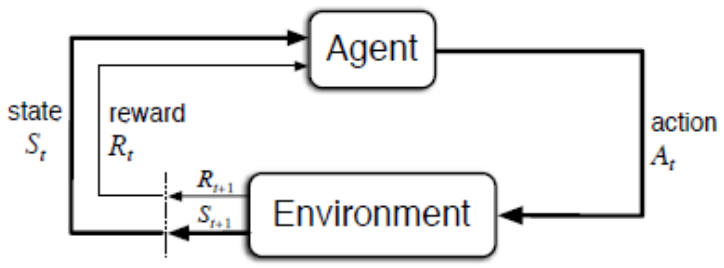

FIGURE 4.1: The agent-environment interaction in RL [79].

4.1.2 Mathematical foundation

4.1.2.1 Markov property

Definition [80]:
A stochastic process $\{X_n, n = 0, 1, 2, ...\}$, with a finite or countable state space, is said to be a Markov chain if for all states $i_0, i_i, ..., i_{n-1}, i, j$, and all $n \geq 0$,

$$P\{X_{n+1} = j | X_0 = i_0, X_1 = i_1, ..., X_{n-1} = i_{n-1}, X_n = i\} = P\{X_{n+1} = j | X_n = i\} \tag{4.1}$$

The RL framework is characterized by this Markov property [79]: the response of the environment at a given time depends only on the representation of the state and the action in the previous step:

$$P\{s_{t+1} = s', r_{t+1} = r | s_t, a_t, r_t, s_{t-1}, a_{t-1}, ..., r_1, s_0, a_0\} = P\{s_{t+1} = s', r_{t+1} = r | s_t, a_t\} \tag{4.2}$$

where s_t, r_t and a_t denote respectively the state, the reward and the action at a given time t.

Starting from a given state, one can predict all the subsequent states and the corresponding rewards by iterating Equation (4.2).

4.1.2.2 Value functions

In order to be able to asses the performance of the agent's choices, RL algorithms are based on the estimation of *value functions*. They can be divided into two types:

- **State-value function:**
  The value of a given state s under a certain policy π is denoted by $V^\pi(s)$ and can be represented by the expected reward when the system is in state s and follows policy π. $V^\pi(s)$ can be written as follows:

$$V^\pi(s) = E_\pi\{R_t \mid s_t = s\} = E_\pi\{\sum_{k=0}^{\infty} \gamma^k r_{t+k+1} \mid s_t = s\} \tag{4.3}$$

where E_π is the expectation given policy π and γ is a discount factor used in order to avoid having an infinite reward in the right-handed side of Equation (4.3).

V^π is called the *state-value function for policy* π.

- **Action-value function:**
  We can also express the value of taking an action a in a given state s under a policy π as follows:

$$Q^\pi(s,a) = E_\pi\{R_t \mid s_t = s, a_t = a\} = E_\pi\{\sum_{k=0}^{\infty} \gamma^k r_{t+k+1} \mid s_t = s, a_t = a\} \tag{4.4}$$

  Q^π is called the *action-value function for policy* π.

4.1.2.3 Bellman equation and optimality equations

The state-value function can also be written as follows:

$$V^\pi(s) = \sum_a \pi(s,a) \sum_{a'} P^a_{ss'}[R^a_{ss'} + \gamma V^\pi(s')] \tag{4.5}$$

where:

- $P^a_{ss'}$ is called the transition probability. It represents the probability of going from state s to state s' after performing action a. It can be expressed as follows:

$$P^a_{ss'} = Pr\{s_{t+1} = s' | s_t = s, a_t = a\} \tag{4.6}$$

- $R^a_{ss'}$ expresses the expected reward given any state s, action a and a next state s'. It can be written as:

$$R^a_{ss'} = Pr\{r_{t+1} | s_t = s, a_t = a, s_{t+1} = s'\} \tag{4.7}$$

Equation (4.5) is called the *Bellman Equation* for V^π. It shows a recursive relationship between a given state and its subsequent states. Solving a RL task means finding the *optimal state-value function* V^* defined for any state s by:

$$V^*(s) = \max_\pi V^\pi(s) \tag{4.8}$$

The optimal policy is the one having the optimal state-value function for any given state within the state space.

Similarly, the optimal policy has the optimal action-value function Q^* for any pair (state-action) which can be represented as follows:

$$Q^*(s,a) = \max_{\pi} Q^{\pi}(s,a) = E\{r_{t+1} + \gamma V^*(s_{t+1}) | s_t = s, a_t = a\} \tag{4.9}$$

4.1.3 Exploitation-exploration dilemma in RL

By interacting with the environment, the agent acquires some knowledge which he can *exploit* when making his future decisions. He can also choose to *explore* new actions in order to discover the optimal solution and be able to achieve better rewards in the future. Choosing the exploitation approach is the best thing to do so as to maximize the reward in the following step but exploration can be more advantageous for the long run. This is called the *exploration-exploitation dilemma*. One common solution to tackle this problem is the ϵ-greedy algorithm defined as follows:

$$Next\ action = \begin{cases} A^* & \text{with probability 1 - } \epsilon_{exp} \\ \\ Random\ action & \text{with probability } \epsilon_{exp} \end{cases} \tag{4.10}$$

with A^* the best action known so far and $\epsilon_{exp} \in [0,1]$ the probability of exploration.

Several methods exist in the literature that enable to solve a RL problem. They can be classified into two categories: model-based approaches such as MDP which can be solved using DP algorithms and model-free approaches such as TD methods. We present in the following sections their application for the management of ASM.

4.2 Model-based learning

4.2.1 Markov Decision Process (MDP) framework

The theoretical basis for RL problems is represented by the so-called MDP. They are also referred as stochastic dynamic programs or stochastic control problems

and they represent a mathematical framework for sequential decision making when the outcomes are uncertain [81]. As the name implies, MDPs satisfy the Markov property.

MDP is a proven framework that enables to solve decision making problems that can be described by an interaction between an agent and its environment. For this sake, we can use it for the ASM management.

4.2.2 Modeling ASM problem using MDPs

a. System model

We use in this study a similar modeling approach and notations as in [82] and extend it to the case of ASMs. We consider a single base station and a generic idle period I in which the base station goes into repeated sleep periods. Each sleep period corresponds to a sleep mode level l and is characterized by its duration θ_l and its power consumption P_l. This can be seen as a sequential decision making problem in which the base station chooses in multiple decision points which level to use. A user's request may arrive during a sleep period. It is put in a buffer until the base station wakes up and serves it.

Let τ be the inactivity period, i.e., the time between the start of the first sleep period and the arrival of the first user during the idle period. τ is a random variable with a probability density function denoted by $f_\tau(t), t \geq 0$. It has been shown empirically that τ is heavy tailed and can thus be represented by the hyper-exponential distribution [82] [83] [84].

Thus,

$$f_\tau(t) = \sum_{i=1}^{n} q_i \lambda_i exp(-\lambda_i t), \quad \sum_{i=1}^{n} q_i = 1 \tag{4.11}$$

where n are the phases of the hyper-exponential distribution and $\lambda = (\lambda_1, ..., \lambda_n)$ and $q = (q_1, ..., q_n)$ its parameters.

Let T_k denote the time at the end of the kth sleep period and B_k its duration, $k \in \mathbb{N}^*$. The time at the start of the first sleep period is denoted by T_0. Hence, $T_k = \sum_{i=1}^{k} B_i$ and T_X corresponds to the end of the generic idle period. This scheme is illustrated by Figure 4.2.

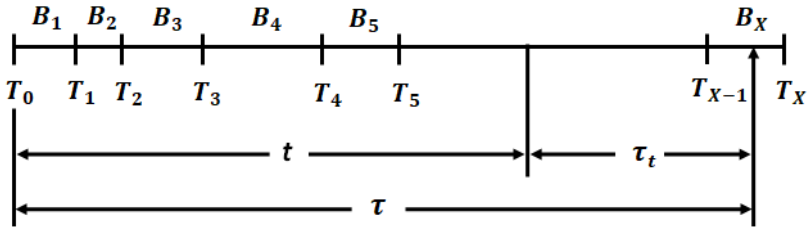

FIGURE 4.2: Generic inactivity period

At the end of each sleep period T_k, the base station checks if there was a user request during period B_k. If the buffer is empty, the base station chooses the next sleep level for the next period. Note that it can stay in the current sleep level or switch to another one (deeper or lighter).

We consider that each sleep period k begins by a deactivation period and is followed by a sleep period and then a warm up period in order to activate the base station, or some of its components. As the power model suggests [74], the power consumption during a sleep level is equal to the power consumption during the activation period corresponding to it. For the sake of simplification, we assume that the power consumed during all these three sleep mode mechanisms is the same and is equal to P_l, where l is the sleep mode level during this period.

If the base station finds that the buffer contains at least one request, the idle period finishes and the base station starts serving the waiting users. A delay is incurred since the users were buffered until the base station wakes up for checking. This buffering duration depends on the length of the last sleep period and its type. The first service request will be delayed by $T_X - \tau$.

b. Cost function

We define a cost function V as a weighted sum of the total energy consumption and the added delay resulting from the sleep policy as follows:

$$V := \mathbb{E}[\epsilon(T_X - \tau) + (1 - \epsilon)T_X \sum_{l=1}^{L} w_l P_l] \tag{4.12}$$

where ϵ is a normalized weight ($\in [0, 1]$) that denotes the importance given to the delay and $1 - \epsilon$ represents the weight given to the energy consumption, w_l is the proportion of time during which sleep mode l was chosen, P_l is the corresponding

power consumption and L is the number of sleep levels. Our target is to find the policy which minimizes the cost function V.

ϵ should be taken in such a way so as to satisfy the network operator's objective regarding energy reduction and QoS requirement in terms of delay constraint which depends on the different use cases in 5G networks and whether they are delay-sensitive or not. The network operator can impose thresholds on both metrics: energy reduction and delay, and the values of ϵ have to be tuned accordingly.

V can also be written as follows:

$$V = -\epsilon\mathbb{E}[\tau] + \eta\mathbb{E}[T_X] \tag{4.13}$$

where $\eta = \epsilon + (1-\epsilon)\sum_{l=1}^{L} w_l P_l$.

For a hyper-exponential distributed off-time τ, we have:

$$\mathbb{E}[\tau] = \sum_{i=1}^{n} \frac{q_i}{\lambda_i} \tag{4.14}$$

$$\mathbb{E}[T_X] = \sum_{k=0}^{\infty}\sum_{i=1}^{n} q_i \mathcal{T}_k(\lambda_i)\mathbb{E}[B_{k+1}] \tag{4.15}$$

where $\mathcal{T}_k(\lambda_i) = \mathbb{E}[e^{-\lambda_i T_k}]$.

Then, V can be expressed as follows:

$$V = -\epsilon\mathbb{E}[\tau] + \eta\sum_{k=0}^{\infty}\sum_{i=1}^{n} q_i \mathcal{T}_k(\lambda_i)\mathbb{E}[B_{k+1}] \tag{4.16}$$

c. MDP characteristics

The problem presented above can be seen as a sequential decision making problem and thus can be solved using MDP framework. The elements of the MDP are:

- **Decision epochs:** they correspond to T_{k-1}, the time denoting the beginning of each sleep period k until achieving a terminal state representing the end of a generic idle period I.

- **State space:** in each decision point, the agent decides which sleep level to perform. Based on this choice, a duration of sleep is imposed and the system evolves in time and approaches the end of the idle period. By preferring a sleep level to another, the agent has to take into consideration the time left until the end of the idle period, so-called residual off-time.

  Distribution of the residual off-time:
  Let τ_t denote the residual off-time at time t. The tail of τ_t can be written as follows:

$$P(\tau_t > a) = P(\tau > t + a)|\tau > t) = \frac{P(\tau > t + a)}{P(\tau > t)} \tag{4.17}$$

$$= \frac{\sum_{i=1}^{n} q_i e^{-\lambda_i t} e^{-\lambda_i a}}{\sum_{j=1}^{n} q_j e^{-\lambda_j t}} \tag{4.18}$$

$$= \sum_{i=1}^{n} g_i(\mathbf{q}, t) e^{-\lambda_i a} \tag{4.19}$$

  where:

$$g_i(\mathbf{q}, t) := \frac{q_i e^{-\lambda_i t}}{\sum_{j=1}^{n} q_j e^{-\lambda_j t}}, i = 1, ..., n \tag{4.20}$$

  Thus, the conditional residual off-time is also hyper-exponentially distributed with parameters λ and $g(\mathbf{q}, t)$, with $g(\mathbf{q}, t)$ being the n-tuple of functions $g_i(\mathbf{q}, t)$ for $i \in [1, n]$.

  At each decision point, the system space can be represented by $\mathbf{q}$, the current probability distribution of the residual off-time. The initial state is denoted by $\mathbf{q}^0$, the probability distribution of the total off-time. At each stage, the probability distribution of the residual off-time is updated through the operator $\mathbf{g}$ given by Equation (4.20). The probability distribution at time t_k is $\mathbf{q} = \mathbf{g}(\mathbf{q}^0, t_k)$. The state space is then the set of the different probability vectors $\mathbf{q}$ which can be infinite. We limit ourselves to a finite set S.

- **Action space:** it corresponds to the different possible sleep levels. We denote it by Ω.

- **Transition probabilities:** the probability of going from state $\mathbf{q}$ to state $\mathbf{q'}$ after entering sleep level l (of length θ_l) is given by $P_{\mathbf{q},l,\mathbf{q'}} = \mathbb{1}_{\mathbf{q'}=g(\mathbf{q},\theta_l)}$ where the operator $\mathbb{1}$ takes the value 1 if the condition is verified and 0 otherwise.

Figure 4.3 illustrates this formulation. We start in the initial state $\mathbf{q}^0$ (top circle). We choose an action corresponding to sleep mode level l among the four ASM choices. This leads us to the second state $\mathbf{q'} = \mathbf{g}(\mathbf{q}^0, \theta_{SM})$ where θ_{SM} is the duration of the chosen sleep mode. Starting from $\mathbf{q'}$, we again have four possible choices and so on. In order to have a finite state space, one can limit the depth of the tree to a certain level.

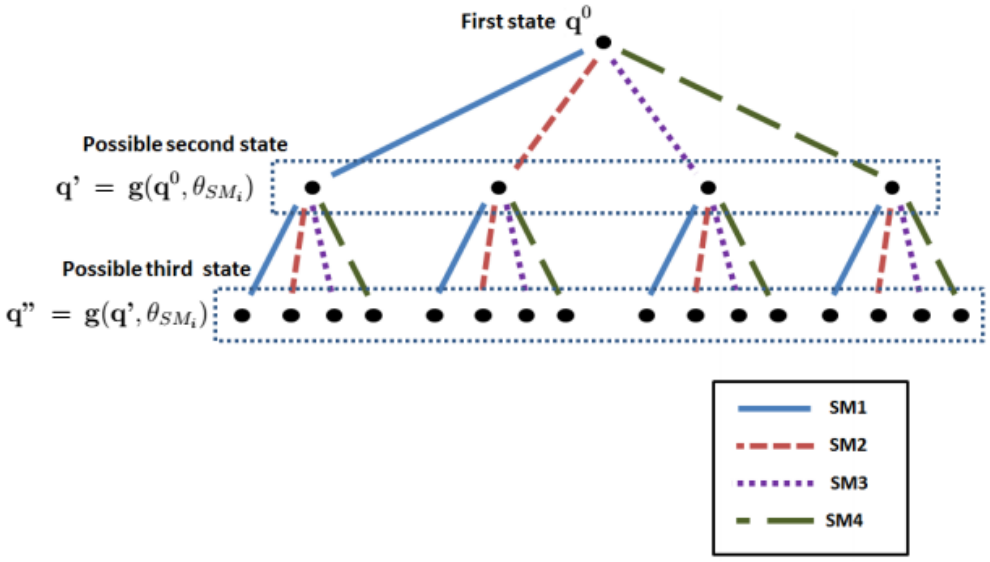

FIGURE 4.3: Possible states and transitions during an idle period

d. Dynamic programming solution

DP is a collection of algorithms enabling to compute an optimal policy when the model is perfectly known, as is the case in MDP [79].

We use the following DP:

$$V_k^*(t_k) = \min_{l \in \Omega} \{\mathbb{E}[c(t_k, l)] + P(\tau_{t_k} > \theta_l) V_{k+1}^*(t_{k+1})\} \tag{4.21}$$

where:

- $V_k^*(t_k)$ is the optimal cost at time t_k.
- t_k corresponds to the observation point at the end of sleep period k.
- θ_l denotes the duration of sleep level l.

- τ_{t_k} is the conditional residual off-time at time t_k.
- $c(t_k, l)$ is the stage cost at t_k when the control is l (the chosen sleep level).
- $P(\tau_{t_k} > \theta_l)$ represents the transition probability.

The per stage cost can be written as follows:

$$c(t, l) = \epsilon \mathbb{E}[(\theta_l - \tau_t) 1_{\tau_t < \theta_l}] + (1 - \epsilon) E_l \tag{4.22}$$

where $\mathbb{E}[(\theta_l - \tau_t) 1_{\tau_t < \theta_l}]$ and E_l represent respectively the delay and energy consumption of sleep level l, both normalized.

As in [82], we can replace the subscript t_k in the cost function V (Equation (4.21) by the current state $\mathbf{q}$. Note that V is defined for a given initial state. DP allows us to solve V for any initial state.

The DP algorithm can then be written as:

$$V(\mathbf{q}) = \min_{l \in \Omega} \{\mathbb{E}[c(\mathbf{q}, l)] + P(\tau(\mathbf{q}) > \theta_l) V(g(\mathbf{q}, \theta_l))\} \tag{4.23}$$

with the cost function being changed as:

$$c(\mathbf{q}, l) = \epsilon \mathbb{E}[(\theta_l - \tau(\mathbf{q})) 1_{\tau(\mathbf{q}) < \theta_l}] + (1 - \epsilon) E_l \tag{4.24}$$

The delay term can be computed as follows [82]:

$$\mathbb{E}[(\theta_l - \tau(\mathbf{q})) 1_{\tau(\mathbf{q}) < \theta_l}] = \theta_l - \sum_{i=1}^{n} q_i \frac{1 - e^{-\lambda_i \theta_l}}{\lambda_i} \tag{4.25}$$

e. Value iteration algorithm

In order to solve the DP, we make use of the Value Iteration algorithm presented in Table 4.1. Proofs of convergence are given in [82].

g. Numerical illustration

In the following, we restrict ourselves to three ASM levels (SM_1, SM_2 and SM_3) as the power consumption of the SM_4 is very close to the power consumption in

Initialize $V(\mathbf{q}) = 0, \forall \mathbf{q} \in S$

Repeat

$$\begin{aligned} &\Delta \leftarrow 0 \\ &\text{For each } \mathbf{q} \in S \\ &\quad v \leftarrow V(\mathbf{q}) \\ &\quad V_{k+1}(\mathbf{q}) = \min_{l \in \Omega}\{c(\mathbf{q}, l) + P(\tau(\mathbf{q}) > \theta_l) V_k(g(\mathbf{q}, \theta_l))\} \\ &\quad \Delta \leftarrow \max(\Delta, |v - V(\mathbf{q})|) \end{aligned} \tag{4.26}$$

until $\Delta < \eta$ (small positive number)

Output a deterministic policy π, such that:

$$\pi(\mathbf{q}) = \text{argmin}_{l \in \Omega}\{c(\mathbf{q}, l) + P(\tau(\mathbf{q}) > \theta_l) V(g(\mathbf{q}, \theta_l))\}$$

TABLE 4.1: Value Iteration algorithm

SM_3, as can be seen in Table 3.4, but its corresponding wake up time is much larger than in SM_3 (0.5 s compared to 5 ms).

The problem presented in this section corresponds to an infinite horizon MDP. The tree presented in Figure 4.3 representing the possible transitions grows exponentially. If we limit its depth to a certain value D denoting the number of times we can repeat the shortest sleep level (SM_1) and if we have only 3 possible sleep levels, then the number of states is:

$$\chi = \sum_{i=0}^{D} 3^i \tag{4.27}$$

As an example, if the length of the mean idle period is taken equal to 50 ms then $D = 360$ and $\chi = 8.7$ x 10^{171}. This causes a problem of complexity to run the Value Iteration algorithm because there is a sweep over all the possible states as can be seen in Equation (4.32). This requires also a very large hardware memory in order to store all the value functions for every possible state. For the sake of illustration, we present the following results.

- System configuration:

We consider a base station with the same configuration as in Section 3.4: 2x2 MIMO, Radiated Power: 46 dBm, Bandwidth: 20 MHz. We consider in this section only two sleep mode levels: SM_2 and SM_3. We recall their power consumptions in Table 4.2.

TABLE 4.2: Power consumption values in Watts

Active	**Idle**	**SM_2**	**SM_3**
250	109	14.3	9.51

The parameters of the hyper-exponential distribution are taken as $\lambda = [10, 500]$ and $q = [\frac{1}{2}, \frac{1}{2}]$.

- Performance evaluation:

The policies achieved at the limit of the Value Iteration algorithm are used in an offline manner to evaluate the potential energy savings and impact on the delay by iterating the algorithm for 10000 episodes, each of them has a length generated according to the hyper-exponential distribution. Figures 4.4 and 4.5 show respectively the energy reduction achieved by the chosen policy for each ϵ and the delay that it incurs.

We observe that when ϵ is low, we reach high energy savings (up to 91%) with an average delay around 14.6 ms. The more we increase ϵ, the more weight we give to the delay. Thus, fewer levels of sleep will be used (starting from $\epsilon = 0.7$) which induces a decrease in the energy savings but also less impact on the delay. When $\epsilon = 1$, only the lowest sleep mode level (SM_2) is chosen. In this case, the average delay is around 1 ms and the energy reduction reaches 86.88%. Note that the power consumption of the illustrative SM_2 and SM_3 levels are not very different, as shown in Table 4.2, which explains that the decrease in the energy reduction shown in Figure 4.4 is not very large.

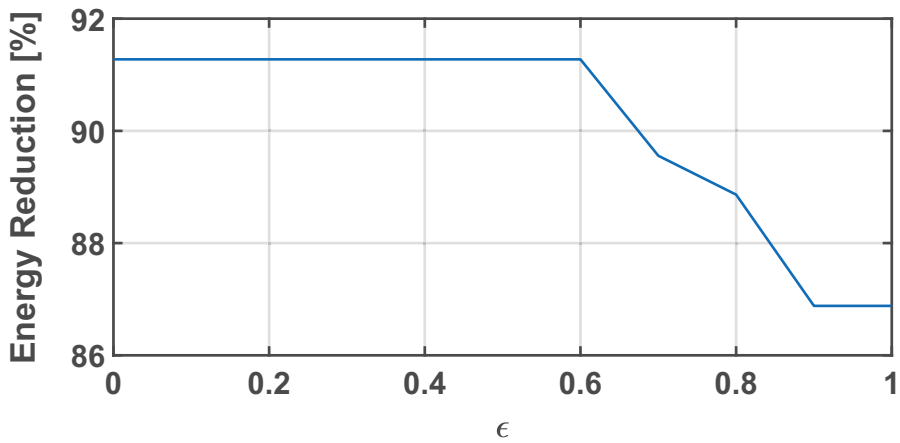

FIGURE 4.4: Energy reduction achieved by the different policies

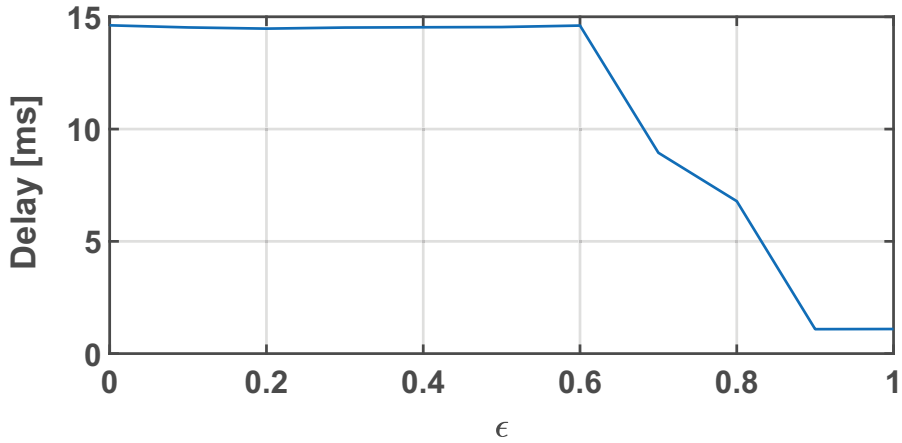

FIGURE 4.5: Delays induced by the different policies

h. Simplified MDP model

- System model:

We consider again a generic idle period and divide it now into equal intervals of length ζ each. ζ can be taken equal to the duration of the shortest sleep level (SM_1). It includes the duration of deactivation + the sleep period + the activation. So, $\zeta = 142\mu s$. For the sake of simplification and in order to have sleep durations that can be written as multiples of ζ, we take $\zeta = 200\mu s$. The base station can go into consecutive sleep periods until the arrival of a user or until a stopping time. The final interval in which occurs the arrival corresponds to the absorbing interval. We denote its end by T_X.

Our target is, as above, to reduce the energy consumption in this generic idle period while taking into consideration the impact on the delay that has to be reduced

also, depending on the priorities of the operator regarding the two metrics. We use the same definition of the global cost function V as in Equation (4.12):

$$V := \mathbb{E}[\epsilon(T_X - \tau) + (1-\epsilon)T_X \sum_{l=1}^{L} w_l P_l] \tag{4.28}$$

Our objective is, as in the previous approach, to find the policy which minimizes the cost function V.

Each interval in the idle period is labeled by its index i which corresponds to the state of the system and is characterized by the time T_{i-1} corresponding to its beginning (this time represents the elapsed time starting from the beginning of the idle period) as shown in Figure 4.6. T_0 denotes the beginning of the idle period.

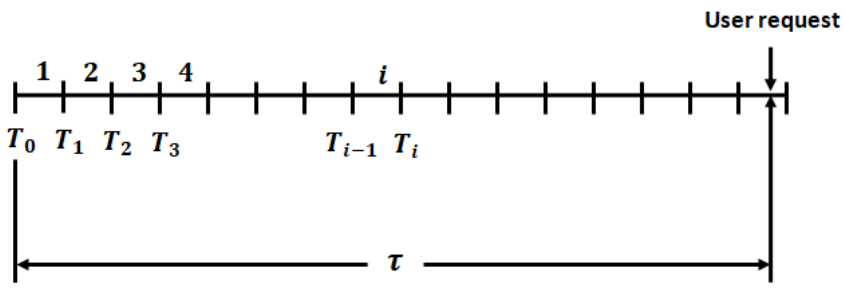

FIGURE 4.6: Generic idle period

The base station can enter into consecutive sleep modes which can have different durations and as a consequence result in different next states. Upon completion of each of them, the base station wakes up to check whether there was a user request that arrived during the last sleep period. If so, the base station remains awake to serve the awaiting user, otherwise it chooses the next sleep level to enter for the next period. If it corresponds to SM_1 then the state of the system (the index of the current time interval) is incremented only by 1, if it is SM_2, SM_3 or SM_4, the index will be incremented respectively by 10, 100 or 1000. We denote δ_l the increment factor corresponding to the chosen sleep level l.

Then, the elements of the MDP can be written as follows:

- State space S: the indexes of the time intervals.
- Action space Ω: the different sleep mode levels.

- Transition probabilities: $P(s' = j|s = i, l) = \mathbb{1}_{j=i+\delta_l}$
- Cost function: the cost function at state i when choosing action l can be written as a weighted sum of the delay and the energy consumption factor as follows:

$$c(i, l) = \epsilon\mathbb{E}[(T_{i-1} + \theta_l - \tau)\mathbb{1}_{T_{i-1}<\tau<T_{i-1}+\theta_l}] + (1 - \epsilon)E_l \tag{4.29}$$

  where T_{i-1} is the time denoting the beginning of the interval indexed by i, θ_l is the duration of sleep mode l and E_l is a normalized energy consumption factor for level l.

  The delay term can be computed as follows:

$$\mathbb{E}[(T_{i-1} + \theta_l - \tau)\mathbb{1}_{T_{i-1}<\tau<T_{i-1}+\theta_l}] = T_{i-1} + \theta_l - \sum_{j=1}^{n} q_j \frac{e^{-\lambda_j T_{i-1}} - e^{-\lambda_j (T_{i-1}+\theta_l)}}{\lambda_j} \tag{4.30}$$

  with n is the number of the phases of the hyper-exponential distribution.

The DP algorithm can be written as:

$$V(i) = \min_{l\in\Omega}\{c(i, l) + P(\tau > T_{i-1} + \theta_l)V(j)\} \tag{4.31}$$

where $j = i + \delta_l$ and $P(\tau > T_{i-1} + \theta_l) = \sum_{j=1}^{n} q_j e^{-\lambda_j (T_{i-1}+\theta_l)}$

The Value Iteration algorithm for this approach is given by Table 4.3.

- Numerical application:

Figure 4.7 shows the achieved policies at the limit of the Value Iteration. It shows that the system starts in the deepest possible sleep level (in this example it is SM_3) which will be repeated for some period of time before switching to the second level (SM_2) then the last one (SM_1). The differences between the different policies is the time spent in each sleep mode level, which depends on the tradeoff between the delay and the energy reduction, i.e., the value of ϵ.

Figure 4.8 shows the variation of the energy reduction as a function of the weight given to the delay. The figure shows that the energy reduction is a decreasing

Initialize $V(i) = 0, \forall i \in S$

Repeat

$$\begin{aligned}
&\Delta \leftarrow 0 \\
&\text{For each } i \in S \\
&\quad v \leftarrow V(i) \\
&\quad V_{k+1}(i) = \min_{l \in \Omega}\{c(i,l) + P(\tau > T_{i-1} + \theta_l)V_k(j)\}, \text{where } j = i + \delta_l \\
&\quad \Delta \leftarrow \max(\Delta, |v - V(i)|)
\end{aligned} \tag{4.32}$$

until $\Delta < \eta$ (small positive number)

Output a deterministic policy π, such that:

$$\pi(i) = \text{argmin}_{l \in \Omega}\{c(i,l) + P(\tau > T_{i-1} + \theta_l)V(j)\}$$

TABLE 4.3: Value Iteration algorithm

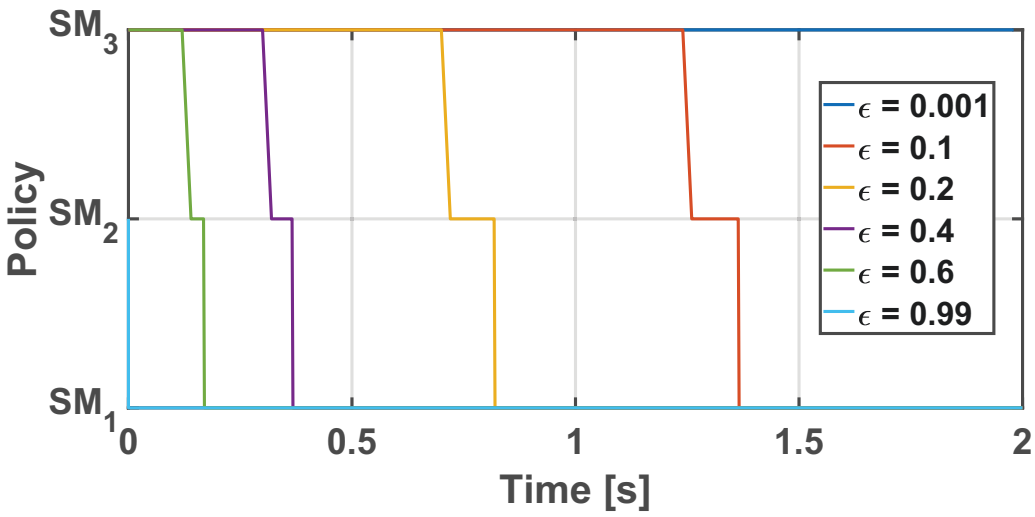

FIGURE 4.7: Achieved policies

function of ϵ. It reaches its maximum for ϵ very low. In this case, the energy reduction is about 90%. When the delay is prioritized over the energy reduction, the energy savings reach 50%.

Figure 4.9 illustrates the impact of the achieved policies on the delay. When the energy reduction is prioritized, the added delay incurred by the sleep modes can reach 10 ms. This value decreases as ϵ increases. For $\epsilon \approx 1$, the delay becomes negligible.

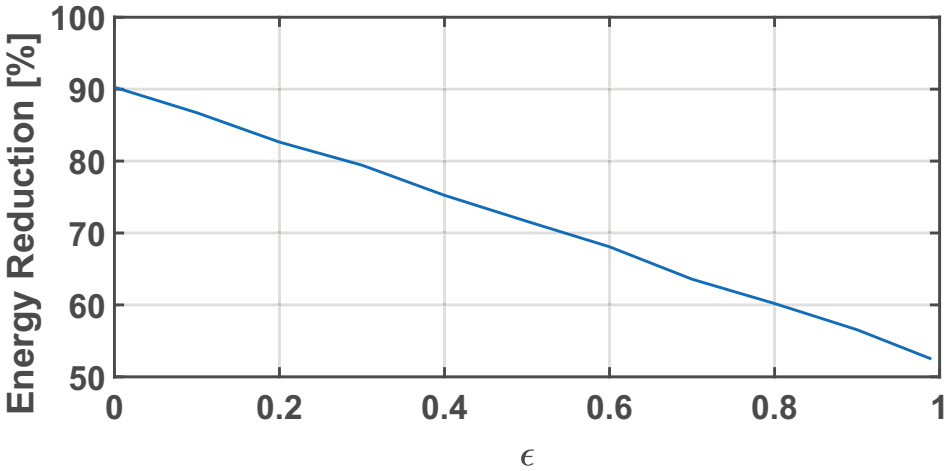

FIGURE 4.8: Energy reductions with the different achieved policies

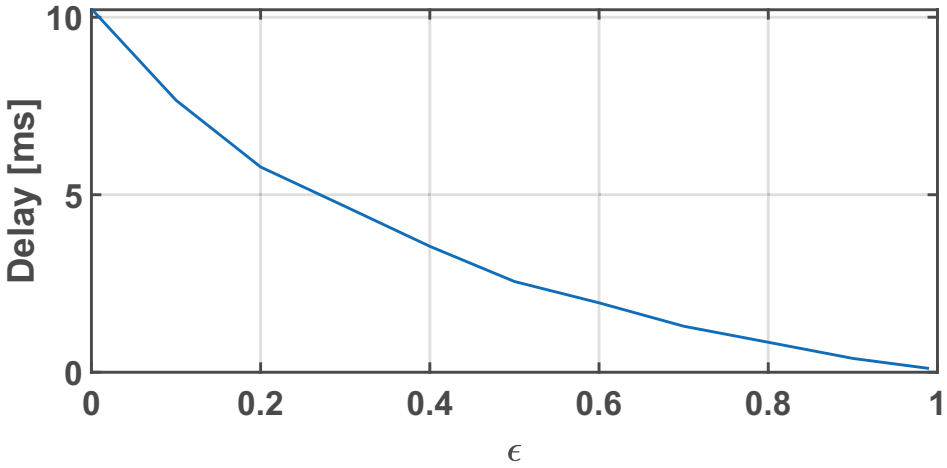

FIGURE 4.9: Impact on the delay induced by the derived policies

4.3 Model-free learning

We address in this section the ASM problem based on a model-free learning approach in order to be able to find an optimal solution when less information is available for the agent, for instance transition probabilities between the states as well rewards/costs.

4.3.1 Temporal-Difference (TD) formalism for ASM

Building on the conclusion of the previous section which shows that the optimal policy consists in using the sleep mode levels in a gradual manner going from the deepest to the lowest depending on the weight given to delay and energy reduction, we propose in this section to impose a pre-defined path in which the sleep periods

are gathered into blocks. Each of them consists of only one sleep level comprising one or more elementary sleep periods. This pre-defined path requires an ordering of the different sleep mode levels.

We can manage the sleep levels using this strategy: starting from the deepest level then waking up the base station gradually until reaching the idle mode as illustrated in Figure 4.10. This can be considered as jointly an energy-greedy and delay-cautious approach because it aims to maximize the energy gains by choosing to profit directly from the deepest level before going to higher ones in which the delay is minimal when the user is more probable to arrive. Depending on the weight that will be given to the delay, this energy *greed* will be lighter in order to get a compromise between the two metrics.

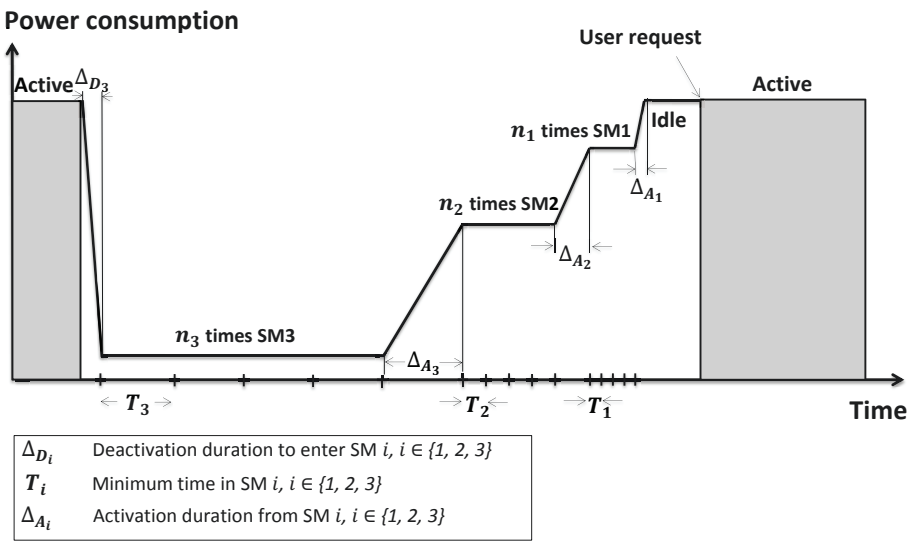

FIGURE 4.10: Energy-greedy implementation strategy for ASMs

The time spent in each level has to be well defined depending on the tradeoff between delay and energy reduction. This is the target of our learning agent. This approach may not yield an optimal policy as it restricts the freedom of the agent of choosing any sleep level after having finished the previous one as is done in the previous section but it has the advantage of reducing the complexity of the problem, and, again, matches the results found in the previous section.

We model this system using a very common TD algorithm called *Q-learning* [85] whose application to our problem is presented in the next section.

4.3.1.1 Q-learning proposal

We consider that the decisions are taken whenever the base station switches from an active mode to an idle one and whenever the sleep period for a certain sleep mode level elapses. Let n_i denote the number of times the base station can repeat SM_i, for $i \in \{1, 2, 3\}$. We define an episode as the time between the departure of the last user served by the base station and the arrival of the next one. The beginning of an episode represents the decision point for the agent to choose n_3, the number of times we can repeat SM_3. Similarly, after spending n_3 times in SM_3, the base station has to take a decision for the next step: choose n_2 and then n_1 after the time allowed of SM_2 elapses. So, the actions are taken at transition points between sleep mode levels. The type of transition is defined by the policy, namely (n_3, n_2, n_1), and the actions consist of the number of times the next sleep mode is repeated. Note that according to the policy defined above, if the system is in SM_i, it is repeated a number of times n_i. Hence, the decision times for this problem are not fixed but are flexible depending on the users' and sleep modes' dynamics in the network. Let us denote by t_0 the time of departure of the last user served by the base station. So the set of decision times for our problem can be written as follows:

$$T = \{t_0, t_0 + n_3T_3, t_0 + n_3T_3 + n_2T_2, t_0 + n_3T_3 + n_2T_2 + n_1T_1\}.$$

where θ_i denotes the minimum duration for SM_i. At time $t_0 + n_3T_3 + n_2T_2 + n_1T_1$, the only possible action for the base station is to wake up. It corresponds to the terminal state in which the base station will remain until the arrival of the next user. The departure of that user, if no one else is being served by the base station by that time, corresponds to the start of the next episode. If a user arrives while the base station is in sleep mode, the activation of the base station is triggered and the user has to wait for it to wake up.

The Q-learning approach is based on the estimation of a state-value function denoted by Q which links a state s to an action a and is updated in each iteration.

Table 4.4 presents the pseudo-code summarizing the Q-learning algorithm:

where :

- an episode in our model corresponds, again, to an idle period: the time between the end of a transmission and the beginning of another one.

Initialize $Q(s, a)$ arbitrarily

Repeat (for each episode):
  Initialize s
  Repeat (for each step of episode):
    Choose a from s using policy derived from Q (e.g., ϵ-greedy)
    Take action a, observe R, s'
    $Q(s, a) \leftarrow Q(s, a) + \alpha[R + \gamma \max_{a'} Q(s', a') - Q(s, a)\ ]$
    $s \leftarrow s'$
  until s is terminal

TABLE 4.4: Q-learning algorithm [79]

- s denotes the current state of the system and s' the following state after performing action a.
- R is the reward achieved by choosing action a.
- α is the learning rate.
- γ is the discount factor describing the weight given to future rewards.

4.3.1.2 Q-learning characteristics

State space:
It corresponds to the different states of the base station during its inactivity period. It can be in one of the different sleep modes SM_1, SM_2 or SM_3 or in none of them (idle state).

$$S = \{\text{idle, } \mathrm{SM}_1, \mathrm{SM}_2, \mathrm{SM}_3\}.$$

Action space:
The action space contains the possible decisions to be made at each decision point. The action is to choose how many times the base station can stay in the following sleep mode level. We denote by N_i the set of possible values that n_i can take, for $i \in \{1, 2, 3\}$.
So, the action space is:

$$A_s = N_3 \text{ x } N_2 \text{ x } N_1$$

Cost function:

The objective is to find in each decision point the optimal n_i which minimizes a cost function R for the following sleep level l. R can be defined as the weighted sum of the normalized energy consumption factor denoted by E_l that depends on the chosen sleep level l and the resulting delay D.

Hence, R can be written as follows:

$$R = \epsilon D + (1 - \epsilon)E_l \tag{4.33}$$

where ϵ is a normalized weight ($\epsilon \in [0, 1]$) that denotes the importance given to the two factors D and E_l.

4.3.1.3 Discretizing action space

The ASMs are intended to be used during the idle periods of the base station. They are most profitable when these idle periods are large enough to be able to put the base station in the deepest possible level for long periods.

As defined above, the action space is continuous and infinite. An action can be any positive value which makes the problem very complex to solve. In order to build a tractable and less complex system, we can discretize and truncate the action space. This can done as a function of the average idle period.

An action n_i can be written as follows:

$$n_i = \lfloor x_i n \rfloor \tag{4.34}$$

where:

- x_i is the number of times to repeat sleep mode i in order to cover all the idle period only by this level. It can be defined as $x_i = \frac{\tau_{mean}}{\theta_i}$ with τ_{mean} the average idle period and θ_i the duration of sleep mode i.
- n is a multiplicative factor taken in such a way so as to have different possibilities of sleep duration for each sleep mode level while being around the optimal value x_i. We consider $n \in \{0.01, 0.02, 0.03, 0.04, 0.05, 0.06, 0.07, 0.08, 0.09, ...$ $0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10\}$ in our numerical experiments shown next.

4.3.2 Implementation results

- Configuration model:

As in the previous section, we consider that the length of the idle period τ is generated according to a hyper-exponential distribution. We recall that the probability density function can be written as:

$$f_\tau(t) = \sum_{i=1}^{n} q_i \lambda_i exp(-\lambda_i t), \quad \sum_{i=1}^{n} q_i = 1 \tag{4.35}$$

with n the phases of the hyper-exponential distribution and $\lambda = (\lambda_1, ..., \lambda_n)$ and $q = (q_1, ...q_n)$ its parameters.

To illustrate our algorithm, we consider a generic idle period with an average length of 10 s and we take the learning parameters as follows: $\gamma = 0.1$; $\epsilon_{exp} = 0.1$ and $\alpha = \frac{1}{N_{s,a}}$; where $N_{s,a}$ is the number of visits of state-action pair (s, a).

- Convergence analysis:

The convergence criteria is based on the computation of the maximum variation of the quality-value $Q(s, a)$ in each iteration for all the state-action pairs (s, a). Figure 4.11 shows the convergence behaviour during the learning phase with $\epsilon = 0.2$ and $\tau_{mean} = 10$ s. The maximum variation tends to zero for a sufficiently high number of iterations (on the order of 10^6).

- Performances results:

The proposed approach is tested for different values of ϵ defining different tradeoffs between energy consumption reduction and delay.

After the learning phase, we exploit the derived policy and assess its performance in terms of energy consumption reduction and delay increase. Our baseline scenario is when we do not use any sleep mode.

Figure 4.12 presents the repartition of the different states of the base station as a function of ϵ. We can see that for $\epsilon \approx 0$ (the priority is to maximize the energy

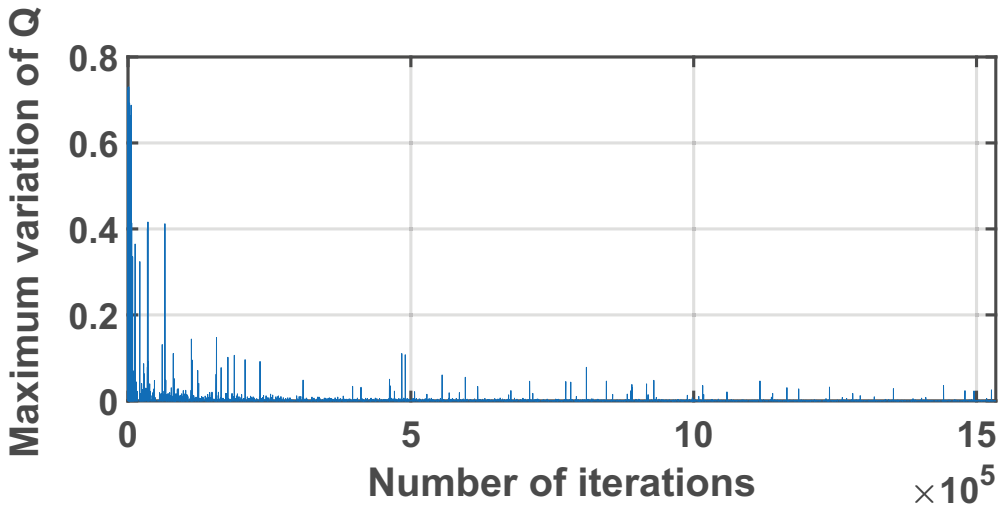

FIGURE 4.11: Convergence evolution

gain), SM_3 is used almost all the time ($\approx$ 100% of time). Whereas, when $\epsilon \approx 1$ (we have a high constraint on the delay), SM_3 is least used ($\approx$ 19% of time) and more time is given to the idle mode so as to anticipate the arrival of a user. In between, as ϵ increases we shift gradually from SM_3 to the two other levels then the idle mode.

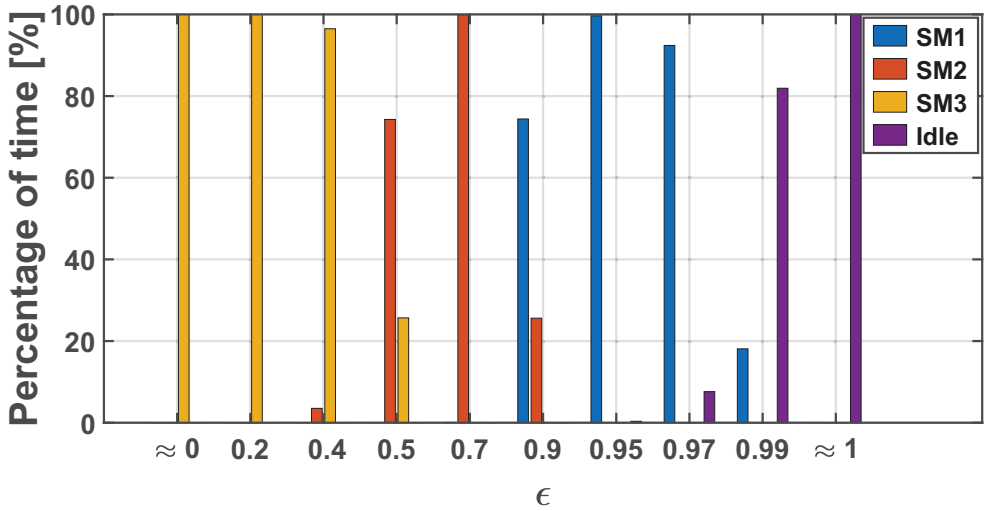

FIGURE 4.12: Histograms for the different sleep mode policies as a function of ϵ

Figure 4.13 shows both the energy gain and the delay increase resulting from each selected policy.

As expected, the lower ϵ, the higher the energy gain because deeper sleep modes are allowed to be repeated more times. This gain can achieve up to 90%. This is

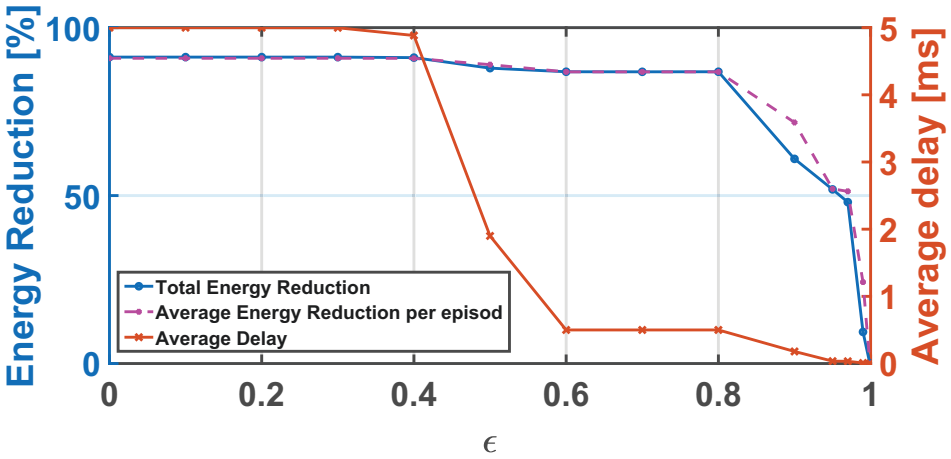

FIGURE 4.13: Performance assessment of the selected policies during the exploitation phase

translated also into an increase of the delay which can reach up to 5 ms. When $\epsilon = 0.97$, the energy reduction is almost 50% while the impact on the delay is negligible. This is because the base station was either in SM_1 or in idle mode during all the idle periods as shown in Figure 4.12.

4.3.3 Simulation-based approach

We now study our Q-learning algorithm in a realistic scenario with varying load due to arrivals and departures of users in the network. To do so, we use the Q-learning algorithm in our network simulator described in Section 3.4.1.

We consider five different values of ϵ: 0.001, 0.5, 0.85, 0.95 and 0.999. For $\epsilon \approx 0$, the energy consumption reduction is prioritized, whereas when $\epsilon \approx 1$, it is the delay that counts the most. In the cases in between, different weights are given to the two factors. We consider a Poisson arrival process of the users with different means which yield the following values of load: 2%, 5%, 10%, 17%, 42% and 60%. We recall that the load represents the percentage of time the base station is active with respect to the total simulation time as expressed in 3.4.1.

Our target is to find the optimal policy (combination of the sleep modes) depending on these values of the load and on the weights given to the energy reduction and delay (values of ϵ).

a. Output policies

Table 4.5 presents the different policies, i.e., the triplet (n_3, n_2, n_1), that are derived using our Q-learning algorithm depending on the value of ϵ for the different considered arrival rates.

TABLE 4.5: Deduced policies for different values of ϵ and the load

Load		$\epsilon \approx 0$	$\epsilon = 0.5$	$\epsilon = 0.85$	$\epsilon = 0.95$	$\epsilon \approx 1$
2%	n_3	13888	1388	0	0	0
	n_2	138888	138888	138888	0	0
	n_1	391236. 978090 1956181	978090 1956181	1956181	1956181	0
5%	n_3	4629	462	0	0	0
	n_2	46296	23148	46296	0	0
	n_1	326030; 652060	652060	652060	652060	0
10%	n_3	2314	231	0	0	0
	n_2	23148	23148	23148	0	0
	n_1	326030	326030	326030	326030	0
17%	n_3	1388	138	0	0	0
	n_2	13888	6944	13888	0	0
	n_1	97809; 195618	195618	195618	195618	0
42%	n_3	555	55	0	0	0
	n_2	5555	555	2777	0	0
	n_1	15649; 39123; 78247	78247	78247	78247	0
60%	n_3	396	39	0	0	0
	n_2	3968	3968	793	0	0
	n_1	27945; 55890	55890	55890	55890	0

The more we increase ϵ the more we reduce the time spent in SM_3 giving more opportunities for the next levels.

The performance evaluation is done by exploiting the policies that were derived offline in new simulations that consider only these chosen policies. We then assess the energy consumption and compare it to a baseline scenario in which no sleep mode is used. We also evaluate the impact of the considered sleep policy on the users' delay.

b. Energy consumption reduction with ASM

Figure 4.14 shows the energy consumption reduction achieved for different loads and different values of ϵ. The highest energy gain ($\approx 90\%$) is achieved in low load with the lowest ϵ. The more we increase the load, the more we reduce the energy gain as we use less sleep modes between the users' arrivals. For a given value of load, the energy gains decrease with ϵ, as when we increase ϵ, we give more weight to the delay so that we use the sleep modes for shorter periods to prevent the arrival of users during the sleep state. Even with this constraint ($\epsilon = 0.95$ for instance), we can achieve up to 50% of energy reduction in low loads. The energy reduction decreases with the load because when the load increases we have less time between two consecutive transmissions to put the base station into sleep mode. Even for high values of loads, the energy gain is also significant. For instance, for a load of 30%, the energy reduction is between 25 % to almost 50%, depending on the chosen ϵ.

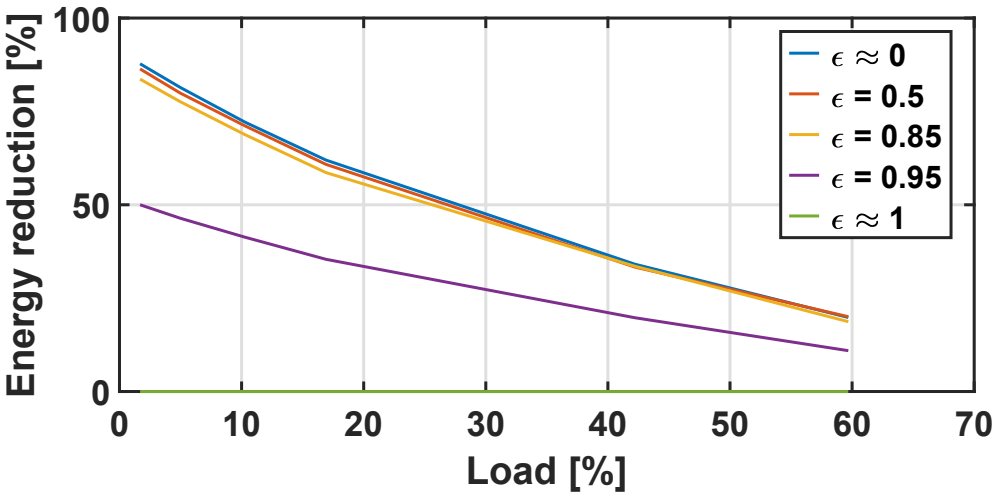

FIGURE 4.14: Energy consumption reduction

c. Influence on users' latency

Figure 4.15 shows the variation of the added delay caused by the sleep strategy for different values of load and ϵ. When the load is very low ($\approx 2\%$) and when the priority is given to the energy reduction ($\epsilon \approx 0$), the delay reaches up almost 5 ms. This value decreases with the load because less users will be buffered as there will be less idle periods in the base station. We observe also that as we increase ϵ, we can reduce this impact on delay until having no (or very little) influence (lowest curves, for $\epsilon = 0.95$ and $\epsilon = 0.999$).

As we can deduce from Figures 4.14 and 4.15, even for high constraint on the delay ($\epsilon = 0.95$), we can achieve high energy savings (almost 50 % in low loads, and 25% saving for 30% of load) with a very negligible impact on the delay. This case is very suitable for a URLLC scenario which is delay-critical.

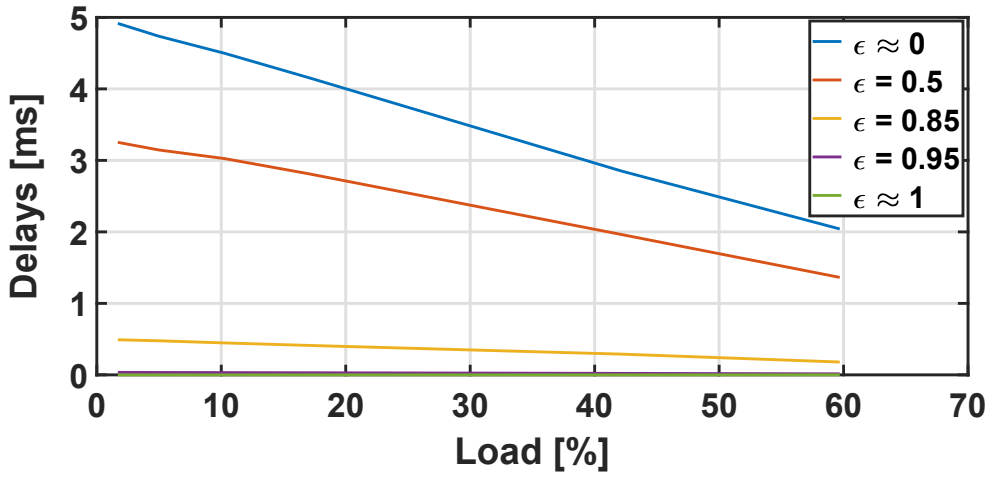

FIGURE 4.15: Impact on the delay

Implementation issues:

We presented in this chapter learning models that can be applied in an offline manner: we derived the optimal policies which can be used to construct a codebook mapping the traffic conditions to the corresponding achieved policy. Then, based on the information of the traffic condition that can be collected from the network, we can use the constructed codebook to know which policy is the most suitable. Also, the different values of ϵ have to be well tuned by the network operator depending on its objectives regarding the energy costs and the preservation of users QoE, and depending also on the different requirements of 5G use cases.

Chapter 5

General Conclusion and Perspectives

We presented in this dissertation several approaches enabling to reduce the energy consumption in 5G base stations while taking into consideration their impact on the users' latencies. Our target is to find efficient methods that can help us manage different levels of sleep modes characterized by their different durations and power consumption levels. This feature is called *Advanced Sleep Modes*. We aim in our work to find the optimal policy that enables us to use the most adequate sleep level, or the best combination of the different levels, during idle periods of the base stations depending on the traffic conditions and system patterns.

Our first solution consisted in using the different levels in a gradual manner going from the lightest until the deepest ones. The solution is validated using a large scale network simulator that enables to buffer the users' who arrive during the sleep periods and use different possible periodicities of the control signals, mainly the PSS and SSS. An FTP-like traffic was considered and different scenarios were studied in which we change the synchronization periodicity and traffic demand. The performance with respect to energy consumption, throughput and latency was analyzed and compared to a reference implementation where no sleep mode is used. Our results proved the necessity of the lean carrier design for 5G networks and how it can impact drastically the energy reduction when using the sleep modes. The reason behind this is that by reducing the amount of control signals we can use deeper levels of sleep modes thus we can reduce more the energy consumption. However, by allowing this we can increase the impact on the users' latencies since

the users whose requests occur during the sleep periods will have to wait until the base station wakes up again and this wake up time is larger when we use deeper levels. As some use cases in 5G are very delay-sensitive like URLLC, other solutions have to be found in order to satisfy the delay constraint and be able to profit from the ASM feature.

We proposed a second approach based on Markov Decision Processes (MDP) in order to derive the optimal policy for the management of the different sleep levels in an idle period which is hyper-exponentially distributed, as is the case of the idle periods in real mobile networks. The proposed solution enables us to derive the best strategy which consists in finding the optimal sleep level to use in each state of the system, taking into account the tradeoff between energy savings and delay.

Our third approach is also based on MDP framework and has the advantage of reducing significantly the complexity and memory constraints presented in the previous solution, by reducing the dimension of the state space. Instead of representing the state at each decision epoch by the probability distribution of the residual off-time as in the previous approach, the simplified model takes into consideration only our position within the total inactivity period. Equal time intervals were considered during a generic idle period and each of them is represented by its index which refers to the state of the system. Based on this index, an optimal action corresponding to the most suitable sleep level has to be taken. Our results show that this solution is very efficient as it enables us to find the optimal combination of different sleep levels within the idle period taking into consideration, again, the compromise between energy reduction and impact of the sleep strategy on users delay.

A fourth approach was to derive the orchestration strategy for the different sleep levels when we do not have full knowledge of the system's dynamics (for instance when the transition probabilities between the states are unknown). For this, we used the Q-learing algorithm to find out the best durations for the different levels based on the users' dynamics. The approach allows to find the best combination of the sleep levels according to the cost function defined based on the tradeoff between the energy reduction and delay.

The proposed solutions of orchestration (using MDP and Q-learning) do not take into account the periodicity of signaling in the decision process. A possible extension of this work is to include it in the model, firstly as an input parameter so

that the strategy of the ASM implementation depends also on this periodicity, and secondly as an output included in the strategy of the network operator in order to define the best periodicity to use, depending on the cost function that has to be well tuned. This cost function has to take into account the tradeoff between the energy savings and the delays, as well as the cost of increasing the signaling periodicity on the energy consumption of the mobile terminals.

In the MDP approach, we assumed that during a single sleep period we go through the three phases of the corresponding sleep mode: the deactivation period, the sleep itself then the reactivation process. If a user request occurs during this period, the three phases have to be completed because we cannot interrupt the decision that has been already made during the last decision epoch. Thus, the user has to wait until the next decision epoch to be served. In a more ideal case, we can consider that the arrival of the user triggers the activation of the base station immediately. Then the corresponding arrival time defines a new decision epoch in which the base station has to take the decision to wake up. The system can then be modelled as a continuous time decision making problem and the discrete time MDP framework would not be adequate as it corresponds to discrete sequential decision making. However, another solution that would be suitable is to use Semi-Markov Decision Processes (SMDP). They allow to generalize the MDP by making it possible to model the system evolution in continuous time and allowing the time spent in a particular state to follow an arbitrary probability distribution. In the SMDP framework, it is possible for the agent to take an action when the system changes its state which makes it possible to apply it for the case of ASM.

The proposed approaches in this work consist on distributed solutions in which each base station takes the decision solely independently of the whole network. We can consider as a perspective a centralized controller that allows to define which levels of sleep to use in a base station taking into account the states and the decisions made for the neighboring ones. This scenario corresponds to a multi-agent learning process. Moreover, the work done in the scope of this thesis does not take into account the mobility of the users. By considering different base stations that can cooperate to use the different sleep modes, the handover process has to be taken into account in this case. Prediction methods can be used in order to derive the possible mobility patterns of the users based on which we can know which level to use in the neighboring base station. One can consider also a shared

strategy between the base stations of different operators so that each of them can reduce its energy consumption and preserve an acceptable QoS/QoE to its users.

The reinforcement learning framework was used in this thesis to derive the best combination of sleep durations during each idle period. A simpler approach is to consider the mean idle period as the possible state of the system and according to it derive the best policy that allows to find which sleep level to use for each state. This can reduce drastically the state and action spaces. For a single average period, the system state is a singleton corresponding to this average value. Thus, the system becomes stateless and a possible framework to solve this problem is the Multi-Armed Bandits (MAB). Another possible solution is to consider various possible values of the average idle period that can be changed in an online manner. We can in this case remove the notion of states and consider the information regarding the mean idle period as a context provided by the environment. In this case, contextual MAB would be a suitable approach to find the optimal strategy.

The ASM feature will be tested in France with different providers. We emphasize that the different durations and power figures corresponding to each level that are used along this work depend on the power model provided by IMEC. Different values can be derived from real tests and may be different from one provider to another but the orchestration methods developed in this study are general enough to be applied to different models.

Bibliography

[1] NGMN Alliance, 5G White Paper, 2015, www.ngmn.org/5g-white-paper.html

[2] H. Ghazzai, E. Yaacoub, A. Kadri, H. Yanikomeroglu and M. Alouini, "Next-Generation Environment-Aware Cellular Networks: Modern Green Techniques and Implementation Challenges," in IEEE Access, vol. 4, pp. 5010-5029, 2016.

[3] S. Buzzi, C. I, T. E. Klein, H. V. Poor, C. Yang and A. Zappone, "A Survey of Energy-Efficient Techniques for 5G Networks and Challenges Ahead," in IEEE Journal on Selected Areas in Communications, vol. 34, no. 4, pp. 697-709, April 2016.

[4] M. Ismail, W. Zhuang, E. Serpedin and K. Qaraqe, "A Survey on Green Mobile Networking: From The Perspectives of Network Operators and Mobile Users," in IEEE Communications Surveys & Tutorials, vol. 17, no. 3, pp. 1535-1556, thirdquarter 2015.

[5] ETSI report, "ETSI RRS05-024," ETSI, 2011.

[6] 3GPP TS 38.331, "Radio Resource Control (RRC) protocol specification (Release 15)," V15.1.0, 2018-03.

[7] Ericsson Mobility Report - June 2019 www.ericsson.com/49d1d9/assets/local/mobility-report/documents/2019/ericsson-mobility-report-june-2019.pdf

[8] Cisco Visual Networking Index: Forecast and Trends, 2017–2022 White Paper www.cisco.com/c/en/us/solutions/collateral/service-provider/visual-networking-index-vni/white-paper-c11-741490.html

[9] A. Fehske, G. Fettweis, J. Malmodin and G. Biczok, "The global footprint of mobile communications: The ecological and economic perspective," in IEEE Communications Magazine, vol. 49, no. 8, pp. 55-62, August 2011.

[10] X. Cao, L. Liu, Y. Cheng and X. S. Shen, "Towards Energy-Efficient Wireless Networking in the Big Data Era: A Survey," in IEEE Communications Surveys & Tutorials, vol. 20, no. 1, pp. 303-332, Firstquarter 2018.

[11] Y. Chen, S. Zhang, S. Xu and G. Y. Li, "Fundamental trade-offs on green wireless networks," in IEEE Communications Magazine, vol. 49, no. 6, pp. 30-37, June 2011.

[12] OPERANET1 - `www.ticnext.eu/project-operanet/`

[13] OPERANET2 `www.bscw.celticplus.eu/pub/bscw.cgi/d3762/OperaNet2-final_lq.pdf`

[14] X. Wang, A. V. Vasilakos, M. Chen, Y. Liu and T. T. Kwon, "A Survey of Green Mobile Networks: Opportunities and Challenges," Mob. Netw. Appl. 17, 1 (February 2012), 4-20.

[15] VCE website - `www.mobilevce.com/frames.htm?core5research.htm`

[16] C. Han et al., "Green radio: radio techniques to enable energy-efficient wireless networks," in IEEE Communications Magazine, vol. 49, no. 6, pp. 46-54, June 2011.

[17] D. Feng, C. Jiang, G. Lim, L. J. Cimini, G. Feng and G. Y. Li, "A survey of energy-efficient wireless communications," in IEEE Communications Surveys & Tutorials, vol. 15, no. 1, pp. 167-178, First Quarter 2013.

[18] M. Gruber, O. Blume, D. Ferling, D. Zeller, M. A. Imran and E. C. Strinati, "EARTH — Energy Aware Radio and Network Technologies," 2009 IEEE 20th International Symposium on Personal, Indoor and Mobile Radio Communications, Tokyo, 2009, pp. 1-5.

[19] EARTH website, `www.cordis.europa.eu/project/rcn/94414/factsheet/en`

[20] GreenTouch white paper `www.s3-us-west-2.amazonaws.com/belllabs-microsite-greentouch/`

uploads/documents/GreenTouch_Green_Meter_Final_Results_18_June_2015.pdf

[21] GWATT interface, www.alu-greentouch-dev.appspot.com/

[22] GreenTouch website www.s3-us-west-2.amazonaws.com/belllabs-microsite-greentouch/index.html

[23] IMEC Power Model Tool, www.imec-int.com/powermodel

[24] D. Sabella, "Green Mobile Networks: the operator view and 5GrEEn project - TREND PhD School in GREEN NETWORKING", Politecnico di Torino, 1-5 July 2013.

[25] M. Olsson, C. Cavdar, P. Frenger, S. Tombaz, D. Sabella and R. Jantti, "5GrEEn: Towards Green 5G mobile networks," 2013 IEEE 9th International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob), Lyon, 2013, pp. 212-216.

[26] M. Masoudi et al., "Green Mobile Networks for 5G and Beyond," in IEEE Access, vol. 7, pp. 107270-107299, 2019.

[27] SooGreen website, www.soogreen.eurestools.eu/

[28] H. Rocha et al., "SooGREEN: Service-oriented optimization of green mobile networks," 2017 15th International Symposium on Modeling and Optimization in Mobile, Ad Hoc, and Wireless Networks (WiOpt), Paris, 2017, pp. 1-8.

[29] H. Kwon and T. Birdsall, "Channel capacity in bits per joule," in IEEE Journal of Oceanic Engineering, vol. 11, no. 1, pp. 97-99, January 1986.

[30] C. He, B. Sheng, P. Zhu and X. You, "Energy Efficiency and Spectral Efficiency Tradeoff in Downlink Distributed Antenna Systems," in IEEE Wireless Communications Letters, vol. 1, no. 3, pp. 153-156, June 2012.

[31] Z. Hasan, H. Boostanimehr and V. K. Bhargava, "Green Cellular Networks: A Survey, Some Research Issues and Challenges," in IEEE Communications Surveys & Tutorials, vol. 13, no. 4, pp. 524-540, Fourth Quarter 2011.

[32] M. Parker and S. Walker, "Roadmapping ICT: An Absolute Energy Efficiency Metric," in IEEE/OSA Journal of Optical Communications and Networking, vol. 3, no. 8, pp. A49-A58, August 2011.

[33] S. Tombaz, K. W. Sung and J. Zander, "On Metrics and Models for Energy-Efficient Design of Wireless Access Networks," in IEEE Wireless Communications Letters, vol. 3, no. 6, pp. 649-652, Dec. 2014.

[34] D. Sabella, M. Z. Shakir, M. A. Imran, K. A. Qaraqe, M.-S. Alouini, A. V. Vasilakos et al., "Energy management in mobile networks towards 5G" in Energy Management in Wireless Cellular and Ad-Hoc Networks, Cham, Switzerland:Springer, 2016.

[35] A. P. Bianzino, A. K. Raju, and D. Rossi, "Apples-to-apples: a framework analysis for energy-efficiency in networks" SIGMETRICS Perform. Eval. Rev. 38, 3 (January 2011), 81-85.

[36] M. Z. Shakir, K. A. Qaraqe, H. Tabassum, M. Alouini, E. Serpedin and M. A. Imran, "Green heterogeneous small-cell networks: toward reducing the CO2 emissions of mobile communications industry using uplink power adaptation," in IEEE Communications Magazine, vol. 51, no. 6, pp. 52-61, June 2013.

[37] H. Claussen, L. T. W. Ho and F. Pivit, "Effects of joint macrocell and residential picocell deployment on the network energy efficiency," 2008 IEEE 19th International Symposium on Personal, Indoor and Mobile Radio Communications, Cannes, 2008, pp. 1-6.

[38] A. J. Fehske, F. Richter and G. P. Fettweis, "Energy Efficiency Improvements through Micro Sites in Cellular Mobile Radio Networks," 2009 IEEE Globecom Workshops, Honolulu, HI, 2009, pp. 1-5.

[39] C-RAN - The Road Towards Green RAN - White Paper, `www.pdfs.semanticscholar.org/eaa3/ca62c9d5653e4f2318aed9ddb8992a505d3c.pdf`

[40] C. I, C. Rowell, S. Han, Z. Xu, G. Li and Z. Pan, "Toward green and soft: a 5G perspective," in IEEE Communications Magazine, vol. 52, no. 2, pp. 66-73, February 2014.

[41] Z. Kong, J. Gong, C. Xu, K. Wang and J. Rao, "eBase: A baseband unit cluster testbed to improve energy-efficiency for cloud radio access network,"

2013 IEEE International Conference on Communications (ICC), Budapest, 2013, pp. 4222-4227.

[42] M. N. Tehrani, M. Uysal and H. Yanikomeroglu, "Device-to-device communication in 5G cellular networks: challenges, solutions, and future directions," in IEEE Communications Magazine, vol. 52, no. 5, pp. 86-92, May 2014.

[43] L. Li, G. Zhao and R. S. Blum, "A Survey of Caching Techniques in Cellular Networks: Research Issues and Challenges in Content Placement and Delivery Strategies," in IEEE Communications Surveys & Tutorials, vol. 20, no. 3, pp. 1710-1732, thirdquarter 2018.

[44] F. Boccardi, R. W. Heath, A. Lozano, T. L. Marzetta and P. Popovski, "Five disruptive technology directions for 5G," in IEEE Communications Magazine, vol. 52, no. 2, pp. 74-80, February 2014.

[45] J. G. Andrews et al., "What Will 5G Be?," in IEEE Journal on Selected Areas in Communications, vol. 32, no. 6, pp. 1065-1082, June 2014.

[46] B. Perabathini, E. Baştuğ, M. Kountouris, M. Debbah and A. Conte, "Caching at the edge: A green perspective for 5G networks," 2015 IEEE International Conference on Communication Workshop (ICCW), London, 2015, pp. 2830-2835.

[47] X. Lu, P. Wang, D. Niyato, D. I. Kim and Z. Han, "Wireless Networks With RF Energy Harvesting: A Contemporary Survey," in IEEE Communications Surveys & Tutorials, vol. 17, no. 2, pp. 757-789, Secondquarter 2015.

[48] S. Bi, C. K. Ho and R. Zhang, "Wireless powered communication: opportunities and challenges," in IEEE Communications Magazine, vol. 53, no. 4, pp. 117-125, April 2015.

[49] Q. Wu, G. Y. Li, W. Chen, D. W. K. Ng and R. Schober, "An Overview of Sustainable Green 5G Networks," in IEEE Wireless Communications, vol. 24, no. 4, pp. 72-80, Aug. 2017.

[50] S. Bu, F. R. Yu, Y. Cai and X. P. Liu, "When the Smart Grid Meets Energy-Efficient Communications: Green Wireless Cellular Networks Powered by the Smart Grid," in IEEE Transactions on Wireless Communications, vol. 11, no. 8, pp. 3014-3024, August 2012.

[51] Cisco white paper "Smart Grid - The Role of Electricity Infrastructure in Reducing Greenhouse Gas Emissions", `https://www.cisco.com/c/dam/en_us/about/ac79/docs/Smart_Grid_FINAL.pdf`

[52] S. Bu and F. R. Yu, "A Game-Theoretical Scheme in the Smart Grid With Demand-Side Management: Towards a Smart Cyber-Physical Power Infrastructure," in IEEE Transactions on Emerging Topics in Computing, vol. 1, no. 1, pp. 22-32, June 2013.

[53] W. Labidi, T. Chahed and S. Elayoubi, "Optimal energy management strategies in mobile networks powered by a smart grid," 2017 IEEE International Conference on Communications (ICC), Paris, 2017, pp. 1-6.

[54] D. Niyato, X. Lu and P. Wang, "Adaptive power management for wireless base stations in a smart grid environment," in IEEE Wireless Communications, vol. 19, no. 6, pp. 44-51, December 2012.

[55] Z. Niu, Y. Wu, J. Gong and Z. Yang, "Cell zooming for cost-efficient green cellular networks," in IEEE Communications Magazine, vol. 48, no. 11, pp. 74-79, November 2010.

[56] Bhaumik, Sourjya et al. "Breathe to stay cool: adjusting cell sizes to reduce energy consumption," Green Networking (2010).

[57] R. Balasubramaniam, S. Nagaraj, M. Sarkar, C. Paolini and P. Khaitan, "Cell Zooming for Power Efficient Base Station Operation," 2013 9th International Wireless Communications and Mobile Computing Conference (IWCMC), Sardinia, 2013, pp. 556-560.

[58] W. Yoro, T. Chahed, M. El Tabach, T. En-Najjary and A. Gati, "Sharing of energy among service categories in wireless access networks using Shapley value," 2016 International Wireless Communications and Mobile Computing Conference (IWCMC), Paphos, 2016, pp. 422-429.

[59] G. Auer et al., "How much energy is needed to run a wireless network?," in IEEE Wireless Communications, vol. 18, no. 5, pp. 40-49, October 2011.

[60] G. Micallef, P. Mogensen and H. Scheck, "Cell size breathing and possibilities to introduce cell sleep mode," 2010 European Wireless Conference (EW), Lucca, 2010, pp. 111-115.

[61] J. Wu, Y. Zhang, M. Zukerman and E. K. Yung, "Energy-Efficient Base-Stations Sleep-Mode Techniques in Green Cellular Networks: A Survey," in IEEE Communications Surveys & Tutorials, vol. 17, no. 2, pp. 803-826, Secondquarter 2015.

[62] P. Frenger, P. Moberg, J. Malmodin, Y. Jading and I. Godor, "Reducing Energy Consumption in LTE with Cell DTX," 2011 IEEE 73rd Vehicular Technology Conference (VTC Spring), Yokohama, 2011, pp. 1-5.

[63] R. Wang, J. S. Thompson and H. Haas, "A novel time-domain sleep mode design for energy-efficient LTE," 2010 4th International Symposium on Communications, Control and Signal Processing (ISCCSP), Limassol, 2010, pp. 1-4.

[64] 3GPP TSG-RAN Benefits of Blank Subframes in Rel-9", Qualcomm Europe, China, 2009.

[65] L. Saker and S. E. Elayoubi, "Sleep mode implementation issues in green base stations," 21st Annual IEEE International Symposium on Personal, Indoor and Mobile Radio Communications, Instanbul, 2010, pp. 1683-1688.

[66] S. Elayoubi, L. Saker and T. Chahed, "Optimal control for base station sleep mode in energy efficient radio access networks," 2011 Proceedings IEEE INFOCOM, Shanghai, 2011, pp. 106-110.

[67] R. Combes, S. E. Elayoubi, A. Ali, L. Saker, and T. Chahed, "Optimal online control for sleep mode in green base stations", Computer Networks 78, (February 2015), 140-151.

[68] P. Lähdekorpi, M. Hronec, P. Jolma and J. Moilanen, "Energy efficiency of 5G mobile networks with base station sleep modes," 2017 IEEE Conference on Standards for Communications and Networking (CSCN), Helsinki, 2017, pp. 163-168.

[69] H. Pervaiz, O. Onireti, A. Mohamed, M. Ali Imran, R. Tafazolli and Q. Ni, "Energy-Efficient and Load-Proportional eNodeB for 5G User-Centric Networks: A Multilevel Sleep Strategy Mechanism," in IEEE Vehicular Technology Magazine, vol. 13, no. 4, pp. 51-59, Dec. 2018.

[70] C. Bouras, G. Diles and D. Ntoutsos, "Sleep Mode Strategies for Dense Small Cell 5G Networks," 2018 10th International Congress on Ultra Modern Telecommunications and Control Systems and Workshops (ICUMT), Moscow, Russia, 2018, pp. 1-6.

[71] L. Saker, S. E. Elayoubi, R. Combes and T. Chahed, "Optimal Control of Wake Up Mechanisms of Femtocells in Heterogeneous Networks," in IEEE Journal on Selected Areas in Communications, vol. 30, no. 3, pp. 664-672, April 2012.

[72] P. Dini, M. Miozzo, N. Bui and N. Baldo, "A Model to Analyze the Energy Savings of Base Station Sleep Mode in LTE HetNets," 2013 IEEE International Conference on Green Computing and Communications and IEEE Internet of Things and IEEE Cyber, Physical and Social Computing, Beijing, 2013, pp. 1375-1380.

[73] M. Klapez, C. A. Grazia and M. Casoni, "Energy Savings of Sleep Modes Enabled by 5G Software-Defined Heterogeneous Networks," 2018 IEEE 4th International Forum on Research and Technology for Society and Industry (RTSI), Palermo, 2018, pp. 1-6.

[74] B. Debaillie, C. Desset and F. Louagie, "A Flexible and Future-Proof Power Model for Cellular Base Stations," 2015 IEEE 81st Vehicular Technology Conference (VTC Spring), Glasgow, 2015, pp. 1-7.

[75] C. Hoymann, D. Larsson, H. Koorapaty and J. Cheng, "A Lean Carrier for LTE," in IEEE Communications Magazine, vol. 51, no. 2, pp. 74-80, February 2013.

[76] 3GPP TSG-RAN WG1 Meeting #88 R1-1703092, "On Requirements and Design of SS Burst Set and SS Block Index Indication", Athens, Greece 13th - 17th February 2017".

[77] 3GPP TSG-RAN WG1 Meeting #88 R1-1702122, "NR Synchronization Complexity and Periodicity", Athens, Greece 13th - 17th February 2017"

[78] 3GPP TR 38.913, Technical Specification Group Radio Access Network; "Study on Scenarios and Requirements for Next Generation Access Technologies" (Release 14).

[79] R. S. Sutton and A. G. Barto, "Reinforcement learning: An introduction" MIT press Cambridge, 1998, vol. 1, no. 1.

[80] S. M. Ross, "Applied Probability Models with Optimization Applications", Dover Publications.

[81] M. L. Puterman, "Markov Decision Processes: Discrete Stochastic Dynamic Programming". Wiley, 2005.

[82] A. P. Azad, S. Alouf, E. Altman, V. Borkar and G. S. Paschos, "Optimal Control of Sleep Periods for Wireless Terminals," in IEEE Journal on Selected Areas in Communications, vol. 29, no. 8, pp. 1605-1617, September 2011.

[83] M. E. Crovella and A. Bestavros, "Self-similarity in World Wide Web traffic: evidence and possible causes," in IEEE/ACM Transactions on Networking, vol. 5, no. 6, pp. 835-846, Dec. 1997.

[84] A. Feldmann and W. Whitt, "Fitting mixtures of exponentials to long-tail distributions to analyze network performance models," Proceedings of INFOCOM '97, Kobe, Japan, 1997, pp. 1096-1104 vol.3.

[85] C. J. Watkins and D. Peter, "Q-learning," Machine Learning, vol. 8, no. 3-4, pp. 279-292, 1992.

Titre : Gestion des modes de veille avancés pour des réseaux 5G économes en énergie

Mots clés : Consommation énergétique, stations de base, modes de veille avancés, délai, politiques de gestion, processus de décision Markoviens, Q-learning.

Résumé : La consommation énergétique des réseaux radiomobiles a été une direction de recherche très active au cours de la dernière décennie et ce, pour des raisons économiques ainsi qu'environnementales. Avec l'énorme croissance du trafic ainsi que la multiplication des équipements mobiles, des nouveaux services et des communications Machine à Machine, la nécessité de réduire la consommation énergétique est devenue de plus en plus urgente surtout avec le déploiement des réseaux 5G.
Nous étudions dans cette thèse une technique dite "modes de veille avancés" qui permet d'éteindre les composants de la station de base de manière progressive en fonction du temps nécessaire pour chacun pour se désactiver et se réactiver de nouveau. Ceci introduit différent niveaux de sommeil possibles. En allant d'un niveau à un autre plus profond nous pouvons réaliser plus d'économies d'énergie puisqu'il y a plus de composants qui sont en veille, mais nous introduisons plus d'impact sur le délai s'il y a des demandes de services qui arrivent pendant cette période de veille. L'opérateur doit trouver alors des politiques de gestion efficaces pour gérer ce compromis entre la réduction d'énergie et la minimisation de l'impact sur le délai.
Dans ce contexte, nous proposons des méthodes de gestion des modes de veille avancés basées spécifiquement sur des modèles d'apprentissage, à savoir les processus de décision Markoviens et le Q-learning, qui nous permettent de trouver la politique optimale à suivre en fonction des priorités accordées aux deux métriques : la consommation d'énergie et le délai.
Nos solutions montrent que les économies d'énergie peuvent atteindre 90% dans le cas d'un faible trafic lorsque la priorité est accordée à la réduction d'énergie. Plus on augmente la contrainte imposée sur le délai, plus la réduction d'énergie diminue, et aussi l'impact sur le délai. Nos résultats montrent que même si la contrainte sur le délai est très forte, nous pouvons aussi avoir des économies d'énergie élevées (environ 50%) alors que l'impact sur le délai devient négligeable.

Title : Management of Advanced Sleep Modes for Energy-Efficient 5G Networks

Keywords : Energy consumption, Base stations, Advanced Sleep Modes, delay, management solutions, Markov Decision Processes, Q-learning.

Abstract : The energy consumption of mobile networks has been an active research direction in the last decade for both environmental and economic concerns. With the tremendous growth in the traffic as well as the proliferation of devices and new services and the expansion of Machine to Machine communications, the need to reduce the energy consumption became more and more urgent and was emphasized by the expected 5G roll out.
We study in this thesis an *Advanced Sleep Mode* technique enabling to shut down the base station's components in a gradual manner depending on the time needed for each of them to deactivate and reactivate again. This introduces different possible levels of sleep. Going from one level to a deeper one will help us make more energy savings as we deactivate more components but can also incur a larger delay for the users who request a service when the base station is in sleep mode. The network operator has to find efficient management solutions that can handle this tradeoff between energy consumption reduction that can be achieved by the sleep modes, and the minimization of the corresponding induced delay.
To this aim, we propose in this work management solutions based especially on learning techniques, namely Markov Decision Processes and Q-learning, which enable us to find the optimal policy to follow depending on the priorities given to both metrics : energy consumption and delay.
Our solutions show that the energy savings can reach 90% in low traffic when priority is given to energy reduction. The more we care about delay, the more energy saving decreases, as is the case for the induced delay. We show that even when we have a strict constraint on the delay, we can still achieve high energy savings (around 50%) while the added delay by the sleep mode is negligible.

Institut Polytechnique de Paris
91120 Palaiseau, France