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# Radio resource allocation in 5G cellular networks powered by the smart grid and renewable energies

Ali El Amine

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# THESE DE DOCTORAT DE

L'ÉCOLE NATIONALE SUPERIEURE MINES-TELECOM ATLANTIQUE  
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de l'Information et de la Communication (MathSTIC)*  
Spécialité : Informatique

Par

**Ali EL AMINE**

## **Radio resource allocation in 5G cellular networks powered by the smart grid and renewable energies**

Allocation des ressources radio dans les réseaux cellulaires 5G alimentés par le smart grid et les énergies renouvelables

Thèse présentée et soutenue à **RENNES** le **12 novembre 2019**

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***“If I have seen further it is by standing on the shoulders of  
giants”***

Sir Isaac Newton

---

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# Abstract

The heated 5G network deployment race had begun between competitors to outperform one another and be the most innovative followed by a rapid progress towards standardization. Unlike previous generations, 5G envisions to support extremely wide diversity of services and applications with different requirements in terms of reliability, network availability, data rate and latency with high energy efficiency. This thesis focuses on studying the role of energy and its behavior while designing and operating wireless cellular networks. We consider different and complementary approaches and parameters, including energy efficiency techniques (i.e., radio resource management and sleep schemes), renewable energy sources, smart grid and tools from machine learning, to bring down the energy consumption of these complex networks while guaranteeing a certain quality of service adapted to 5G use cases.

In the past decade, a lot of research efforts have been devoted to design energy efficient cellular networks not only to reduce the energy consumption, but also to limit the carbon footprint induced by these systems. Focusing on renewable energy to bring down the Operational Expenditure (OpEx) costs for telecom operators while respecting the environmental regulations opened opportunities for new business models. However, it is not trivial to design and operate such networks given the complex nature of these networks. In addition to radio resource management, green cellular networks require the optimization of using renewable energy that entails high management complexity due to its erratic and intermittent nature. Moreover, considering the energy storage element (i.e., battery), a critical component in renewable energy-equipped systems, and the Smart Grid environment provide additional dimensions to the problem and open new research challenges.

In this work, we start by a review of the literature in order to identify the different research directions in energy efficiency green wireless networks. Following the extensive research under these areas, we highlight several aspects in which the problematic of green cellular networks needs more exploration.

Consequently, we first study the effect of equipping base stations with renewable energy sources. Due to the high capital costs of these systems and the infeasibility to equip renewable energy systems to all base station sites, we study the percentage of sites to be powered with hybrid energy supplies (renewable energy and Smart Grid). In particular, we focus on the impact of equipping sites with renewables on the operational cost and the performance of a cellular network to decide how much to invest in renewable energy, i.e., number of sites equipped with renewable energy sources, sizing of renewable energy and battery capacity. Our study for instance shows that it is enough to equip 30% of sites with renewables in order to realize an operational cost gain of 60%.

Then, we evaluate the contribution of each service the network is providing and their effect on the network energy consumption. We consider Key Performance Indicators (KPIs) putting forward each service contribution to energy consumption. Using these KPIs, we propose some energy management strategies, leading to performance amelioration and energy savings up to 11.5% points compared to other benchmark algorithms, under renewable energy and smart grid environment.

Focusing on the storage element (i.e., battery) that requires expensive investment cost both in terms of Capital Expenditure (CapEx) and OpEx, we include important constraints on the battery that is prone to irreversible aging mechanisms to expand its life span. Then, we propose several energy management algorithms that aim at saving energy while respecting the battery constraints. Our results show a gain of 20% in terms of electric bill reduction compared to an existing algorithm, and 35% battery life time enhancement.

Recently, artificial intelligence has received significant attention as a highly effective alternative to conventional methods. In particular, we take advantage of Reinforcement Learning (Q-learning) to orchestrate different levels of sleep modes to save energy given a user Quality of Service (QoS). By considering advanced sleep mode levels compliant with 5G

requirements, we demonstrate the performance of these sleep schemes under the energy-delay-tradeoff problem.





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# Thesis Publications

- Ali El-Amine, Hussein Al Haj Hassan, and Loutfi Nuaymi. Analysis of energy and cost savings in hybrid base stations power configurations. In 2018 IEEE 87th Vehicular Technology Conference (VTC Spring), Porto, Portugal, 2018.
- Ali El-Amine, Hussein Al Haj Hassan, and Loutfi Nuaymi. Services kpi-based energy management strategies for green wireless networks. In 2018 IEEE 29th Annual International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC), Bologna, Italy, 2018.
- Ali El-Amine, Hussein Al Haj Hassan, and Loutfi Nuaymi. Battery aging-aware green cellular networks with hybrid energy supplies. In 2018 IEEE 29th Annual International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC), Bologna, Italy, 2018.
- Ali El-Amine, Hussein Al Haj Hassan, and Loutfi Nuaymi. Energy and resource allocations for battery aging-aware green cellular networks. In 2018 IEEE Global Communications Conference (GLOBECOM), 2018.
- Ali El-Amine, Hussein Al Haj Hassan, Iturralde Mauricio, and Loutfi Nuaymi. A distributed Q-Learning approach for adaptive sleep modes in 5G networks. In 2019 IEEE Wireless Communications and Networking Conference (WCNC), Marrakech, Morocco, 2019.
- Ali El-Amine, Hussein Al Haj Hassan, Iturralde Mauricio, and Loutfi Nuaymi. Location-Aware sleep strategy for Energy-Delay tradeoffs in 5G with reinforcement learning. In 2019 IEEE 30th Annual International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC), Istanbul, Turkey, 2019.



- Meysam Masoudi, Mohammad Galal Khafagy, Alberto Conte, Ali El-Amine, et al. Green mobile networks for 5G and beyond. *IEEE Access*, 2019.
- Hadi Sayed, Ali El-Amine, Hussein Al Haj Hassan, Loutfi Nuaymi and Roger Ashkar. Reinforcement learning for Radio Resource Management of Hybrid-Powered Cellular Networks. In 2019 IEEE 12th International Workshop on Selected Topics in Wireless and Mobile computing (STWiMob), WiMob workshop, Barcelona, Spain, 2019.

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# List of Acronyms

**3GPP** 3rd Generation Partnership Project

**APC** Area Power Consumption

**AGE** Area Green Efficiency

**AEE** Absolute Energy Efficiency

**ASM** Advanced Sleep Mode

**A-GNSS** Assisted Global Navigation Satellite Systems

**AoA** Angle-of-Arrival

**AI** Artificial Intelligence

**BS** Base Station

**CapEx** Capital Expenditure

**CPP** Critical-Peak Pricing

**CSRA** Coverage Supply Redundancy Architecture

**CRAN** Cloud-RAN

**CLA** Cell Layout Adaptation

**CRS** Cell Reference Signals

**CoO** Cell of Origin

**DP** Dynamic Programming

**DTX** Disconteneous Transmission

**DoD** Depth of Discharge

- DSM** Demand-Side Management
- DR** Demand Response
- DAP** Day-Ahead Pricing
- DQL** Deep Q-Learning
- ECI** Energy Consumption Index
- ETSI** European Telecommunications Standards Institute
- ECG** Energy Consumption Gain
- EMU** Energy Management Unit
- EDT** Energy-Delay-Tradeoff
- E-CID** Enhanced Cell ID
- FQL** Fuzzy Q-Learning
- GEE** Global Energy Efficiency
- GPU** Graphics Processing Unit
- HetNet** Heterogeneous Network
- HAMRL** Heuristically-Accelerated Multiagent Reinforcement Learning
- ICT** Information and Communication Technology
- IoT** Internet of Things
- IoE** Internet of Everything
- ITU** International Telecommunication Union
- IMT-2020** International Mobile Telecommunications-2020
- ICA** Independent Component Analysis
- KPI** Key Performance Indicator
- LTE** Long Term Evolution
- LTE-U** Long Term Evolution Unlicensed
- LTE-A** Long Term Evolution Advanced

- 
- MARL** Multi-Agent Reinforcement Learning
- MNO** Mobile Network Operator
- MBSFN** Multicast Broadcast Single Frequency Network
- ML** Machine Learning
- MBS** Macro Base Station
- MDP** Markov Decision Process
- NFV** Network Function Virtualization
- OpEx** Operational Expenditure
- OTDoA** Observed Time Difference of Arrival
- PAR** Peak-to-Average Ratio
- PBCH** Physical Broadcast CHannel
- PRS** Positioning Reference Signal
- PCA** Principal Component Analysis
- QoS** Quality of Service
- RAN** Radio Access Network
- RE** Renewable Energy
- RRM** Radio Resource Management
- RTP** Real-Time Pricing
- RB** Resource Block
- RL** Reinforcement Learning
- RRC** Radio Resource Control
- RSRP** Reference Signal Received Power
- RTT** Round Trip Time
- SG** Smart Grid
- SDN** Software Defined Network

**SE** Spectral Efficiency

**SM** Sleep Mode

**SWM** Series of Worst Months

**SoC** State of Charge

**SoH** State of Health

**SINR** Signal-to-Interference Noise Ratio

**SS** Synchronization Signaling

**SBS** Small Base Station

**SON** Self-Organizing Network

**SSN** Self-Sustaining Network

**TOUP** Time-Of-Use Pricing

**TTI** Transmission Time Interval

**TMY** Typical Meteorological Year

**TDoA** Time Different of Arrival

**TD** Temporal Difference

**UDN** Ultra Dense Network

**URLLC** Ultra Reliable Low Latency Communication

**WSEE** Weighted Sum Energy Efficiency

**WPEE** Weighted Product Energy Efficiency

**WMEE** Weighted Minimum Energy Efficiency

## **1.1 Challenges surrounding mobile networks: the big picture**

We live in the digital era. The Internet has become an essential part of our daily lives. Humans and machines are now connected globally over the Internet, with more than 750 million connected households and over 6.8 billion mobile subscribers (as many mobiles as people in the world) [1]. The trend is of further increase and appears to have no signs of slowing down in the near future due to the ongoing new services and applications, especially wireless traffic (e.g., mobile) that is dominating the Information and Communication Technology (ICT) sector with more than 75% [2]. Today, more than 5 million videos are watched on YouTube and 67,000 images are uploaded to Instagram every minute, as shown in Figure 1.1. Based on CISCO VNI mobile traffic report, it is estimated that the global mobile data traffic will witness an increase of seven-fold between 2016 and 2021 [3]. However, this radical surge of ICT devices and services has pushed corresponding energy consumption and its footprint on the environment to grow at a staggering rate. It has been estimated that the ICT industry consumes more than 5% of the world's electrical energy surpassing more than 50% that of the avionic one, releasing into the atmosphere about 2% of the global CO<sub>2</sub> emissions [4]. These numbers are expected to increase by year 2030 to reach 51% and 23% of electricity consumption and carbon footprint, respectively due to ICT [5].

More specifically, mobile networks are among the top energy consumers with a contribution share of more than 0.5% of the total energy supply worldwide [6], a number that is increasing with the growth number of subscribers, traffic demand, connected devices and offered services. With such an increment in the demand, the mobile industry is facing an



Figure 1.1 – What do we do on the Internet in 60 seconds <sup>1</sup>.

economic and environmental problems. On one hand, the revenues of mobile operators are decreasing every year. For instance, the Average Revenue Per User (ARPU) of Vodafone Germany has been shrinking annually by 6% in the period 2000-2009 [7]. One of the reasons for this decline in revenues is the increase of the Operational Expenditure (OpEx) of these networks, which is mostly dominated by energy costs. On the other hand, there is an increase awareness in protecting the environment, and strict regulations on pollutant emissions. For instance, some governments (e.g., India) are adopting rules obliging telecom operators to consider green energy. The above reasons followed with the rise in the energy price during the last years have led energy consumption to become a primary concern in the design of future generation wireless systems. Specifically, the fifth generation (5G) cellular network<sup>2</sup> will have to consider energy efficiency as one of its key pillars for the economical sustainability of ICT.

<sup>2</sup><https://www.ericsson.com/res/docs/2014/5g-what-is-it-for.pdf>

<sup>2</sup>We use the terms *mobile network* and *cellular network* interchangeably throughout this thesis.

## 1.2 5G: towards energy efficient cellular networks

Ever since the first real mobile telephone call, a few decades ago, the evolution of mobile networks up to 4G has been driven with the aim of optimizing performance metrics such as data rate, throughput and latency. The revolution of 5G is different. A new figure of merit has emerged in the design of future cellular networks: *Energy Efficiency*. Indeed, 5G technology will have to support the proliferating traffic demand, providing a wide range of connected devices and services. Unlike earlier generations, 5G networks are required to simultaneously provide a diversity of services with different requirements in their service levels. Specifically, there is a broad consensus today that categorizes these services. They are defined by International Telecommunication Union (ITU) and International Mobile Telecommunications-2020 (IMT-2020) and are divided into three categories [8]:

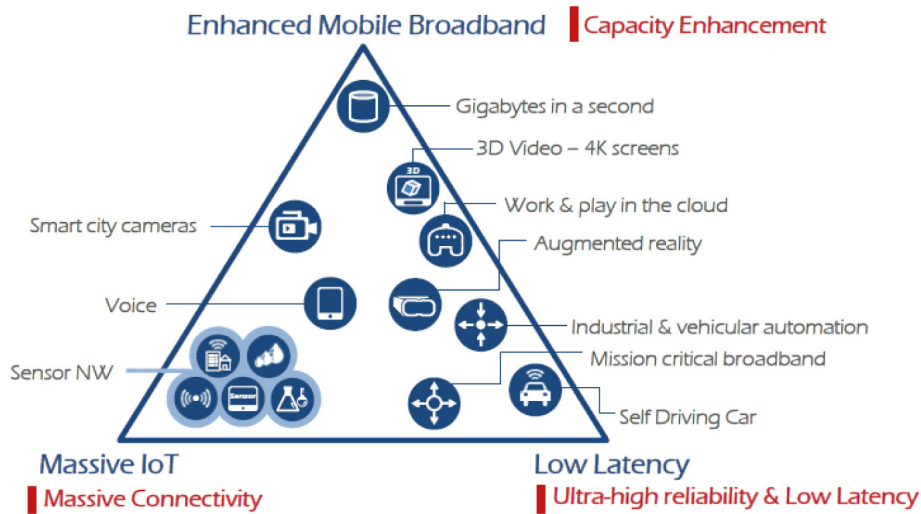
1. **mMTC - Massive Machine Type Communications:** 5G will need to suit a whole raft of connected devices with heterogeneous quality of service requirements. The objective of this category is to have a unifying connectivity fabric with enough flexibility to support the exponential increase in the density of connected devices.
2. **eMBB - Enhanced Mobile Broadband:** as an extension to 4G broadband services, the aim of this category is to have an ultra high-speed connection for both indoors and outdoors, with uniform quality of service, even on the cell edges.
3. **URLLC - Ultra-Reliable and Low Latency Communication:** this use case is for services that are delay sensitive, and thus require stringent requirements for latency and reliability to ensure increased reactivity.

The service requirements for each of the above categories are remarkably distinct in terms of reliability, throughput, latency, among others. For instance the first category (mMTC), which envisions the Internet of Things (IoT) paradigm, requires broad coverage, low power consumption and relatively low throughput. On the other hand, eMBB services are data

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<sup>2</sup><http://5g.ieee.org/standards>





(Source: ETRI graphic, from ITU-R IMT 2020 requirements)

Figure 1.2 – 5G use cases <sup>3</sup>.

rate hungry (e.g., ultra high-definition (8K) videos and virtual/augmented reality wireless streaming), while URLLC services need to be extremely reliable with a target latency below 1 ms.

According to these objectives, 5G must be able to support users with throughput and peak throughput of 10 and 20 times higher than what is currently available, respectively. The density of the maximum connection will be 10 times more and the latency divided by at least 10 (the target latency point is 1 ms, which is today between 30 and 40 ms). In order to cater this vision and to satisfy the proliferating traffic demand, 5G technology is envisioned to support 1000 times increase in capacity and 100 times more connected devices than today's 4G networks [9]. In this regard, three paradigms have emerged:

1. Spectrum sharing: boost the capacity by exploiting unused and unlicensed spectrum, such as mmWave and Long Term Evolution Unlicensed (LTE-U).
2. Ultra Dense Networks: boost the Spectral Efficiency (SE) by reducing the distance between transmitter and receiver and improve the frequency reuse.

3. Massive MIMO: boost multiplexing gain and SE by deploying an array of antennas at the BSs side.

The technologies listed above enhance the system capacity and performance from different angles. However, this gain does not come for free. For example with Ultra Dense Networks (UDNs), a promising trend to realize this concept is to exploit Heterogeneous Networks (HetNets) architecture, where BSs using different transmission power and technologies coexist to increase the network capacity. In such a deployment, the traditional macro BS will be replaced or complemented with multiple overlapping tiers of smaller cells, that extend the system capacity, due to higher spatial reuse, and thus better spectral efficiency. Despite these benefits, many challenges have been identified from such an ultra dense scenario. Among many issues related to interference management, mobility management and macro cell offloading that make next generation cellular networks challenging to control and operate, researchers have pointed out that such systems are power hungry, due to their high capacity requirements. Even with new design architectures including Cloud-RAN (CRAN) [10], Software Defined Networks (SDNs) [11], Network Function Virtualization (NFV) [12] and Fog Computing [13] that offer higher flexibility, control and network operation, a big effort is still needed to reduce the energy consumption. In fact, these architectures are not designed to reduce the energy consumption of 5G networks. Thus, relying on the above paradigm and architecture to achieve this ambitious goal is not sustainable, and it will lead to a serious energy crunch.

### **1.3 Detering the energy crunch**

In order to deter the energy crunch, energy efficiency has become a major key pillar in the design and operation of future mobile networks. Different and complementary approaches have been proposed to enhance the energy efficiency of these networks. They include but not limited to radio resource management, cell layout adaptation, deployment of heterogeneous networks and cognitive radio. In addition, using RE sources has become another effective approach for Mobile Network Operators (MNOs) to further save energy, while respecting the environmental regulations. In this regard, several projects were developed focusing on this metric

in cellular networks, such as EARTH [14], TREND [15], GreenTouch [16], OPERA-Net [17], OPERA-Net 2 [18], 5GrEEen [19] and SooGreen [20].

In wireless cellular networks, Radio Access Network (RAN) consumes the major part of energy with the BS using 75 – 80% of the network's energy [21]. Hence, providing energy harvesting capabilities to cellular BSs from RE sources is an attractive and promising solution for green cellular networks. Consequently, a new line of research is emerging going beyond energy efficiency to energy sustainability. In this paradigm, RE will be an essential element in the sustainability of future 5G networks, especially for underdeveloped countries that lack reliable grid connectivity. For example, in India out of 400,000 BSs, more than 70% face power cuts that last more than 8 hours per day. In order to combat this outage in electricity, MNOs rely on diesel generators spending around US\$ 1.4 billion and producing more than five metric-tons of CO<sub>2</sub> [22]. Currently, it is estimated that there are around 320,100 off-grid (i.e., not connected to the grid) and 701,000 non-reliable grid (i.e., with many power outages) BSs in the world. These numbers are expected to grow by 22% and 13% by the year 2020, respectively [23].

Powering BSs with RE sources is not only appealing for countries with poor-grid conditions. Well-developed countries with mature energy markets can also take advantage of energy harvesters to increase their savings, reduce CO<sub>2</sub> emissions and sell excess energy produced by these green sources back to the grid, increasing their revenues. The latter is possible thanks to the evolution of the power grid into a smarter one - the Smart Grid (SG). Under this infrastructure, the flow of energy is bi-directional (i.e., from the source to the consumer and vice-versa). This promising infrastructure is expected to enhance the efficiency, reliability, economics and sustainability of the production and distribution of electricity. Thus, considering the SG is crucial when studying the energy behavior of future mobile networks. Moreover, the advancement in renewable harvesters are improving the efficiency of generating electricity from green sources, and thus decreasing the cost of deploying such systems. For instance, the current efficiency of available commercial solar panels built with traditional technologies (i.e., crystalline silicon) ranges between 15 – 20%. New technologies, such as Concentrating Photovoltaics (CPV), allow to further enhance these values to more than twice (up to 39%), however they are still under test and not yet available in the market [24].

In addition to the economic and environmental benefits of using RE under the SG infrastructure, precise sizing and dimensioning of RE systems is required, due to their high capital costs. A task that entails a trading off between energy self-sustainability, service continuity and feasibility constraints. Moreover, due to the erratic and intermittent nature of RE, intelligent management is required to efficiently use it and to ensure service reliability. One way to address the natural limitation of RE is the use of batteries to store the harvested energy in order to add flexibility in its utilization. Furthermore, in order to satisfy new services and applications under a green efficient framework, coupling of radio resource optimization and power allocation optimization is the ultimate goal towards green mobile networks. However, this coupling of radio and power resources introduces new challenges on optimizing green energy enabled mobile networks. Hence, designing and operating such networks is not trivial due to their high complexity.

A lot of work exist in the literature that deal with the above mentioned topic. We can note for instance the work of L. Suarez in [21] that defines the different techniques to enhance the energy efficiency of future networks, and the thesis of H. Al Haj Hassan in [25] that focuses on the radio resource allocation algorithms for energy efficient future cellular networks powered by RE sources and the SG.

This thesis is a continuation of the work done in [25]. It extends the work to cover RE proper sizing, battery management to extend its lifespan, impact of different services the network is providing on energy consumption through special KPIs and machine learning-type algorithms to include intelligence in the system in order to cope with the 5G services diversities and requirements.

## **1.4 Thesis objectives**

From what we have discussed above, using RE for mobile networks is a promising solution to establish green cellular networks and push towards energy-efficient and sustainable communication systems, while opening opportunities for new business models. However, the integration of RE and the SG with the diverse requirements of 5G presents new challenges on optimizing green energy enabled networks. Besides reducing the energy consumption and the CO<sub>2</sub> emissions, future networks should be able

to cope with different types of services with various requirements in order to satisfy a wide range of user types. Since 5G envisions a diversity of use cases as shown in Fig. 1.2, the network should be able to manage its resources to satisfy at its best the different Quality of Service (QoS) requirements while respecting green constraints.

The objective of this thesis is to design and operate cellular networks powered by RE and the SG, while focusing on the crucial role of energy. We give special attention to the battery, an important element of RE systems that plays a critical role in the design of sustainable mobile networks, thus requiring precise management. In addition to the use of RE, we consider various energy and radio resource management techniques. We study different objectives, such as minimizing the electric bill of the operator, enhancing service-based KPIs and managing the tradeoff between energy savings and delay. While it is important to save energy, future networks must be able to alleviate the impact on the QoS to be delivered.

## 1.5 EU Celtic-Plus Project: SooGreen

The work developed in this thesis was part of an industry-driven European Celtic-Plus project under the name service-oriented optimization for green mobile networks (*SooGreen*) that was launched in 2015 [20]. SooGreen was built around the need for reducing the energy consumption of mobile networks, while alleviating the carbon footprint in the ICT sector. In light of the traffic explosion, SooGreen provides a holistic view on energy problems in wireless networks shedding light on the contribution of different services to energy consumption. A number of objectives were defined in this project spanning access and core networks. These include modeling of energy consumption per service, definition of new KPIs to assess the energy efficiency, exploiting and studying new energy-efficient network architectures, and exploiting the use of RE in the SG environment. This being said, SooGreen project focuses on the energy efficiency and sustainability paradigms in a service oriented network. By the end of this project, a synthesis work that tells the story of green mobile networks for 5G and beyond has been published in [26].

## 1.6 Thesis contribution

The study of the state of the art allowed us to have a wide overview of the existing work in the context of energy efficient green mobile networks. Consequently, we first propose a methodology to study and analyze the impact of equipping sites with renewable energy sources and batteries on the operational cost and the performance of cellular networks. In contrast to most studies in the literature and to the best of our knowledge, we are the first to study partially renewable energy-equipped wireless systems. This is of great importance considering the high capital costs of these systems and the feasibility of implementing them on all sites.

Then, we study the grid energy savings taking into account efficient battery usage that is prone to irreversible degradations that reduce its maximal capacity. While most studies in the literature solely focus on minimizing the grid energy consumption in renewable energy systems, we propose several algorithms that not only bring down the grid energy consumption, but also preserve the battery lifetime which is the most expensive part in renewable energy systems.

Finally, we study the energy-delay-tradeoff problem in wireless cellular networks under advanced sleep mode levels. Different from binary sleep mode schemes (On-Off) that are well investigated in the literature, we consider multi-level sleep modes that are compliant with 5G networks. Thus, we propose a methodology for reducing the energy consumption of a 5G cellular network while ensuring a good quality of service. This methodology permits the operator to freely manage the tradeoff between energy saving and service delay. In order to handle the high complexity of the dynamic environment, we resolve to reinforcement learning tools from machine learning to solve the stochastic optimization problem by means of interaction with this environment.

## 1.7 Thesis outline

The remainder of thesis is organized as follows. Chapter 2 reviews the state of the art on energy-efficient cellular networks. We start by discussing the different techniques found in the literature to save energy in 5G networks. Then, we elaborate on the use of RE as a mean to enhance

the energy efficiency and reduce the carbon footprint of future networks. We highlight the important role of the future grid (i.e., the SG) in achieving the green paradigm. Finally, we discuss how Artificial Intelligence (AI) constitutes a powerful tool for next generation networks.

In Chapter 3, we present a framework to study and analyze the impact of equipping sites with RE sources on the operational cost and performance of the network. We evaluate the energy efficiency of the network using advanced KPIs that put forward the contribution of each service the network is providing to energy consumption. We extend the work in Chapter 4 to include important battery requirements for proper utilization and longer lifetime. We propose several algorithms that manages the network resources (radio and energy) to minimize the electric bill of the operator, while preserving the life of the battery.

In Chapter 5, we focus on the specific requirements of 5G networks. In this regard, we study advanced sleep schemes that are compliant with 5G. We study the problem of energy-delay-tradeoffs for different 5G use cases. Thus, we propose several algorithms based on reinforcement learning, in particular Q-learning, to derive optimal sleep mode policies in order to balance between energy savings and service delay. Finally, we conclude this thesis while opening new potential research directions in Chapter 6. We note that in Appendix B, we give a background on reinforcement learning, a machine learning tool widely used in decision making for complex problems.

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# Related Research in Energy-Efficient Green Cellular Networks

## 2.1 Introduction

The term *green* in cellular networks is directly related to the share of  $CO_2$  emissions released from operating telecommunication systems from the core to the access network all the way to the user mobile terminal. Since the amount of  $CO_2$  released into the atmosphere is proportional to the operational activities of these systems, green wireless technology also includes economic benefits (i.e., reduce energy costs) and better practical usage (i.e., enhanced battery life in mobile terminals). Thus, the notion of *green* in telecommunication systems can have a more meaningful understanding in evaluating energy savings.

Since their existence, the design philosophy of cellular networks was to maximize the Spectral Efficiency (SE), and to optimize the coverage, capacity and throughput. However, it is clear that such configuration does not necessarily achieve high energy efficiency, thus its energy savings are rather limited. One of the main reasons behind the reduced energy efficiency is that traditional cellular networks are designed to endure peak traffic and extreme conditions. Hence, most of these networks are over dimensioned with redundancy to provide additional capacity and to avoid unexpected events. As a result, during non-peak hours these systems are significantly underutilized, creating the opportunity for potential energy savings. Since the goal of green cellular networks contradicts with tradi-



tional design objectives, a new networking paradigm design is needed to maintain the same service quality of these existing networks while reducing the energy consumption in the future.

In this chapter, we review the state of the art related to cellular networks. We present four different yet complementary approaches towards energy efficient cellular networks. First, we discuss the important energy efficiency techniques and approaches used in 5G networks. They cover cellular architecture, radio resource management and sleep mode techniques. Second, we highlight the importance of integrating Renewable Energy (RE) sources into cellular Base Stations (BSs). We extract from the state of the art related to this area the main features for designing a RE-powered cellular network. Then, we extend the above approaches to include the interaction between these networks and the Smart Grid (SG) architecture. Hence, we discuss the advantages provided by the SG framework and its impact on the network energy efficiency. Finally, we discuss the potentials of artificial intelligence approaches in orchestrating and managing the resources for these increasingly complex, heterogeneous and evolving future networks.

## 2.2 Green Cellular Networks

As a response to the increase in mobile cellular networks energy demand, a lot of research focused on enhancing the energy efficiency of these systems. One of the earliest insights into the potential of existing cellular networks to operate in an energy aware manner dates back to the work in [27]. In this work, the authors proposed a framework to evaluate the potential to save energy and maximize the energy efficiency by exploring three different areas in mobile radio networks: component, link and network levels. They stressed out that higher energy efficiency can be achieved not by optimizing a single aspect or component but by a joint optimization of these different areas. In order to understand the relationship between the different areas in mobile networks on bringing down the energy consumption, the authors in [21] proposed a model for energy-efficient techniques having a stacked structure of layers, where enhancement in the lower layers brings more savings to the upper ones (see Fig. 2.1). These approaches can be classified into the following categories:

- *Component layer*: this layer is considered at the base of the RAN energy efficiency. Work under this layer includes adaptive power amplifier, energy optimized hardware, and adaptive radiation patterns using beamforming. The enhancement at this layer reduce the energy consumption of the BS's components, allows to relax the design constraints and facilitates the operation of the upper layers. However, considering only the component approach is not enough to achieve large-scale savings due to underutilization of resources, which is why the need for upper layers.
- *Environmental learning and information layer*: the next layer includes Cognitive Radio (CR) that optimizes the SE by adapting the radio devices transmission parameters based on sensing external conditions. The idea of (CR) is to intelligently detect holes in the spectrum and dynamically jump into (and out of) them very rapidly by reconfiguring the transmission and reception parameters to match the channel's conditions.
- *RRM layer*: this layer includes mechanisms such as power control, Disconteneous Transmission (DTX), antenna adaptation, and radio resource allocation. In other words, techniques under this layer deals with transmission power control and optimization of transmission resources in time and bandwidth. Under this layer, tradeoffs in spectrum/energy, bandwidth/power and delay/power are studied.
- *Coverage extension techniques layer*: this layer spans HetNets and relays. RRM will be very useful in such networks by allowing cooperation between different tiers of the networks, and hence providing further energy and cost savings.
- *Cell Layout Adaptation (CLA) layer*: finally on the top of the stack, CLA includes cell size shaping such as cell breathing and switching-off techniques. This layer has the potential of saving higher energy compared to the other layers as we will see later.

Following the above energy efficiency framework, there exist different approaches and techniques that can be adopted to improve the energy efficiency of future 5G cellular networks.

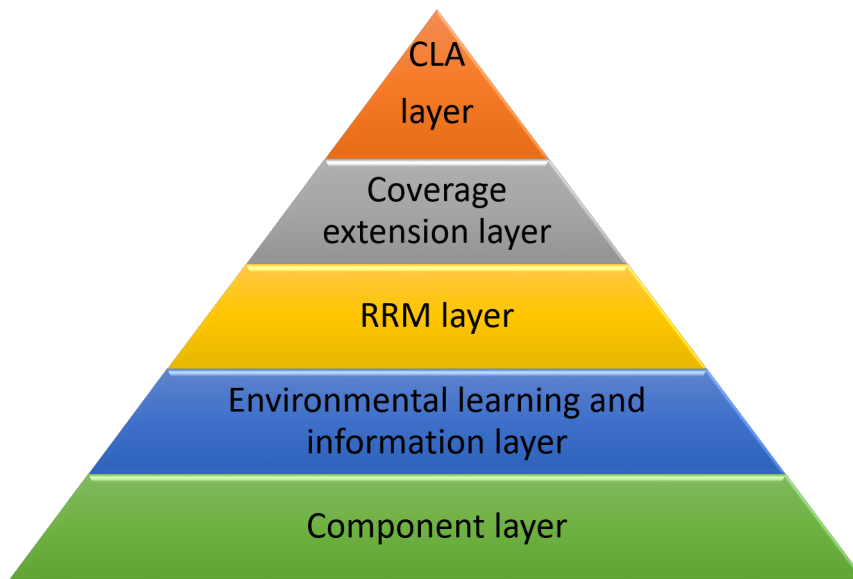


Figure 2.1 – Stacked framework for energy efficiency approaches in cellular networks [21].

### 2.2.1 Energy efficiency techniques for 5G networks

The literature on 5G green networks is huge with a lot of surveys such as [28, 29, 30, 31, 32]. In particular, BS energy saving has gathered significant attention in recent years. In fact, a lot of energy is wasted as a result of traffic load variation at the BS site. According to the power consumption breakdown in Fig. 2.2, the major part of energy demand comes from the BS, consuming more than 50% of the power in a cellular network [33]. In this regard, we start by discussing the different types of BSs and their power consumption models before shedding some light on the different energy efficiency techniques in the literature.

#### Modeling of BS power consumption

5G architecture envisions an ultra-dense deployment of BSs to ensure connectivity and capacity to the enormous traffic. A key solution to embrace such technology is to deploy different types of BSs. According to the literature, there exist several types of BSs: Macro, micro, pico and femto BSs. These cells are characterized by a coverage area, capacity, energy consumption and cost. While macro BSs are distinguished with their high coverage area and capacity, they have a high energy profile (in the order of thousands of watts) that slightly scale with the variations of

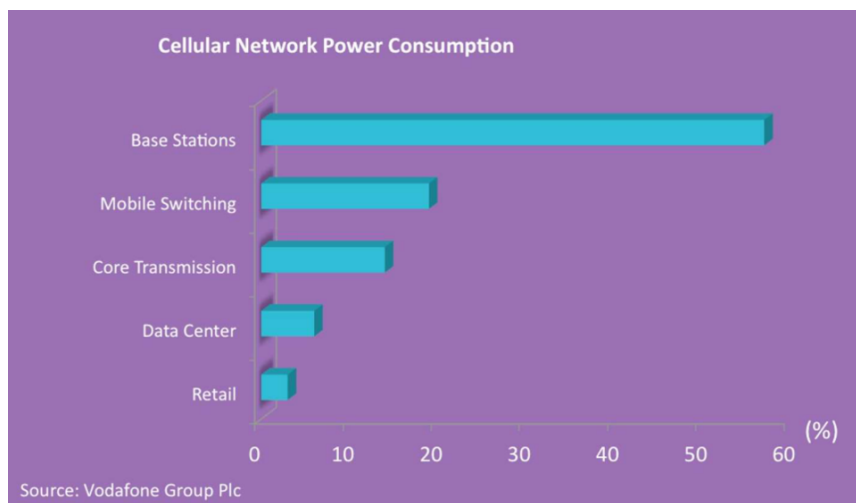


Figure 2.2 – Cellular network power consumption breakdown [33].

traffic. In 5G, these types of BSs will be deployed to provide a baseline connectivity over a large area. On the other hand, smaller cells (micro, femto and pico) have shorter range, lower energy consumption and better adaptation to the traffic variations. These types of cells are deployed as hot-spots inside the macro area to extend the network capacity and improve SE where needed. In Fig. 2.3, we compare between the different types of BSs in terms of their coverage capabilities and energy profiles.

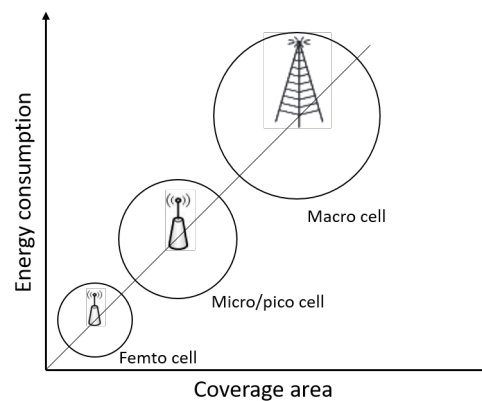


Figure 2.3 – Cell energy consumption vs coverage area [30].

In order to evaluate the energy consumption of the different types of BSs, several power consumption models are proposed in the literature. In [14] and as a part of the Energy Aware Radio and Network Technologies (EARTH) project, a detailed power consumption model for the different types of BSs is provided. The proposed model takes several factors into

account and can be summarized in the following equation:

$$P_{in} = N_{Trx} \cdot \frac{\frac{P_{out}}{\eta_{Pa} \cdot (1 - \theta_{feed})} + P_{RF} + P_{BB}}{(1 - \theta_{DC})(1 - \theta_{Ms})(1 - \theta_{cool})} \quad (2.1)$$

where  $P_{in}$ ,  $P_{out}$ ,  $P_{RF}$  and  $P_{BB}$  are the input, transmission, radio frequency chain and baseband engine powers, respectively.  $N_{Trx}$  is the number of transceivers and  $\eta_{Pa}$  is the efficiency of the amplifier. Finally,  $\theta_{DC}$ ,  $\theta_{Ms}$  and  $\theta_{cool}$  designate the losses incurred due to DC-DC power supply, mains supplies and active cooling, respectively. However, and due to the nearly linear relationship between the RF power and  $P_{out}$ , (2.1) can be approximated as follows:

$$P_{in} = \begin{cases} N_{Trx} \cdot (P_0 + \Delta_p \cdot P_{out}), & 0 < P_{out} \leq P_{max}, \\ N_{Trx} \cdot P_{sleep} & P_{out} = 0. \end{cases} \quad (2.2)$$

where  $P_0$  is the static power consumption at zero load, and  $\Delta_p$  is the slope of the load dependent parameter.  $P_{sleep}$  is the power consumption when the BS switches to sleep mode. In order to evaluate the energy consumption for the different types of BSs, we present in Table 2.1 the power model parameters.

Table 2.1 – Power model parameters for different BS types [14]

BS type	$N_{Trx}$	$P_{max}$ (W)	$P_0$ (W)	$\Delta_p$	$P_{sleep}$ (W)
Macro	6	20	130	4.7	75
RRH	6	20	84	2.8	56
Micro	2	6.3	56	2.6	39
Pico	2	0.13	6.8	4.0	4.3
Femto	2	0.05	4.8	8.0	2.9

Even though the power model in [14] has been widely used, a more recent and advanced model has been developed by GreenTouch in [34] that takes into account a broader range of BS types, features, configurations and technologies that span over the time range of 2010-2020. In order to evaluate the energy consumption, an online power model tool called IMEC is provided in [35]. Using this model, we compare in Fig. 2.4, the energy consumption of a 3 sector macro BS for different years in which the BS is assumed to be deployed (i.e., hardware component technology year).

While the energy consumption is upper bounded by EARTH model [14], GreenTouch illustrates the potential energy savings with future hardware technology year.

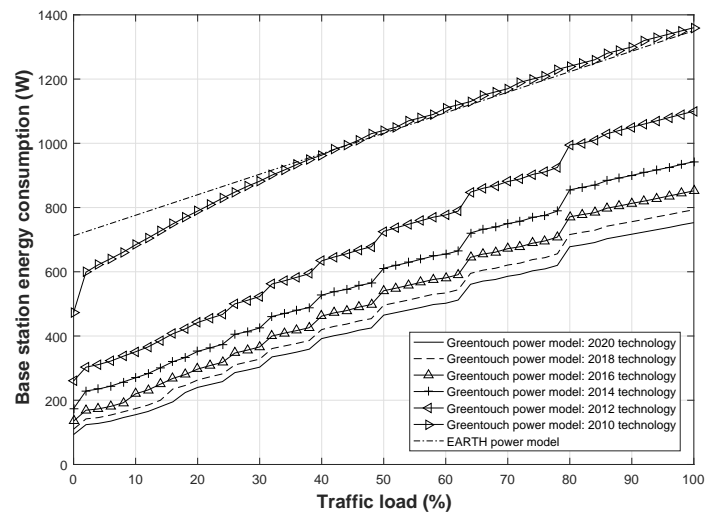


Figure 2.4 – Power consumption of a 4x4 MIMO BS (3 sectors) for different traffic loads. Radiated Power: 46 dBm, Bandwidth: 10 MHz.

In addition, GreenTouch identified four distinct Sleep Modes (SMs) levels by grouping sub-components with similar transition latency when being activated or deactivated. The presented model enables to quantify the power consumption of the BS in each of the four SMs. These are:

- SM 1: it considers the shortest time unit of one OFDM symbol (i.e.  $71\mu s$ ) comprising both deactivation and reactivation times. In this mode only the power amplifier and some processing components are deactivated.
- SM 2: it corresponds to the case of sub-frame or Transmission Time Interval (TTI) (i.e. 1 ms). In this SM, more components enter the sleep state.
- SM 3: it corresponds to the frame unit of 10 ms. Most of the components are deactivated in this mode.
- SM 4: this is the deepest sleep level. Its unit corresponds to the whole radio frame of 1s. It is the standby mode where the BS is out of operation but retains wake-up functionality.

Higher energy savings can be achieved when switching BSs to a deeper SM, since more components will be deactivated. However, this will be associated with longer transition latency which may impact the QoS in the network. In Table 2.2, we present the SMs levels characteristics.

Table 2.2 – BS Sleep Modes Characteristics [34].

<b>Sleep level</b>	<b>Deactivation duration</b>	<b>Minimum sleep duration</b>	<b>Activation duration</b>
SM 1	35.5 $\mu$ s	71 $\mu$ s	35.5 $\mu$ s
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

### Green solutions and technologies for 5G networks

BS ON-OFF switching is considered among the best methods to save energy since it does not require changes to current network architecture, and it is easy to implement. This well known method initially proposed in IEEE 802.11b [36] has attracted a lot of attention on the research community. Approaches under this category aim at turning off some resources in the cellular radio architecture, when the traffic is low and in some cases when it is delay-tolerant. We distinguish between two types of sleep schemes: Binary SM (On and Off) and multi-level SM. In binary SM, the BS shuts down completely when the traffic load is low to save energy. The literature around binary SM is rich with many existing surveys [28, 37, 38, 39]. For example, the authors in [40] studied energy savings problem by switching-off macro BSs under converge constraints using stochastic geometry. Their results achieved an energy efficiency gain of around 60% compared to the case where all the BSs are active. In [41], the authors opted to maximize the energy efficiency of a HetNet by deriving the optimal BS On-Off policy and user association subject to throughput performance. In this regard, the authors proposed a centralized solution that finds the optimal policy using linear programming. Then, a distributed scheme based on user bidding approach is proposed that converges to a Nash equilibrium optimal solution. In [42], the authors studied the energy-delay-tradeoff problem in a BS sleeping scenario, since shutting-off a BS can bring extra user-perceived delay. Thus, answering to

the question: "how much energy can be saved by trading off a certain amount of delay". In order to avoid frequent BS mode-changing operations, a hysteresis time parameter is considered where the BS waits some time before switching to sleep if there are no service requests. The authors in [43] applied dynamic programming to find the optimal BS ON-OFF policy given the on-grid energy price in order to minimize the on-grid energy cost purchased by the operator while assuring the downlink transmission quality at the same time.

In contrast to binary BS models (active and sleep), recent models have split the SMs state into several levels [44, 45, 46, 47]. Considering that a BS can switch different SM levels gives it more flexibility to adjust with the type and pattern of traffic, hence enhancing the system performance. In [44], the energy efficiency of a HetNet is studied by switching small cells to different SM levels while preserving the QoS. Using stochastic geometry, the authors determined the optimal operating probability for each SM level of each BS. In [45, 46, 47], the authors proposed to reduce the energy consumption of a cellular network by gradually deactivating the components of the BS following GreenTouch model in [16]. A concept that is known in [46, 47] as Advanced Sleep Mode (ASM). This model is suitable for service applications that require stringent delay requirements, since the activation/deactivation times from the different sleep mode levels are in the scale of milliseconds (e.g., SM1, SM2 and SM3 in Table 2.2). In Chapter 5 of this thesis, we study multi-level SMs on the network performance. In contrast to existing work, we focus on the model provided by GreenTouch [16] that is compliant with 5G requirements on the periodicity of synchronization signals that are required to be transmitted periodically.

Cell DTX is another type of SM that was introduced in 4G networks standards (LTE Rel-8) including Long Term Evolution (LTE), Long Term Evolution Advanced (LTE-A) and WiMAX to reduce the energy consumption of BSs [48]. Unlike long term sleep schemes that are designed to switch off the cell completely during low traffic periods, cell DTX switches off transceivers when there are no data to transmit or receive, thus ensuring fast cell activation upon request. In this regard, a BS switches off for a very short time (millisecond scale). We note here that this is equivalent to SM 1 previously discussed. The energy saving potential of cell DTX has been thoroughly discussed in the literature [48, 49]. In contrast to WCDMA where the cell needs to continuously transmit a control and pilot channels, LTE Rel-8 provides 6 subframes that can be used for Multicast



Broadcast Single Frequency Network (MBSFN) during which the BS can be switched to sleep mode. In [48], the authors evaluated the energy savings in the MBSFN sub-frames of an LTE radio downlink frame and showed that it is possible to significantly reduce the energy consumption of the BS by 89% using DTX. In a similar study in [50], the authors obtained up to 90% energy reduction at low traffic by optimally selecting the number of active subframes in each LTE frame in a cellular network.

Besides cell layout adaptation techniques, transmit power adaptation (power control) has been extensively studied in the literature as one of the most prominent power saving technique under the RRM layer. This is because power control helps mitigating the interference in addition to reducing the power consumption [51, 52, 53]. However, this technique is considered risky for the operators to apply, because it may result in coverage holes that may reduce the QoS for the users. Multiantenna systems (MIMO) are yet another energy-efficient technique under RRM layer. Cui *et al.* were the first to analyze the energy efficiency in MIMO systems [52]. They showed that the optimal number of transmit antennas used for MIMO transmission that maximizes the energy efficiency depends on the Signal-to-Noise-Ratio (SNR). Spatial-domain sleep modes for MIMO systems was studied by Bougard *et al.* [54] who introduced the idea of smart MIMO for improving the energy efficiency according to the channel conditions by adapting the transmission mode packet-per-packet among space-division multiplexing (SDM), space-time coding (STC) and switching off individual antenna ports. In [55], the authors established an antenna adaptation technique as a MIMO resource allocation problem to adapt the number of transmit antenna, switching between MIMO and SIMO in an uplink system is considered to save energy.

The combination of several energy saving techniques has also been studied. For instance, [56] proposed to minimize the BS power demand by optimizing the tradeoff between antenna adaptation, power control and DTX. Similarly, [57, 58, 59] considered minimizing the energy consumption of a macro cell using power control and DTX in a flat-fading channel. The problem is to find the time during which the BS has to be switched to sleep and to allocate power when the BS is active to minimize its energy consumption. They demonstrated that power control is more significant for larger BSs (macro and micro) than small cells (pico and femto). In [59], the authors computed the energy savings from cell DTX to be around 40%.

### 2.2.2 What is green: metrics to evaluate greenness

As energy efficiency has emerged to become a key performance metric for future 5G networks, several metrics have been used to evaluate the efficiency of these networks. Given the various proposals to improve the energy efficiency, a framework is essential to assess the performance and compare different schemes. In [60], the authors categorized the energy efficiency metrics into three levels: facility, equipment and network level metrics. For all the levels, the metrics are defined in a distinct matter. In fact, the various metrics reveal that energy efficiency is a subjective concept that depends on the point of view and perspective on how to assess the network. In the following, we classify the energy efficiency metrics into three categories. Then we summarize them in Fig 2.5.

#### Classical energy efficiency metrics

In its classical form, the energy efficiency is the ratio between the total amount of information transmitted to the total power consumption (Bit-per-Joule). Due to its simplicity, this metric has been widely used in the literature [61, 62, 63]. With the emergence of 5G technologies, several variant metrics have emerged. We differentiate between single and network link communications. With single link communication, the energy efficiency metric is represented by the ratio between the energy cost and the benefit produced after sustaining this cost as shown in (2.3). Several benefit functions have been employed in the literature, such as system capacity (achievable rate), throughput and outage capacity.

$$EE = \frac{\text{benefit}}{\text{energy consumption}} \text{ [bits/Joule]} \quad (2.3)$$

In a network link communication, the expression becomes more involved. Depending on the benefits and costs, two approaches can be distinguished [31]:

- **Network benefit-cost ratio.** This metric is called Global Energy Efficiency (GEE), and it is defined as the ratio between the sum of all individual benefits of the different links and the total power consumed in the network. A considerable amount of work focused on maximizing this metric [64, 65, 66, 67, 68, 69, 70, 71].

- **Multi-objective approach.** Since GEE does not allow tuning of individual energy efficiencies of different network nodes, an alternative method is to consider each individual node's energy efficiency as a different objective to maximize. This leads to maximizing a combination of different individual node's energy efficiencies according to some increasing function. Different combining functions have been addressed: Weighted Sum Energy Efficiency (WSEE) ([69, 72, 73]), Weighted Product Energy Efficiency (WPEE) ([69, 74]) and Weighted Minimum Energy Efficiency (WMEE) ([71, 75]).

### Energy efficiency metrics on BS sleep mode techniques

Similar to the previous classical metrics, evaluating energy efficiency metrics for sleep mode techniques can be done on two levels: component and system levels.

- **Component or node level.** Metrics at this level assess the energy efficiency of the site (e.g., BS). A rough approximation to estimate savings from sleep mode techniques is to consider the ratio of the fraction of time the BS spends in sleep mode to a fixed period of time ( $T_{sleep}/T_{total}$ ). This metric has been used in various studies, such as [76, 77]. Another metric is the Energy Consumption Index (ECI). It is evaluated as the ratio between the site energy consumption (e.g., BS) over a KPI that could be either coverage area or throughput ( $ECI = p_{site}/KPI$ ). Here  $p_{site}$  takes into account the energy savings due to sleep mode. Some examples in evaluating this metric can be found in [78, 79].
- **System level.** At this level, the energy efficiency is measured as the average power consumption per user or unit area. Several metrics are proposed at this level. For instance, European Telecommunications Standards Institute (ETSI) proposed a performance indicator (PI) for rural and urban areas. The former consider the average power consumption per coverage area, while the later measures the average power consumption per user [80]. Similarly, an Area Power Consumption (APC) metric is considered in [78] that measures the power consumption in a designated area covered either by a single BS or a whole network. Another metric that takes into account the power consumption and requested capacity is proposed also in [78]. Con-

sidering HetNets, metrics such as Energy Consumption Gain (ECG) and Area Green Efficiency (AGE) are proposed in [81, 82], respectively. These metrics take into account the aggregated energy savings from switching different tiers of BSs to sleep mode. Taking the cost of carbon footprint has been also considered in evaluating energy efficiency metrics. In particular, [83] proposed an Absolute Energy Efficiency (AEE) metric that takes into account the absolute temperature that is directly related to carbon emission.

For a complete and detailed overview on the green metrics for BS sleep mode techniques, the reader can refer to the survey in [37].

### **Energy efficiency metrics on BS service categories**

The green metrics proposed above address a large diversity of ICT sectors from single link to network levels. However, they focus solely on the hardware and infrastructure of the networks. Currently, around 80% of the mobile traffic is generated by service providers (e.g., Google, Apple, Facebook and Amazon). Hence, energy efficiency metrics should take into account not only the hardware part, but also the service delivered by the hardware.

One of the earliest work investigating energy efficiency metrics of ICT services was in [84]. The metric evaluated the energy consumption per unit of service (KWh/hour/user). In [85], the authors developed a model to determine the energy consumed per bit on a device. Preist *et al.* [86] proposed a statistical model to evaluate the overall energy consumption needed for a digital service. Taking both fixed and variable energy components of a BS, the authors in [87] proposed a model to share the energy responsibility between different service categories. Since the variable part is load dependent, its energy share is proportional to the traffic. However, in order to strike a fair sharing for the fixed part (not load dependent), the fixed energy is divided among the services based on Shapley Value, a cooperative game-theoretic concept. With such model, and based on the "RUN" KPI provided by ETSI [88], the authors evaluated the energy efficiency of each service a mobile BS is providing. In Chapter 3 of this thesis, we evaluate this KPI to measure the performance of the network at the service level. We then extend this metric to include the energy consumed from RE sources.

Most of the energy efficiency metrics presented above can be used together with each others. However, a conflict may arise in some cases between different metrics because they are not consistent all the time. For example, an energy gain in one site or BS can result in an energy loss in another neighboring site. This can happen when a BS switches to sleep mode to save energy but its users offload to another cell, thus increasing its energy consumption. Thus, and in order to measure these metrics in a meaningful way, a minimum requirement on QoS should be taken into account, such as coverage probability, blocking probability and minimum rate requirement.

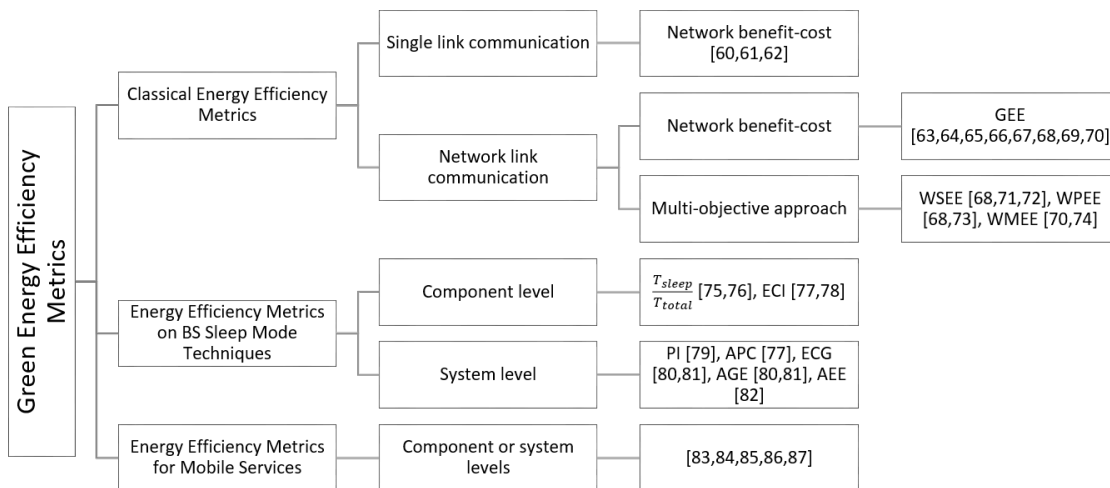


Figure 2.5 – Energy efficiency metrics.

## 2.3 Cellular networks powered by renewable energy sources

Besides the different energy-efficient techniques discussed above on green wireless communications (CLA, RRM, cognitive radio and hardware enhancement), providing energy harvesting capabilities to cellular BSs has been widely accepted as a promising avenue to optimize the energy efficiency, lower energy consumption and reduce the carbon footprints and OpEx for mobile operators. In this regard, a lot of attention has been drawn from academia and industry promoting the use of RE

in the functioning of the cellular network infrastructure. In its technical report [89] and technical specification [90], 3rd Generation Partnership Project (3GPP) explicitly supports the use of RE in mobile cellular networks. Companies, such as Ericsson and Alcatel-Lucent, have started to scavenge RE resources for rural areas with limited grid connectivity. Real worldwide implementation and deployment of solar panels to power BSs have reached 43,000 sites in 2014, and this number is expected to grow up to 390,000 by year 2020 [23]. Despite these motivations and insights, this domain is still widely open to further exploration and development.

Using RE in wireless cellular networks does not only reduce the amount of energy bought from the grid, but also introduces the concept of energy sustainability, in particular for off-grid networks that do not have access to the power grid. To this end, several aspects should be taken into consideration when designing a RE-powered mobile network: cellular network architecture and planning that includes the type of BSs and how they are deployed; RE harvesting models that play a critical role in the design of energy management control to efficiently utilize the harvested energy; Dimensioning of RE systems (including the harvester and the storage elements) that is critical for energy sustainability, service continuity and feasibility constraints.

In the following, we discuss the above mentioned aspects before presenting the literature on RE-aware green cellular networks.

### **2.3.1 Cellular network architecture and planning**

Adopting RE to power BSs requires initial investment cost, thus careful planning of cellular networks is desired to minimize the Capital Expenditure (CapEx) of these systems. In contrast to static loads that require a fixed amount of energy to guarantee a certain level of performance, in mobile networks the power consumption of a BS can be adapted according to the availability of green energy while satisfying the QoS. This can be achieved by Radio Resource Management (RRM) optimization and offloading users to neighboring cells when the users are covered by multiple BSs. Therefore, by optimizing the transmission strategies and layout of cellular BSs, significant minimization of green energy harvesters size can be attained.

In [91], the authors investigated energy sharing techniques for RE-powered BSs to reduce the size of RE systems. They distinguished between two mechanisms: direct energy transfer and non-direct energy transfer. While the former is obtained through wired or wireless sharing of energy between different BSs, the later includes traffic offloading and transmission cooperation. On the other hand, 5G cellular networks envision dense deployment of BSs with small coverage areas per cell. In this regard, it is possible to apply non-direct energy transfer. For example, in [92], the authors introduced Coverage Supply Redundancy Architecture (CSRA) for off-grid wireless cellular BSs solely powered by RE sources. In order to reduce the service outage probability, the BSs are deployed closer to each others than the usual planning. In this way, the transmission power of the BSs can be varied based on the energy availability without degrading the QoS. Due to coverage redundancy, a user for instance has the option to connect to several BSs to maintain connectivity.

With the rise of 5G, HetNets gained a lot of attention as a promising architecture to boost the network capacity. It defines a multi-tier wireless network composed of several types of BSs using the same access technology and spectrum. Under this architecture, small cells powered by RE or power grid are deployed inside the area of grid-powered macro BSs. These cells are placed such that they overlap with each others to provide hotspots in certain areas of the macro cell. On one hand, this architecture enhances the SE of the network. On the other hand, it enjoys the benefits of a fully grid-powered network with the potential to save grid energy, and provides connectivity in areas where there is no power grid. An example of such architecture is adopted in [93], where small BSs are solely powered by RE sources. In order to deal with energy shortage, these cells can switch to sleep mode, while the users get offloaded to the macro BS. Another similar example can be found in [94] where small cells enjoy hybrid energy sources (RE and grid). In order to save energy, the authors relied on non-direct energy transfer between small cells through energy cooperation. A RRM policy is applied based on power control to maximize the RE utilization.

Another architecture in RE systems is to consider a RE power farm where the energy harvesting sources and batteries are centralized. The advantage of this approach is that it leads to a more efficient use of the space, it makes the cooperation of excess RE between BSs easier and it al-

leviates the deployment of larger RE generators, which are more efficient. Work under this architecture can be found in [43].

### **2.3.2 Dimensioning and deployment of renewable energy**

Sizing of RE systems is a critical task when designing a green cellular network. It involves a tradeoff between feasibility, energy sustainability and service continuity. We distinguish between two architectures when designing RE-powered cellular networks: stand-alone cellular BSs that are solely powered by RE sources and hybrid-powered BSs from power grid and RE.

In stand alone cellular BSs, the objective is to minimize the BS service power while maintaining a certain outage probability. Therefore, the sizing of PV cells (in the case of solar RE) and energy storage (battery) should be carefully chosen. It is clear that bigger RE sources and storages lead to higher sustainability and power grid independency; however they result in higher CapEx, and in some cases infeasibility due to area constraints. Hence, a tradeoff should be made to find the optimal size of RE systems. In [95], the authors developed a framework to evaluate the outage probability as a function of the PV cell and battery sizes. Based on multi-state Markov model for the RE resource, the authors derived the optimal combination of PV panel/battery sizes subject to outage probability constraint. A methodology is proposed in [96] for dimensioning the size of RE system to power a stand alone BS. Different than most studies that assume RE prediction based on Typical Meteorological Year (TMY) data for solar radiation, the authors employ the use of more advanced and higher accuracy model based on Series of Worst Months (SWM). The methodology starts by first obtaining the outage probability for a given sizing of PV cell and batteries. Then, a cost optimization is derived from the PV panel and battery size depending on the outage probability limit. A two-state Markov model is proposed in [97] to determine the optimal battery size of a stand alone BS in order to decrease the number of insufficient supply days to a predefined level. Another Markov model is designed but for the solar radiation in [98] in order to derive the best sizing of the needed storage. In [99], the authors applied stochastic queue theory to model the RE arrival, battery storage state and BS energy consumption. The goal is to design



a reliable and economical RE-powered system that guarantees service reliability, system durability at a low CapEx. Under these guidelines, an optimal sizing problem is formulated to minimize the CapEx. The problem proved to be NP-hard and the solution was found using adaptive genetic algorithm. In [100], the authors addressed the problem of RE sizing by proposing an analytical framework to evaluate the outage probability of a BS solely powered by RE. A time-discrete Markov process is adopted to model the battery charge level. Then, the model is used to determine the relationship between PV cell size, battery size, RE profile and traffic load on the outage probability.

Under the same architecture of stand alone BSs, other work studied the sizing problem including energy efficiency techniques such as switching BSs to sleep [101, 102]. In [101], the authors studied the impact of different sleep schemes (partial and deep sleep) on the dimensioning of RE. While partial sleep brings 10% additional energy savings, deep sleep saves up to 40% energy. This has the potential to significantly reduce the sizing of RE to almost half. Similarly, in [102], and in order to overcome the challenge of large sizes RE sources, sleep mode technique is used to reduce the energy consumption of the cellular network. In particular, An intelligent energy management controller adapts the BS service as a function of the stored energy.

RE sizing under hybrid-powered architecture has also been investigated in the literature [103, 104, 105, 106, 107, 108]. These studies show that powering a BS from the grid and RE allows significant cost and size reduction compared to the case of stand alone BS (i.e., solely powered by RE). The authors in [103] considered cell sizing problem for both on-grid and off-grid green small cell taking into account battery aging mechanisms. In [104], the authors proposed a dimensioning methodology for a hybrid-powered LTE macro BS over a period of 10 years that goes as follows: 1) identify the daily traffic profile for the BS for the different days of the week. Then, apply a scale factor to the traffic profiles to account for the growth in traffic over 10 years, 2) based on the traffic profiles, the BS daily energy consumption is computed. From that, the BS energy profile is modeled over one week then extended to the whole year, 3) for each year, a possible PV size and batteries are dimensioned based on the daily solar energy profile and the BS power consumption, such that the batteries do not fall below a certain storage limit for a predefined percentage of time, 4) from the different obtained solutions, the battery cumulative

depth of discharge is computed over one year to derive its lifespan, 5) for all solutions, the cost is computed from the initial CapEx and OpEx, 6) finally, the sizing that leads to the minimum cost over 10-year period is considered.

In order to adapt to energy availability, resource on demand strategies are applied to a cluster of BSs powered by both power grid and RE with the possibility to switch to sleep mode [105, 106]. Under different combinations of PV panel and batteries, the authors studied the tradeoff between feasibility constraints, cost expenditures, self-sustainability and battery depletion probability. An interesting outcome of their results pointed that relaxing self-sustainability by 1% point reduces RE size by 41.3%. [107] extended the previous work to include WiFi offloading techniques, and their impact on system dimensioning. The impact of load balancing on dimensioning of RE has also been investigated in [108]. The presented work aims at minimizing the CapEx while satisfying constraints on QoS.

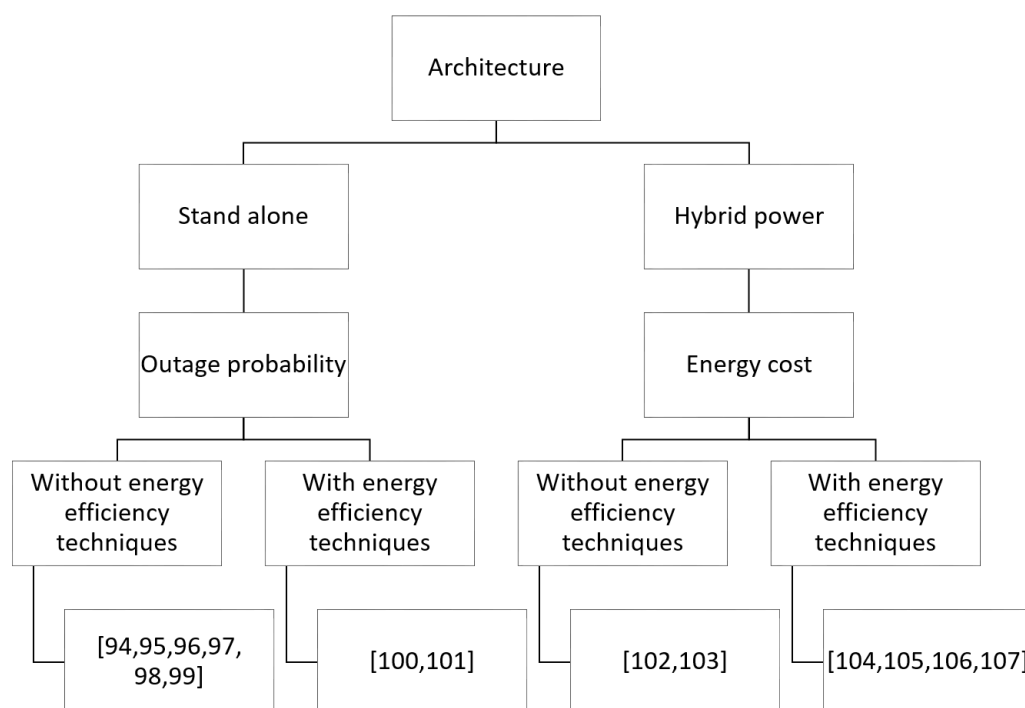


Figure 2.6 – Classification of RE dimensioning approaches.

### 2.3.3 Energy harvesting models

A proper RE system dimensioning strictly relies upon an adequate characterization of RE production. In [109], the authors classified various en-

ergy harvesting models. They distinguished between deterministic and stochastic models.

1) *Deterministic Models*: these models assume full knowledge of energy arrivals and amount in advance (i.e., non-causal information) [110, 111, 112]. They are based on data-sets of real measurements in a given geographical location. On one hand, non-causal energy state information models have the advantage of providing an optimal energy scheduling that can be used to give insight into suboptimal energy scheduling algorithms, and to benchmark fundamental limits on the performance of RE systems. On the other hand, this requires an accurate prediction of RE profile over a long time horizon, which can be time consuming and requires huge data-sets to present accurately the energy harvesting profile.

2) *Stochastic Models*: in stochastic models, RE generation is modeled as a random process. Although these models result in a high computational complexity, they are more efficient than deterministic models. They do not require knowledge of the energy harvesting profile, thus they are suitable for applications when it is hard to predict the behavior of RE. The first family belonging to stochastic models do not capture the correlation in time of the harvested energy from RE sources. It is referred to time-uncorrelated models. Several models exist under this category. For example, in [113, 114, 115, 116], the energy harvesting process is described as a Bernoulli process with a fixed harvesting rate. Other models include uniform process [117], Poisson process [118, 119] and exponential process [120].

The above mentioned models are simple and easy to generate; however, they neglect the temporal correlation properties that exist in most RE sources. Time-correlated models include first-order Markov model, Poisson counting process and non-negative uniform process, two-state Markov model, on-off model and generalized Markov model. For example, in [121] the authors modeled the arrival of energy packets as a first-order Markov chain. In [111], the authors assumed the stochastic process of energy arrivals as a Poisson counting process, while the amount of harvested energy is modeled as a non-negative uniform random variable. Two-state energy harvesting model is used to mimic the time-correlation behavior of some energy sources that can be represented by two states "On" or "Off" [122, 123], or as with weather states of solar harvesting "shaded/cloudy" and "clear" [124, 125, 126, 127, 128]. Other studies consider more than

two states, a model that is known generalized Markov model such as the work in [129, 130].

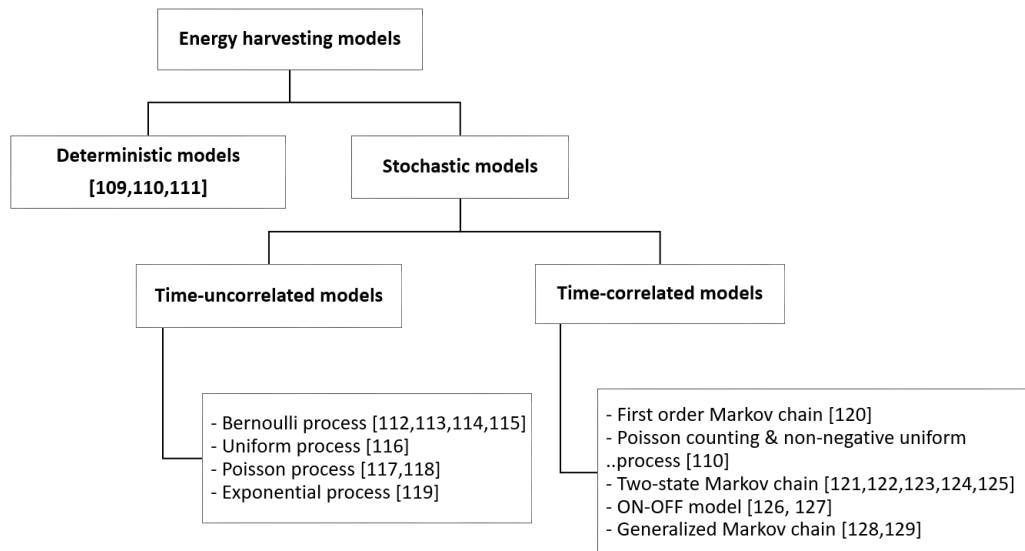


Figure 2.7 – Classification of RE harvesting models [109].

### 2.3.4 Algorithms and approaches for renewable energy-aware cellular networks

One of the earliest insights on intelligent RE management systems can be found in [102]. Based on weather forecast and BS power consumption, the authors proposed a heuristic algorithm, based on the energy stored in the battery that adapts the BS service (i.e., transmission power) to maximize the utilization of RE and to minimize the service outage. At the network level, the energy outage problem has been studied in [131], where BSs are either powered by hybrid energy sources or only by RE. In order to avoid energy depletion, BS sleep is used not only to reduce energy consumption, but also to store harvested energy for future use. The optimal BS sleep policy is found using dynamic programming. Then a suboptimal greedy algorithm is designed to overcome the high complexity of the offline policy.

In heterogeneous network architectures, the problem of jointly maximizing the number of served users and minimizing the radio resource

consumption in a two-tier cellular network powered solely with RE is studied in [132]. To address this problem, adaptive user association based on the availability of RE is proposed. The authors formulated an offline algorithm that is solved based on gradient descent method, then a heuristic policy is proposed that encourages users to be associated with low power cells since larger ones have higher chance to become early capacity bottleneck. In [133, 134], the authors derived the fundamental limit on the BSs availability in a  $k$ -tier network powered only by RE sources. A BS is considered available when it has enough RE to stay active. Using tools from random walk theory and stochastic geometry, the authors derived the fraction of time a BS can stay active independently of the others. Using tools from stochastic geometry, the authors in [135] studied the call completion problem in a two-tier HetNet, where all the BSs are solely powered by RE. Given that a BS can switch off to recharge its battery, users can offload to neighboring cells which might have an impact on the network performance. In this regard, the authors derived the upper and lower bounds on the call completion probability and its impact on the system parameters. Their results revealed that macro BSs have the dominant impact on the call completion probability.

While the above literature focuses on BSs solely powered by RE sources, hybrid-powered BSs have been extensively studied. For example, [136, 137] studied the problem of grid energy minimization for a single BS powered by the power grid and RE. In [136], the authors proposed a heuristic energy management policy that decides when to use the harvested energy and when to store it in the battery taking into account the energy storage level and the price of electricity. In [137], the authors considered mixed traffic types with different requirements to study the tradeoff between users' satisfaction and energy savings.

In large-scale hybrid-powered networks, the authors in [138] studied the problem of the electric bill reduction of a cellular network powered by power grid and RE in a variable electricity price environment. In order to maximize the utilization of RE, the authors considered RE allocation and energy consumption minimization by switching off BSs and RRM techniques. Due to the complexity of the problem (NP-hard), a heuristic suboptimal algorithm was proposed to adjust the network configuration in order to better use the harvested energy. In a similar architecture, minimizing the on-grid energy cost in a large-scale cellular network is proposed in [43]. However, using stochastic geometry and dynamic programming,

the authors succeeded in obtaining the optimal BS On/Off policy that minimizes the grid energy cost while respecting the QoS of the users. Then, a suboptimal algorithm was proposed to alleviate the high complexity of dynamic programming.

The tradeoff between energy savings and QoS in HetNets powered by both grid power and RE has been studied in [139, 140]. In [139], the authors considered optimal user association to reduce the on-grid power consumption, while respecting the traffic delivery latency. In this regard, a user association algorithm is proposed that takes into account the BS traffic load and harvested energy in order to make user association decisions. In [140], the authors extended the previous work to include BS power control as well. Since the problem of power control is non-convex, a greedy heuristic algorithm is proposed to achieve power control operations. First, the power control vector for the BSs is determined, then the optimal user association policy is reached iteratively through the broadcast of a coalition factor calculated based on the traffic load and available green energy budget.

The concept of energy sharing between BSs powered by hybrid sources has been investigated in [141, 94, 142]. In [141], the authors opted to optimize the energy savings for a cellular network powered by both power grid and RE where the BSs are connected by resistive power lines to share energy. When the RE and BS energy consumption profiles are deterministic for all sites of the network, the authors demonstrated that optimal energy sharing policy can be found using linear programming. On the other hand, when the profiles are stochastic, an online greedy algorithm is proposed. Efficient resource allocation in a two-tier wireless network is studied in [94] where small cells share their harvested energy through the infrastructure of the power grid. By analyzing the theoretical gain of the proposed model, additional gain was brought from energy cooperation. In [142], the authors tackled the problem of the distributed randomness in RE generation to supply the time-varying mobile traffic by reshaping the spatial RE and traffic by means of energy sharing and load balancing. Under a grid aggregator architecture, BSs are able to inject/draw energy to/from the grid with the objective to minimize the grid energy consumption. To this end, a mixed-integer nonlinear programming is formulated that is proved to be NP-hard. Thus, a centralized and distributed sub-optimal algorithms are proposed to balance the profile of the harvested

energy with the traffic load to reduce the grid energy expenditure of the whole network.

In Table 2.3, we summarize the work done in RE-powered cellular networks according to the different architectures.

## 2.4 Smart Grid-aware cellular networks

So far, we have presented the gravity of energy efficiency in the context of cellular networks in reducing the network energy consumption (Section 2.2). Then, we highlighted the benefits of using RE sources in lowering the energy footprint and bringing higher energy savings, thus further enhancing the energy efficiency metric (Section 2.3). As a result, a new concept evolved known as energy sustainability that focuses on the utilization of RE. On the other hand, the SG is emerging allowing a bidirectional communication and energy flow between its components. This enables RE powered BSs to sell, share and better utilize the harvested energy. Consequently, a new paradigm is unfolding that takes into account, in addition to energy consumption and RE utilization, the interaction with the SG. Fig. 2.8 illustrates the evolution of energy management concepts under the architecture of cellular networks [143].

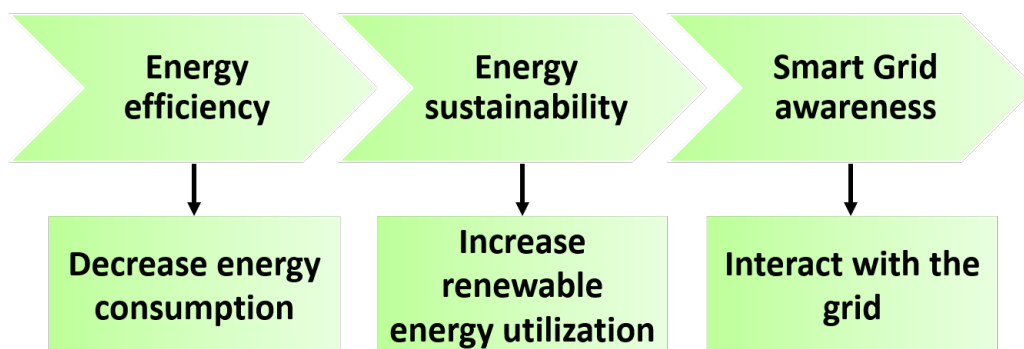


Figure 2.8 – Evolution of energy management concepts [143].

Table 2.3 – Classifications of the different approaches in RE-aware cellular networks.

<b>Ref</b>	<b>Architecture</b>	<b>Contributions</b>
[102]	Single BS solely powered by RE	Heuristic algorithm that adapts the BS transmission power to maximize the utilization of RE and minimize the service outage
[131]	Homogeneous network partially powered by RE alone	Optimal BS sleep policy to reduce energy consumption and service outage
[132, 133, 134, 135]	HetNet solely powered by RE sources	<ul style="list-style-type: none"> <li>- Offline algorithm that max the number of served users, while min the consumed radio resources [132]</li> <li>- Fundamental limits on BS availability with BS On/Off [133, 134]</li> <li>- Derivation of upper and lower bounds for call completion probability [135]</li> </ul>
[136]	Single BS powered by RE and power grid	Heuristic algorithm that manages the utilization of RE based on the traffic load and price of electricity
[137]	<ul style="list-style-type: none"> <li>- Single BS powered by RE and power grid</li> <li>- Mixed traffic type</li> </ul>	Study the tradeoff between users' satisfaction and energy savings
[138, 43]	Homogeneous network powered by RE and power grid	<ul style="list-style-type: none"> <li>- Heuristic algorithm that adjusts the network configuration to minimize the grid energy cost [138]</li> <li>- Optimal and heuristic On/Off policies to minimize grid energy cost [43]</li> </ul>
[139, 140]	HetNet network powered by RE and power grid	Study the tradeoff between energy savings and service latency
		- Optimize energy savings for deterministic and stochastic RE and BS power profiles



### 2.4.1 The Smart Grid - SG

In contrast to traditional power grid that allows only one-way energy flow (from centralized generators to electricity consumers), the SG [144] makes it possible, through advanced metering infrastructure, to have a bi-directional flow of energy and information between grid and consumers. The SG is thus considered an evolution of the 20th century classical power grid with the aim of improving in an automated fashion the efficiency, reliability, economics and sustainability of the production and distribution of electricity. In Table 2.4, we give a short comparison between existing power grid and the smart grid

Table 2.4 – A short comparison between traditional power grid and the smart grid [145, 144]

<b>Power Grid</b>	<b>Smart Grid</b>
Electromechanical	Digital
One-way communication	Two-way communication
Centralized generation	Distributed generation
Few sensors	Sensors throughout
Manual monitoring	Self-monitoring
Manual restoration	Self-healing
Failures and blackouts	Adaptive and islanding
Limited control	Pervasive control
Few customer choices	Many customer choices

In the SG framework, passive users become dynamic entities that can participate and interact with the power grid almost in real time, by means of a bidirectional communication channel. This creates a new entity known as "prosumers". A prosumer is a combination of a typical energy consumer and an energy provider (for example, by means of RE generation). This entity plays a critical role in improving the efficiency, economics and sustainability of the power grid, such as decreasing the high peak hour demand and flattening the energy consumption by spreading it across the different hours of the day, thus reducing the overall plant and capital cost requirements. In order to adapt the energy demand to the supply, several Demand-Side Management (DSM) approaches exist to guide consumers to use less energy during peak-hour demand, or shifting their con-

sumption to off-peak periods, such as real-time pricing and Demand Response (DR) programs.

*Smart pricing* is known as one of the most common techniques to combat peaks in power usage, and thus redistribute or shift the electrical consumption over a certain period of time. In an electricity market, retailers procure electricity from various electricity sources (e.g., pool, electricity derivatives and self-production units). Then, they sell it to the users. There exist various pricing models under the SG architecture: Real-Time Pricing (RTP), Day-Ahead Pricing (DAP), Time-Of-Use Pricing (TOUP) and Critical-Peak Pricing (CPP) [146]. RTP is considered to be one of the most popular techniques for time-based tariff. It is based on sending the electricity prices periodically to the users in a real-time fashion. This approach helps in flattening the energy demand profile, by imposing for instance high energy costs during peak hours and low prices during low consumption periods. Thus, encouraging consumers to shift their energy consumption activities toward low prices cycles. With the advance of communication technology, RTP is expected to dominate the market (particularly the industrial one) due to its advantages in reducing the CO<sub>2</sub> footprint, load balancing and Peak-to-Average Ratio (PAR).

Besides RTP that allows consumers to passively respond to the grid signaling (e.g., MNOs), active participation in the energy market and responding to the grid's specific demands can bring more reduction in the electric bill to the end user. For example, the SG operator may ask its consumers to reduce their energy consumption during peak-hour periods and increase the grid consumption when excess energy is available and demand is low. In return, the SG arranges monetary incentives. These types of services that the users provide to the grid are known as ancillary services [147]. The aim of these services is to reduce the imbalance between the SG supply and demand. By satisfying the grid requests to decrease or increase the energy consumption, the end user receives some reward, resulting in an increase of the profit.

### **2.4.2 The integration of the Smart Grid with cellular networks**

When a wireless cellular network is powered by the SG, only considering energy efficiency in the cellular network may not be enough. In fact, under

the SG environment, consuming more energy can bring more benefits to the consumer than consuming less energy in some cases. This is related to the fact that large amount of RE are expected to be integrated in the SG, and these sources are highly intermittent in nature [148].

Al Haj Hassan *et al.* [143] proposed an integration architecture for RE-powered cellular networks and the SG. They identified five key points that enable cooperation between the two entities: specificity, compatibility, versatility, flexibility and eligibility. In this regard, the SG should recognize the BSs as a special prosumers through special embedded algorithms in the SG management system. On the other hand, logical and physical elements should be added to the mobile network to allow proper interaction between the cellular network and the SG.

The problem of minimizing the electric bill of the MNO powered by RE and the SG has been studied in the literature. The authors in [149] proposed an energy management strategy based on stochastic programming to minimize the electric cost of the operator powered by the SG, RE and batteries, under RTP. In [150], an optimal offline energy management strategy was proposed with a two-way flow of energy. This allows energy to be sold back to the grid. The policy however requires full knowledge of both RE generation and BS power consumption. In order to overcome information non-causality, the previous work was extended in [151] to consider only causal information. By knowing ahead of time the hourly-varying price of electricity, the authors proposed several online algorithms to reduce the billing cost of the operator. Similarly, in [136] the authors proposed an online heuristic algorithm that takes into account the price of electricity and the battery level of charge to take decision either to use the harvested energy or store it in the battery.

While the above mentioned work consider only one BS, other studies focused on multi-BSs cellular networks under RTP environment. For example, [152, 138] proposed an online cost minimization algorithm combining RE allocation and sleep scheme mechanism to reduce the electric bill of the operator, while satisfying the users' demand. In [152], the authors considered an actual network layout from a major MNO in Europe. By considering several configuration variants, the authors realized a decrease in the electric bill of the network by more than half using RE that harvest only 20% of the network's demand. In [138], in addition to RE allocation and sleep scheme policy, the authors also considered radio resource allocation to further decrease the cost of the energy consumed by the network.

Providing ancillary services to the grid to balance its energy load can further decrease the electric bill, and in some cases negative operational cost leading to profit. In [153], the authors applied the concept of delay tolerant users to provide ancillary services to the SG. This approach allows to reduce the overall network energy load by purposely delaying a fraction of users to access the network. In this way, the periods of low energy consumption can be extended, resulting in an overall network energy consumption reduction. The authors took advantage of this concept to reply to the SG requests for providing ancillary services by adjusting the network energy load. In doing so, a negative operational cost of  $-27\%$  has been reached, leading to positive profit. In another work and to respond to the SG requests, the authors in [106] relied on resource on demand strategies to adapt the energy consumption of a cluster of micro BSs powered by RE and connected to the electric grid for power supply. By switching ON and OFF the micro cells, the operator can better respond to the grid's requests to increase or decrease the energy consumption, reaching even more negative operational cost down to  $-120\%$ . In contrast to switching off BSs that may lead to coverage holes, the authors in [154] considered RRM algorithm by deactivating some of the Resource Blocks (RBs) to adapt the network energy profile to better respond to the SG requests, while respecting the QoS of the users. The BS energy state is modeled as a multi-dimensional Markov chain, for which its transition probabilities are derived from the stochastic models of the harvested energy, SG request patterns and the energy management policy adopted.

Considering multiple energy retailers, the authors in [155, 156] considered the problem of maximizing the profit of the MNOs, while minimizing the level of  $\text{CO}_2$  emissions and maintaining a certain QoS. The problem is solved using stochastic geometry to determine the average power needed for each user to achieve the target probability of coverage. Based on this derivation, the total BS power consumption is calculated, and the energy procured from different retailers is decided.

Besides demand-side management, other studies took advantage of the SG architecture to bring down the energy cost for the MNOs. Since the SG allows a two-way flow of energy, a BS can share its harvested energy by means of buying and selling to the grid. In this way, a BS can sell its excess energy production, while another energy deficit site can buy energy from the grid. In [157], the authors studied the problem of energy cost minimization by an MNO under the SG environment. By allowing the

RE-powered BSs to sell their energy to the grid, the authors derived the optimal policy for energy management by solving a constrained optimization problem to reduce the total cost uncured by the operator. In addition to energy cooperation, the authors in [158] focused on user association in a HetNet powered by RE and SG in order to reduce the unnecessary offloading and mitigate the signaling cost and interference. The authors thus studied the tradeoff between offloading and energy-cooperation to maximize the number of connected users, while minimizing the energy transfer loss between BSs.

When the energy consumption and production of a prosumer (e.g., MNO) is not enough to impact the load balancing of the power grid, aggregators form a single purchase unit by combining several prosumers for the purpose of negotiating electricity purchase from the electricity market [159]. This allows aggregators to take action in the DR programs [160]. This single purchase unit is known as a micro-grid, or mini SG. In [161, 162], the authors considered green cellular networks powered by RE and power grid. The BSs of these networks collaborate under a micro-grid architecture to share energy and communication, in order to reduce their total energy cost.

## 2.5 When green meets AI

In addition to transmitting data with lower energy footprint and higher efficiency, next generation wireless networks are required to support a diversity of use cases with different requirements in their service levels, within a highly dynamic environment. Fulfilling these tasks is challenging, since increasingly complex, heterogeneous and evolving. This requires new smart wireless radio technology, sophisticated spectrum utilization and adaptive decision making so that the diverse requirements are satisfied.

Moreover, the number of reconfigurable parameters in future networks is huge. For instance, from 2G to 4G these parameters have increased from 500 in 2G to 1000 in 3G and 1500 in 4G according to [163]. This number is expected to rise to more than 2000 in 5G networks. Therefore, it is essential to enhance the intelligence of these networks in order to realize the Self-Organized-Network (SON) paradigm that features self-configuration, self-optimization and self-healing.

In Fig. 2.9, based on many references such as [164, 165, 166], an intelligent radio is envisioned that is able to learn from previous experience (observations) to improve the system performance by associating a utility function for each action. This vision can only be realized by integrating fundamental notions of AI and Machine Learning (ML) across the wireless infrastructure and end-user devices.

In general, AI is a computation framework that provides intelligence to machines. AI models aim at teaching them how to learn, work and react much like humans. The discipline of this paradigm dates 75 years back, when threshold logic was employed to produce a computational model for neural networks [167]. However, it was until the late 1980s that neural networks gained interest, but the progress was slow due to the limitation in the computing power. Today, and with the advances in Graphics Processing Units (GPUs), AI interest is growing in an unprecedented manner cover a wide range of computer science areas. Among the different techniques that exist under the AI umbrella, ML emerged as a promising technique to absorb knowledge from data and make decisions, predictions and suggestions without being explicitly programmed [164, 166].

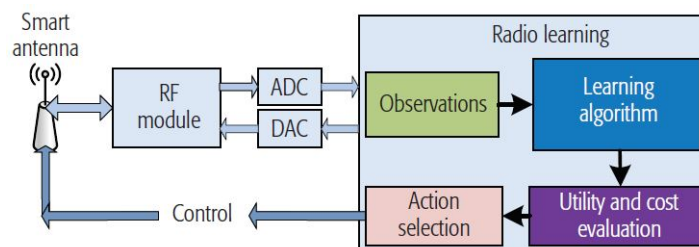


Figure 2.9 – Intelligent radio learning paradigm [164].

### 2.5.1 Machine learning in 5G

AI has matured to cover several discipline techniques such as machine learning, optimization theory, game theory, and meta-heuristics [168]. In particular, machine learning has emerged as one of the most important subfields of artificial intelligence. In future 5G networks, machine learning can be widely used to orchestrate and manage network resources. By embracing intelligence, many of the technical problems of next generation systems such as device-to-device (D2D), large-scale massive MIMO, and heterogeneous networks with different technologies and architectures can be addressed more efficiently. Typically, machine learning can

be classified into three major categories summarized in Fig. 2.10: supervised learning, unsupervised learning and reinforcement learning.

1. **Supervised learning:** in supervised learning, the agent is fed with a set of labeled input examples and their desired outputs provided by a knowledgeable external supervisor. Each example is a pair of a specific situation and its correct action. The aim of this kind of learning is to find the relationship between variables to derive a general rule that maps inputs to outputs by extrapolation and regression. Supervised learning has been widely used for channel estimation and spectrum sensing.
2. **Unsupervised learning:** compared to the above learning process, unsupervised learning is about finding hidden structures in collections of unlabeled data. Therefore, the agent in this category should be able to discover patterns in its inputs. In cellular networks, this type of learning is widely used. Principal Component Analysis (PCA) and Independent Component Analysis (ICA) are famous unsupervised methods that are used to find correlation and hidden structures between variables. For instance, PCA method is used to minimize the complexity of massive MIMO by reducing its receiving matrix. On the other hand, clustering methods (another unsupervised technique) is useful to capture anomalies in the network.
3. **Reinforcement learning:** while supervised learning and unsupervised learning require data sets to train the agent, reinforcement learning learns from interaction with the dynamic environment. With no prior knowledge on system information, reinforcement learning tries to maximize a numerical reward signal by taking actions at each time step, thus mapping states with actions that bring the highest reward. This type of learning is widely used in decision making problems, such as radio resource management and users selection in cellular networks. Under this category, Q-learning is widely used as a tool to solve such problems (the reader can refer to Appendix A for a background on reinforcement learning).

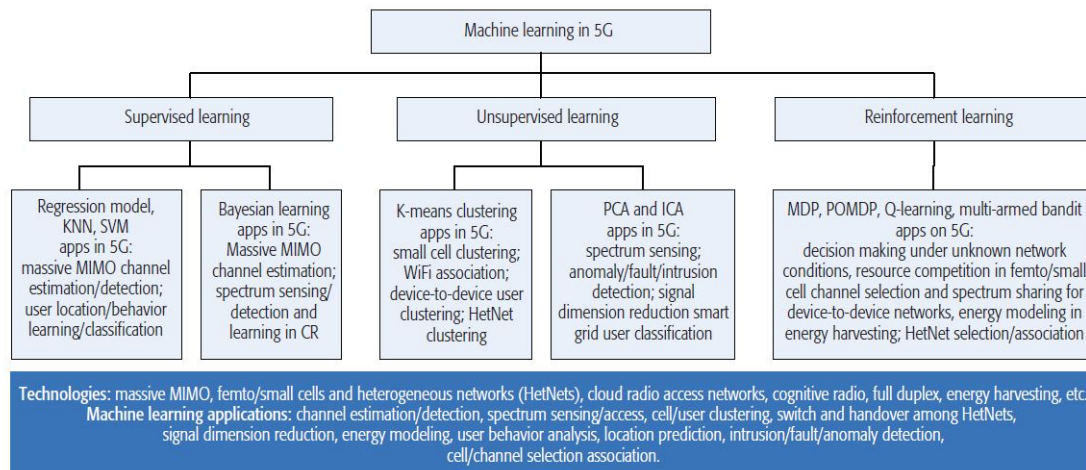


Figure 2.10 – Intelligent radio learning classification for AI tools [164].

## 2.5.2 Reinforcement learning in wireless communications

Since in mobile environment the accuracy of information and the complete model of the environment's evolution are unknown, the model-free reinforcement learning framework has been used to solve stochastic optimization problems in wireless networks. In particular, in sequential decision making problems, reinforcement learning finds the optimal policy by exploring the unknown environment by mean of interaction.

In wireless cellular networks, resource allocation, user scheduling and sleep schemes are traditional decision making problems with high computational complexity, yet very important, due to the dynamic variations of the environment (e.g., traffic profile, interference, harvested energy profile and electricity price). How to make efficient utilization of resources is a brand-new challenge. Besides traditional approaches and tools, a lot of attention has been recently given to Q-learning solutions. For example, distributed Q-learning-based algorithms have been proposed in HetNets where small cells solely powered by RE learn when to switch to sleep by interacting with the environment [169, 93, 170]. The goal of the agent (i.e., small cell) is to reduce the energy consumption, while maintaining a system performance measured by the traffic drop due to insufficient capacity in the macro BS. In [169, 93], the network is modeled as a Multi-Agent Reinforcement Learning (MARL) system. Each small cell implements a distributed Q-learning algorithm to find the optimal policy independent of the other cells. However, due to the lack in coordination between the



BSs with distributed Q-learning, the work was extended in [170]. In addition to reinforcement learning, the authors proposed an additional layer based on neural networks that is centralized. This layer is in charge of extending the distributed Q-learning at each small cell to give additional information that influence the local action to be taken. This type of class of algorithms is known as Heuristically-Accelerated Multiagent Reinforcement Learning (HAMRL) [171].

Q-learning is based on finite Markov Decision Process (MDP), thus the states and actions are quantized into discrete levels. In order to alleviate this problem, Fuzzy Q-Learning (FQL) is introduced. It combines fuzzy inference system and Q-learning. With FQL, the environment can be represented more realistically leading to more efficient models. The authors of [103] used FQL in order to decide how much to charge/discharge a battery powering a BS in order to minimize the electric bill of the operator under the SG environment. The BS is powered by a RE source, a battery and the SG. Using reinforcement learning, the authors showed that their proposed solution achieves better cost reduction compared to a classical Kalman filter based method. Using the same tool (FQL), the authors in [172, 173] investigated the problem of cell DTX for small BSs in a HetNet in order to save energy, while respecting packets latency constraints. FQL is used to derive the optimal control policy to enhance the network energy efficiency. While [172] is interference-limited, [173] consider the interference between the cells in the learning process. Based on the interference level, the cells coordinate to manage the interference in order to further enhance the network energy efficiency.

In another study that considers multi-SM levels, the work in [47] considered reinforcement learning to study the Energy-Delay-Tradeoff (EDT) problem of a BS powered by the grid. By applying Q-learning, the authors studied different policies of SM. Depending on the service use case, the operator can tune the network parameters towards either more energy savings or less service delay.

Traditional reinforcement learning faces the problem of scalability. In simple models where the number of states and actions are limited, reinforcement learning methods are efficient in scavenging optimal policies. However, in more complicated environments and tasks, classical reinforcement learning approaches are not enough. Recently Deep Q-Learning (DQL) based on deep neural networks has been successfully applied to enhance the learning capacity of reinforcement learning in com-

plex tasks [174]. For example, the authors in [175] proposed a deep reinforcement learning approach to manage the resource allocation for effective coexistence of LTE licensed assisted access and WiFi in the unlicensed spectrum. The approach enables BSs to decide on its spectrum allocation policy autonomously with limited information on the network state, while guaranteeing fairness with existing WiFi networks and other LTE licensed assisted access operators. In [176], the authors demonstrated the potential of DQL for dynamic power allocation in wireless networks. With the objective to maximize the weighted-sum rate utility function, the authors proposed a distributed dynamic power allocation scheme based on DQL that is scalable for large networks. Different from existing solutions that try to solve hard optimization problems, the authors show the potential of DQL to solve large scale network problem that cannot be solved with classical optimization tools.

## 2.6 Conclusion

In this chapter, we surveyed the work done in the context of energy-efficient cellular networks. We divided the road towards green 5G networks into four main milestones. The first discussed the important energy efficiency techniques and approaches used for 5G networks. These techniques covered cellular architectures, radio resource management and sleep mode techniques. The second milestone integrated renewable energy sources into cellular base stations. We discussed how empowering cellular networks with hybrid energy sources do not only optimize the energy efficiency of these networks but also reduce the CO<sub>2</sub> emissions and the operational costs for mobile operators. Based on the state of the art, we were able to extract the main aspects for designing a renewable energy-powered cellular network. These included planning of cellular networks, dimensioning of renewable energy systems and characterizing of renewable energy sources with proper models. The third milestone extended the previous ones to include the interaction between these networks and the smart grid architecture. Under this framework, a new energy management concept evolved that takes into account the interaction with the grid by enabling energy sharing between the base stations, demand-side management and ancillary services. This integration with the smart grid allowed to better utilize the harvested energy, thus in-

creasing the energy efficiency of these networks. The last milestone discussed in this chapter was the integration of smart tools and algorithms based on artificial intelligence, in particular machine learning, to orchestrate and manage the resources for the increasingly complex, heterogeneous and evolving future networks. After surveying the literature proposed under this field, we discussed the efficiency of using these tools in achieving green communication. Following the extensive research studied under these different areas, we highlight several aspects in which the problematic of green cellular networks needs more exploration. In Chapter 3, we study the importance of equipping sites with renewable energy sources and batteries. We focus on partially-equipped renewable energy systems. This is of great importance considering the high costs of these systems.

CHAPTER

# 3

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## **USING RENEWABLE ENERGY TO POWER CELLULAR NETWORKS**

### **3.1 Introduction**

Wireless networks have important energy needs. Many benefits are expected when the BSs, the fundamental part of this energy consumption, are equipped with RE systems. Important research efforts have been done to enhance the utilization of RE. The idea is to optimize the use of RE in order to achieve the required objective(s), e.g., reduce the on-grid energy consumption and minimize the electric bill of the network operator. There exist several studies that aim at achieving these goals in a green cellular network powered by RE, batteries and the SG [142, 177, 138, 140, 43]. For instance, the authors in [142, 177] studied the problem of minimizing the on-grid energy consumption of green cellular networks. They used approaches from energy sharing, load shifting and sleep mode techniques to manage the network's resources in order to reduce the on-grid energy consumption. On the other hand, [138, 140, 43] studied the problem of minimizing the electric bill cost of the network operator. Different approaches were also used to achieve this goal, such as RE allocation, radio resource allocation, user association and dynamic power control. However, to the best of our knowledge and after a further look at the state of the art, these efforts did not take into consideration partially RE-equipped systems. The latter is of great importance considering the high cost of these systems and the feasibility of implementing RE systems at

all BSs sites. Thus, it is interesting to study the percentage of sites to be equipped with RE systems. In this context, we propose a framework to study and analyze the impact of equipping sites with RE sources on the operational cost and the performance of a cellular network to decide how much to invest in RE. First, we evaluate the grid-energy savings for different RE system setups. Then, we assess the performance of these systems for different energy management strategies based on advanced KPIs putting forward each service contribution to energy consumption. Using these new KPIs, we propose to adapt some energy management strategies, leading to performance amelioration and new energy savings.

## **3.2 Framework for RE-powered cellular networks**

In order to study RE-powered cellular networks, several parameters should be taken into consideration in the design and operation of these systems. We summarize these parameters as follows (see Fig. 3.1):

### **3.2.1 Input parameters**

These parameters represent the specifications and sizing of the RE system such as: number of sites equipped with RE sources, energy storage capacity and size of RE sources.

#### **Number of sites equipped with RE sources**

Constrained by CapEx costs, deploying RE systems on all sites of a cellular network might not be a feasible economic solution for the operator, especially if the network under study possesses thousands of deployed BSs. As a result, an alternative is to study the network under different number/percentage of sites equipped with RE. These sites will be powered by both RE sources that harvest clean energy and traditional power grid. We can differentiate between two cases: when the harvested energy exceeds the energy demand needed for operation, and when it is not sufficient to power the BS in a certain period of the day. In the former case, the excess amount of energy will be stored in the battery for future transmission use,

i.e., when the price of electricity is high or when the battery storage level is low. The latter case consumes on-grid energy in order to ensure operation and satisfy the users traffic demands and the operator pays the cost of energy consumption following the electricity price set by the electricity provider.

### **Energy storage capacity (KWh)**

Each site equipped with a RE system will be also equipped with an energy storage (battery) to store the harvested energy for later use. We consider several sizes of energy storage capacities ranging from 1 to 20 KWh. We do not set a limit on the depth of discharge (DoD) and we assume ideal batteries, i.e., no energy leakage. In this regard, this framework will provide an insight into suboptimal energy scheduling algorithms, and benchmark fundamental limits on the performance of RE systems.

### **Size of renewable energy sources**

We consider solar energy due to their flexibility compared to other type of RE sources such as wind turbines. The amount of harvested energy depends on the size of solar panels. Here we consider several surface area sizes ranging from 2 to 12.5  $m^2$  with a standard module type (Crystalline-Silicon) having a 15% efficiency.

## **3.2.2 Network management techniques**

Equipping BSs with RE has the benefit of bringing down the on-grid energy operation cost. However, coupled with energy efficient techniques more savings can be brought to the network operator. Under this category, there exist different approaches such as sleep scheme, RB allocation techniques and battery management on the network's cost savings and performance for they bring the highest savings.

### **Cell layout adaptation (CLA)**

This category is on the top in our technique model description, as shown in Fig. 2.1, as it yields the highest energy reduction at the network scale.

Under this category, we focus on sleep scheme that switch BS to sleep mode when its traffic load is low in order to save energy.

### **Radio resource management (RRM)**

These techniques also contribute to energy savings but into a more local reach. The main idea is to optimize the allocation or utilization of transmission resources in order to reduce energy. Here we consider downlink RB allocation. The goal is to allocate sufficient RBs to satisfy a certain QoS constraint and save energy.

### **Environment learning and information exchange (EL-IE)**

Cognitive radio (CR) is defined under this section. The idea of CR is to intelligently detect holes in the spectrum and dynamically jump into (and out of) them very rapidly by reconfiguring the transmission and reception parameters to match the channel's conditions. In the same way, CR is used to optimize spectrum efficiency, it can be used to optimized energy efficiency. Although in this work we do not consider CR, it can be used to further increase cost savings.

### **Battery management**

Intelligent energy management of harvested energy yields to higher on-grid energy cost reduction and hence electric bill reduction. In this work, we evaluate the performance of existing energy management strategies, such as SPAEMA [136] that takes into account the state of the battery and the real time price of electricity in deciding when to store and use the harvested energy.

### **3.2.3 Output parameters**

By setting the input parameters and choosing the energy-efficient technique to be applied in the network, important indicators can be studied such as on-grid energy consumption, electric bill, average rate per BS and other important KPIs.

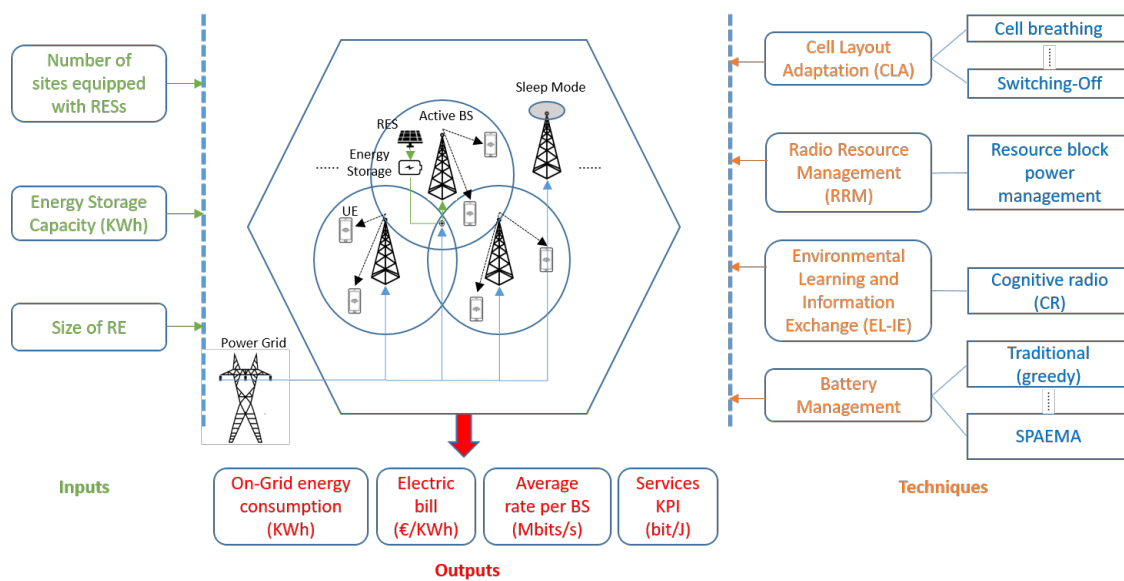


Figure 3.1 – General framework to design and operate cellular networks equipped with renewable energy sources.

### 3.3 System model

In order to evaluate the network under the framework presented above, we consider a wireless cellular network overlaid with  $M$  macro BSs having an inter-cell distance  $D$  and  $K$  mobile users. We denote the set of BSs by  $\mathcal{B} = \{1, 2, \dots, M\}$ , and the set of users served by BS  $m$  by  $\mathcal{U}_m = \{1, \dots, u, \dots, k_m\}$ . Initially, the users are associated with and served by the BSs, based on best Signal-to-Interference Noise Ratio (SINR) that is managed by a centralized energy management unit (EMU). Each user measures the received SINRs by using pilot signals from all BSs and sends it to the EMU. We further consider two sets of BSs. One solely powered by grid energy and is denoted by  $\mathcal{B}^{grid}$ . The other set of BSs is equipped with RE and energy storages (batteries); hence, it is powered by a mix of hybrid energy sources (RE+SG) and is denoted by  $\mathcal{B}^{mix}$ . The total bandwidth of the system  $W$  is shared among the BSs with a frequency reuse factor of one. We consider that the traffic load, on-grid energy price and RE are all varying over time.



### 3.3.1 Network architecture and operations

We consider the architecture in Fig. 3.2. A centralized Energy Management Unit (EMU) manages the operational states of a cluster of BSs. Each user sends all received SINRs from surrounding BSs to the EMU. Based on these measurements, the BSs are set to either active or sleep mode for a fixed period of time. We divide the observation time  $T$  into multiple one-hour periods. Each period is divided into  $L$  time slots. Each slot  $s$  has a duration of  $1/L$  hour. The decision by the centralized EMU on managing the states of the BSs is taken every time slot  $s$ . The decision of the RE allocation is left for the local EMU installed at each BS. Based on the current price of electricity and the state of charge of the battery, the local EMU decides whether to store or use the harvested energy. The decision policies for switching-off BSs and allocating RE are detailed in Section 3.3.4.

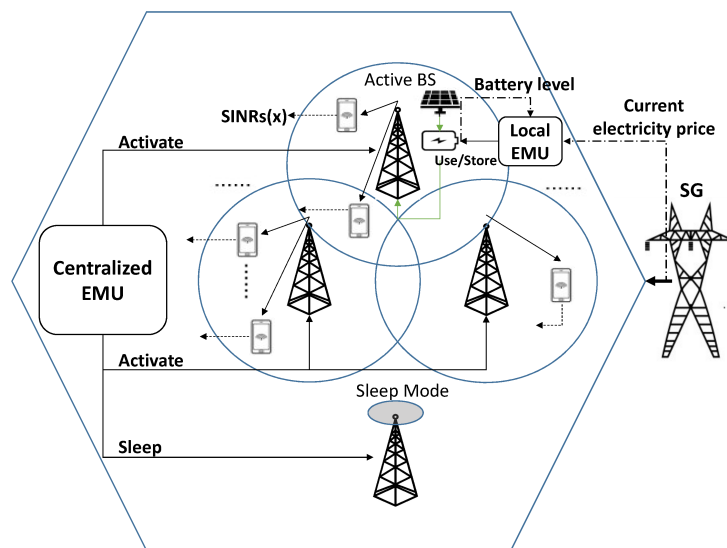


Figure 3.2 – Partially RE-equipped network architecture and operation © 2018 IEEE.

### 3.3.2 Downlink transmission model

We measure the downlink transmission quality between a BS  $m$  and a user  $u$  based on the SINR as follows:

$$\text{SINR}_m(u) = \frac{P_m h_m(u)}{\sigma^2 + \sum_{m' \in \mathcal{B}, m' \neq m} P_{m'} h_{m'}(u)} \quad (3.1)$$

where  $P_m$  is the transmitted power of BS  $m$ ,  $h_m(u)$  is the channel gain from BS  $m$  to user  $u$ , which accounts for the path loss and shadowing effect, and  $\sigma^2$  is the additive white Gaussian noise power density.

We can express the rate offered to a user  $u$  and served by BS  $m$  using Shannon-Hartley theorem as follows:

$$R_m(u) = n_{RB}(u) \times \text{BW}_{RB} \times \log_2(1 + \text{SINR}_m(u)) \quad (3.2)$$

where  $n_{RB}(u)$  is the number of RB allocated to the user  $u$ , and  $\text{BW}_{RB}$  is the bandwidth of one RB.

### 3.3.3 Renewable energy generation, electricity price and traffic load variations

We consider the use of solar panels due to their flexibility compared to other types of RE sources such as wind turbines. In addition, we provide these sites with battery storages in order to store the excess harvested energy for future transmission. The amount of harvested energy varies depending on the location and panel size. In Fig. 3.3, we illustrate an example of the harvested energy generated by a solar panel having a surface area of  $12.5 \text{ m}^2$  in the city of Marseille (France) [178].

The traffic load on the other hand manifests both temporal and spatial diversities. On the temporal diversity, the traffic load of a BS dynamically changes over time as shown in Fig. 3.3. We assume that the users are uniformly distributed in the given area.

### 3.3.4 Online RAN energy management strategy

#### Sleep mode strategy: SINR threshold-based method

The algorithm described in this section aggressively turns off BSs based on an SINR Switch-Off Threshold ( $\text{SINR}_{\text{SOT}}$ ) parameter. It is a modified

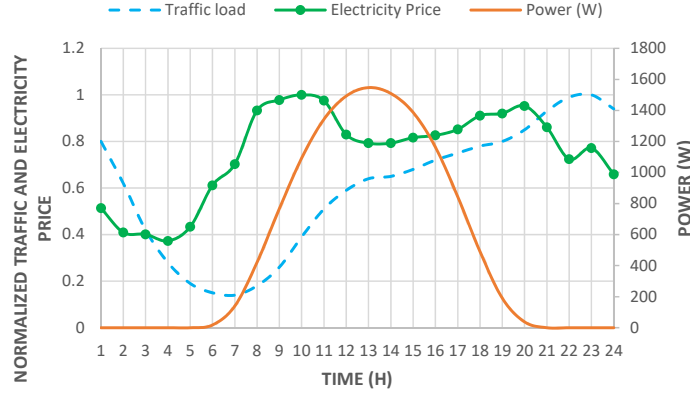


Figure 3.3 – Variations of the average traffic load, average RE power and electricity price [14, 178, 179] © 2018 IEEE.

version of the sleep scheme algorithm presented in [138]. It considers the set of BSs powered solely by grid energy,  $\mathcal{B}^{grid}$ , as candidates to be switched-off. First, it sorts these BSs in increasing order of their traffic loads. Then, starting with BS  $j \in \mathcal{B}^{grid}$  with the lowest load, the algorithm switches it to sleep mode if the measured SINRs between all of its users and all neighboring BSs (except  $j$ ) are above  $SINR_{SOT}$ .

$$SINR_{j'}(u_x) \geq SINR_{SOT}, \forall u_x \in \mathcal{B}_j^{grid} \text{ and } j' \in \{\mathcal{B} \setminus j\}. \quad (3.3)$$

If equation (3.3) is satisfied, BS  $j$  offloads its users to neighboring BSs with the highest received SINRs. The  $SINR_{SOT}$  parameter described in this section is non-operational. In other words, the SINRs of the users offloaded to neighboring BSs will witness a signal improvement due to interference reduction, as a result of switching-off some BSs. The algorithm is summarized in Algorithm 1.

### Resource block policy: Max-Min fairness algorithm

In order to divide the BS radio resources among the users it is serving to satisfy their QoS requirements, we adopt the Max-Min fairness algorithm [180]. Our goal is to maximize the allocation of resources for the most poorly treated user, i.e., maximize the minimum. We chose this algorithm because we assume that all users have an equal right to the resources, and we assume a full buffered system where there is always data to transmit. However and since some users demand fewer resources than others

**Algorithm 1** : Sleep sleep algorithm

- 
- 1: **Define:** BS-User association matrix:  $\mathbf{A} \in \mathbb{Z}_2^{K \times M}$ ; Users associated with BS  $j$ :  $\mathbf{U}_j$
  - 2: **Initialize:**  $\mathbf{A}$  based on best SINR;  $\text{SINR}_{\text{SOT}}$
  - 3: Sort the BSs  $\in \mathcal{B}^{\text{grid}}$  in increasing order of traffic loads
  - 4: **for**  $j = 1 : |\mathcal{B}^{\text{grid}}|$  **do**
  - 5:     Switch off BS  $j$  if eq. (3.3) is satisfied
  - 6:     Offload its users  $\mathbf{U}_j$  to neighboring BSs with highest SINRs
  - 7: **end for**
  - 8: **Output:** Updated BS-User association  $\mathbf{A}$  and BSs modes (active or sleep)
- 

(i.e., users with better channel quality), the algorithm allocates enough resources to users with small demand, and evenly distribute the remaining resources among the big users. Formally, the algorithm can be defined as follows:

- Resources are allocated in order of increasing demand
- No user receives a resource share larger than the demand to achieve his minimum requirement
- Unsatisfied users get an equal share of the resource

First, we define the following entities: the number of required RBs each user must have ( $\mathbf{RB}_{\text{req}} \in \mathbb{N}^{K \times 1}$ ) to satisfy his/her requirement, the scheduled RBs ( $RB_{\text{sch}} \in \mathbb{N}$ ) as the share of resources each user is expected to have following the max-min fairness definition, the RBs allocated for each user by the algorithm ( $\mathbf{RB}_{\text{all}} \in \mathbb{N}^{K \times 1}$ ), and the remaining RBs that were not used ( $RB_{\text{rem}} \in \mathbb{N}$ ). Then, the algorithm computes the share of resources required by each user ( $\mathbf{RB}_{\text{req}}$ ). It starts by dividing the resources evenly among the users, such that no user receives a resource share larger than his demand. Finally, unsatisfied users will share equally the additional radio resources. If all users are satisfied, excess radio resources will be turned off to save energy. In our model, we consider that the BS has a fixed number of resources expressed in terms of RBs. The algorithm is further detailed in Algorithm 2.

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**Algorithm 2** : Max-Min Fairness Algorithm

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- 1: Initialize the total number of RBs ( $RB^{Total}$ ) and the minimum user rate requirement ( $R_{min}$ )
  - 2: Find  $RB_{rem} = RB^{Total}$
  - 3: Find  $RB_{req} \forall m \in \mathcal{U}$  using eq. (3.2) and  $R_{min}$
  - 4: **while**  $RB_{rem} > 0$  **do**
  - 5:     Find  $RB_{sch}$  by dividing the RBs evenly among all users
  - 6:     **for all** users,  $m$  **do**
  - 7:         **if**  $RB_{sch} > RB_{req}(m)$  **then**
  - 8:             Find  $RB_{all}(m) = RB_{req}(m)$
  - 9:             Find  $RB_{rem} = RB^{Total} - RB_{all}(m)$
  - 10:         **else**
  - 11:             Find  $RB_{all}(m) = RB_{sch}$
  - 12:             Find  $RB_{rem} = RB^{Total} - RB_{all}(m)$
  - 13:         **end if**
  - 14:     **end for**
  - 15: **end while**
  - 16: Turn off unused RBs ( $RB_{rem}$ ) to save energy
- 

**Online battery management: SPAEMA algorithm**

Several studies showed that intelligent energy management of harvested energy yields to higher on-grid energy cost reduction resulting in electric bill savings. In this context, we apply the proposed heuristic online battery management algorithm described in [136], that requires only the current state of battery level and electricity price to decide whether to use or store RE. Table 3.1 summarizes the decisions for different cases.

Table 3.1 – SPAEMA decisions for different cases of battery and electricity price.

Battery/price	Low	Medium	High
Low	store	store	use
Medium	store	use	use
High	use	use	use

### 3.3.5 On-grid network power consumption

Following the power model of EARTH [14] described in equation (2.2) and based on the above mentioned algorithms (sleep scheme, RB allocation and battery power management, SPAEMA), we can express the on-grid energy consumption of the network at time stage  $i$  as follows:

$$G_i = \sum_{j=1}^M \left( \overline{SD}_j^{(i)} \times N_{trx} \left( P_0 + \frac{n_{RB}^{(i)}}{n_{RB}^{Total}} \times \Delta_p \times P_{out}^{(i)} \right) + SD_j^{(i)} \times P_{sleep} - RE_j^{(i)} \times E_j^{(i)} \right) \quad (3.4)$$

where  $SD_j^{(i)}$ ,  $\overline{SD}_j^{(i)}$  and  $RE_j^{(i)}$  are binary variables.  $SD_j^{(i)}$  is a switching decision variable that indicates whether BS  $j$  is active ( $SD_j^{(i)} = 0$ ) or in sleep mode ( $SD_j^{(i)} = 1$ ).  $\overline{SD}_j^{(i)}$  is the complement of  $SD_j^{(i)}$ .  $RE_j^{(i)}$  indicates whether BS  $j$  is equipped with RE source or not ( $RE_j = 1$  indicates that BS  $j$  is equipped with RE source).  $E_j^{(i)}$  is the amount of harvested energy allocated at time stage  $i$ . Finally  $P_0$  and  $N_{trx}$  are the static power and the number of transceivers defined in EARTH model [14], respectively. From equation (3.4), a trade-off exists between the number of sites equipped with RE sources and the size of the candidate set of BSs allowed to switch to sleep mode, in order to minimize the energy consumption. In other words, when the number of sites equipped with RE sources increases, less BS will be able to switch off to save energy; however, more green energy will be introduced into the system to minimize the on-grid energy consumption. In the next section, we demonstrate the trade-off between the percentage of sites equipped with RE sources and the operational cost savings.

### 3.3.6 Advanced energy efficiency KPIs

In order to assess the energy efficiency of the network, we adopt the service energy efficiency proposed in [87] that evaluates the service energy efficiency of the network. Thus, we consider several services the network is providing. In contrast to the energy efficiency metric proposed by ETSI in [181], which limits the evaluation of the energy efficiency to operational BSs, we propose an extension that includes the use of RE.

We define the following KPIs that take into account the usage of RE:

*Definition 1 (Global KPI):* we denote by global KPI, the hourly performance evaluation of the energy efficiency of a BS including all the services it is providing. It is calculated as follows:

$$KPI_m(t) = \frac{DV_m(t)}{E_m(t) - RE_m(t)} \quad (3.5)$$

where  $DV_m(t)$  and  $E_m(t)$  are the data volume transmitted and the energy consumed by BS  $m$  at time  $t$ , respectively.  $RE_m(t)$  is the allocated RE for BS  $m$  at time  $t$ , and it depends on the energy harvesting policy.

*Definition 2 (Service KPI):* the service  $i$  KPI is the hourly energy efficiency evaluation of service  $i$  provided by BS  $m$  as follows:

$$KPI_m^i(t) = \frac{DV_m^i(t)}{E_m^i(t) - RE_m^i(t)} \quad (3.6)$$

where  $DV_m^i$  is the volume of the transmitted data by service  $i$ , and  $E_m^i$  is the energy consumed by this service. The latter is evaluated based on Shapley model presented in [87] and is summarized in the next subsection.

We now extend the above mentioned KPIs by defining a new metric scale under which we evaluate our KPI: Network KPI. This metric can be used to evaluate either global or services KPIs.

*Definition 3 (Network KPI):* the network KPI,  $\mathbf{KPI}(t_1, t_2)$  is defined as the hourly average energy efficiency of the entire network including BSs in sleep mode, between times  $t_1$  and  $t_2$ , where  $\mathbf{KPI}(t_1, t_2) \triangleq [KPI(t)]_{t_1 \leq t \leq t_2}$  and:

$$KPI(t) = \frac{1}{M} \sum_{m=1}^M \frac{DV_m(t)}{E_m(t) - RE_m(t)} \quad (3.7)$$

Since this metric is evaluated hourly, it takes hourly discrete values. For example,  $\mathbf{KPI}(1, 24) = [KPI(1), KPI(2), \dots, KPI(24)]$ , where  $KPI(1)$  is evaluated at time = 1 hour.

### Shapley model for energy sharing among BSs

While it is easy to monitor the traffic volume consumed by service  $i$ , its specific energy consumption,  $E_i$ , is not intuitive. In order to evaluate the energy consumed by each service, we use the model proposed in [87] that estimates this energy based on Shapley Value, a coalition game concept.

The energy consumption of the network is composed of two components: a variable one ( $E^V$ ) that varies with the traffic load and a fixed one ( $E^f$ ) independent of the network load. These two components can be easily monitored using appropriate energy consumption models such as EARTH model [14]. Similarly, we can evaluate the energy consumed by service  $i$  as follows:

$$E_i = E_i^f + E_i^V \quad (3.8)$$

While the variable part is shared among the services with proportion to the service traffic, i.e.,  $E_i^V = DV_i/DV_T \times E^V$  ( $DV_T$  is the total data volume), the fixed part is estimated following Shapley Value as follows:

$$E_i^f = \theta_i \times E^f \quad (3.9)$$

and

$$\theta_i(N, p_i) = \left( \sum_{s=1}^N \frac{1}{sC_N^s} \right) p_i + \left( \sum_{s=2}^N \frac{(C_{N-1}^{s-2} - C_{N-1}^{s-1})C_{N-2}^{s-2}}{C_{N-1}^{s-1}C_{N-1}^{s-2}sC_N^s} \right) (1 - p_i) \quad (3.10)$$

where  $\theta_i$  is the share of energy for service  $i$  following Shapley Value,  $N$  is the number of services (players),  $p_i$  is the traffic portion ( $p_i = \frac{DV_i}{DV_T}$ ), and  $C_N^s$  is the binomial coefficient.

Compared to uniform and proportional sharing of fixed energy component, Shapley model achieves a trade-off among all services. That is to say, it does not penalize major services as much as proportional sharing, and it is also a good trade-off for small services as it does not condemn them with high fixed energy as in uniform sharing. By combining the equations of (3.6), (3.8), (3.9) and (3.10), the KPI of service  $i$  is evaluated as follows:

$$KPI_m^i(t) = \frac{DV_m^i(t)}{\theta_i \times E_m^f(t) + \phi_i \times E_m^V(t) - RE_m(t)} \quad (3.11)$$

where  $\phi_i$  is the proportional share of the service variable energy,  $\phi_i = DV_i/DV_T$ .  $E_m^f$  and  $E_m^V$  are calculated using EARTH model [14].

### KPI maximization: problem formulation

Considering both QoS and battery capacity constraints, we aim at maximizing the KPI by the efficient use of RE. We consider a network of LTE BSs having a percentage of its sites equipped with RE. Here we consider that the users have a minimum rate constraint that is translated into a



QoS. We assume that the BSs always have data to transmit. Our goal is to maximize the average network KPI over a time duration  $T$ . We express the optimization problem as follows:

$$\max_{\mathbf{RE}(T), \mathbf{S}(T)} \frac{1}{T} \sum_{t=t_1}^{t_2} KPI(t) \quad (3.12)$$

subject to:

Quality constraint:

$$r_m(u) \geq R_{min}, \forall u \in \mathcal{U}_m, \forall m \in \mathcal{B} \quad (3.13)$$

System constraint:

$$\frac{\sum_{u \in \mathcal{U}_m} w_u}{W} \leq 1, \forall m \in \mathcal{B} \quad (3.14)$$

$$P_m \leq P_{max} \quad (3.15)$$

Renewable energy availability constraint:

$$RE_m(t) \leq B_m(t) \quad (3.16)$$

where  $\mathbf{RE}$  and  $\mathbf{S}$  are the RE utilization for each BS equipped with RE and the state of each BS (active or sleep) in the network at each time horizon, respectively.  $r_m(u)$  is the rate offered to user  $u$  by BS  $m$  using Shannon-Hartley theorem.  $w_u$  is the bandwidth allocated for user  $u$ .  $RE_m(t)$  and  $B_m(t)$  are the allocated harvested energy and the available energy stored in the battery for BS  $m$ , at the beginning of stage time  $t$ , respectively; where  $RE_m^s(t) = RE_m^s(t-1) + RE_m^a(t) - RE_m(t)$ , and  $RE_m^s(t)$  and  $RE_m^a(t)$  are the stored energy and the harvested energy allocated by BS  $m$  at time  $t$ , respectively.

Problem (3.12) is a non-convex fractional problem due to its objective function. In the next section, we propose a heuristic online algorithm that efficiently utilizes the harvested energy, and decides which BSs to switch to sleep state in order to improve the KPI. The above formulated problem maximizes the network global KPI. The same problem can be formulated for the services KPIs.

### 3.3.7 Adaptation of energy management strategies

Enhancing the KPI requires maximizing the throughput of the network while minimizing the on-grid energy consumption. The two parameters

that directly affect this improvement are traffic load and RE. SPAEMA, an energy management algorithm described in [136], is an online algorithm that decides how to manage RE (store it in battery or use it) based on the battery State of Charge (SoC) and the price of electricity, in order to reduce the electric bill of the operator. Thus, it does not require any future knowledge of RE nor traffic load using prediction applications. In [136], we showed that SPAEMA outperforms the traditional algorithm that uses RE whenever it is available. However, since the objective has shifted from reducing the electric bill of the operator to increasing our KPIs, adaptation of our previously proposed algorithm (SPAEMA) is needed to match our new objective. Thus, we propose a new algorithm that adapts SPAEMA to satisfy the newly introduced objective. Then we extend the proposed algorithm for further enhancement.

### Proposed algorithm 1 - STAEMA

We suggest the Simplified Traffic-Aware Energy Management Algorithm (STAEMA) that is an evolution of SPAEMA. The major motivation behind this adaptation is to preserve the simplicity of SPAEMA and avoid high complexity. In contrast to SPAEMA that ignores the traffic load of the network, which is an important parameter in our studied KPIs, our proposed algorithm manages the use of RE by taking into account the SoC of the battery and the traffic load. Similar to SPAEMA, we quantify each of the traffic and battery storage states into 3 discrete levels: low, medium and high. Table 3.2 shows the applied decisions for different cases.

Table 3.2 – STAEMA decisions for different cases of battery and traffic load.

Battery/Traffic	Low	Medium	High
Low	store	store	use
Medium	store	use	use
High	use	use	use

The decisions summarized in the table below are designed to store the harvested energy in the battery when its SoC is low, and then use it at high traffic load. This setup will minimize the waste of RE caused by battery overflow, and compensate for the increase in energy consumption caused by the increased traffic load.

Both SPAEMA and STAEMA do not switch BSs  $\in \mathcal{B}^{mix}$  to sleep mode. In the next algorithm, we extend the latter algorithm to allow hybrid powered BSs to switch to sleep mode.

### Proposed algorithm 2 - Extended-STAEMA

Extended-STAEMA (Ext-STAEMA) allows BSs equipped with RE sources to switch to sleep mode. It modifies the candidate set  $\mathcal{B}^c$  to include BSs  $\in \mathcal{B}^{mix}$ .

When a BS switches to sleep mode, its KPI drops to zero, since it is not transmitting data anymore, and hence, affecting the network KPI as shown in Fig. 3.4. At  $t_1$ , both BSs are active (consuming energy and transmitting data) with different KPI values. At  $t_2$ ,  $BS_2$  switches to sleep mode. During this time, the users offload to  $BS_1$ , increasing its data transmitted volume, thus increasing its KPI, while the KPI of  $BS_2$  drops to zero. In order to better handle this degradation in the network KPI, we decide to put the BSs equipped with RE sources to sleep, in the case where the traffic load is high and the battery SoC is low. The motivation behind this is to preserve the energy stored in the battery for a longer period of time and to enhance the KPI of the neighboring BSs by transmitting more data to the newly offloaded users. We summarize the decisions in Table 3.3.

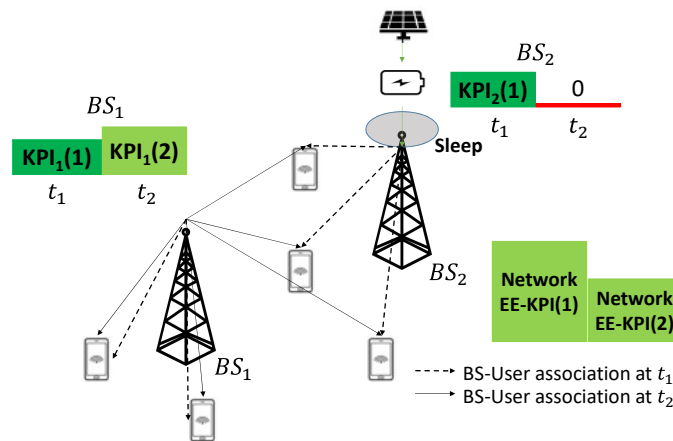


Figure 3.4 – Illustration of the STAEMA algorithm operation: At  $t_1$ , both BSs are active. At  $t_2$ ,  $BS_2$  switches to sleep mode, and its users offload to  $BS_1$   
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The decision of switching BS  $m \in \mathcal{B}^{mix}$  to sleep mode, in the case when the SoC of its battery is low and the traffic is high, depends whether the

Table 3.3 – Extended-STAEMA decisions for different cases of battery and traffic load.

Battery/Traffic	Low	Medium	High
Low	store	store	use/ sleep
Medium	store	use	use
High	use	use	use

condition of switching off  $m$  is satisfied in equation (3.3). If not,  $m$  will use its stored energy to power its components.

### 3.4 Results and discussion

In this section, we first evaluate the energy and operational cost savings of a partially RE-equipped network. Then, we assess the performance of this network over the different services it provides using the advanced KPIs metric proposed. We obtain our result via Monte-Carlo method using MATLAB. The month of June is considered as an example to harvest solar energy due to its high solar potential (7.08 KWH/day/ $m^2$ ). We assume that the load is randomly distributed among the BSs following the traffic load variation in Fig. 3.3.

In order to evaluate the energy efficiency of the services provided by the cellular network, we consider five service categories: two large ones (streaming and web) and three smaller ones (download, voice and other minor data services). We set  $T = 24$  hours and evaluate the  $KPI(t)$  on an hourly basis. From equation (3.5), whenever the harvested energy ( $RE_m(t)$ ) is higher than the energy consumed by BS  $m$  ( $E_m(t)$ ), the excess RE is stored in the battery. In Table 3.4, we summarize the simulation parameters and traffic proportions of each service taken from a real European operator data set [87].

Table 3.4 – Parameters’ values and assumptions.

Parameters	Values
Number of BSs	25
Number of sectors	3
Bandwidth	10 MHz, FDD
Maximum transmitted power	43 dBm
Inter-cell distance	1000 m
RB	50
$BW_{RB}$	180 KHz
Number of users K	400
User min. required rate	1 Mb/s
Noise power	-174 dBm/Hz
$P_0$	118.7 W
$\Delta_p$	5.32
Number of slots per hour period L	10
Battery capacity	5 KWh
Services	Traffic proportions [87]
Streaming	34%
Web	30%
Download	13%
Voice	9%
Other data	14%

### 3.4.1 Energy and operational cost savings

We define the operational cost gain as follows:

$$\text{Operational Cost Gain} = 1 - \frac{\sum_{i=1}^L E_c^g(i) \times p(i)}{\sum_{i=1}^L E_{FL}^g \times p(i)} \quad (3.17)$$

where  $E_{FL}^g$  is the on-grid energy consumption of the network without RE at full load, i.e., using all radio resources.  $E_c^g(i)$  is the on-grid energy consumption at time instant  $i$ , with RE and using the online energy management strategies described in Section 3.3.4.  $p(i)$  is the price of electricity at time instant  $i$ .

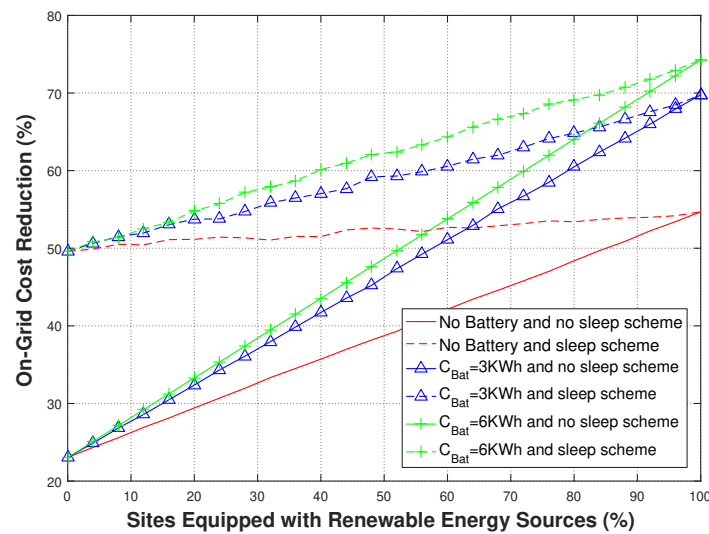


Figure 3.5 – Percentage of on-grid cost reduction over one day, with a  $12.5\text{m}^2$  solar panel surface area © 2018 IEEE.

We consider several parameters when studying the operational cost gain of the network. In addition to evaluating this gain over different percentage of sites equipped with RE, we investigate the impact of the size of solar panels and the capacity of battery storages on this gain over one day. In Fig. 3.5, we quantify the on-grid cost gain of equation (3.17) versus the percentage of sites equipped with RE, for different battery capacity sizes. The 20% gain obtained when none of the sites are equipped with RE sources and no sleep scheme is considered, is a result of the RB allocation algorithm, described in Algorithm 2, that turns off excess RBs and hence, reduces the energy consumption. We observe that equipping only 30% of sites with RE sources, achieves a cost saving gain of roughly 58%, while we can reach up to 75% when all BSs are equipped with solar panels that harvest no more than 35% of the total energy demand at full load. This amount of harvested energy is related to the panel surface area of  $12.5\text{m}^2$  used in this setup.

Fig. 3.6 illustrates the operational cost gain versus battery capacity sizes, for different percentage of sites equipped with RE sources. We demonstrate the case where sleep mode is not activated, to emphasize the battery capacity impact on the gain achieved solely by RE. The results uncover a cost reduction of around 68% with a  $12.5\text{m}^2$  solar panel surface area. However, this result is obtained when all the sites are equipped with RE. We also observe that the cost gain is divided into three regions. The first shows a linear increase in the gain versus the battery capacity.

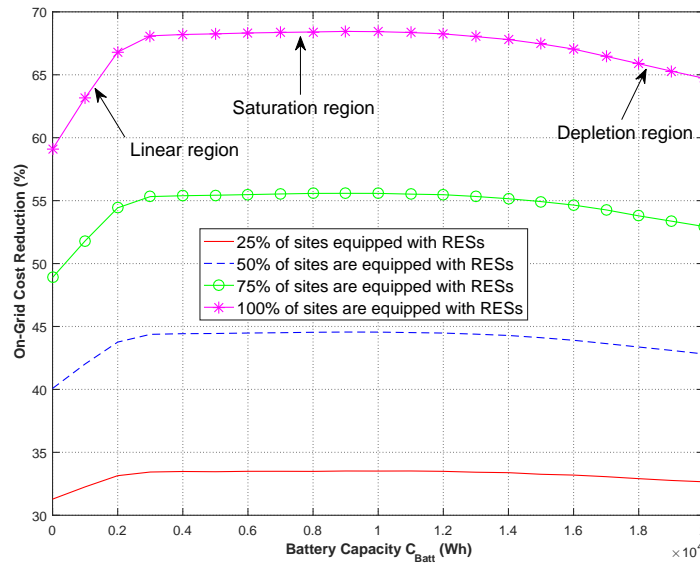


Figure 3.6 – Percentage of on-grid cost reduction over one day with a  $12.5\text{m}^2$  solar panel surface area, without sleep mode © 2018 IEEE.

As the size of the battery increases, less green energy will be lost due to battery overflow. The second region is denoted as the saturation region. In this region, further increase in the battery capacity brings no significant gain. In this case, the harvested energy is fully used and there is no waste in RE. The last region is the depletion region for large battery capacities. Its behavior is related to the energy management strategy used (here, it is SPAEMA). Based on SPAEMA, if the battery level is low, the harvested RE will be stored in the battery until it reaches a certain threshold (i.e., medium battery level). However, this threshold increases when the battery capacity is increased. Hence, for large batteries, SPAEMA doesn't properly manage RE and it will keep on storing this energy until this threshold is reached.

Fig. 3.7 shows the operational cost savings for different solar panel surface areas. Results show that by increasing the size of PV panels, the impact on cost savings from RE increases compared to the savings obtained from sleep scheme only. However, equipping small solar panels with a surface area less than  $6\text{m}^2$  (harvesting less than 10% of the network total energy demand), degrades the cost savings, compared to the case when using the sleep scheme algorithm described in Algorithm 1. This is because solar panels with such harvesting capabilities save less energy than switching off BSs. In this work, we do not consider the cost

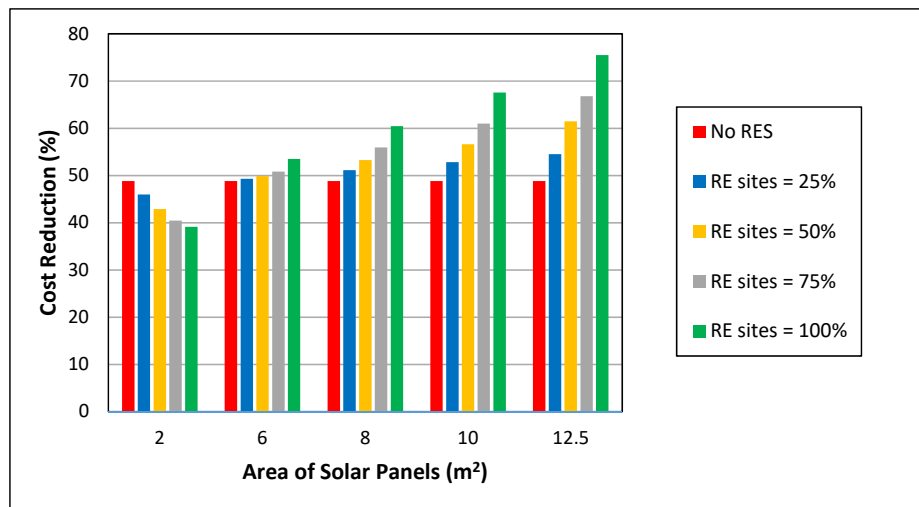


Figure 3.7 – Percentage of on-grid cost reduction for different panel sizes with sleep mode over one day, with a battery capacity of 3 KWh © 2018 IEEE.

of equipping these sites with RE sources and battery storages. We focus only on the OpEx cost.

Fig. 3.8 illustrates the cost gain versus  $SINR_{SOT}$ . The results show that as the percentage of sites equipped with RE increases, the impact of  $SINR_{SOT}$  on the cost gain decreases. For instance, when less BSs are equipped with RE sources, more will be able to switch to sleep mode and hence, the SINR switch-off threshold will impact a bigger set of BSs.

### 3.4.2 Impact of RE and sleep scheme on the energy efficiency KPI metric

We evaluate the network energy efficiency KPI for the different services the network is providing in Fig. 3.9. We evaluate the network KPI for the different services the network is providing. These values are calculated in the absence of RE and energy management strategies. From the obtained results, we observe that the KPIs of the services are proportional to their traffic volumes, i.e., the larger the service is, the higher is its KPI. And even though Shapley energy model puts more weight on larger service categories, their KPI is higher due to their increased traffic volume.



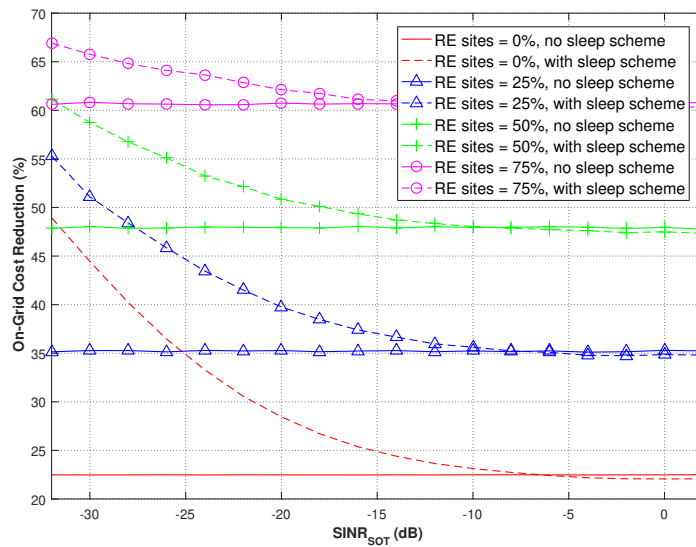


Figure 3.8 – Impact of SINR<sub>SOT</sub> on the on-grid cost gain, with a 12.5m<sup>2</sup> solar panel surface area and a battery capacity of 3 KWh © 2018 IEEE.

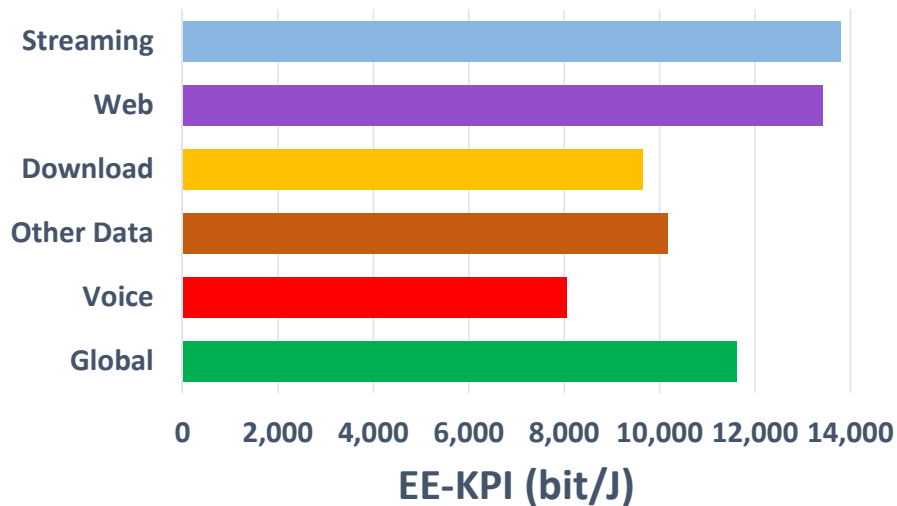


Figure 3.9 – Evaluation of the network global and services KPIs in the absence of RE and energy management techniques © 2018 IEEE.

### 3.4.3 Network performance evaluation

In order to assess the performance of the network, we evaluate the KPI metric for the streaming service, since it brings the largest traffic load with the highest KPI as shown in Fig. 3.9. We compare SPAEMA, STAEMA and extended-STAEMA with the greedy algorithm that uses harvested energy whenever available and stores the excess RE in the battery.

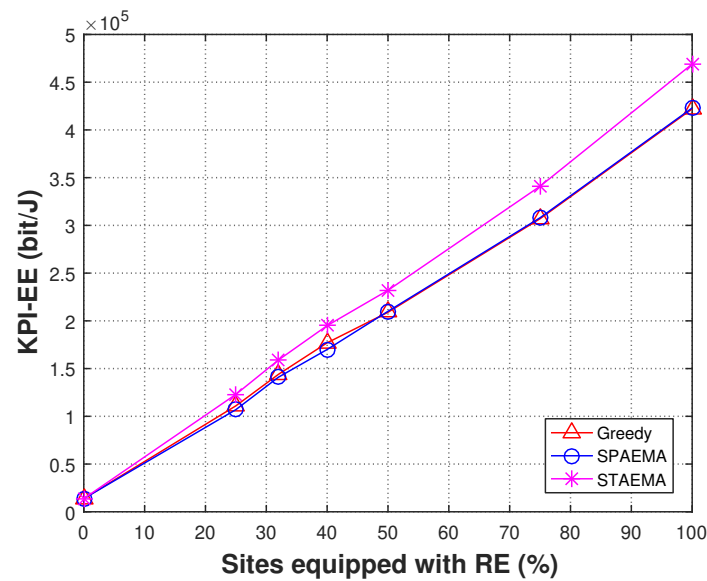


Figure 3.10 – Comparison of the network streaming KPI with different energy management strategies without sleep scheme © 2018 IEEE.

Fig. 3.10 illustrates the performance of the network streaming KPI for different percentages of sites equipped with RE without sleep mode. The system achieves the lowest KPI when the energy allocation policy does not take into account traffic volume (greedy and SPAEMA). On the other hand, STAEMA results in an enhancement in the KPI up to 11.45% in comparison with the other two. The reason behind the similar performances of greedy and SPAEMA algorithms is that they both ignore traffic load variations.

In Fig. 3.11, we present the results while considering sleep scheme. Ext-STAEMA algorithm, that widens the candidate set of BSs allowed to switch to sleep mode to include BSs equipped with RE, performs slightly better than STAEMA (~ 2% points). This tells us that under these traffic-aware algorithms, our KPI has reached its limit. The reason is because our metric does not valorize grid energy savings of the network. Despite having similar performances of KPI, Ext-STAEMA saves more energy than the other algorithms (up to 8% more savings), as shown in Table 3.5. This can be explained by the wider set of BSs that can be put to sleep mode, and thus saving more energy.

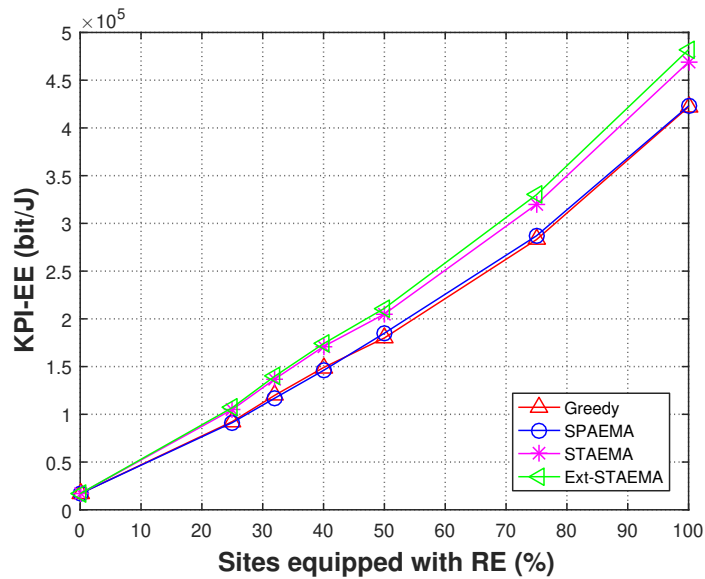


Figure 3.11 – Comparison of the network streaming KPI with different energy management strategies with sleep scheme © 2018 IEEE.

Table 3.5 – Total energy savings of the network.

Algorithms	Total Energy Savings (%)			
	% of sites equipped with RE			
	25%	50%	75%	100%
Greedy	37.75	40.8	44.3	50.5
SPAEMA	37.75	40.8	44.3	50.5
STAEMA	38.13	40.8	44.3	50.5
Ext-STAEMA	40.46	45.5	51.7	58.4

### 3.5 Conclusion

In this chapter, we have presented a global framework to study cellular networks powered by RE systems. We demonstrated the effect of equipping BSs with RE sources on the operational cost savings for different input parameters ranging from RE dimensioning to different energy management techniques. Furthermore, we have studied advanced energy efficiency metrics that put forward the contribution of each service the network is providing. Using these KPIs, we proposed to adapt some existing energy management strategies. On one hand, the proposed adaptations achieved better performance and outperformed several benchmark algo-

rithms. On the other hand, these KPIs revealed a limitation by not reflecting grid-energy savings.

In the following chapter, we extend the work by taking into consideration the behavior of the batteries (the energy storage element) when designing energy management strategies. In particular, we focus on extending the battery lifetime while maximizing the operational grid cost savings.



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# Battery Aging-Aware Green Cellular Networks with Hybrid Energy Supplies

## 4.1 Introduction

In the previous chapter, we studied the operational cost savings and performance of a hybrid energy-powered cellular network partially equipped with RE sources. In this chapter, we focus on the storage element (i.e., battery) that is prone to irreversible aging mechanisms, thus requiring precise management that considers not only energy cost, but also constraints preventing fast battery degradation. The latter is of great importance given the high capital costs of these elements. However, most studies in the literature did not consider the impact of the battery utilization on its capacity degradation. Among the few studies that considered the aging of the batteries while studying cellular networks powered by RE sources is the work in [103]. In this study, the authors showed that by respecting some battery constraints, the battery lifespan can be enhanced up to 50% of its initial state of health per year. Thus, resulting in an increase in the OpEx cost savings. However, this work considered the case of a single BS and assumed non-causal information of the system, including traffic load, RE generation and BS power consumption profile.

In contrast to [103], in this work we first include a short summary for the important battery requirements before proposing an online en-

ergy management algorithm that considers both energy cost and battery health that does not depend on the future system information. In this regard, we propose the Battery Aging and Price-Aware (BAPA) algorithm that brings down the grid energy consumption of a BS, while preserving the energy storage element. Then, we extend the algorithm to include cooperation between the BSs of a cellular network, while respecting the constraints on the battery to expand its lifespan in the Joint Power Allocation and Resource Sharing with Sleep Mode (JPARS-SM) algorithm.

First, we present the details of the battery model in Section 4.2. Then, we formulate the power and resource allocation problem for a single BS model in Section 4.3. We evaluate the optimal energy allocation by solving the linear convex optimization problem. Next, we evaluate BAPA, an online resource allocation algorithm, and we compare it with the optimal policy. Finally, we extend the work to multi-BSs systems with the JPARS-SM algorithm in Section 4.4. Due to the complexity of the formulated problem (Mixed-Integer Non-Linear Programming - MINLP), we investigate the energy and resource allocation problems with the potential to switch off BSs by proposing a heuristic online algorithm.

## 4.2 Efficient lithium battery utilization

Compared with traditional batteries, i.e., lead acid and nickel cadmium, lithium batteries technologies feature high energy density, high power density, high energy efficiency, large service life and environmental friendliness [182]. However, a typical used battery generates expensive investment cost due to its finite life span. This operational limitation is a result of irreversible degradations from chemical and physical changes, affecting its electrical performance, and hence, degrading its efficiency. In the following, we describe the constraints imposed on the battery that prevent its fast capacity degradation.

A typical battery is described by the following metrics:

1. SoC: it is the ratio of the remaining charge of the battery to the total charge while the battery is fully charged [182].

$$\text{SoC}(t) = \frac{B(t)}{B_{max}} \quad (4.1)$$

2. Depth of Discharge (DoD): it is used to describe how much the battery is discharged. A fully charged battery (100%) means that its DoD is 0%. On the other hand, a battery delivering 30% of its energy (with 70% energy reserved) has a DoD of 30%.
3. State of Health (SoH): it is a figure of merit that represents the condition of the battery compared to its ideal conditions [182]. It can be defined as the ratio of the current capacity and the rated capacity given by the manufacturer:

$$\text{SoH}(t) = \frac{C_{ref}(t)}{C_N} \quad (4.2)$$

where  $C_{ref}(t)$  is the current capacity at time  $t$  and  $C_N$  is the rated nominal capacity.

The degradation of the battery reference capacity is caused by two aging processes: during operation (i.e., cycling), denoted by cycle aging; and at rest, denoted by calendar aging. In the following, we summarize the battery constraints used in our work.

1. *Cycle aging*: it is the result of the energy exchange with battery (charging and discharging). It depends on the battery SoC variations [183]. Fig. 4.1 illustrates the ideal operating range of SoC that is recommended for lithium batteries [184]. As a result, the lithium battery usage is restricted on a specific range of:

$$B(t) = [20\%, 90\%] \quad (4.3)$$

By staying in this interval, the battery makes more (dis)charging cycles.

2. *Calendar aging*: the battery calendar life is the time elapsed until the battery becomes unusable. It is mainly influenced by the battery temperature and time [185]. Thus, in order to operate the lithium battery in a safe operating area restricted to temperature, the (dis)charge currents should be limited. Consequently, the following constraint must be respected:

$$|B(t) - B(t-1)| \leq \alpha \times B(t-1), \forall t = 2, \dots, T \quad (4.4)$$

where  $\alpha$  takes a value between 0 and 1 and  $T$  is in hours (i.e.,  $T = 24$  hours).



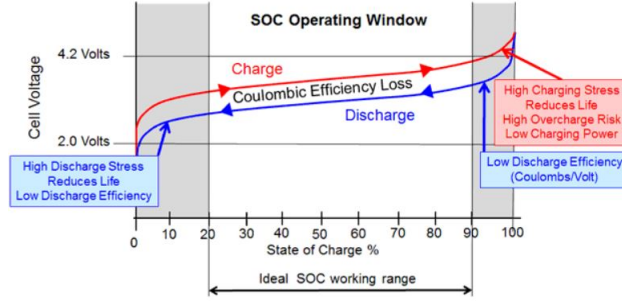


Figure 4.1 – Recommendation for the operating range of SoC for lithium ion battery [184].

The relationship between the variations in the SoC and the SoH is linear [183]:

$$\text{SoH}(t + \Delta t) = \text{SoH}(t) - Z \cdot [\text{SoC}(t) - \text{SoC}(t + \Delta t)] \quad (4.5)$$

where  $Z$  is an experimental function of SoC that is denoted by the linear aging coefficient. This coefficient depends on the battery technology. It is defined as follows:

$$Z = \begin{cases} 85 \times 10^{-6}, & \text{if } 20\% \leq \text{SoC}(t) \leq 90\% \\ \chi \times 85 \times 10^{-6}, & \text{otherwise} \end{cases} \quad \forall t, \quad (4.6)$$

where  $\chi$  is a scalar strictly greater than one.

In addition to the capacity degradation, the battery witnesses energy losses while (dis)charging. Each time the battery is (dis)charged with  $E$  units of energy, only  $\eta \cdot E$  is used/stored, where  $0 \leq \eta \leq 1$  represents the storage efficiency.

### 4.3 Single BS model: offline vs online solutions

We start by studying the problem of grid energy savings maximization for one BS before extending it to multi-BSs. We decompose the problem into three sub-problems: resource sharing, grid energy purchase policy and power allocation. The main notations used in this chapter are described in Table 4.1.

### 4.3.1 System operational model

#### System architecture

As illustrated in Fig. 4.2, we consider the architecture composed of:

- A BS covering an area of radius  $R$  and serving  $K$  mobile users. Let  $\mathcal{U} = 1, \dots, K$  be the set of served users. The users request a minimum data rate,  $R^{req}$ .
- A RE source (Photo-Voltaic (PV) system) that harvests solar energy to produce electricity.
- A battery to store energy either from the PV system or the power grid (i.e., SG). This storage unit allows flexibility in the energy utilization.
- The SG as the second source in providing energy to the system. It can directly power the BS or get stored in the battery for future use (e.g., when the price of electricity is low). Thus, there is no constraint from the power demand of the BS on the SG side.
- A local EMU responsible for managing the flow of energy and allocating power (grid and RE) to efficiently maximize the utilization of RE, and thus minimizing the grid energy cost.

The amount of RE generated during time  $t$ , denoted by  $RE(t)$ , can be stored in the battery ( $E^b(t)$ ) and can also be used directly ( $E^{BS}(t)$ ). Similarly, the amount of grid energy purchased from the SG is used to power the BS ( $E^{g,BS}(t)$ ) and, if necessary, to store in the battery ( $E^{g,b}(t)$ ) for future use<sup>1</sup>. This results in the following equalities:

$$RE(t) = E^{BS}(t) + E^b(t) + w(t) \quad (4.7)$$

$$E^g(t) = E^{g,b}(t) + E^{g,BS}(t) \quad (4.8)$$

where  $w(t)$  is the amount of wasted RE. The local EMU manages the allocation of RE, whether to be used or stored in the battery. It also decides when and how much to store grid energy.

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<sup>1</sup>Without loss of generality, we can normalize the duration of each time slot to be a unit of time so that we use the terms "power" and "energy" interchangeably.

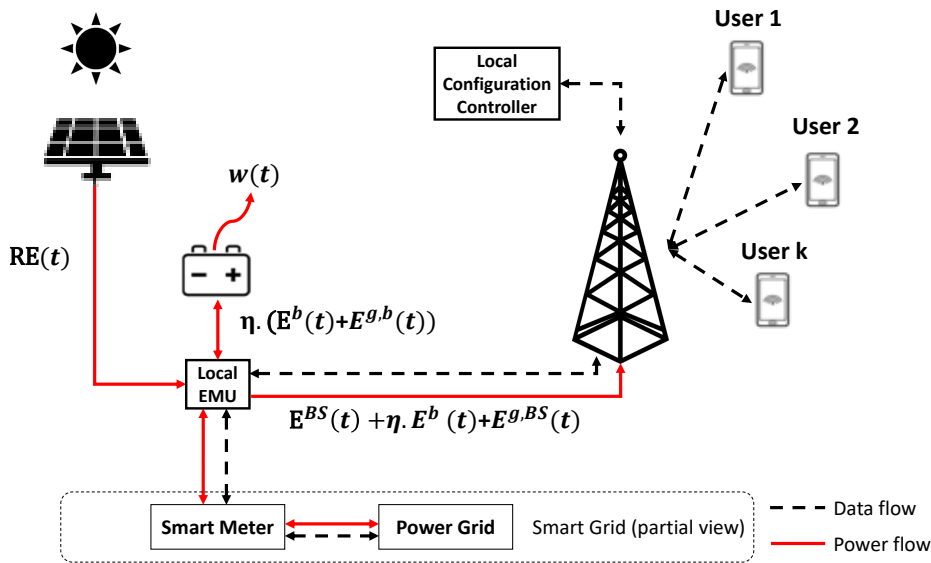


Figure 4.2 – System architecture. The BS serves  $K$  users and is powered by a hybrid energy source.

### Time scales for network operations

Due to the fast variations of the load distribution and the downlink wireless channels compared to the slow variations of the grid energy prices and the amount of harvested RE, we consider two time scales in our model. One is longer than the other. As shown in Fig. 4.3, each large-time scale period is decomposed into  $L$  time slots. During these time slots, only the channel gains and the position of the users vary. We define the large-time scale periods long enough so that the network traffic load, the RE arriving rate and the price of electricity are unchanged during each of these time periods.

### Energy storage

As shown in Fig. 4.2, the battery can store the harvested energy from the local PV system and the on-grid energy that is purchased from the SG. At each time slot, the local EMU decides how much energy to store from the RE source, and how much to buy from the grid, by jointly considering the BS energy demand, the hybrid energy storage, the price of electricity and the battery constraints imposed on the battery to prevent fast capacity degradation.

Table 4.1 – Notations

$RE$	Amount of RE generated
$E^b$	Amount of RE store in the battery
$E^{BS}$	Amount of RE used to power the BS directly from the PV panel
$p$	BS power consumption
$E^b$	Energy used from the battery to power the BS
$E^g$	Energy bought from the smart grid
$E^{g,b}$	Energy bought from the smart grid and stored in the battery
$E^{g,BS}$	Energy bought from the smart grid and used to power the BS
$a$	Buying energy price from the smart grid
$G$	Green energy budget
$h$	Channel gain due to path loss
$\sigma^2$	Noise power density
$s$	Short time scale slot
$x$	User-Base station association parameter
$y$	Share of resources the BS allocates to a user
$W_{RB}$	Bandwidth of one resource block
$n_{RB}$	number of resource blocks allocated
$n_{RB}^{Total}$	Total number of resource blocks
$R$	Maximum rate achieved
$R^{req}$	Required data rate
$SoC$	State of charge
$SoH$	State of health
$C_{ref}$	Battery reference capacity
$C_N$	Battery nominal capacity
$B$	Battery capacity
$B_0$	Battery initial capacity
$B_{max}$	Battery size
$\alpha$	Battery maximum (dis)charging rate
$DoD$	Depth of discharge

Denote the storage level of the battery at the beginning of time slot  $s$  of time  $t$  as  $B_{L(t-1)+s} \geq 0$ , the amount of the grid energy purchased and stored in the battery as  $E_{L(t-1)+s}^{g,b} \geq 0$ , and the amount of energy drawn

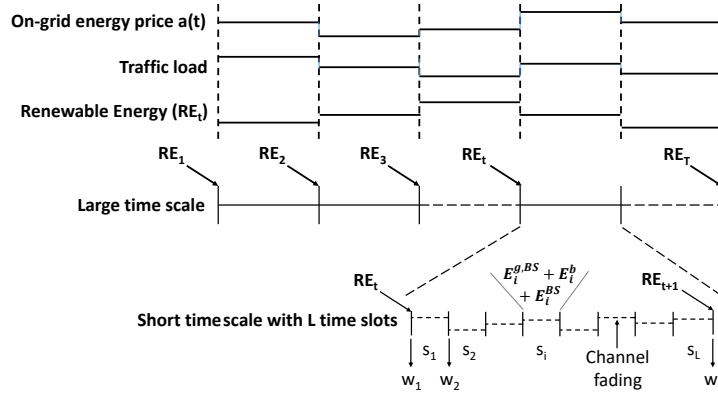


Figure 4.3 – System time scales. The price of electricity, the traffic load and the RE arrivals vary slowly compared to the channel fading and users distribution © 2018 IEEE.

from the battery to power the BS as  $E_{L(t-1)+s}^b \geq 0$ . To make sure that the BS uses only the energy that is available before the beginning of each time slot, we impose the following energy causality constraints:

$$B_{L(t-1)+s} = B_0 + \sum_{i=1}^t \sum_{j=1}^{\mathcal{F}(i)} (\eta(E_{L(i-1)+j}^b + E_{L(i-1)+j}^{g,b}) - \eta \cdot E_{L(i-1)+j}^b - w_{L(i-1)+j}) \geq 0, \quad \forall t = 1, \dots, T, \forall s = 1, \dots, L. \quad (4.9)$$

where  $\mathcal{F}(i)$  is described as follows:

$$\mathcal{F}(i) = \begin{cases} L, & i = t-1 \\ s-1, & i = t \end{cases} \quad (4.10)$$

The term  $w$  introduced refers to the amount of RE lost at the end of the observed slot. This is due to the limited battery capacity,  $B_{\max}$ . Consequently, the battery has to discard the excess harvested energy ( $w$ ), to satisfy the following battery capacity constraints:

$$B_{L(t-1)+s} \leq B_{\max}, \quad \forall t = 1, \dots, T, \forall s = 1, \dots, L. \quad (4.11)$$

### 4.3.2 Joint power and resource allocation: offline approach

Denote by  $a(t)$  the real-time price of electricity at each time step  $t$ . We aim at minimizing the on-grid energy consumption of the energy harvesting BS taking into account the battery degradation model. This is achieved

by jointly allocating the power between the power grid, the RE source, the battery, and managing the network radio resources.

In the following, we formulate the offline power and resource allocation problem for the hybrid wireless system. The first set of optimization variables are the vector of power allocation  $\mathbf{p} = (\mathbf{p}_t)_{t=1,\dots,T} \in \mathbb{R}_+^T$  used for the BS, and the matrix of the share of resource allocation  $\mathbf{y} = (\mathbf{y}_t, \mathbf{u})_{t=1,\dots,T, u \in \mathcal{U}} \in \mathbb{Z}_2^{T \times K}$  used for the served users. In addition, we optimize the following four power usage vectors for the BS: (1) the grid-BS power vector  $\mathbf{E}^{\mathbf{g}, \mathbf{BS}} = (\mathbf{E}_t^{\mathbf{g}, \mathbf{BS}})_{t=1,\dots,T} \in \mathbb{R}_+^T$  used from the power grid to power the BS, (2) the battery-BS power vector  $\mathbf{E}^{\mathbf{b}} = (\mathbf{E}_t^{\mathbf{b}})_{t=1,\dots,T} \in \mathbb{R}_+^T$  used to power the BS from the battery and (3) the grid-battery power vector  $\mathbf{E}^{\mathbf{g}, \mathbf{b}} = (\mathbf{E}_t^{\mathbf{g}, \mathbf{b}})_{t=1,\dots,T} \in \mathbb{R}_+^T$  bought from the power grid and stored in the battery. Finally, we optimize the use of RE vectors  $\mathbf{E}^{\mathbf{BS}}$  and  $\mathbf{E}^{\mathbf{b}} = (\mathbf{E}^{\mathbf{BS}}, \mathbf{E}^{\mathbf{b}})_{t=1,\dots,T} \in \mathbb{R}_+^T$ .

$$\min_{\mathbf{p}, \mathbf{y}, \mathbf{E}^{\mathbf{g}, \mathbf{BS}}, \mathbf{E}^{\mathbf{b}}, \mathbf{E}^{\mathbf{g}, \mathbf{b}}, \mathbf{E}^{\mathbf{BS}}, \mathbf{E}^{\mathbf{b}}} \sum_{t=1}^T \sum_{s=1}^L \alpha_t (p_{L(t-1)+s} + E_{L(t-1)+s}^{\mathbf{g}, \mathbf{b}} - \eta E_{L(t-1)+s}^{\mathbf{b}} - E_{L(t-1)+s}^{\mathbf{BS}}) \quad (4.12)$$

Given that  $E_i^{\mathbf{g}, \mathbf{BS}} = p_i - \eta E_i^{\mathbf{b}} - E_i^{\mathbf{BS}}$ , and from equation (4.8), we can rewrite equation (4.12) as follows:

$$\min_{\mathbf{p}, \mathbf{y}, \mathbf{E}^{\mathbf{g}, \mathbf{BS}}, \mathbf{E}^{\mathbf{b}}, \mathbf{E}^{\mathbf{g}, \mathbf{b}}, \mathbf{E}^{\mathbf{BS}}, \mathbf{E}^{\mathbf{b}}} \sum_{t=1}^T \sum_{s=1}^L \alpha_t \times E_{L(t-1)+s}^{\mathbf{g}} \quad (4.13)$$

subject to:

$$y_{L(t-1)+s, m} \times W_{RB} \times \eta_{RB}^{\text{Total}} \times \log_2(1 + \text{SNR}_{L(t-1)+s, m}) \geq R^{\text{req}}, \quad \forall t = 1, \dots, T, \forall s = 1, \dots, L, \forall m \in \mathcal{U}, \quad (4.14)$$

$$E_{L(t-1)+s} = E_{L(t-1)+s}^{\mathbf{b}} + E_{L(t-1)+s}^{\mathbf{BS}} + w_{L(t-1)+s}, \quad \forall t = 1, \dots, T, \forall s = 1, \dots, L, \quad (4.15)$$

$$E_{L(t-1)+s}^{\mathbf{g}} = E_{L(t-1)+s}^{\mathbf{g}, \mathbf{b}} + E_{L(t-1)+s}^{\mathbf{g}, \mathbf{BS}}, \quad \forall t = 1, \dots, T, \forall s = 1, \dots, L, \quad (4.16)$$

$$p_{L(t-1)+s} = E_{L(t-1)+s}^{\mathbf{g}, \mathbf{BS}} + \eta \cdot E_{L(t-1)+s}^{\mathbf{b}} + E_{L(t-1)+s}^{\mathbf{BS}}, \quad \forall t = 1, \dots, T, \forall s = 1, \dots, L, \quad (4.17)$$

$$\sum_{m \in \mathcal{U}} y_{L(t-1)+s, m} \leq 1, \quad \forall t = 1, \dots, T, \forall s = 1, \dots, L, \quad (4.18)$$

$$\mathbf{p} \geq 0, \mathbf{y} \geq 0, \mathbf{E}^{\mathbf{g}} \geq 0, \mathbf{E}^{\mathbf{b}} \geq 0, \mathbf{E}^{\mathbf{g}, \mathbf{BS}} \geq 0, \mathbf{E}^{\mathbf{g}, \mathbf{b}} \geq 0, \mathbf{E}^{\mathbf{BS}} \geq 0, \mathbf{E}^{\mathbf{b}} \geq 0, \quad (4.19)$$

Energy Storage Constraints: (4.3),(4.4),(4.9),(4.11).

The first set of constraints (equation 4.14) guarantees a minimum rate requirement for the users in order to satisfy a certain QoS level. Next, we have the harvested energy usage, grid energy usage and BS power equality constraints in equations (4.15), (4.16) and (4.17), respectively. Then, the resource allocation constraints are given in equation (4.18). Furthermore, the energy storage constraints are summarized in equations (4.9) and (4.11). The causal energy constraints in equation (4.9) ensure that the total RE used up until the  $i$ -th time slot will not exceed the available amount that was harvested and stored in the previous  $(i-1)$ -th time slots. On the other hand, equation (4.11) is the battery capacity constraint. Consequently, in case of battery overflow, the excess energy must be discharged through the auxiliary variable  $w$ . Moreover, equations (4.3) and (4.4) describe the battery usage constraints. Finally, we have the non-negative vectors constraints in (4.19).

The offline optimization problem described above is a linear program, thus convex. Hence, it can be solved efficiently using an optimization solver such as MATLAB using the dual-simplex algorithm. We denote this by the offline approach and we use it to calculate the optimal allocation values as a reference for comparison later in Section 4.5.1. Since solving the above formulated problem requires the knowledge of all system variables in advance, in the next section we will develop an online algorithm that achieves near-optimal solution without the requirement of future knowledge.

### 4.3.3 Battery aging and price-aware (BAPA) algorithm: online approach

In this section, we provide an online solution based on the design philosophy of the offline algorithm. The latter gives insight on the importance of storing grid energy to use it later when the price of energy is low. We present Battery Aging and Price-Aware (BAPA), a new algorithm that does not require the knowledge of RE generation. We decompose the problem into three subproblems: resource sharing problem, grid energy purchase problem and power allocation problem. In Algorithm 3, we summarize BAPA algorithm.

### Resource sharing problem: Max-Min fairness algorithm

The reader can refer to Algorithm 2 in Section 3.3.4. We note that this algorithm is executed every small time slot ( $s$ ).

### Grid energy purchase problem

We measure the average amount of energy ( $P^{avg}$ ) required to power the BS during the observation time  $T$  following the traffic load prediction in [14].

$$P_{L(t-1)+s}^{avg} = \sum_{i=t}^T \sum_{j=s}^L p_j^{est} \quad (4.20)$$

(4.20) gives the average power required for the BS to be in operational mode from time  $t$  until the end of the day. The value of  $p^{est}$  is an estimate of the power consumption of the BS during a time slot. It is tuned according to the power model in Section 2.2 under extensive simulations for different percentage of traffic load.

*Proposition 1 (sub-optimal on-grid energy purchase):* the amount of purchased energy from the grid should satisfy the following conditions:

1. *Condition #1:* low present on-grid electricity price.  $a(t) \leq \min(a(t+1), \dots, a(T))$ .
2. *Condition #2:* low future renewable energy.  $\sum_{i=t}^T \sum_{j=s}^L E_{L(i-1)+j} \leq P_{L(t-1)+s}^{avg}$ .

If the above conditions are satisfied:

$$E_{L(t-1)+s}^{g,b} = \min \left( (B_{max} - B_{L(t-1)+s}) \times \alpha, (P_{L(t-1)+s}^{avg} - \sum_{i=t}^T \sum_{j=s}^L E_{L(i-1)+j}) \times \alpha \right). \quad (4.21)$$

where  $\alpha$  is the current restriction coefficient that limits the (dis)charging rate of the battery to keep it in a safe operational area restricted to temperature. It will not allow the battery to be (dis)charged more than  $\alpha$  percent of its current capacity.

Proposition 1 decides when to purchase grid energy, and how much to store in the battery. Condition # 1 allows buying grid energy only when



the price is at its lowest compared to the future price. This policy is in accord with the daily grid energy price that is low at the beginning of the day and assumes future knowledge of the electricity price [179]. However, condition # 2 requires the exact amount of RE that will be harvested in the future. Since this information is not known, we will predict this energy using weather forecast programs, such as [178]. Thus, we can rewrite condition # 2 as follows:

$$G_{L(t-1)+s} \leq P_{L(t-1)+s}^{avg} \quad (4.22)$$

where  $G_t$  is the green energy budget predicted from time  $t$  until the end of the observation time.

### Power allocation problem

The power allocation problem is divided into two parts. The first part (Line 10 of Algorithm 3) finds the allowed amount of RE that can be stored in the battery ( $E^b$ ), while respecting the battery constraints in equations (4.3) and (4.4). The second part (Lines 11-18 of Algorithm 3) decides whether to use the battery to power the BS or save its energy for future use.

Next, we summarize the process of BAPA algorithm in Fig. 4.4. In the diagram, we show the three different parts of the algorithm:

1. Grid energy purchase policy: decides when and how much to buy energy from the grid and stores it in the battery.
2. RE usage: decides how much of the harvested energy is stored in the battery and how much is directly used to power the BS.
3. Battery utilization: decides when to use the battery and when to store energy.

#### 4.3.4 Complexity of the proposed algorithm

The offline formulated problem is an LP (Linear Program) which can be efficiently solved [186]. Here we used the simplex method that is known to perform very well with such models. Regarding the online algorithm

**Algorithm 3** : BAPA Algorithm

- 
- 1: Initialize the battery range of operation, its current restriction parameter ( $\alpha$ ) and its DoD
  - 2: Predict the green energy budget,  $G(1)$ , for the whole day
  - 3: **for**  $t = 1 : T$  **do**
  - 4:     **for**  $s = 1 : L$  **do**
    - \\Subproblem 1: resource Sharing Problem
    - 5:         Obtain  $y_{L(t-1)+s}$  by solving Max-Min algorithm
    - \\Subproblem 2: grid Energy Purchase Problem
    - 6:         Find  $p_{L(t-1)+s}$  from [35]
    - 7:         **if** conditions 1 and 2 in proposition 1 are satisfied **then**
    - 8:             Find  $E_{L(t-1)+s}^{g,b}$  from eq. (4.21)
    - 9:             **end if**
    - \\Subproblem 3: power Allocation Problem
    - 10:         Find  $E_{L(t-1)+s}^b$  and  $E_{L(t-1)+s}^{BS}$  from eq. (1),  $p_{L(t-1)+s}$  calculated in line 6 and the battery constraints eq. (4.3) and (4.4)
    - 11:         **if**  $G_{L(t-1)+s} \geq p_{L(t-1)+s}^{min}$  **then** (use battery)
    - 12:             Find  $E_{L(t-1)+s}^b$ , such that  $p_{L(t-1)+s} = \eta \cdot E_{L(t-1)+s}^b + E_{L(t-1)+s}^b$ , while satisfying (4.3), (4.4) and (4.9)
    - 13:             Update  $B_{L(t-1)+s} = B_{L(t-1)+s} + \eta \cdot E_{L(t-1)+s}^b - E_{L(t-1)+s}^b$
    - 14:             Find  $E_{L(t-1)+s}^{g,BS} = p_{L(t-1)+s} - E_{L(t-1)+s}^{BS} - E_{L(t-1)+s}^b$
    - 15:             **else** (store in the battery)
    - 16:                 Find  $B_{L(t-1)+s} = B_{L(t-1)+s} + \eta \cdot E_{L(t-1)+s}^b$
    - 17:                 Find  $E_{L(t-1)+s}^{g,BS} = p_{L(t-1)+s} - E_{L(t-1)+s}^{BS}$
    - 18:             **end if**
  - 19:     **end for**
  - 20: **end for**
-

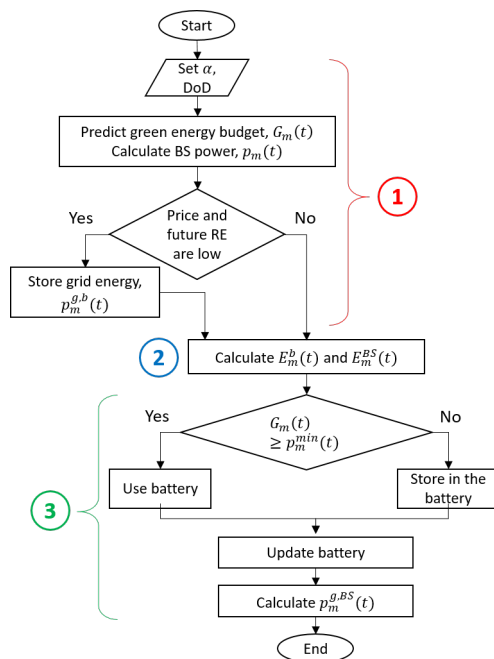


Figure 4.4 – BAPA algorithm flowchart.

(BAPA), it is divided into three parts. The first part uses the Max-Min fairness algorithm that has a complexity of  $O(nLP(n, m))$ , where  $LP(n, m)$  is the complexity of an LP with  $n$  feasible set defined by  $m$  linear inequalities [187]. The remaining two parts have a linear time complexity as can be observed from Algorithm 3.

## 4.4 Multi BS model: online approach

We extend the previous work to multi BS cellular networks. In contrast to the work in Section 4.3, we study the case of cellular networks where BSs can cooperate under RE and SG environment, while respecting the constraints imposed on the battery to expand its lifespan. We consider a large-scale wireless cellular network where a percentage of its sites is equipped with local RE and battery storages. These sites are powered by a hybrid energy source (RE and SG). Under this model, we investigate the allocation of RE, the possibility to store grid energy for future use and the potential to switch off BSs.

### 4.4.1 Problem formulation

We aim at minimizing the grid energy bought from the SG while satisfying the users' QoS (i.e., minimum rate requirement), and reducing the battery aging. This is achieved by allocating the power flow between the RE source, the battery storages, the SG and the BSs. In addition, we consider switching-off some BSs, and resource allocation between active BSs and their served users to save energy. In the following, we consider that  $(\mathbf{p}, \mathbf{E}^{g,BS}, \mathbf{E}^{g,b}, \mathbf{E}^b, \mathbf{E}^{BS}, \mathbf{E}^b) = (\boldsymbol{\phi}_{t,m})_{t=1,\dots,T,m \in BS^{mix}} \in \mathbb{R}_+^{T \times BS^{mix}}$  where  $\boldsymbol{\phi}$  is a matrix variable,  $\boldsymbol{\pi} = (\boldsymbol{\pi}_{t,m})_{t=1,\dots,T,m \in \mathcal{B}} \in \{0, 1\}$ ,  $\mathbf{x} = (\mathbf{x}_{t,m,u})_{t=1,\dots,T,m \in \mathcal{B}, u \in \mathcal{U}_m} \in \{0, 1\}$  and  $\mathbf{y} = (\mathbf{y}_{t,m,u})_{t=1,\dots,T,m \in \mathcal{B}, u \in \mathcal{U}_m} \in \mathbb{W}^{T \times M \times K}$ . The problem can be formulated as follows:

$$\min_{\substack{\mathbf{p}, \mathbf{E}^{g,BS}, \mathbf{E}^{g,b}, \\ \mathbf{E}^b, \mathbf{x}, \mathbf{y}, \boldsymbol{\pi}, \mathbf{E}^{BS}, \mathbf{E}^b}} \sum_{t=1}^T \text{Cost}(t) = \sum_{t=1}^T \sum_{m \in \mathcal{B}} a(t) \left( \pi_m(t) (p_m(t) + E_m^{g,b}(t) - \eta \cdot E_m^b(t) - E_m^{BS}(t)) + (1 - \pi_m(t)) p_m^{sleep}(t) \right) \quad (4.23)$$

Given that:

$$E_m^{g,BS}(t) = p_m(t) - \eta \cdot E_m^b(t) - E_m^{BS}(t) \quad (4.24)$$

and from equation (4.8), we can rewrite equation (4.23) as follows:

$$\min_{\substack{\mathbf{p}, \mathbf{E}^{g,BS}, \mathbf{E}^{g,b}, \\ \mathbf{E}^b, \mathbf{x}, \mathbf{y}, \boldsymbol{\pi}, \mathbf{E}^{BS}, \mathbf{E}^b}} \sum_{t=1}^T \sum_{m \in \mathcal{B}} a(t) \left( \pi_m(t) E_m^{g,BS}(t) + (1 - \pi_m(t)) p_m^{sleep}(t) \right) \quad (4.25)$$

subject to:

$$y_m(t, u) \times \text{BW}_{RB} \times \eta_{RB}^{Total} \times \log_2(1 + \text{SINR}(t, u)) \geq R^{req}, \quad \forall u \in \mathcal{U}_m, \forall m \in \mathcal{B}, \forall t = 1 \dots T, \quad (4.26)$$

$$p(t) = E^{g,BS}(t) + \eta \cdot E^b(t) + E^{BS}(t), \forall t = 1 \dots T, \quad (4.27)$$

$$\sum_{u \in \mathcal{U}} y_m(u) \leq 1, \forall m \in \mathcal{B}, \quad (4.28)$$

$$\sum_{m \in \mathcal{B}} x_u(m) = 1, x_u(m) \in \{0, 1\}, \forall u \in \mathcal{U}, \quad (4.29)$$

$$\mathbf{p} \geq 0, \mathbf{E}^g \geq 0, \mathbf{E}^b \geq 0, \mathbf{E}^{g,BS} \geq 0, \mathbf{E}^{g,b} \geq 0, \mathbf{E}^{BS} \geq 0, \mathbf{E}^b \geq 0, \quad (4.30)$$

Other constraints: (4.3),(4.4),(4.7),(4.8),(4.9),(4.11).

where  $\mathbf{x}$  represents the BS-user association matrix, and  $\pi_m$  is a binary variable that represents the state mode of BS  $m$  ( $\pi_m = 1$ : BS is active;

$\pi_m = 0$ : BS is in sleep mode). The first set of constraints (equation 4.26) guarantees a minimum rate requirement for the users in order to satisfy a certain QoS level. Next, we have the RE usage, grid energy usage and BS power equality constraints in equations (4.7),(4.8) and (4.27), respectively. The causal energy constraint in equation (4.9) ensures that the total RE used up until time  $t$  will not exceed the available amount that was harvested and stored in the previous time slot  $t - 1$ . On the other hand, equation (4.11) is the battery capacity constraint. Consequently, in case of battery overflow, the excess energy must be discharged through the auxiliary variable  $w$ . Equations (4.3) and (4.4) restrict the SoC operating range and the (dis)charging current of the battery, respectively. Finally, the resource allocation and BS-User association constraints are given in equations (4.28) and (4.29). The last set of constraints (4.30) depict the non-negative constraints of the vectors.

The problem formulated above is a Mixed-Integer Non-Linear Programming (MINLP) problem, which is hard to solve due to its non-convexity. In the next section, we propose a new online heuristic sub-optimal solution. And we will show that it performs better than some existing online algorithms.

#### 4.4.2 Description of the proposed algorithm

Due to the complexity and the non-causality of RE information in the problem formulated above, in this section we propose a distributed online solution that manages the energy allocation between the RE source, the SG and the batteries of the BSs equipped with RE. Hence, in the following, we develop an algorithm that does not require information about future RE generation.

##### **Joint Power Allocation and Resource Sharing with Sleep Mode (JPARS-SM)**

The algorithm is summarized in Algorithm 4 as follows. We start by setting the SINR threshold ( $SINR_{SOT}$ ) that specifies when the BS can switch to sleep mode (Section 3.3.4). This threshold is set in order to obtain the best trade-off between QoS and energy savings. Then after setting the BS-Users association and resource allocation matrices ( $x$  and  $y$ ), JPARS-

SM scans for the BSs solely powered by the power grid and checks the possibility to switch them to sleep mode, one by one, starting with the BS having the lowest load following (3.3). Finally, we apply the battery aging and price aware algorithm (i.e., BAPA detailed in Section 4.3.3) on the remaining BSs (equipped with RE) to efficiently allocate the power between the RE source, the SG and the battery in order to minimize the electric bill of the operator.

---

**Algorithm 4** : Joint Power Allocation and Resource Sharing with Sleep Mode (JPARS-SM) Algorithm

---

```

1: Initialize the  $SINR_{SOT}$ 
2: Set  $x(t = 1)$  based on best SINRs method
3: Find  $y(t = 1)$  by solving Max-Min fairness algorithm
4: for  $t = 1 : T$  do
5:   for  $m = 1 : M$  do
6:     if (eq. 3.3) is satisfied then
7:       Switch  $m$  to sleep mode
8:       Update  $x(t)$  by offloading users to nearest BSs with highest
       received SINRs
9:       Update  $y(t)$  by solving Max-Min fairness algorithm
10:    end if
11:    if  $m \in \mathcal{B}^{mix}$  then
12:      Find  $E_m^g(t)$  and  $B_m(t)$  by solving BAPA algorithm in Section
      4.3.3
13:    end if
14:  end for
15: end for

```

---

Next, we summarize the process of Algorithm 4 in Fig. 4.5. In the diagram, we show the different parts of the algorithm:

1. Sleep mode strategy: aggressively turns off BSs not equipped with RE based on an SINR threshold.
2. Max-Min Fairness algorithm: manages the allocation of RBs among the users to satisfy their requirements. It turns off excess RBs to save energy.

3. BAPA algorithm: manages the allocation of energy between the grid, the RE source and the battery efficiently in order to minimize the grid energy consumption as described in Section 4.3.3.

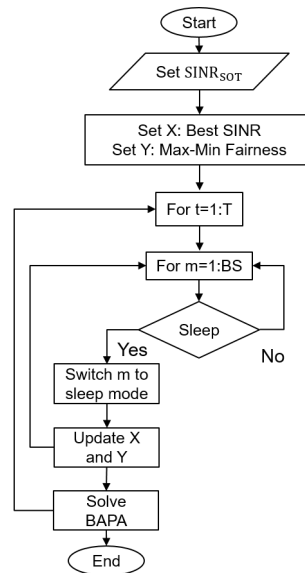


Figure 4.5 – JPARS-SM algorithm flowchart.

## 4.5 Results and discussion

In this section, we evaluate our proposed algorithms under the battery model detailed in Section 4.2. First, we evaluate the performance of BAPA algorithm by considering a macro BS covering a radius of 500 m equipped with a RE source and battery, and connected to the SG. This is done by comparing BAPA with two benchmark algorithms: the optimal policy detailed in Section 4.3.2, and an online algorithm called SPAEMA that decides when to store RE and when to use it based on the SoC of the battery and the current price of electricity. Then, we provide simulation results to study the behavior of JPARS-SM algorithm in a cellular network partially powered by RE sources. We evaluate the energy cost gains for both systems models, as well as the evolution of the battery health.

For both systems, we consider uniformly distributed users in the simulation area requesting simultaneously data. We use lithium type batteries with a DoD of 70%. Furthermore, we restrict the (dis)charging battery rate  $\alpha = 0.3$ . In other words, during one hour, the battery cannot be

(dis)charged more than 30% of its current capacity. Table 4.2 details the assumptions and parameters used in our simulation.

Table 4.2 – Parameters' values and assumptions.

Parameters	Values
BS area radius R	500 m
Number of sectors	3
Bandwidth	10 MHz, FDD
Maximum transmitted power	43 dBm
RB	50
$W_{RB}$	180 KHz
Max. number of users K	single BS: 20; multi-BSs: 400
User min. required rate	single BS: 4 Mb/s; multi-BSs: 1 Mb/s
Noise power	-174 dBm/Hz
$P_0$	118.7 W
$\Delta_p$	5.32
Number of time slots per hour period L	10
Battery energy efficiency $\eta$	0.96

#### 4.5.1 Performance evaluation of BAPA algorithm

In Fig. 4.6, we plot the normalized grid energy consumption of the BS for different daily average RE generation rates ( $RE_{Total}$ ), where  $E_{Total}$  is the average daily energy demand of the BS. The grid energy consumption is normalized with the BS energy demand at full load. Furthermore, we size the battery capacity in proportion to the PV cell installed. In other words, the bigger the solar panel is, the larger the battery capacity becomes. In the following, we consider three PV panel sizes, each with different daily average RE generation rate. First, BAPA consumes excess grid energy at the beginning of the day, as shown at  $t=1,3,4,5$ . During these periods, our algorithm buys energy from the grid and stores it in the battery for future use. By inspecting the grid energy purchase policy in proposition



1, we observe that the grid energy is at its lowest during these periods, hence condition #1 is satisfied. Regarding condition #2, we equip the BS with PV cells that harvest energy less than the demand required by the BS during the day. Thus, at the beginning the day, condition #2 is always satisfied. Second, we observe that the bigger the PV cell is (bigger battery capacity, resp.), the more the system is able to store grid energy during the first hours of the day. This is because BAPA restricts the charging rate of the battery based on its current capacity, in order to preserve its SoH. As a result, small batteries will not be able to store enough grid energy for future use.

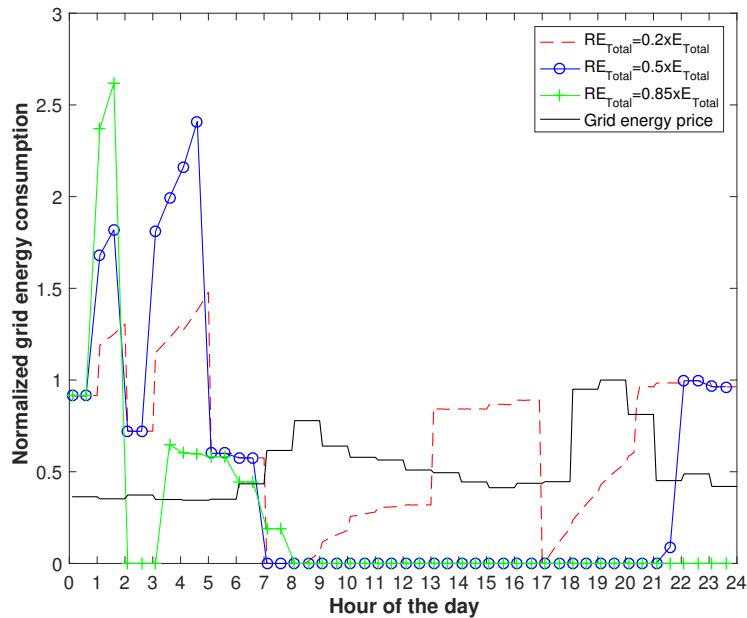


Figure 4.6 – Grid energy consumption for different PV cell sizes © 2018 IEEE.

In Fig. 4.7, we compare our algorithm (BAPA) with the optimal solution and SPAEMA. We observe that the performance of our algorithm is close to the optimal energy and resource allocation problem (up to 99%), whereas SPAEMA diverges away from optimality. The reason is twofold: first, BAPA allows the possibility to store grid energy when the price is low and to use it later at high energy prices. Second, SPAEMA is a threshold based algorithm that depends on fixed battery SoC and current energy price thresholds. Hence, increasing the battery capacity for instance, forces SPAEMA to store more energy until the threshold of using RE is reached. BAPA, on the other hand, depends on the current price of electricity with respect to

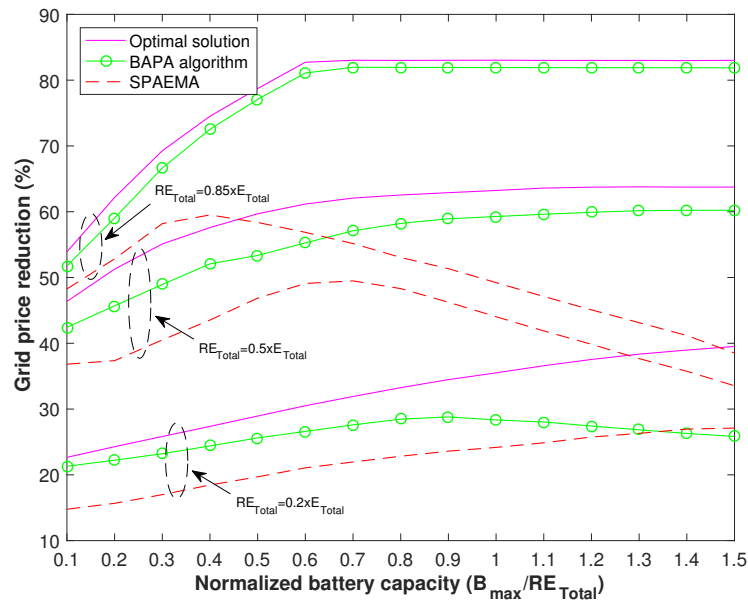


Figure 4.7 – Performance evaluation of BAPA algorithm with the optimal solution and a benchmark online algorithm © 2018 IEEE.

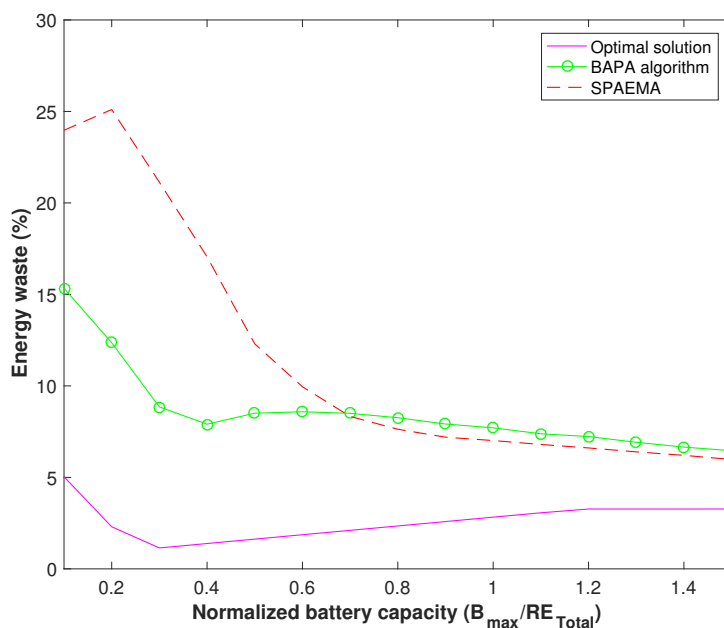


Figure 4.8 – Energy waste with solar panel that harvests 50% of the total BS energy demand © 2018 IEEE.

future prices, and on the difference between the available RE and required energy demand. This results in a more efficient RE utilization compared with SPAEMA.

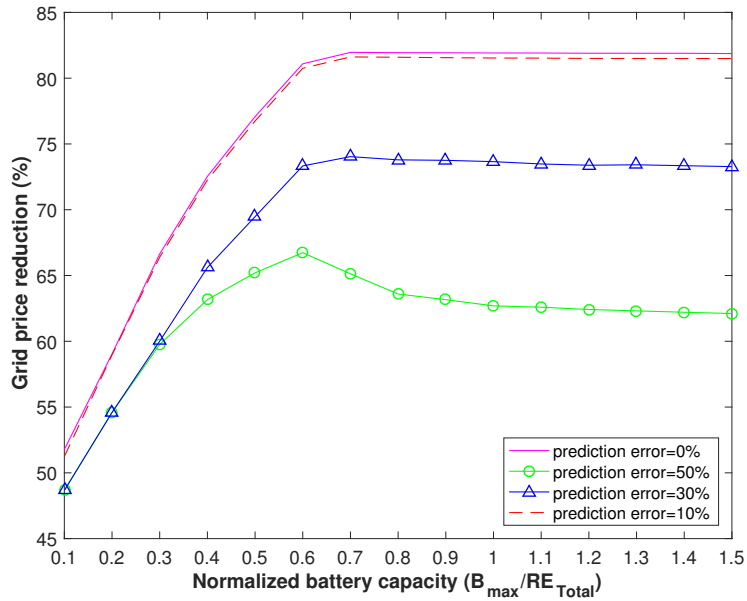


Figure 4.9 – On-grid price reduction with different harvested energy prediction errors © 2018 IEEE.

We illustrate the waste of energy in Fig. 4.8. We consider the case of a solar panel harvesting 50% of the total BS energy demand. We observe that for high battery capacities, BAPA shows slightly higher energy losses than SPAEMA (4% points). The reason is that BAPA algorithm stores energy from the grid. However, due to the battery inefficiency, some of this energy is lost, resulting in additional waste in energy compared with SPAEMA.

BAPA algorithm relies on the RE predicted throughout the day. As discussed in Section 4.3.3, this prediction is based on weather forecast programs, and thus is prone to errors. In Fig. 4.9, we show that a prediction error of 10% in the harvested RE degrades the performance of BAPA by less than 1% point. Whereas a prediction error of 30% decreases the grid price reduction to about 7% points.

#### 4.5.2 Evaluation of JPARS-SM algorithm under battery constraints

The battery aging constraints limit the usage of the stored energy. Thus, on the short term, we expect to observe a degradation in the system performance, in terms of grid energy electric bill. In Fig. 4.10, we compare

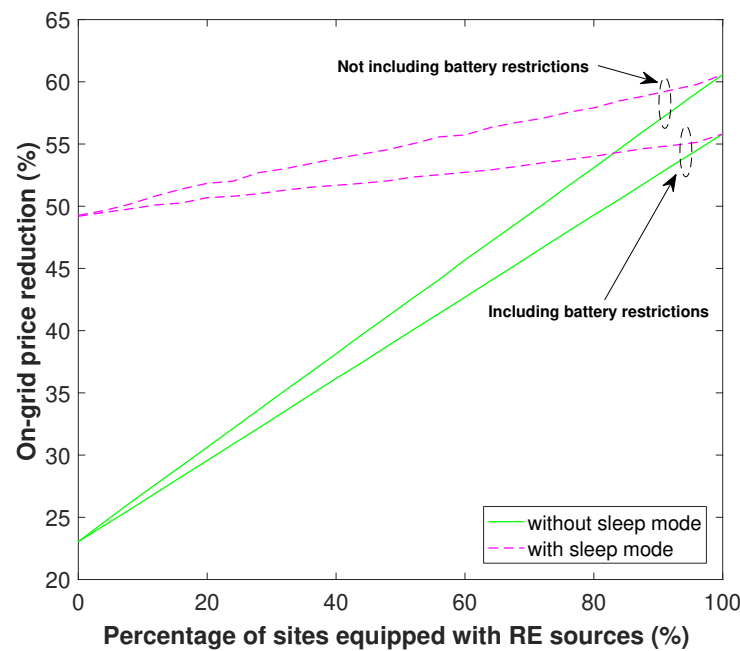


Figure 4.10 – On-grid price reduction over one day under battery aging constraints with JPARS-SM. The solar panels harvest 50% of the total BS energy consumption and equipped with a 3 KWh batteries © 2018 IEEE.

the grid cost over one day for different percentage of sites equipped with RE. We observe a decrease of 5% points in the cost reduction gain with strict battery utilization compared with aggressive utilization that ignores battery degradations. The 23% price reduction obtained when none of the BSs are equipped with RE source is a result of the resource allocation (Max-Min fairness) algorithm that turns off excess RBs to save energy. However, and by looking at the long term operational cost of the system in Fig. 4.11, we observe that while respecting the battery aging constraints, we lose on average 40% of the battery initial capacity after one year compared to 75% when these constraints are ignored. The latter results in a decrease in the operational cost of about 4% compared to JPARS-SM algorithm, after one year. The details of estimating the battery capacity degradations are derived in [185]. Even though these degradations are pessimistic, they serve as a benchmark to compare the different algorithms.

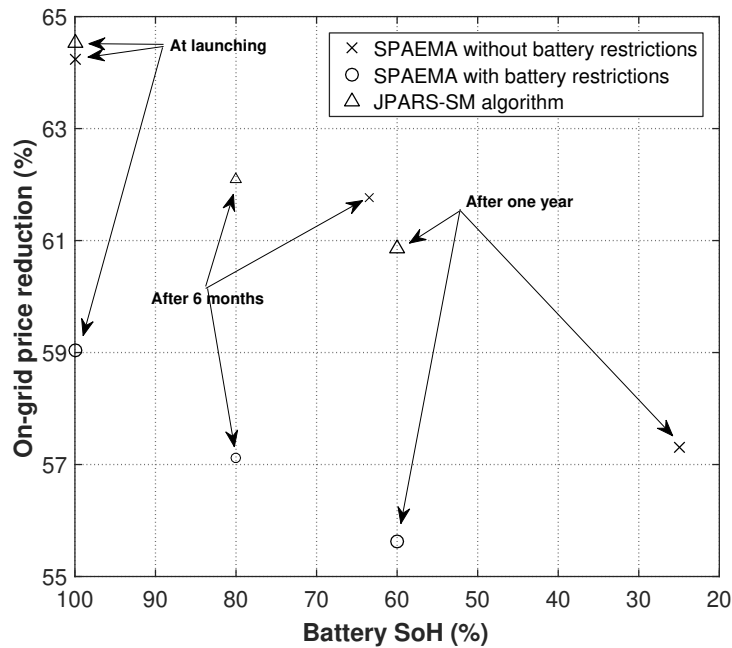


Figure 4.11 – Grid energy cost savings and average evolution of the battery SoH after time © 2018 IEEE.

### Performance of JPARS-SM algorithm

In this section, we evaluate the performance of JPARS-SM algorithm by comparing it with the benchmark scheme (SPAEMA that decides when to store RE and when to use it based on the SoC of the battery and the current price of electricity). We evaluate this benchmark under two cases: with and without battery degradation constraints. JPARS-SM algorithm outperforms the benchmark for the distinct cases and for the different percentage of sites equipped with RE, as shown in Fig. 4.12. With high daily average RE (85% of the total BS energy demand), our algorithm surpasses SPAEMA by more than 15% cost reduction points. This amelioration is the result of storing grid energy when the price is low, and then use it at high electricity prices. Such operation avoids using grid energy at high prices and thus, decreases the operational cost of the operator. The down performance in the case of low average RE, is due to the limited battery capacity that restricts the proper energy allocation between the energy stored from the grid and from the RE source. With a small battery capacity, our algorithm stores energy from the grid but is not able to use it efficiently due to the battery constraint in equation (4.4) that limits the (dis)charging capacity during a time step.

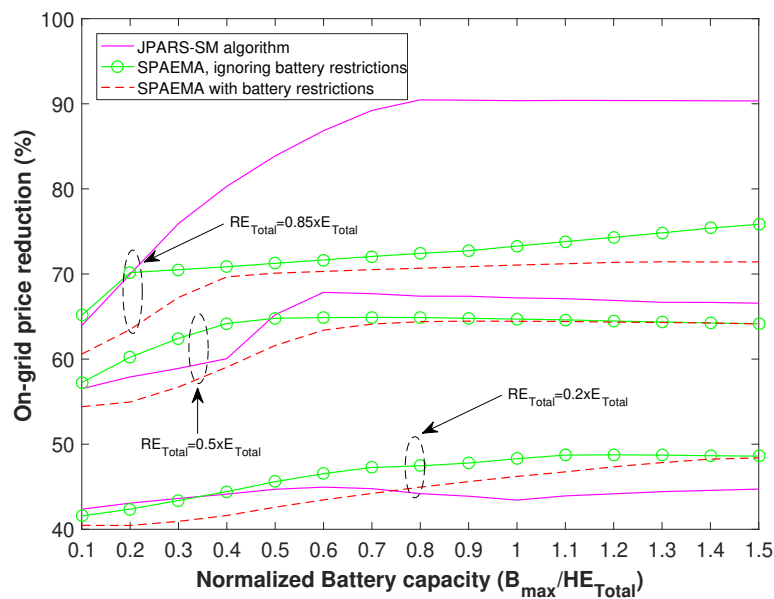


Figure 4.12 – Performance evaluation comparison of JPARS-SM and SPAEMA algorithms for different average amount of RE (all sites are equipped with RE) © 2018 IEEE.

We illustrate the waste of energy in Fig. 4.13 and 4.14. The waste of energy reduces when applying sleep mode, as shown in Fig. 4.13. When some BSs switch to sleep mode, some of their users offload to BSs equipped with RE, increasing their energy consumption and thus, their RE usage. This will avoid battery overflow. From Fig. 4.14, JPARS-SM algorithm shows slightly higher energy losses in the case of large battery capacity. This is because the (dis)charging rate limit of the battery increases with its size allowing more energy to be stored/used. And since our algorithm allows the possibility to store energy from the grid for future use, more energy is lost (due to battery inefficiency) compared to the benchmark algorithm that ignores storing energy from the grid.

## 4.6 Conclusion

In this chapter, we have addressed the problem of grid energy consumption in hybrid-powered BS equipped with RE. In contrast to most studies that focus only on reducing the OpEx cost of the operator by bringing down the grid energy consumption of the network, our work takes into account the battery degradation model that represents a significant cost to the operator. We proposed BAPA, an online energy management al-

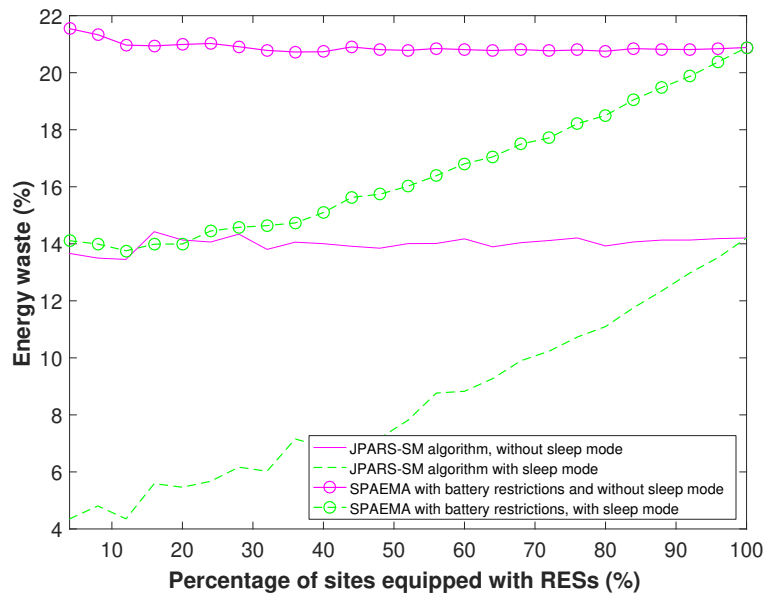


Figure 4.13 – The waste in energy caused by battery overflow and battery inefficiency with and without sleep mode © 2018 IEEE.

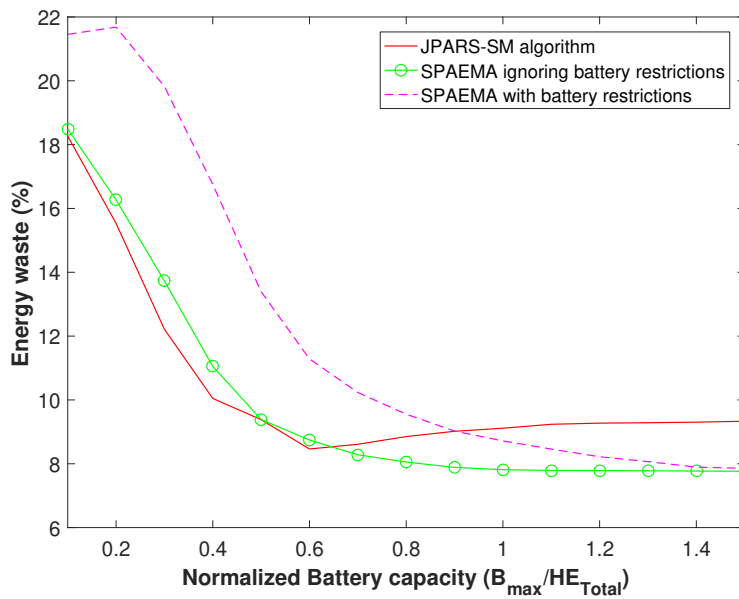


Figure 4.14 – Comparison of the RE waste for the different algorithms © 2018 IEEE.

gorithm that brings down the grid energy consumption of the operator for one BS, while preserving the life of the battery. Our results show that BAPA can reach up to 99% grid energy savings compared to the optimal solution and outperforming a benchmark algorithm. Then, we extended the model to multi-BS cellular network by jointly considering RE management, resource allocation and sleep mode, under battery aging constraint

model. Simulation results have shown that even though the operator loses 5% points in operational cost savings when restricting the battery usage on the short term, the battery calendar aging will be enhanced by 35% points in comparison with the case where we do not restrict the battery usage.





CHAPTER

# 5

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## **Reinforcement Learning for Energy-Delay Tradeoff Policy in 5G Networks**

### **5.1 Introduction**

In our previous work, we focused on reducing the energy cost of cellular networks powered by RE sources, batteries and the SG. By including energy efficiency techniques such as switching off BSs, significant cost reductions were witnessed along with better RE utilization. However, due to the complexity of the network environment, we resorted to heuristic sub-optimal algorithms because solving for the optimal solution was of high complexity since the problems formulated were non-convex, and impractical for real-time implementation because they require significant time and computational resources to converge. In addition, in 5G networks, the environment is getting increasingly complex due to the heterogeneous and evolving future architecture, technologies and services. This requires new smart tools that are able to learn and handle such environments in order to satisfy the diverse requirements. In this regard, in this chapter we rely on machine learning, and in particular Q-learning that paves the way towards optimality by exploring and interacting with the environment, and relying only on the current state of the cell. In contrast to offline approaches that require full system knowledge to solve the problem, Q-learning alleviates the non-causal system information making it a

promising solution for real-time application. A background on Q-learning is summarized in Appendix B.

In this chapter, we study the problem of Energy-Delay-Tradeoff (EDT) in wireless cellular networks under the advanced Sleep Mode (SM) levels proposed by GreenTouch and compliant with 5G [34]. First, we demonstrate the advantage of having a multi-level SM scheme compared to binary SM on the network performance, in terms of energy and delay. We define the delay as the latency added until the BS reactivates from its sleeping state. We propose an adaptive SM algorithm based on Q-learning that controls the states of the BSs in order to maximize the weighted-sum between energy savings and added service delay. We show that using different combinations of SM levels achieves better performance than in the case of binary SM. Encouraged by the results obtained, we then study the use case of users handover between cells under these SM levels. By taking into account the geographical location and velocity of users, we propose a Q-learning-based algorithm that decides the best sleep scheme policy to reduce the service delay of a user moving across a network and passing through different BSs, while maximizing the network energy savings. Finally, we consider a more general scenario of a HetNet where small cells are allowed to switch to different SM levels. By taking into account the interference between the cells, the buffer size of each cell and the packets' time-to-live, we propose a Q-learning algorithm that puts the small BSs to different SM levels to maximize the energy savings, while respecting the delay constraints imposed by the service.

## 5.2 Energy savings sleep modes for 5G

With the emergence of 5G networks, specific requirements are defined on the periodicity of Synchronization Signaling (SS) bursts. This imposes a constraint on the maximum period a BS can be deactivated. Unlike long term sleep schemes that are designed to switch off the BS completely when the traffic is low for long periods of time (e.g., minutes time scale), a new SM model was introduced by GreenTouch [35] that respects the requirements of 5G. The different levels are described in Table 2.2 of Section 2.2.1. Implementing these different stages of SM in 4G networks is challenging due to backwards compatibility and reference signaling requirements. However, in 5G, the Cell Reference Signals (CRS) are removed

[188, 189] making it possible for a BS to explore these different SM levels paving the road to the ultimate goal of achieving almost zero power consumption at zero load. Along with SM and users' dynamics, the BS has to wake up periodically to send signaling bursts of SS and Physical Broadcast Channel (PBCH). It has been agreed in 3GPP [188, 189] that the transmission periodicity of the SS/PBCH block can be set to any value among [5, 10, 20, 40, 80, 160 ms]. With these values, SM 4 cannot be used. Hence, we limit our work to the first three SM levels (SM 1, SM 2 and SM 3).

## 5.3 Adaptive sleep mode levels in 5G networks

In this section, we study multi-SM levels that are compliant with 5G requirements. We investigate the potential of having different SM levels compared to binary schemes on bringing down the grid energy consumption of the network while satisfying the users requirements. In this regard, we consider a cellular network with unbalanced traffic where each BS chooses its appropriate SM level in order to achieve a desirable balance between energy consumption and latency. We propose an adaptive sleep scheme algorithm based on Reinforcement Learning (RL) that controls the states of the BSs, where each BS has access only to its local information in order to learn the best energy saving policy.

In contrast to most prior work in the literature that consider binary sleep schemes [69, 41, 42, 43], we focus here on multi-SM levels that are compliant with 5G requirements. To the best of our knowledge, few studies exist on multi-level sleep schemes. For instance [44] studied switching small cells to different sleep mode levels. However, the proposed scheme is not suitable for 5G networks as it violates the sleep time duration for the synchronization periodicity. In [45, 46, 47], the authors studied advanced SM levels which correspond to gradual deactivation of the BSs components in order to decrease the energy consumption of the BS. Even though the used sleep model does not violate the 5G requirements, [45, 46] focused on the energy savings potential and not the best SM policy to be applied, while [47] is limited to only one BS. In contrast to previous work, we do not limit our work to only one type of SM, rather we consider a network where each BS can choose different SM states to switch to. We

propose a distributed Q-learning approach that finds the best policy for each BS in order to reduce the energy savings while maintaining the QoS of the users under the 5G requirements.

### 5.3.1 System model

We study multi-level SM in a large-scale wireless downlink cellular network composed of  $M$  BSs serving  $K$  users, under 5G signaling constraints. We emphasize the potential of traffic-aware scheduling, where each group of BSs in the network can switch to different SM levels (SM 1, SM 2 or SM 3) as shown in Fig. 5.1. As previously discussed, we omit the use of SM 4, since its minimum sleep duration time exceed the SS/PBCH block periodicity.

Whenever a user requests a service from a BS in SM, it triggers the activation mode, and the user is buffered until the BS wakes up. This has an impact on the latency added to the system. The deeper the SM is, the more time the user will have to wait until the BS reactivates. The BS should then choose the appropriate SM level to switch to in order to achieve the desired balance between energy consumption and latency. When the user is served and if the BS is in idle mode (active but not serving any users), it goes back to its SM level to save energy until the next user arrival. We define the service delay as the time a user waits in the buffer until the BS reactivates.

We further consider BSs with different users arrival rates. Thus, we divide the BS into two sets. One corresponds to the BSs with high users arrival rate denoted by  $\mathcal{B}^{\text{Dense}}$ , and the other grouping the BSs with low users arrival rate denoted by  $\mathcal{B}^{\text{Light}}$ , such that  $|\mathcal{B}| = |\mathcal{B}^{\text{Dense}}| + |\mathcal{B}^{\text{Light}}| = M$ . Note that the users are uniformly distributed within the cell of each BS.

In order to study the EDT problem, we propose a methodology that allows the operator to freely manage the tradeoff between energy consumption and service delay according to the different requirements of the 5G use cases, such as Ultra Reliable Low Latency Communication (URLLC). In this regard, we propose an adaptive sleep scheme algorithm based on RL that controls the states of the BSs, where each BS has access only to its local information, in order to learn the best energy saving policy while considering delay. With this algorithm, the operator can tune the policy either towards saving more energy or maintaining a strict level of QoS.

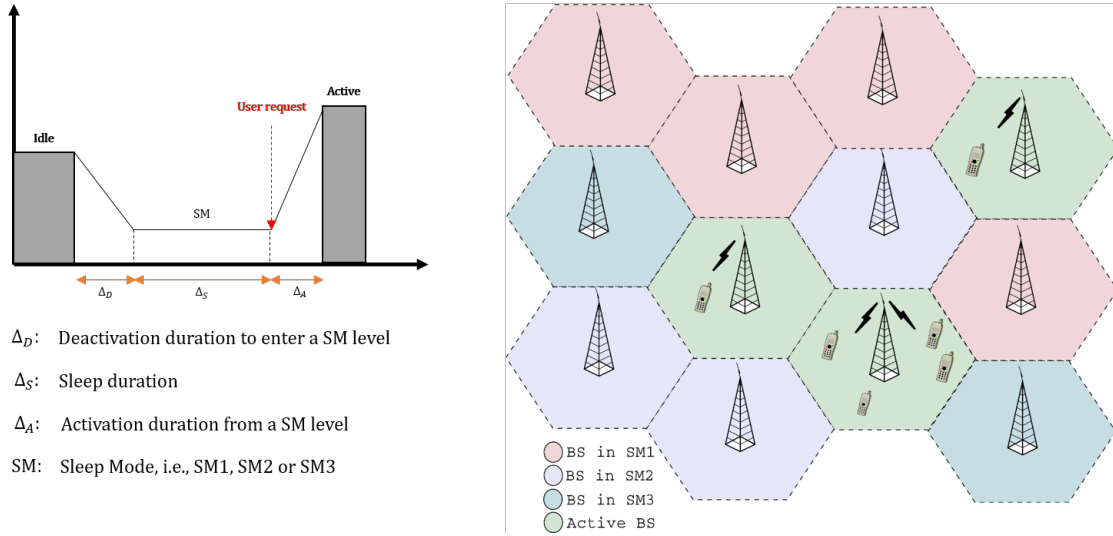


Figure 5.1 – Adaptive sleep mode levels: Network description.

### 5.3.2 Adaptive partial sleep scheme algorithm

In this section, we present the proposed Q-learning-based algorithm that controls the states of the BSs. Consider the state representation  $\mathcal{S}$  of the BSs. Each BS can be active (serving users), in sleep mode (SM 1, SM 2 or SM 3) or idle (active but not serving any user).

$$\mathcal{S} = \{\text{Active, Idle, SM 1, SM 2, SM 3}\}$$

We define the set of possible actions  $\mathcal{A}$  the state to which the BS can switch to. In contrast to schemes that implement only one type of SM (i.e., SM 1, SM 2 or SM 3), in this work we emphasize the potential of traffic-aware scheduling where each of BS in a given network can switch to different SM levels. This will fully utilize the advantages of BSs in the different states for both energy savings and delay reduction. For instance, SM 1 level reduces the effect of switching on and off, thus it has a minor impact on the delay. Consequently, this SM level can be used for delay sensitive services. On the other hand, a BS in SM 3 saves more energy but better suits delay tolerant users. We call such a schedule an adaptive partial scheme. The best policy is then to determine how many BSs chose to switch to SM 1, SM 2 and SM 3.

An episode starts with all the BSs in idle mode, and it finishes when all the users are served. The users arrive at the beginning of the episode. During each episode, a BS chooses an action, then stores a quality-value linking the states  $s \in \mathcal{S}$  to the chosen action  $a_m \in \mathcal{A}$  following Eq. (B.9). The

action consists of choosing the best sleep mode level having the highest Q-value.

Our goal is to find the best combination of SM levels each group of BSs can switch to in order to maximize the reward  $r_m^t$ . We assume in this work that in an episode, a BS can choose to switch to only one SM level. We define the reward as the weighted-sum of the energy gain  $G$  and the added delay  $D$ , both resulting from the sleep mode level chosen during an episode.

$$r = (1 - w)G - w \cdot D \quad (5.1)$$

where  $w \in [0, 1]$  is a parameter which controls the tradeoff between energy gain and the delay performance. Note that for  $w = 0$ , the problem reduces to maximizing the energy gain without considering the added delay, whereas for  $w = 1$  the problem becomes minimizing the delay. We note the delay measured in this work is the time a user has to wait in the buffer until the BS reactivates from its sleep mode state.

### 5.3.3 Results and discussion

#### Simulation parameters

We consider a network of 25 BSs with an inter-site distance of 500 m. We model the arrival of the users following a Log-normal distribution with mean  $\lambda_a$  and variance  $\nu$ . We consider that a user request to download a file with mean size 4 MBytes. The file size follows a Weibull distribution having a CDF of  $F(x) = 1 - e^{-(x/\lambda)^k}$ , where  $\lambda > 0$  is the scale parameter, and  $k > 0$  is the shape parameter. Table 5.1 summarizes the assumptions and parameters used in our simulation.

In order to show the impact of SM levels on the energy consumption, we consider in this study a low load traffic with mean arrival rate  $\lambda_a = 1$  user/s/Km<sup>2</sup>. We run 500 independent simulations on Matlab in order to acquire the average energy gain and the average added delay on the performance of the network. From [35], we found the power figures for the different states of the BS. These values are given in Table 5.2.

Table 5.1 – Simulation Parameters.

<b>Parameter</b>	<b>value</b>
Antenna height	30 m
BS Tx Power	45 dBm
Bandwidth	20 MHz
Thermal noise	-174 dBm/Hz
Pathloss	$128.1 + 37.6 \log_{10}(d)$ dB [190]
Shadowing	Log-normal (6 dBm)
User's arrival	Log-normal, $\lambda_a = 1$ , $\nu = \lambda_a/10$
Service type	file with mean=4 Mb
Scale parameter	$\lambda = 441.305$
Shape parameter	$k = 0.8$

Table 5.2 – Power Consumption of a  $2 \times 2$  MIMO BS.

<b>Active</b>	<b>Idle</b>	<b>SM 1</b>	<b>SM 2</b>	<b>SM 3</b>
250 W	109 W	52.3 W	14.3 W	9.51 W

### Algorithm convergence

The Q-learning algorithm requires a training phase in which the agent explores the state-action couples to converge towards the best policy. Fig. 5.2 shows the convergence of the momentary Q-values (initialized to zero) corresponding to the best action over the different states summed over all the BSs with  $w = 0.7$ . Then, the best policy is stored in a look-up table that will be used during the exploitation process. We can observe that after 100 iterations, the algorithm converges for all BSs and over all the state-action pairs.

### Numerical results

In Fig. 5.3, we present the distribution of the states of the BSs for different values of  $w$ , where 25% of the sites  $\in \mathcal{B}^{Dense}$ . We observe that when energy saving is prioritized over delay ( $w = 0$ ), all BSs choose SM 3 that saves energy the most, whereas staying active policy is preferred when the users are delay sensitive ( $w = 1$ ). The states combination is observed for other values of  $w$ . In these cases, we observe a gradual shift SM 3 to the other states. The incentive behind this shift is in the non-uniformity



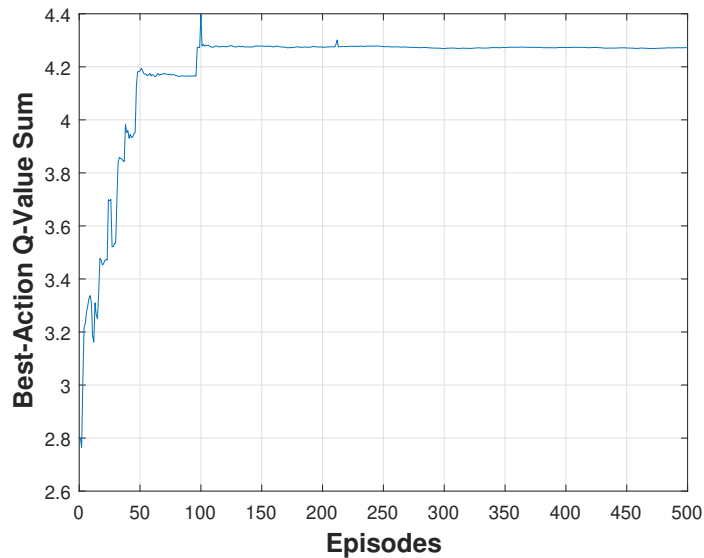


Figure 5.2 – Convergence of the adaptive partial scheme algorithm © 2019 IEEE.

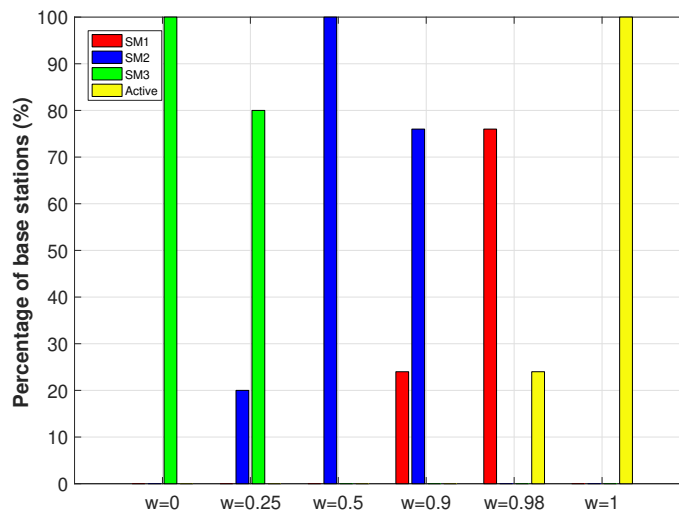


Figure 5.3 – States of the BSs for different values of  $w$  © 2019 IEEE.

distribution of the traffic resulting in having some BSs with no traffic (since the overall traffic is low), thus able to switch to a deeper sleep mode level than the others.

Figures 5.4 and 5.5 illustrate the average network energy savings and added delay for different values of  $w$  and for different percentage of BSs with higher users arrival rate. We observe that the performance of the system depends on the reward function and in particular  $w$ . The highest energy saving gain is reported at around 90% when  $w = 0$  but at a cost of increased delay (5ms). It is then important to carefully choose  $w$  in

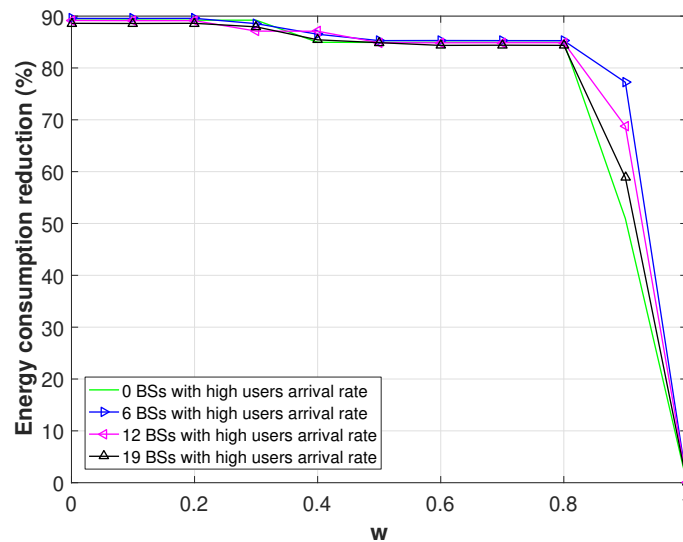


Figure 5.4 – Average network energy savings of our proposed algorithm for different users distribution © 2019 IEEE.

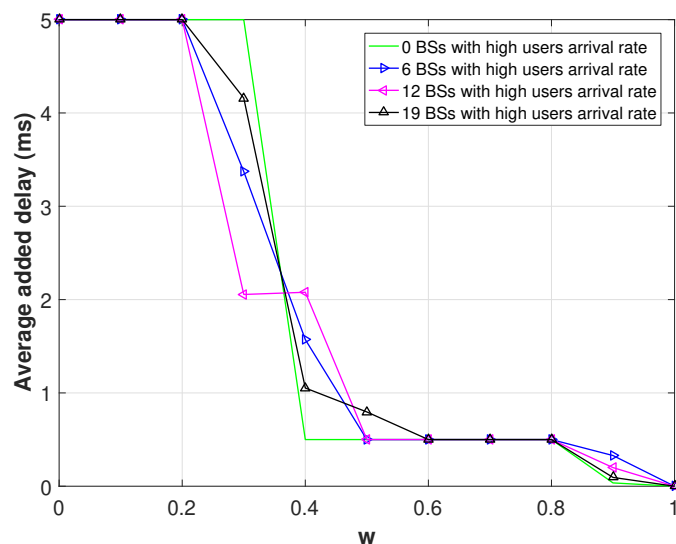


Figure 5.5 – Average network added delay of our proposed algorithm for different users distribution © 2019 IEEE.

order to satisfy the requirements of the different 5G use cases. We also note that having an unbalanced traffic diversifies the best policy for each BS, and thus we observe better performance when having different arrival rates for each BS.

In Fig. 5.6 and Fig. 5.7, we compare our algorithm with a benchmark that uses only one type of sleep mode. We observe that the adaptive scheme outperforms all three benchmarks in terms of energy savings. Even though using SM 3 only has slightly better energy savings for some

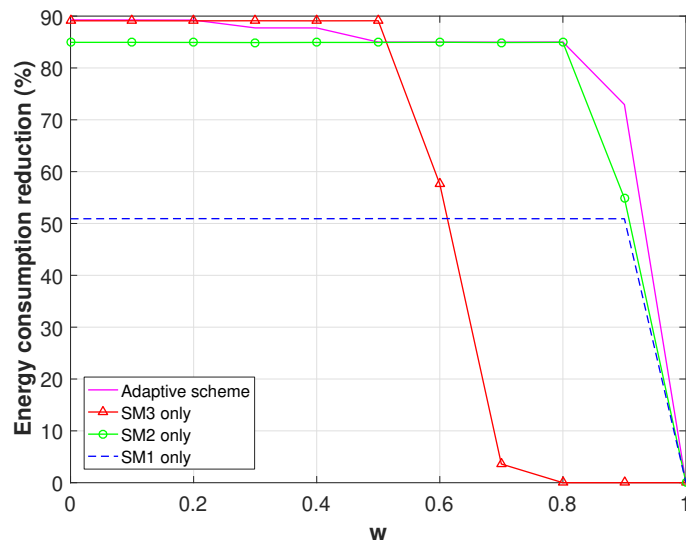


Figure 5.6 – Energy savings comparison between our proposed algorithm and the cases of using only one type of sleep mode © 2019 IEEE.

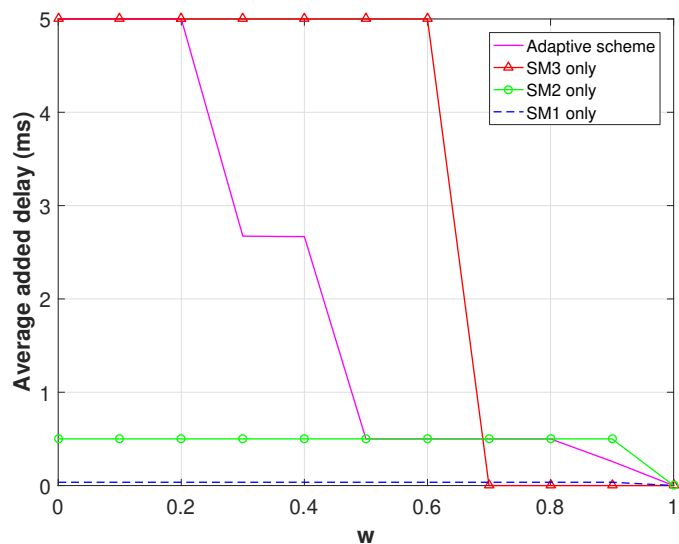


Figure 5.7 – Added delay comparison between our proposed algorithm and the cases of using only one type of sleep mode © 2019 IEEE.

range of  $w$ , it adds more delay to the user as shown in Fig. 5.7. Thus, for applications when there is a hard restriction on delay, using SM 3 only may not be tolerated, rather an adaptive scheme is required. Similarly, in applications where both delay and energy consumption are considered, the adaptive scheme algorithm finds its best policy to combine the different sleep modes to achieve the necessary requirements.

In order to show the performance of our proposed algorithm, we compare the reward that evaluates both the energy savings and added delay

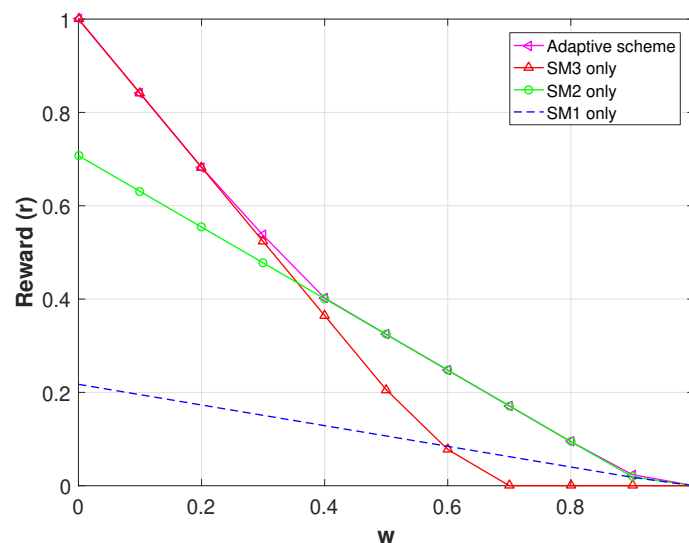


Figure 5.8 – Reward comparison between our proposed algorithm and the cases of using only one type of sleep mode © 2019 IEEE.

in Fig. 5.8. We notice that the adaptive algorithm combines the advantages of the different sleep mode levels in order to maximize the reward. For instance, the adaptive algorithm prefers SM 3 when the users are delay tolerant (small  $w$ ) and SM 1 when the users are delay sensitive. The combination of these states gives a higher reward than if these states were solely chosen. We also note that the reward converges to zero for  $w = 1$ . This is because, for this value, the cost function in (5.1) reduces to minimizing the added delay ( $\min D$ ). Hence, when the BS is already in active mode,  $r = D = 0$ .

## 5.4 Location-aware sleep strategy for energy-delay tradeoff

In the previous section, we demonstrated the advantage of having a combination of different SM levels compared to having only one type of SM in a wireless cellular network. In this section, we study a use case based on multi-level SM. We consider a user requesting a delay-sensitive service (e.g., real-time service) and moving between the cells of the network. In order to maximize the user experience (i.e., minimize the delay), nearby inactive BSs should anticipate a handover by either switching to lighter

SM levels (for faster activation) or to active mode in order to reduce the service delay when a user is handed over to another cell.

In this context, we propose a Q-Learning-based algorithm that controls the state of the BS depending on the geographical location of the user and his/her moving velocity in order to learn the best policy that maximizes the tradeoff between energy savings and delay. First, we describe the dynamic user model and system model considered in our scenario. Then, we summarize the most important positioning methods in LTE, before proposing our Q-Learning algorithm.

### 5.4.1 Dynamic user model

We consider two cases for users service requests from a BS:

1. Camping in a gNB: in this case, the user is in any of the three 5G Radio Resource Control (RRC) modes: connected, idle or inactive [191].
2. Handover arrival: in this case, a user already performing a service transmission/reception from a BS and is moving towards the coverage of a neighboring BS. The user is handed to another BS for service continuation.

In the first case, when a service is being called for the first time, the delay impact on the user is tolerable since the transmission has not yet started. However, in the case of a handover (case 2), the service might be interrupted or degraded if the BS hosting the user is inactive (i.e., in sleep mode). This might have a severe impact on the QoS of the transmission. It is important to note that if the requested service is of type non real-time (e.g., web browsing), then this delay will have a less impact on the QoS since non real-time services are delay tolerant.

### 5.4.2 Network operation

In this work, we consider the case of real-time services, and in particular the handovers of users between BSs. The objective is to jointly minimize the delay associated with handovers, and the energy consumption of the network. As shown in Fig. 5.9, we consider a user being served by BS A moving towards BS B with a velocity  $v$  (Km/h). Since BS B is not serving

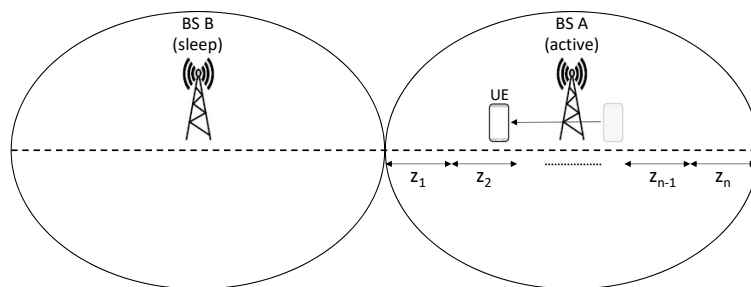


Figure 5.9 – Scenario example: A user moving towards a neighboring BS  
© 2019 IEEE.

any users, it decides to switch to a specific  $SM_i$  level for a fixed and pre-defined period of time  $T_{SM_i}$ . This decision depends on the position of the user from BS B, i.e., the closer the user moves towards BS B, the lighter its SM level becomes. Since positioning with LTE is not always accurate and is prone to measurement errors, we divide the geographic region of interest (the region of neighboring sites) into several zones ( $z_1, z_2, \dots, z_n$ ). Each zone corresponds to a region that can be detected by the BS. For example, if a user is in zone  $j$  ( $z_j$ ), the BS senses the presence of the user in  $z_j$ , but it does not know its exact location. The size of these regions depends on the accuracy of the positioning method used, i.e., the smaller the zone size, the more accurate the user position is measured.

### 5.4.3 Coordinated Vs. non-coordinated BSs

When a BS switches to a SM level, it can no longer sense the position of the neighboring users nor if he/she entered the serving area of the BS. In this regard, we distinguish between two network models. The first considers that the BSs in the network do not communicate among themselves. Thus, when a user enters the area of a BS in  $SM_i$ , the user will have to wait until the sleep duration  $T_{SM_i}$  elapses in addition to the time required from the BS to re-activate. The second model considers the coordination between the cells. Consequently in this case, when a user enters the area of a BS in  $SM_i$ , neighboring active BSs will notify the sleeping BS to wake up to serve the user. The added delay will thus be only the time required from the BS to wake up.

### 5.4.4 Location-aware sleep mode strategy

#### Positioning methods with LTE

In wireless networks, positioning is very challenging due to the user mobility and the dynamic nature of both the environment and radio signals. On the other hand, the FCC set some stringent requirements on the accuracy of positioning especially for emergency services [192]. As a result, 3GPP described an architecture, standards and methods for LTE to support different positioning techniques that reach a high level of accuracy as requested by the regulations.

LTE supports three positioning techniques: Assisted Global Navigation Satellite Systems (A-GNSS), Enhanced Cell ID (E-CID), and Observed Time Difference of Arrival (OTDoA).

1. A-GNSS: to overcome the line of sight and low signal level drawbacks problems of GNSS, the cellular network assists the GNSS receiver to increase its positioning operation. A-GNSS works best in outside conditions with clear view of the sky (line of sight).
2. E-CID: this method is based on Cell of Origin (CoO) that estimates the position of the device in the geographical area of its serving BS. Since this method is not accurate enough (linked to the cell size), E-CID performs measurements on radio signals such as Reference Signal Received Power (RSRP) and Time Different of Arrival (TDoA) to measure the Round Trip Time (RTT) and Angle-of-Arrival (AoA) for more accuracy. With E-CID, it is also possible to have information on the direction of the device.
3. OTDoA: according to the LTE specification [193], this method relies on the downlink radio signals from multiple BSs to compute the user position. In [193], LTE standard specifies Positioning Reference Signal (PRS) that is dedicated for positioning purposes. By properly configuring the PRS and with interference management techniques, the error in position can be significantly improved to 1 meter, however, at the expense of decreasing the spectral efficiency [194].

Each of the above proposed technique has its advantages and limitations. In Table 5.3, we summarize the differences between these methods. To improve positioning in challenging radio environment, hybrid positioning

using the above methods is also supported in Release 10 [195]. For more details on LTE positioning, the reader is referred to [196].

Table 5.3 – Comparison of LTE positioning techniques.

Technique	Accuracy	Limitations
A-GNSS	High (10-15 m)	Requires line of sight
E-CID	Low (80-800 m)	Variable accuracy depending on the environment
OTDoA	Medium-High (10-40 m but can go down to 1 m at the expense of SE)	Requires synchronized network and operator dependency

### Proposed Q-Learning algorithm

We define the set of possible actions  $\mathcal{A}$  the state of the BS, i.e., active or in sleep mode ( $SM_1$ ,  $SM_2$  or  $SM_3$ ). The BS chooses the appropriate action based on the geographical zone the user lies in. Thus, we define the state space and action space as follows:

$$\mathcal{S} = \{z_1, z_2, \dots, z_n\}$$

$$\mathcal{A} = \{\text{Active}, SM_1, SM_2, SM_3\}$$

The number of zones depends on the accuracy of the positioning method used, and it spans the area of the closest neighboring BSs.

An episode starts when a user asks for a service, moves towards a neighboring cell, and finishes when the handover is complete. During each episode, the neighboring BS that the user is approaching to, changes its state by taking an action following Eq. (B.10). Then, it stores a quality-value linking the states  $s \in \mathcal{S}$  to the chosen action  $a_m \in \mathcal{A}$  following Eq. (B.9). The optimal policy consists of choosing the best sleep mode level having the highest Q-value.

The goal is to find the best policy for each state (zone) along which the user is moving in order to maximize the reward  $r_m^t$ , where  $m$  refers to the  $m$ -th BS and  $t$  to the designated time slot. We define the reward as the



weighted-sum of the energy gain  $G$  and the added delay  $D$ , both resulting from the sleep mode level chosen during an episode.

$$r = (1 - w)G - w \cdot D \quad (5.2)$$

where  $w \in [0, 1]$  is a parameter which controls the trade-off between energy gain and the delay performance. We note that in the delay-tolerant services case (e.g., web browsing),  $w \rightarrow 0$ , thus emphasizing on saving energy. In the other case where the service is delay-sensitive (e.g., VoIP),  $w \rightarrow 1$ . We note that the weight parameter ( $w$ ) is freely chosen by the operator depending on the 5G use cases.

---

**Algorithm 5** : Q-Learning Algorithm

---

- 1: Initialize  $q(s, a) = 0, \forall s \in \mathcal{S}$  and  $\forall a \in \mathcal{A}$ .
  - 2: Set the weight  $w$ , and the average user velocity  $v$ .
  - 3: **procedure** Training ( $Q(s, a)$ )
  - 4: **while** Learning **do**
  - 5:   Visit state  $s$ .
  - 6:   Select an action  $a$  using  $\epsilon$ -greedy rule in (B.10).
  - 7:   Receive a reward  $r$ .
  - 8:   Observe next state  $s'$ .
  - 9:   Update the Q-value  $q(s, a)$  from (B.9).
  - 10: **end while**
  - 11: **end procedure**
  
  - 1: **procedure** Online
  - 2: From  $Q(s, a)$ , store best action in Q-table  $\forall s \in \mathcal{S}$  and  $\forall a \in \mathcal{A}$ .
  - 3: Run Q-Learning.
  - 4: **end procedure**
- 

In details, the training phase consists of running the BS (agent) with different instances of user arrivals in an offline fashion. After this step is completed, the system goes online. During this phase, a Q-table stores the best policy using the trained Q-values of the previous offline step. The algorithm is described in Algorithm 5. It should be noted that during the online phase, the system is always exploring to learn new policies. However, this exploration is reduced compared to the offline training phase. That is why under the online procedure of Algorithm 5, we re-run the Q-learning algorithm, but this time with a trained Q-values.

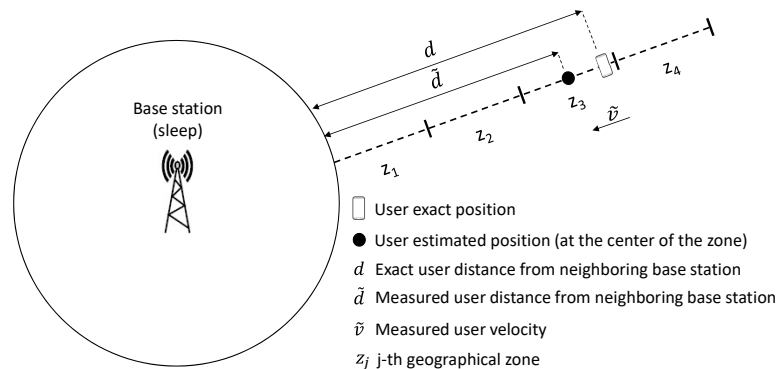


Figure 5.10 – User positioning measurement following DS-SM algorithm © 2019 IEEE.

### Delay-Sensitive Sleep Mode (DS-SM) algorithm: heuristic approach

In contrast to the Q-Learning-based algorithm that includes an offline training phase with a high degree of system information knowledge (e.g., exact user position,  $d$ , and velocity,  $v$ ), we propose a Delay-Sensitive Sleep Mode (DS-SM) online algorithm that takes decisions on which sleep mode level to switch to based on the estimated measured position ( $\tilde{d}$ ) and velocity ( $\tilde{v}$ ). We use this algorithm as a benchmark to study the performance of the Q-Learning algorithm described in the previous section.

When a user reaches a geographical zone ( $z_j$ ), the estimated distance from the neighboring cell ( $\tilde{d}$ ) is calculated from the center of the zone it is located, as shown in Fig. 5.10. The estimated velocity on the other hand is related to the actual velocity by the following expression:  $\tilde{v} = v + \alpha$ , where  $\alpha$  is the error in the measurement. The BS takes the decision to switch to  $SM_i$  in a geographic zone ( $z_j$ ) if after the sleep duration  $T_{SM_k}$  has elapsed ( $i, k \in \{1, 2, 3\}$ ), the user did not enter the neighboring cell, thus minimizing the delay. If the user enters the neighboring cell while it is inactive, his/her QoS will degrade due to the added delay resulting from the waking up time from  $SM_i$  level. In order to maximize the energy savings, the algorithm starts with the deepest sleep mode level allowed (i.e.,  $SM_3$ ). The algorithm is summarized in Algorithm 6.

---

**Algorithm 6** : Delay-Sensitive Sleep Mode (DS-SM) Algorithm

---

```

1: Measure user location  $\tilde{d}$  and velocity  $\tilde{v}$ .
2: Repeat until handover is complete.
3: for  $i = 3 \dots 1$  do
4:   if  $T_{SM_i} \times \tilde{v} < \tilde{d}$  then
5:     Switch the BS to  $SM_i$ .
6:     Update  $\tilde{d}$  after  $T_{SM_i}$  is elapsed.
7:     Set  $i = 3$ .
8:   else
9:     if  $i = 1$  then
10:      Switch the BS to active mode until handover is complete.
11:    end if
12:  end if
13: end for
14: Output: Energy consumption and network added delay.

```

---

### 5.4.5 Results and discussion

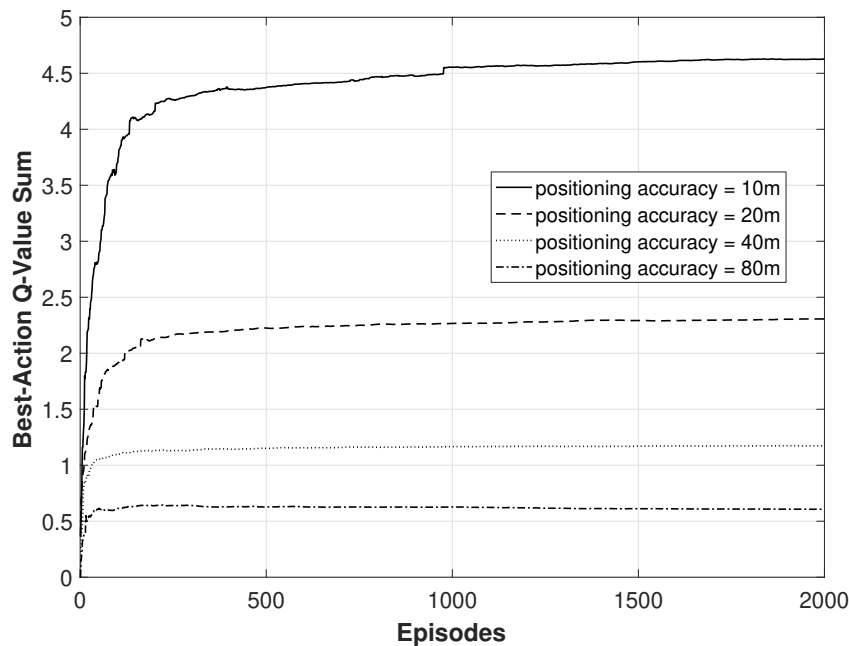
#### Simulation parameters

In this section, we demonstrate the performance of the proposed approach for deciding SM levels for neighboring BSs. We consider a low traffic period where a BS serves a user with a continuous real-time service. We focus on the delay as the performance metric for QoS. The reason is twofold. First, we consider a low traffic period. Thus, bandwidth is not a problem. Second, we focus on real-time services, such as VoIP call, that do not require high throughput, but are delay sensitive. The user is randomly generated in a geographical zone and moving towards a neighboring BS with a constant velocity. We further consider that the inter-site distance is 800 m.

From [35], we found the power figures for the different states of the BS. Then we define the sleep duration times for each SM level as:  $T_{SM_1} = 0.5s$ ,  $T_{SM_2} = 10s$  and  $T_{SM_3} = 30s$ . The reason behind these values is to minimize the measurements done by the BS for user positioning. Table 5.4 summarizes these values.

Table 5.4 – Power Consumption and sleep duration of a  $2 \times 2$  MIMO BS.

State	SM 1	SM 2	SM 3	Idle
Power consumption (W)	52.3	14.3	9.51	109
Sleep duration ( $T_{SM_i}$ ) (s)	0.5	10	30	-

Figure 5.11 – Convergence of the Q-Learning algorithm for  $w = 0.5$  © 2019 IEEE.

### Algorithm convergence

First, we analyze the convergence of the proposed Q-Learning algorithm for  $w = 0.5$ . In Fig. 5.11, we evaluate the impact of the system positioning accuracy on the performance of the Q-Learning training phase. It is clear to observe that as the system accuracy decreases (e.g., from 10 m to 80 m), the learning delay decreases as well. For instance, after 50 episodes the Q-Learning algorithm converges for a positioning accuracy of 80 m, whereas, 400 episodes are required for a sharper accuracy of 10 m. This is related to the number of states that increases with higher accuracy. Thus, requiring more time to converge. Once the algorithm converges, we stop the training phase and exploit the obtained policies. Then, we store the best policy in a look-up table that will be used during the exploitation phase.

### Energy consumption and service delay tradeoff

In figures 5.12 and 5.13, we present the tradeoff between the average network energy consumption and added delay for different values of  $w$  with and without BSs coordination, respectively. We set the positioning accuracy to 10 m. In other words, the difference between two geographical zones is 10 m. We normalize the energy consumption with the case when the BS is always in idle mode. First, we observe that significant energy savings up to 92% (corresponding to the normalized energy consumption of 0.098) can be achieved using the multi-level sleep modes. The proposed Q-Learning algorithm allows a wide range of control over the energy consumption. For instance, with  $w = 0$ , the energy consumption is the lowest. However, this is at the expense of added service delay that is at its highest. This is because for this case, the SM policy is chosen solely considering energy savings. We distinguish between coordinated and uncoordinated policies. When we have coordination among BSs, the highest delay achieved corresponds to the time the BS needs to re-activates from the deepest sleep mode which is 5ms. However, in the uncoordinated policy, this delay is significantly higher and close to 16 seconds. The reason behind this remarkable increase is that in the case of non-coordination, the BS will have to wait until the sleep duration time  $T_{SM_i}$  previously defined is elapsed. This delay converges to zero when  $w \rightarrow 1$ . For  $w = 1$ , we observe that the energy consumption is higher, but the delay is zero. So when the user arrives to the neighboring cell, the BS is already active. When  $w$  is higher than zero, the geographic zones close to the BS will set it to active mode. The Q-learning starts by setting the first zone closer to the BS to activate it. As  $w$  increases, more zones set the BS to active mode in order to minimize the delay. Another interesting observation to make is the slight increase in energy consumption from  $w = 0.1$  to  $w = 0.2$  while the delay decreases significantly. The reason behind this is not about having longer deep SM (SM 3) duration, but to organize the actions in such a way to keep the lighter  $SM_i$  closer to the edge of the BS. It is then important to carefully choose  $w$  in order to satisfy the requirements of the different 5G use cases.

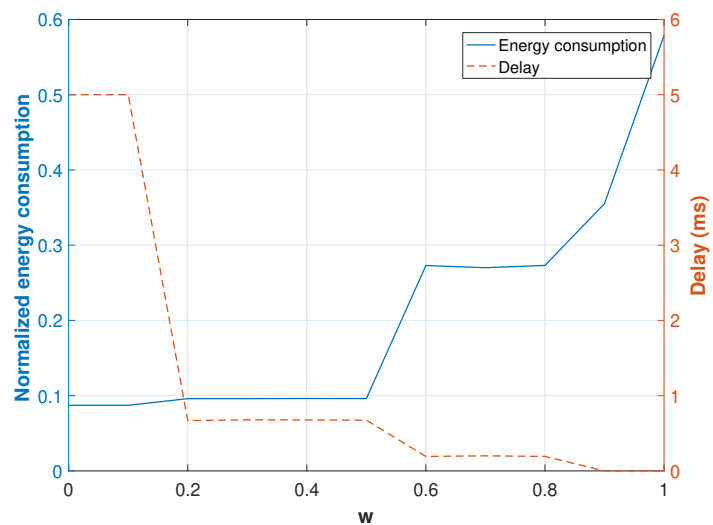


Figure 5.12 – Performance assessment of the selected policies during the online phase with BSs coordination © 2019 IEEE.

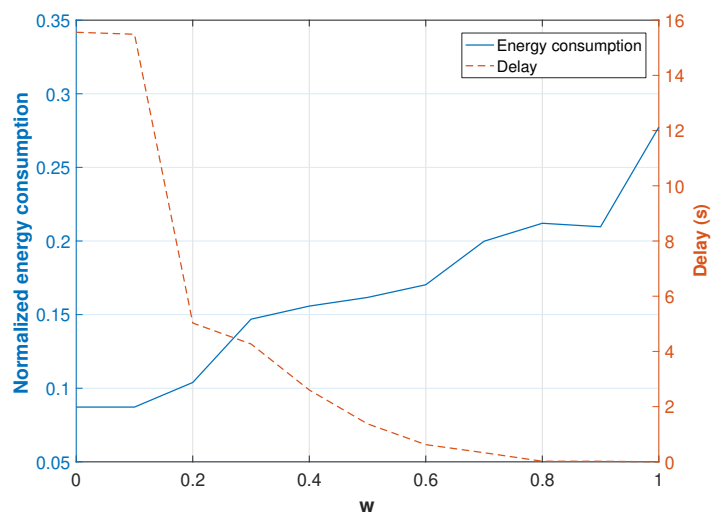


Figure 5.13 – Performance assessment of the selected policies during the exploitation phase without BSs coordination © 2019 IEEE.

### Performance evaluation

As a benchmark for comparison, we consider the DS-SM online scheme presented in Section 5.4.4. This algorithm does not depend on  $w$ . However, its goal is to minimize the service delay while reducing the energy consumption. Hence, the corresponding  $w$  in the Q-Learning algorithm can be found for the case where the delay is minimized. Since DS-SM also takes into account the energy consumption, we look for the first smallest value of  $w$  that minimizes the delay. For example in Fig. 5.12, this

corresponds to  $w = 0.9$ . We note that the value of  $w$  for the designated condition changes for different user velocity and position accuracy. In the following, we compare the reward expression in Eq. (5.2) that takes into account both energy consumption and service delay. For a fair comparison, this weighted parameter will be also used when computing the reward resulting from the DS-SM algorithm the same way it is computed for the Q-Learning algorithm. We note that this reward can be regarded as a utility function of  $w$ .

From Fig. 5.14, we show that the Q-Learning algorithm leads to a higher reward than DS-SM and in particular for low positioning accuracy. The poor performance in DS-SM results from choosing the policy based on the inaccurate positioning techniques (always in the center of the zone), since it does not include a training phase to tune these decisions to optimize the reward. For low position accuracy (e.g., 90 m), the gap between the user's real and measured positions increases. This results in a performance degradation for both algorithms. However, DS-SM adds high delay when  $R(w) < 0$ .

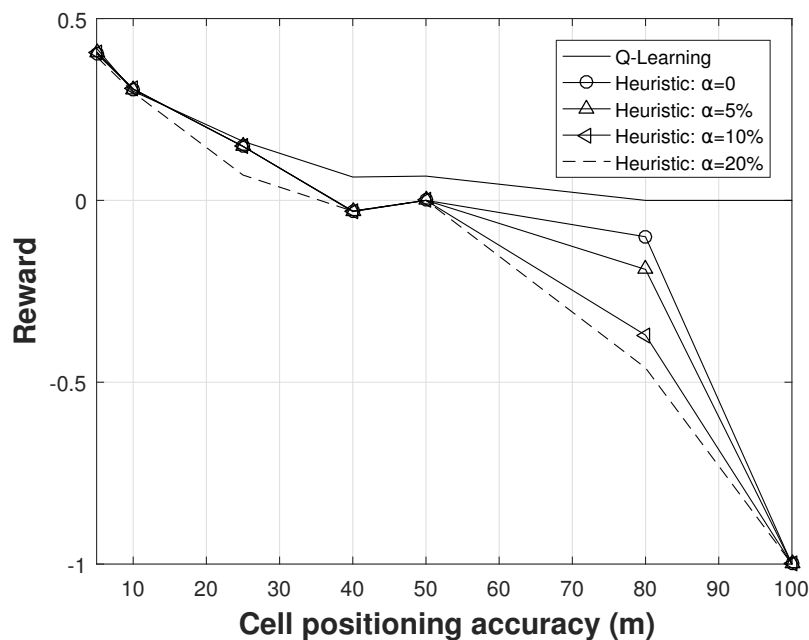


Figure 5.14 – Performance comparison between Q-Learning and DS-SM algorithms with different user velocity measurement accuracies ( $\alpha$ ) © 2019 IEEE.

## 5.5 Delay-constrained energy-optimal small base stations multi-sleeping control

We go further in this work to consider the scenario of a two-tier heterogeneous multi-cell network composed of Macro Base Stations (MBSs) and Small Base Stations (SBSs). Together, these BSs serve a total of  $K$  users. The SBSs are densely deployed in the coverage area of the macrocells and operate in a dedicated carrier to create a local hotspot that will increase the system capacity in the designated area where needed. In order to enhance the system energy efficiency, these SBSs can dynamically switch to different SM levels. This will not only save energy and limit the CO<sub>2</sub> footprint, but it will also enhance the system capacity by limiting the interference between neighboring cells. Distributed local network controllers (e.g., SDN) are in charge of managing the activity of these cells (see Fig. 5.15). In other words, each SBS is equipped with a local controller. We note that for binary SM levels (ON and OFF), finding the set of active SBSs that minimizes the energy consumption of the network is a combinatorial NP-hard problem [197, 198]. Thus, finding the optimal solution of this problem requires high computational complexity. In this work, we further add another layer of complexity by considering multi-level SMs. In order to solve this problem, the local controller for each SBS manages its state by means of interacting with the environment in order to map what to do (action) when faced with a current situation (state). Consequently, we rely on reinforcement learning to solve this problem. In particular, each SBS at each iteration receives the data requested from the users and stores them in its dedicated buffer. Then, it measures the expected average interference from its neighboring cells and its downlink throughput. The local controller uses this information to control its activity, as we detail later in this section.

### 5.5.1 Network model

In our model, we consider connected users continuously requesting packets during a fixed period of time. We focus on the hotspot area where the users are connected to the SBSs based on best-SINR method. We use the term block of data to describe the overall packets requested by users during a time slot  $t$  (ms), and thus contained in one block. In this work, we



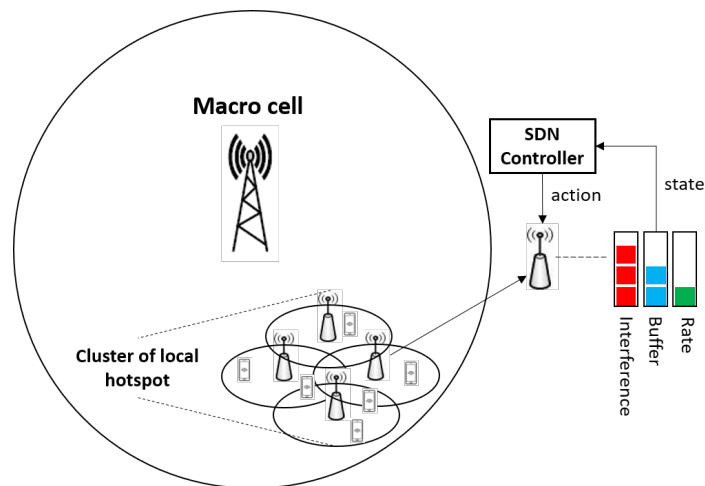


Figure 5.15 – Heterogeneous network architecture with distributed controllers.

do not focus on the inter-packet dynamics. We rather consider a continuous flow of data at each time step with an average size  $n$  (kbits) that is first buffered in the SBS buffer before being transmitted to the designated users.

At each time slot  $t$ , a block of data (composed of several packets) is buffered and stacked in the designated cell buffer. The size of this block  $n$  depends on the number of users being served in the cell and users' requirement based on the service. For a SBS  $j$  serving  $k$  users, the size of the block of data is calculated as follows:

$$n(j) = k \times [\text{PacketSize}] \quad (5.3)$$

where the size of the packet depends on the users rate requirement.

Furthermore, this block of data is characterized by a Time-To-Live (TTL)  $l$  (ms), which is the latency constraint above which the remaining data are lost. Here, we consider that the block of data can be partially served in case the serving time was not enough to deliver it all, due to high interference and/or inactivity of the cell (i.e., in sleep mode). Moreover, the cell buffer operates in FIFO (First Input First Output) fashion. One can relate such service to a current or future 5G delay-tolerant application where the order of the packets does not matter.

If a user requests a packet from a SBS in a SM state, e.g., SM 1, SM 2, or SM 3, it will be buffered until the SBS activates in a future time step. Thereafter, the SBS manages the available radio resources to serve the users during the transmission time slot. The state of the SBS has an

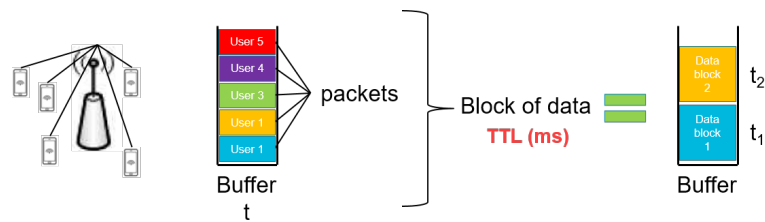


Figure 5.16 – Illustration of data block.

impact on the latency added to the system. The deeper the SM level is, the more time the user will have to wait until the SBS reactivates.

### Data block illustration

In order to clarify more the term *data block*, we illustrate in Fig. 5.16 an example of 5 users requesting packets from a SBS at a given time  $t$ . In this case, the total amount of packets requested during this period is 5 packets. If the users rate requirement is 1000 kbits/sec each, and the users packets are requests every 10 ms, then each packet has a size of 10 kbits. Consequently, the size of the data block is  $n = 50$  kbits. This block is then served to the users using any scheduling algorithm, such as round robin.

### 5.5.2 Problem formulation

Following the above system description, we can model the problem as a discrete-state MDP, where a SBS  $m$  in a state  $s_m(t)$  takes an action  $a_m(t)$  and transitions to another state  $s_m(t + 1)$ . We denote by  $\mathcal{S} = \{R, B, I_l\}$  the state space of the SBS, where  $R$ ,  $B$  and  $I_l$  are the sets related to the cell throughput, buffer state, and the estimated spectral efficiency loss (bit/s/Hz) due to the interference from nearby active SBSs, per SBS, respectively. In this work, we assume that the users request a service with an average packet size  $n$  (kbits). The time needed to complete this service depends on two factors: The buffering time until the SBS re-activates, and the capacity of the serving SBS that is highly affected by the co-channel interference from neighboring cells.

At each time slot, the local controller decides an action  $a_m(t) \in \mathcal{A} = \{Active, SM1, SM2, SM3\}$  for a SBS after observing its state. In order to evaluate the cost associated with each action-pair, we use the function

that takes into account the power consumption of the SBS, and the users' QoS:

$$c(s, a) = (1 - w) \cdot P(s, a) + w \cdot d(s, a) \quad (5.4)$$

where  $P(s, a)$  is the power consumption of the SBS that is calculated based on the imec power model in [35],  $w$  is a weighting factor that prioritizes between the power consumption and the QoS, and  $d(s, a)$  indicates the data lost due to exceeding the delay constraint either from the operational state of the cell (i.e., in sleep) or the high interference level limiting the cell throughput. We note that the power consumption and the data loss variables are normalized based on the case when the cells are always active.

In order to solve the above MDP, we first need to derive the transition probabilities and cost from one state to another. Then, a backward dynamic programming needs to be performed to evaluate the optimal value function, in order to derive the optimal policy. However, this requires a complete knowledge of the system information. To alleviate the non-causal system information, we rely on Q-learning to find the optimal policy by only exploring and interacting with the current state of the system.

### 5.5.3 Q-learning algorithm

At time slot  $t$ , the local state of the small cell  $m$  is  $s^m(t) = \{r^m(t), b^m(t), i_l^m(t)\}$ . The states have been quantized into 4,3 and 3 levels, respectively. We chose these levels of quantization to balance between performance and complexity. Due to the limited number of state-action pairs, Q-learning is able to pave the way towards optimality, thus there is no need for Deep Q-learning. In order to explore different combinations of states, we make the users move inside their serving cell at each time slot in a way that they do not handover other cells. We define an episode as a fixed simulation run where the users in motion request data continuously with a given minimum rate requirement. During this episode, the users move in a predefined and deterministic pattern, and the algorithm explores different states to find the optimal policy that minimizes the cost function in (5.4). After the training phase is complete, the system goes online and operates in real-time. The Q-Learning algorithm is described in Algorithm 7.

---

**Algorithm 7** : Distributed Q-Learning

---

```

1: procedure Training ( $Q_T^m(s, a)$ )
2: Initialize the positions of the users, their trajectory and  $q^m(s, a) = 0, \forall m \in \mathcal{M}, \forall s \in \mathcal{S}$  and  $\forall a \in \mathcal{A}$ .
3: Set the weight  $w$ , and the average user velocity.
4: while Learning do
5:   for  $m \in \mathcal{M}$  do
6:     \ \ Run Q-Learning
7:     Visit state  $s^m$ .
8:     Select an action  $a^m$  using  $\epsilon$ -greedy rule in (B.10).
9:     Calculate the cost  $c^m$ .
10:    Observe next state  $s'^m$ .
11:    Update the Q-value  $q^m(s, a)$  from (B.9).
12:   end for
13: end while
14: end procedure

```

```

1: procedure Online
2: for  $m \in \mathcal{M}$  do
3:    $Q^m(s, a) = Q_T^m(s, a)$ 
4:   Run Q-Learning.
5: end for
6: end procedure

```

---

## 5.5.4 Results and discussion

### Simulation parameters

In this section, we evaluate the performance of the proposed multi-level Q-learning small cell control through numerical results. We consider a HetNet composed of a macro BS covering a cluster of 4 neighboring small cells. This cluster is placed inside the macro cell to increase the SE in the designated area, therefore plays the role of a hotspot. A service traffic with latency constraint of 100 ms is simulated for the users inside this cluster. These results obtained are averaged over hundreds of independent runs that simulate 10 seconds of network activity. At the beginning of a run, the users are randomly deployed in the cluster. The rest of the simulation parameters are detailed in Table 5.5.

Table 5.5 – Simulation Parameters.

<b>Parameter</b>	<b>value</b>
SBS radius	40 m
SBS Tx Power	30 dBm
Bandwidth	10 MHz
Thermal noise	-174 dBm/Hz
SBS pathloss	$16.9 \log_{10}(d) + 32.8 + 20 \log_{10}(f_c) +$ shadowing dB [199]
SBS carrier frequency	$f_c = 3.5$ GHz
Shadowing	Log-normal (3 dBm)
Min. dist. SBS-SBS	20 m
Min. dist. SBS-user	5 m
Number of users	30
User velocity	1.5 m/s

### Online and offline algorithm convergence

We analyze the convergence of the proposed Q-learning algorithm for different values of  $w$  during the training phase in figures 5.17 and 5.18. During this phase, the system is fed with a training episode that describes the dynamics of the network: the users are moving in the designated area, they are requesting service packets, and the small cells are reacting (i.e., taking action to switch to different modes) based on their partial view of the environment that defines their local states (cell throughput, cell buffer size and estimated spectral efficiency loss). By repeating this episode a number of epoch of times, each cell should learn how to map its observable states to actions. In order to maximize the efficiency of the algorithm to choose the appropriate action when facing a given state, the training episode should cover as much states as possible so that when the system goes online, the probability of visiting an unvisited state is minimized. The design of the training episode is important so that the agent gathers enough experience from the environment, which is critical in stabilizing the Q functions, thus forging the best policy.

In Fig. 5.17, we observe that the system converges after few iterations (around 10 iterations for most values of  $w$ ). When  $w = 0$  and  $w = 1$ , the equation in (5.4) simplifies to minimizing energy consumption and service delay only, respectively. In these two special cases, the agent (i.e., small

cell) is able to find the best policy relatively fast compared to other values of  $w$ . It is worth noting that for  $w = 1$ , minimizing the cost function in (5.4) leads to a cost value of zero (i.e., delay=0), thus a Q-value of zero as well. This can be observed from the curve converging to zero. On the other hand, when  $w \in ]0, 1[$ , the agent needs more time to capture the tradeoff between energy and delay, thus requiring more epochs to finally converge.

In Fig. 5.18, we illustrate an example of the convergence behavior of the system, where we plot the evolution of the average network cost function in (5.4) and the average cells states, on a per epoch basis. The later corresponds to the average cells states distribution over each epoch. We take the example where  $w = 0$ . During the first iterations of the training, the system explores different policies. This can be observed by almost having a uniform cells states distribution. With the evolution of epochs, each cell learns the best policy, which is in this example biased to switching to the deepest SM level in order to save the highest amount of energy. The reason behind having some actions other than SM3 is the  $\epsilon$ -greedy algorithm that randomly chooses an action  $\epsilon$ -percentage of times (where  $\epsilon$  is a small number less than 10%).

An interesting observation about the convergence time of the offline training phase in Fig. 5.17 can be made. The time required to train offline the Q-functions is relatively small and is in the same order of magnitude compared to the number of iterations needed to train the system in the online phase in Fig. 5.19. During this phase, the system runs without any previous knowledge about the environment and learns to adapt on the spot. This can be observed in Fig. 5.19 where we notice an increase in the number of iterations required for the Q-functions to stabilize. Nevertheless, this increase is of couple of iterations more, and thus insignificant. The major reason behind this increase is that with the online mode, the episode is changing in each iteration in contrast to the training phase where the training episode is fixed. This dynamic nature of the iteration makes it harder for the agent to learn as opposed to static episode. As a result, it is possible to avoid the offline training phase and run the system directly online.

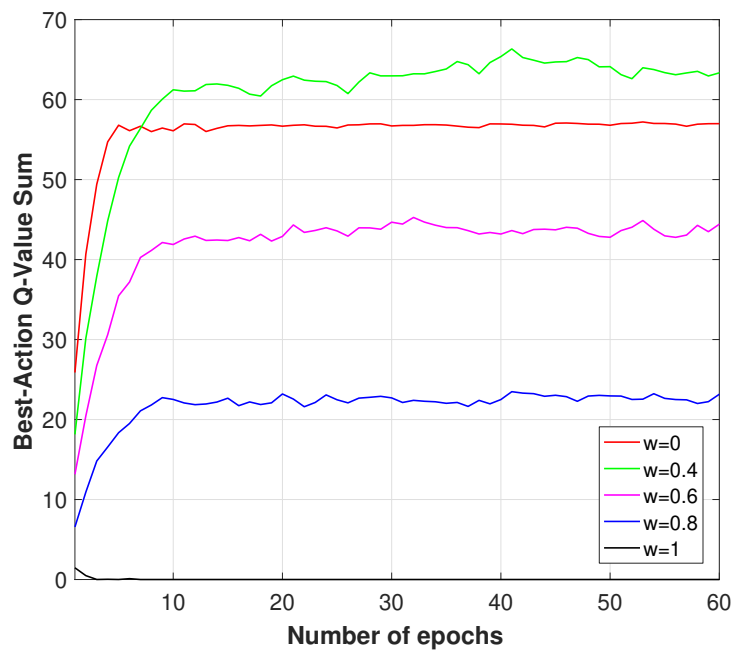


Figure 5.17 – Convergence of the proposed Q-learning algorithm.

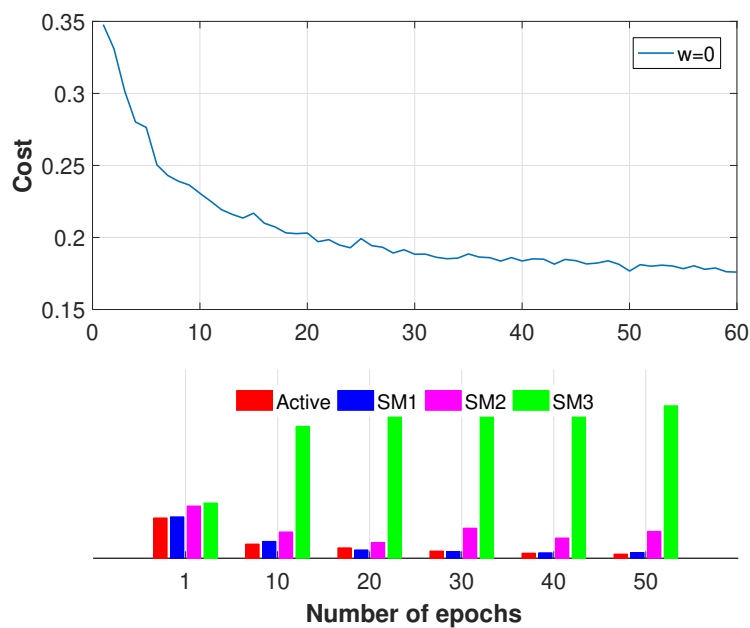


Figure 5.18 – Example of the evolution of the cost function.

### Policy analysis

In Fig. 5.20, we report the different policies of the SBSs for different values of the tuning parameter  $w$ . Similar to Fig. 5.3, we observe that the system tends to save more energy when  $w$  approaches zero by switching to the deepest SM most of the times, while a gradual shift to active mode

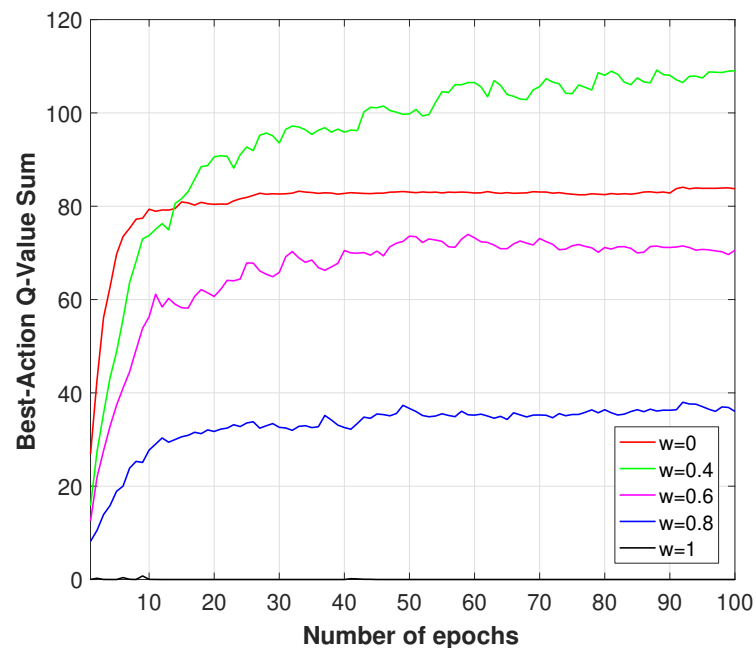


Figure 5.19 – Convergence of the proposed Q-learning online algorithm.

is observed when increasing  $w$ . However, it is interesting to highlight the behavior for  $w = 1$ . For this case, the cells are required to be active for a minimum period of time to minimize the delay (around 37% of the time). During the remaining time and after satisfying the agent's goal, the cell switches randomly to any of its states. This can be observed by the uniformly distributed state modes for SM 1, SM 2 and SM 3, while the active mode has a higher probability in order to satisfy the delay constraint of 100 ms.

In Fig. 5.21, we illustrate the average percentage cell energy consumption normalized to the case where the cell is always on (i.e., without sleep mode) and the average small cell delay as a function of  $w$ . We compare our proposed Q-learning algorithm (QL) with another QL algorithm that considers two states only (active and SM 3). This algorithm is referred to as binary SM-QL algorithm. We observe that our multi-SM-QL algorithm outperforms the binary QL algorithms for all values of  $w$ . This is due to the added flexibility with multi SM levels on saving energy. By tuning the value of  $w$ , the operator can shift the performance of his network towards either energy saving or QoS.



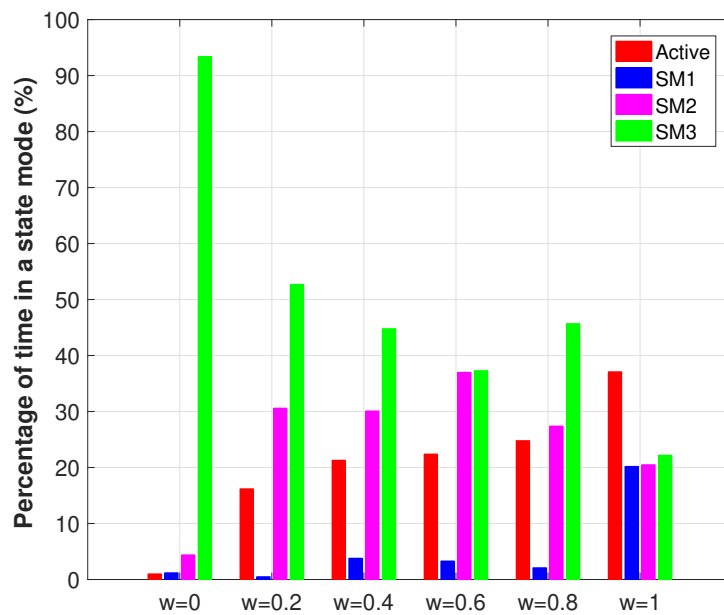


Figure 5.20 – Different SM policies as a function of  $w$ .

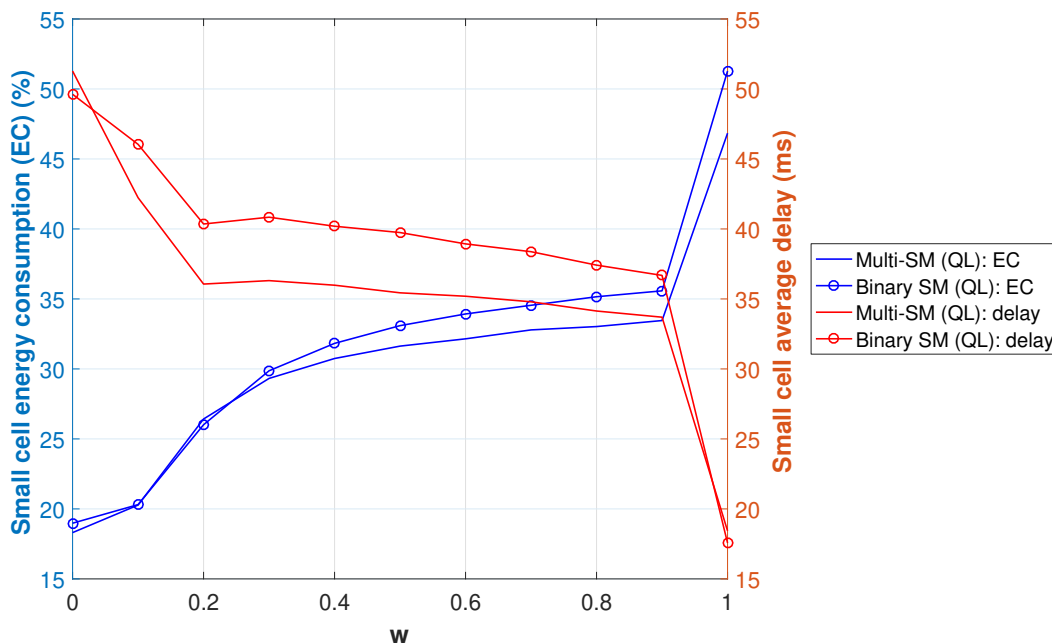


Figure 5.21 – Performance assessment and comparison as a function of  $w$ .

### Performance analysis

To be able to analyze the performance of the policies, it is important to show the dynamics and behavior of the data being served to the users. For instance, it is not enough to report a maximum average delay of around 50 ms when the delay constraint is 100 ms, as shown in Fig. 5.21. For

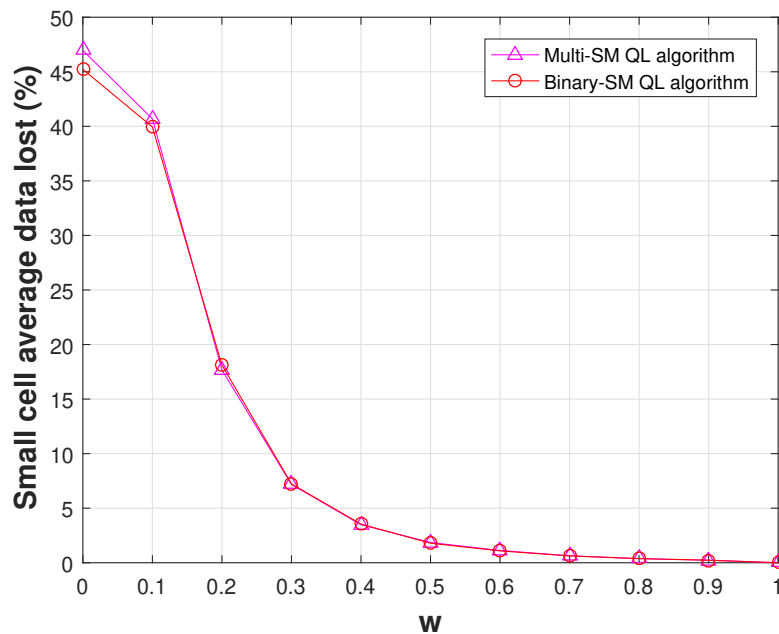


Figure 5.22 – Data blocks drop rate assessment.

instance when  $w = 0$ , more than half of the requested data are lost as shown in Fig. 5.22. This is because the values reported in Fig. 5.21 do not consider the dropped data but the average delay of the served data. Moreover, in order to have a closer look on the delay for the individual data blocks being requested, we plot the Cumulative Distribution Function (CDF) in Fig. 5.23 to analyze the performance of the policies while zooming on the dynamics of the data being served. We observe that for  $w = 1$ , all the data blocks are served within 60 ms delay. This value increases when  $w$  decreases until some data blocks reach 100 ms delay. For instance, around 90% of the data blocks requested are served within a delay of 40ms, 60ms and 80 ms for  $w = 1$ ,  $w = 0.8$  and  $w = 0$ , respectively.

## 5.6 Conclusion

In this chapter, we investigated the problem of energy savings and delay associated with 5G networks. While it is critical to reduce the energy consumption of these networks, hard constraints are agreed on, in the 5G requirements to periodically activate 5G cells for signal synchronization. Since BS sleeping significantly reduces the energy consumption of the BS (up to 92%), it is coupled with QoS degradation by bringing additional delay to the users. Thus, we proposed a methodology for reducing the

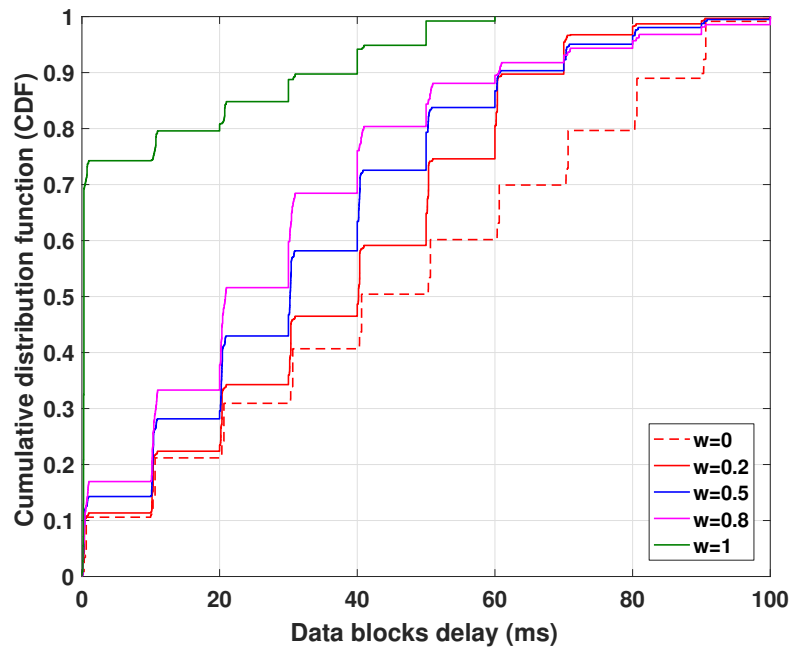


Figure 5.23 – Data blocks delay assessment.

energy consumption in a cellular network while ensuring a good QoS. This methodology allows the operator to freely manage the tradeoff between energy consumption and service delay. In order to achieve the best policy for a given tradeoff, we used Q-learning to learn the best actions to take by interacting with the environment.

Throughout this chapter, we have first demonstrated the advantage of having multi-level Sleep Modes (SMs) on the network performance in terms of energy savings and added delay. Thus, we proposed a Q-learning based algorithm that controls the states of the BSs in a network. We showed that under these SM levels, one can achieve an energy gain up to 90% when we relax the service delay and 50% when the QoS is strict. Based on this work, we studied a use case scenario with a real-time service. Then, we considered the problem of handovers between cells. We proposed another Q-learning algorithm that controls the state of the BSs depending on the geographical location and moving velocity of neighboring users. We also showed that our Q-learning-based algorithm outperforms a heuristic scheme. Finally, we extended the work to include the co-channel interference between the cells in a heterogeneous network covered by a macro BS. Based on the interference level of a given cell, its buffer state and its expected throughput, we designed a distributed Q-learning algorithm that decides the state of the cell in order to deliver to

the users the required data for the service demanded under a delay constraint. This has been achieved while minimizing the energy consumption of the network.



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# Conclusions and Perspectives

## 6.1 Conclusions

In this thesis, we studied energy-efficient green cellular networks. In Chapter 2, we reviewed the existing work in the context of energy-efficient cellular networks. We divided the road towards green 5G networks into four main milestones. The first discussed the important energy efficiency techniques and approaches used for 5G networks. These techniques covered cellular architectures, radio resource management and sleep mode techniques. The second milestone illustrated the use of renewable energy sources in powering cellular base stations. We discussed how empowering cellular networks with hybrid energy sources do not only optimize the energy efficiency of these networks but also reduce the CO<sub>2</sub> emissions and the operational costs for mobile operators. Based on the state of the art, we were able to extract the main aspects for designing a renewable energy-powered cellular network. These included planning of cellular networks, dimensioning of renewable energy systems and characterizing of renewable energy sources with proper models. The third milestone extended the previous ones to include the interaction between these networks and the smart grid architecture. Under this framework, a new energy management concept evolved that takes into account the interaction with the grid by enabling energy sharing between the base stations, demand-side management and ancillary services. This integration with the smart grid allowed to better utilize the harvested energy, thus increasing the energy efficiency of these networks. The last milestone discussed in this chapter is the integration of smart tools and algorithms based on artificial intelligence, in particular machine learning, to

orchestrate and manage the resources for the increasingly complex, heterogeneous and evolving future networks. After surveying the literature proposed under this field, we discussed the efficiency of using these tools in achieving green communication. Following the extensive research studied under these different areas, we highlighted several aspects in which the problematic of green cellular networks needs more exploration.

In this context, we proposed in Chapter 3 a framework to study and analyze the impact of equipping sites with renewable energy sources on the operational cost and the performance of cellular networks. To the best of our knowledge, we were the first to study partially renewable energy-equipped wireless systems. This was of great importance considering the high capital costs of these systems and the feasibility of implementing them on all sites of a network. We analyzed the energy and cost savings for various energy management strategies and different sizing of renewable energy systems in a hybrid-powered cellular network. We proposed several energy management strategies based on current states of traffic load, battery level and price of electricity leading to performance amelioration and increased energy savings. In order to assess the performance of the network, we adopted advanced metrics that put forward each service contribution to energy consumption. Using this framework, mobile operators can estimate how much to invest in renewable energy for an electric bill cost reduction. Our study of the relationship between cost savings and percentage of sites equipped with renewable energy showed significant results. For instance, a cost gain of around 60% was realized when 30% of the base stations are equipped with solar panels that harvest only 35% of the total network energy demand.

Most of existing work on renewable energy-equipped systems did not take into account the energy storage element (i.e., the battery) that is the most expensive element in renewable energy systems, and it is prone to irreversible degradation. In Chapter 4, we start by a synthesis on the important constraints on the battery usage in order to prolong its lifespan. Based on this synthesis, we proposed an online algorithm called BAPA (Battery Aging and Price-Aware) that brings down the grid energy consumption of a base station while preserving the battery. A key novelty in the proposed algorithm was that it buys excess energy from the grid to use it later (e.g., buy additional energy when the price is low and use it when the price is high). BAPA also showed an impressive performance leading in some cases to 99% close to the optimal offline solution that

required full knowledge of the system information. Following this algorithm, we extended the work to the case of cellular networks where base stations can cooperate under renewable energy and smart grid environment while respecting the constraints imposed on the battery. Thus, we proposed the JPARS-SM algorithm (Joint Power Allocation and Resource Sharing with Sleep Mode). In addition to the benefits of BAPA algorithm, JPARS-SM switches off underutilized base stations to save more energy. Our work showed that despite a slight decrease in the operational cost savings (around 5% points) compared to the case where we have no constraints on the battery, the battery gained 35% points for longer life duration.

In Chapter 5, we studied the problem of energy-delay-tradeoff in wireless cellular networks under advanced sleep mode levels compliant with 5G. We proposed a methodology for reducing the energy consumption of a 5G cellular network while ensuring a good quality of service. This methodology permits the operator to freely manage the tradeoff between energy savings and service delay. Due to the nature and high complexity of the problem in exploring the unknown dynamic environment, model-free reinforcement learning, in particular Q-learning, has been used to solve the stochastic optimization problem by means of interaction with the environment. This tool has proved to be very efficient in decision making problems, since it does not require future knowledge of the environment and is able to adapt to changes. While it is important to reduce the energy consumption of these networks, hard constraints are agreed on it the 5G requirements to periodically activate 5G cells for signaling synchronization. These strict requirements impose a constraint on the maximum period of time a base station can be deactivated. In this regard, we proposed first a distributed Q-learning algorithm that controls the states of the base stations (active or sleep) in order to maintain a desirable tradeoff between energy savings and added service delay. We focused on 5G sleep mode levels that respect the 5G requirements. We showed that having a combination of different states of sleep modes in a network can achieve better performance than having only one sleep mode state. For example, our simulations revealed an energy gain ranging between 90% and 50% for rate and delay tolerant users, respectively.

The interesting results obtained from using advanced 5G sleep mode levels encouraged us to explore more their potentials. Consequently, we studied a use case application for multi-level sleep modes where we con-



sidered the problem of handovers between cells. Unlike prior work that considered only binary sleep mode levels and static users, we proposed a Q-learning algorithm that controls the state of the base stations depending on the geographical location and moving velocity of neighboring users to maximize the tradeoff between energy savings and delay. We showed the Q-learning-based algorithm was able to achieve a good performance compared to a heuristic suboptimal scheme.

Finally, we extended the previous simplified model to include the co-channel interference between the cells and the mobility of users in a heterogeneous network covered by a macro base station. Based on the interference level of a given cell, its buffer state and its expected throughput, we designed a distributed Q-learning algorithm that decides the state of the cell in order to deliver to the users the required data service under a delay constraint while minimizing the energy consumption of the network.

## 6.2 Future work

The work done in this thesis in the different areas of green cellular networks can be considered as a step towards 5G networks to meet the stringent end-user application requirements while maintaining a low energy footprint. The latter targets several objectives, among reducing carbon emissions, reducing grid energy consumption and reducing the electric bill for the operators. Throughout our work, we found that there are a lot of opportunities to be explored. In Chapter 2, we have identified different research directions in energy-efficient cellular networks. In particular, we have highlighted four main research axis: energy efficiency techniques and approaches for 5G networks, integrating renewable energy sources to cellular base stations, operating cellular networks under the smart grid architecture to include the interaction between these two systems, and applying tools from machine learning to manage the increased complexity of these systems. In the following, we state some ideas and perspectives that we consider as a possible extension of our work.

Our first contribution that studied partially equipped renewable energy systems focused on the operational cost savings for the operator. A natural extension would be to take into account the capital costs of these systems. Knowing that equipping sites with renewable energy requires initial investment, it would be interesting to have an economic study that

shows how much capital investment is needed to achieve the desirable operational cost savings. In this way, the operator will be aware of all the costs (capital and operational) when deciding to invest in these systems. Consequently, it is possible to update the KPIs proposed in Chapter 3 to reflect the cost of energy obtained from green harvesters.

Following the economic study, an interesting idea would be to consider only batteries without energy harvesters. Based on the location of the base stations or the renewable energy profiles, the choice of equipping solar panels or not can be studied. Taking advantage of the interaction with the smart grid, the base station can provide ancillary services by increasing its energy consumption and storing it in the battery in return for some monetary incentives. Another case would be to buy excess energy and store it when the price of electricity is low to use it later when the price gets higher while taking into account the battery restrictions.

Moreover, in contrast to a specific type of battery, we can study the system under different battery types with different indicators such as battery efficiency and battery cycle. In Chapter 4, we studied hybrid-powered cellular networks while focusing on the battery, however, we focused only on the impact of the energy exchange with the battery on its lifetime. An interesting analysis could include the cost of replacing the battery after it exceeds its duty cycles.

To further exploit the potential of green cellular networks and in particular renewable energy systems, new architectures need to be considered, such as heterogeneous networks. Some researchers already started to work in this direction [94, 169, 93, 170]. In order to save energy, small cells are switched-off, and their users are offloaded to the macro base stations. However, the tradeoff between the energy saved from turning-off these small cells and the increased energy in the macro base stations is not well investigated, given that the energy consumption profile of the macro cell increases much more significantly with the traffic load than in the case of small cells.

Another important contribution is to extend the work of Chapter 5 to include users of different types and requirements. It would also be very interesting to study the performance of the system for different synchronization signals periodicity required for 5G base stations. In order to manage the high complexity of this scenario, in addition to the classical Q-learning tools used in this chapter, a possible extensions could be to take

advantage of other machine learning tools, such as fuzzy Q-learning and deep Q-learning to better handle cases where the number of possible states is huge.

Although the 5th generation cellular system was envisioned to be a carrier for Internet of Everything (IoE) services, the ongoing development of 5G networks is continuously exposing the limitations of this system [200]. With the emergence of new IoE services, such as eXtended reality (XR) services, haptics, flying vehicles, brain-computer interface, and connected autonomous systems [201], two main questions arise: can 5G deliver such services? and how much energy does it cost? In this regard and in order to overcome these challenges, a disruptive 6th generation system is expected to support this variety of applications. 6G will extend the past trends of 5G to include new services and recent revolution in wireless devices, artificial intelligence, computing, sensing and 3D environmental mapping.

6G will envision several new system trends [201]. One of the interesting trends is going from Self-Organizing Networks (SONs) to Self-Sustaining Networks (SSNs). In Chapter 5, we have studied SONs where the network adapts its functions to specific environment states based on reinforcement learning. In SSNs, the network must be also able to maintain a high KPI under a dynamic and more complex environment by sustaining its resource usage and management including the use of renewable energy. In order to achieve the vision of SSN, AI (particularly deep learning) will play a critical role in creating SSNs.

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# **Appendices**





# A

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## **Résumé en français: allocation des ressources radio dans les réseaux cellulaires 5G alimentés par le smart grid et les énergies renouvelables**

### **A.1 Contexte générale et motivation**

Nous vivons une révolution numérique où l'Internet est devenu un élément essentiel de notre vie quotidienne. Les humains et les machines sont maintenant connectés globalement sur Internet avec plus de 750 millions de foyers connectés et plus de 6.8 milliards d'abonnés mobiles (autant de mobiles que de personnes dans le monde) [1]. La tendance est à la hausse et ne semble pas avoir de signe de ralentissement dans un avenir proche en raison des nouveaux services et applications en cours en particulier le trafic sans fil (par exemple mobile) qui domine le secteur de

Technologies de l'Information et de la Communication (TIC) jusqu'à 75% [2]. Aujourd'hui plus de 5 millions de vidéos sont visionnées sur YouTube et 67,000 images sont téléchargées sur Instagram toutes les minutes. D'après le rapport sur le trafic mobile VNI de CISCO, il est estimé que le trafic mondial de données mobiles devrait être multiplié par sept entre 2016 et 2021 [3]. Cette augmentation radicale des appareils et services TIC a poussé la consommation d'énergie correspondante et son impact sur l'environnement à se développer à un rythme effarant. On estime que le secteur du TIC consomme plus de 5% de l'énergie électrique mondiale dépassant plus de 50% de celle de l'avionique libérant dans l'atmosphère environ 2% des émissions mondiales de CO<sub>2</sub> [4]. Ces chiffres devraient augmenter d'ici 2030 pour atteindre 51% et 23% de la consommation d'électricité et de l'empreinte carbone respectivement en raison du TIC [5].

Plus précisément les réseaux mobiles figurent parmi les principaux consommateurs d'énergie avec une part de contribution supérieure à 0.5% de l'approvisionnement total en énergie dans le monde [6]. Un chiffre qui augmente avec le nombre croissant d'abonnés la demande de trafic les appareils connectés et les services proposés. Avec une telle augmentation de la demande le secteur du TIC est confronté à des problèmes économiques et environnementaux. D'une part les revenus des opérateurs de téléphonie mobile diminuent chaque année. Une des raisons de cette baisse des revenus est l'augmentation des dépenses opérationnelles de ces réseaux qui est principalement dominée par les coûts de l'énergie. D'autre part il y a une sensibilisation accrue à la protection de l'environnement et une réglementation stricte sur les émissions de polluants. Les raisons évoquées ci-dessus liées à la hausse du prix de l'énergie au cours des dernières années ont amené la consommation d'énergie à devenir une préoccupation majeure dans la conception des systèmes sans fil de la future génération. Plus précisément, le réseau cellulaire de cinquième génération (5G) devra considérer l'efficacité énergétique comme l'un de ses piliers essentiels pour la durabilité économique du TIC.

Dans les réseaux cellulaires mobiles sans fil, le réseau d'accès radio consomme la majeure partie de l'énergie tandis que la station de base utilise 75 à 80% de l'énergie du réseau [21]. Par conséquent, fournir des capacités de récupération d'énergie aux stations de base cellulaires à partir de sources d'énergies renouvelables est une solution attrayante et prometteuse pour les réseaux cellulaires écologiques. En-

tre temps un nouveau domaine de recherche émerge allant au-delà de l'efficacité énergétique mais aussi de la durabilité énergétique. Dans ce paradigme, les énergies renouvelables constitueront un élément essentiel de la durabilité des futurs réseaux 5G en particulier pour les pays sous-développés dépourvus de connectivité réseau fiable. Par exemple, en Inde sur 400,000 stations de base plus de 70% subissent des coupures de courant de plus de 8 heures par jour. Contre cette panne d'électricité les opérateurs dépendent de générateurs diesel dépensant environ 1.4 milliard de dollars US et produisant plus de cinq tonnes de CO<sub>2</sub> [22]. à l'heure actuelle on estime qu'il existe environ 320,100 stations de base hors réseau (c.-à-d. non raccordés au réseau) et 701,000 réseaux non fiables (c.-à-d. avec de nombreuses pannes de courant) dans le monde. Ces chiffres devraient augmenter de 22% et 13% d'ici à 2020 respectivement [23].

Alimenter les stations de base avec des sources d'énergies renouvelables n'est pas seulement attrayant pour les pays dont les conditions de réseau sont médiocres. Les pays développés dotés de marchés de l'énergie bien établis peuvent également tirer parti des récupérateurs d'énergie pour accroître leurs économies réduire leurs émissions de CO<sub>2</sub> et revendre au réseau l'énergie excédentaire produite par ces sources vertes augmentant ainsi leurs revenus. Ce dernier est possible grâce à l'évolution du réseau électrique en un réseau plus intelligent - le Smart Grid (SG). Sous cette infrastructure le flux d'énergie est bidirectionnel (c.-à-d. de la source au consommateur et inversement). Cette infrastructure prometteuse devrait améliorer l'efficacité la fiabilité l'économie et la durabilité de la production et de la distribution d'électricité. Il est donc crucial de prendre en compte le SG lors de l'étude du comportement énergétique des futurs réseaux cellulaires mobiles. De plus, les progrès réalisés dans les systèmes de récolte des énergies renouvelables améliorent l'efficacité de la production d'électricité à partir de sources vertes réduisant ainsi le coût de déploiement de tels systèmes. Par exemple l'efficacité actuelle des panneaux solaires commerciaux disponibles construits avec les technologies traditionnelles (c.-à-d. le silicium cristallin) est comprise entre 15 et 20%. Les nouvelles technologies telles que le photovoltaïque à concentration (PVC) permettent d'améliorer encore ces valeurs plus de deux fois (jusqu'à 39%) mais elles sont toujours à l'essai et ne sont pas encore disponibles sur le marché [24].

Outre les avantages économiques et environnementaux liés à l'utilisation des énergies renouvelables sous l'infrastructure SG, un dimensionnement précis de ses systèmes sont nécessaires en raison de leurs coûts d'investissement élevés. Une tâche qui implique un compromis entre l'autosuffisance énergétique la continuité de service et les contraintes de faisabilité. De plus, en raison de la nature irrégulière et intermittente de ce type d'énergie, une gestion intelligente est nécessaire pour les utiliser efficacement et pour garantir la fiabilité du service. Une façon de remédier à la limitation naturelle de l'énergie renouvelable consiste à utiliser des batteries pour stocker l'énergie récupérée afin d'accroître la flexibilité de son utilisation. En outre afin de satisfaire les nouveaux services et applications en respectant les contraintes écologiques, le couplage entre optimisation des ressources radio et optimisation de l'allocation de puissance est l'objectif ultime des réseaux de téléphonie mobile verts. Cependant ce couplage des ressources radio et électriques introduit de nouveaux défis pour optimiser les réseaux de téléphonie mobile utilisant l'énergie verte. Par conséquent la conception et l'exploitation de tels réseaux n'est pas anodine en raison de leur grande complexité.

L'objectif de cette thèse est de concevoir et d'exploiter des réseaux cellulaires alimentés par les énergies renouvelables et le SG tout en mettant l'accent sur le rôle crucial de l'énergie. Nous accordons une attention particulière à la batterie, élément important des systèmes à énergie renouvelable, qui joue un rôle essentiel dans la conception de réseaux mobiles durables nécessitant ainsi une gestion précise. Outre l'utilisation des énergies renouvelables, nous examinons diverses techniques de gestion des ressources énergétiques et radio. Nous étudions différents objectifs tels que la réduction de la facture d'électricité de l'opérateur l'amélioration des indicateurs de performance clés basés sur le service et la gestion du compromis entre les économies d'énergie et les retards. Comme il est important d'économiser de l'énergie les réseaux futurs doivent pouvoir atténuer l'impact sur la qualité de service à livrer.

## **A.2 Contribution et organisation du manuscrit**

L'étude de l'état de l'art nous a permis d'avoir une vue d'ensemble des travaux existants dans le contexte des réseaux de téléphonie mobile à haute efficacité énergétique. Par conséquent, nous avons d'abord proposé une méthodologie pour étudier et analyser l'impact de l'équipement des sites en sources d'énergies renouvelables et en batteries sur le coût de fonctionnement et la performance des réseaux cellulaires. Contrairement à la plupart des études dans la littérature et au meilleur de nos connaissances nous sommes les premiers à étudier les systèmes sans fil dotés d'une énergie partiellement renouvelable. Cela revêt une grande importance compte tenu des coûts d'investissement élevés de ces systèmes et de la faisabilité de leur mise en oeuvre sur tous les sites.

Ensuite nous étudions les économies d'énergie du réseau en tenant compte de l'utilisation efficace de la batterie sujette à des dégradations irréversibles réduisant sa capacité maximale. Alors que la plupart des études dans la littérature se concentrent uniquement sur la réduction de la consommation d'énergie du réseau dans les systèmes à énergies renouvelables, nous proposons plusieurs algorithmes qui non seulement réduisent la consommation d'énergie du réseau mais préservent également la durée de vie de la batterie qui est la partie la plus chère des systèmes à énergies renouvelables.

Enfin nous étudions le problème du compromis délai d'énergie dans les réseaux cellulaires sans fil avec des niveaux de mode de veille avancés. Différents des schémas de mode de veille binaire (On-Off) qui sont bien étudiés dans la littérature nous considérons des modes de veille à plusieurs niveaux compatibles avec les réseaux 5G. Ainsi nous proposons une méthodologie pour réduire la consommation d'énergie d'un réseau cellulaire 5G tout en garantissant une bonne qualité de service. Cette méthodologie permet à l'opérateur de gérer librement le compromis entre économie d'énergie et délai de service. Afin de gérer la grande complexité de l'environnement dynamique, nous avons décidé de renforcer nos algorithmes avec des outils issus de l'apprentissage automatique afin de résoudre le problème d'optimisation stochastique au moyen d'une interaction avec cet environnement.

Le reste de la thèse est organisé comme suit. Le Chapitre 2 examine l'état de l'art en matière de réseaux cellulaires éco-énergétiques. Nous commençons par discuter des différentes techniques trouvées dans la littérature pour économiser de l'énergie dans les réseaux 5G. Ensuite nous développons l'utilisation des énergies renouvelables comme moyen d'améliorer l'efficacité énergétique et de réduire l'empreinte carbone des futurs réseaux. Nous soulignons le rôle important du futur réseau (c.-à-d. le SG) dans la réalisation du paradigme vert. Enfin nous discutons de la manière dont l'Intelligence Artificielle (IA) constitue un outil puissant pour les réseaux de prochaine génération.

Dans le Chapitre 3, nous présentons un cadre permettant d'étudier et d'analyser l'impact de l'équipement des sites en sources d'énergies renouvelables sur les coûts opérationnels et les performances du réseau. Nous évaluons l'efficacité énergétique du réseau à l'aide d'indicateurs de performance clés avancés qui mettent en avant la contribution de chaque service fourni par le réseau à la consommation d'énergie. Nous étendons le travail du Chapitre 4 pour inclure des exigences importantes en matière de batterie pour une utilisation correcte et une durée de vie prolongée. Nous proposons plusieurs algorithmes qui gèrent les ressources du réseau (radio et énergie) afin de minimiser la facture électrique de l'opérateur tout en préservant la durée de vie de la batterie.

Dans le Chapitre 5, nous nous concentrons sur les exigences spécifiques des réseaux 5G. A cet égard nous étudions les systèmes de sommeil avancés conformes à la 5G. Nous étudions le problème des compromis de délai d'énergie pour différents cas d'utilisation de la 5G. Ainsi nous proposons plusieurs algorithmes basés sur l'apprentissage par renforcement en particulier Q-learning afin d'en déduire des stratégies optimales en mode veille afin d'équilibrer économie d'énergie et délai de service. Enfin nous concluons cette thèse en ouvrant de nouvelles pistes de recherche potentielles dans le Chapitre 6. Nous notons qu'en annexe nous donnons un aperçu de l'apprentissage par renforcement un outil d'apprentissage automatique largement utilisé dans la prise de décision pour des problèmes complexes.

## A.3 Résultats

Dans le Chapitre 3, nous présentons une méthodologie pour étudier et analyser l'impact de l'équipement des sites en énergies renouvelables sur les coûts opérationnels et la performance d'un réseau cellulaire afin de décider du montant des investissements dans les énergies renouvelables. Nous évaluons les économies d'énergie de réseau pour différentes configurations de systèmes d'énergie renouvelable. Nous considérons différents paramètres d'entrée tels que le nombre de sites équipés en énergie renouvelable, le dimensionnement de l'énergie renouvelable et le dimensionnement de la batterie. Nous considérons également différentes techniques de gestion de réseau telles que les systèmes de veille, l'allocation de ressources radio et la gestion de batterie. En définissant les paramètres d'entrée et en choisissant les techniques économes en énergie à appliquer dans le réseau, nous étudions des indicateurs importants tels que la réduction des coûts sur le réseau. Dans Figure A.1, nous quantifions le gain de coût sur le réseau par rapport au pourcentage de sites équipés en énergie renouvelable, pour différentes tailles de capacité de batterie. Le gain de 20% obtenu lorsqu'aucun des sites n'est équipé de sources d'énergie renouvelables et qu'aucun système de sommeil n'est pris en compte est le résultat de l'algorithme d'allocation de blocs de ressources qui désactive les blocs de ressources excédentaires et réduit donc la consommation d'énergie. Nous constatons que le fait de n'équiper que 30% des sites en sources d'énergie renouvelables génère un gain une économie d'environ 58%, tandis que nous pouvons atteindre 75% lorsque toutes les stations de base sont équipées de panneaux solaires ne récoltant pas plus de 35% de la demande totale d'énergie à pleine charge. Cette quantité d'énergie récupérée est liée à la surface de panneau de 12.5 m<sup>2</sup> utilisée dans cette configuration.

Nous avons proposé dans Chapitre 4 une suite de ce travail en prenant en compte le comportement des batteries (l'élément de stockage d'énergie) lors de la conception de stratégies de gestion de l'énergie. Nous nous attachons en particulier à prolonger la durée de vie de la batterie tout en maximisant les économies de coûts du réseau opérationnel. À cet égard, nous proposons le Battery Aging and Price-Aware (BAPA) algorithme qui réduit la consommation d'énergie d'une station de base tout en préservant l'élément de stockage d'énergie. Ensuite, nous étendons l'algorithme pour inclure la coopération entre les stations de base d'un



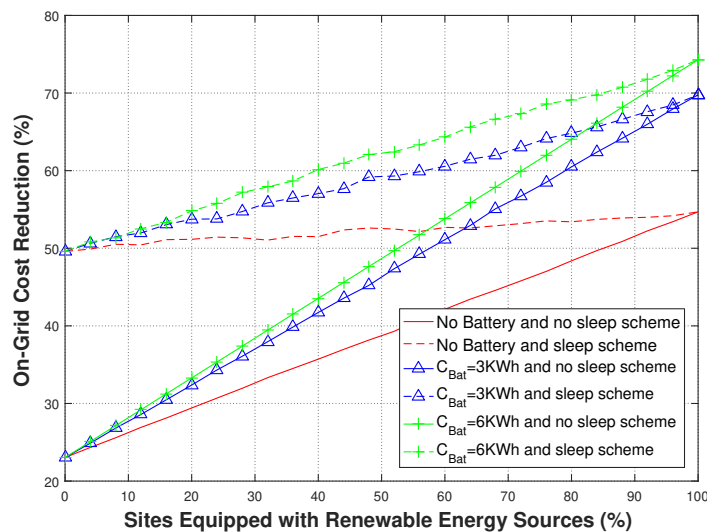


Figure A.1 – Percentage of on-grid cost reduction over one day, with a 12.5m<sup>2</sup> solar panel surface area.

réseau cellulaire, tout en respectant les contraintes imposées à la batterie pour prolonger sa durée de vie dans Joint Power Allocation and Resource Sharing with Sleep Mode (JPARS-SM) algorithm. Afin d'évaluer notre algorithme proposé, nous illustrons dans Figure A.2 la performance de notre algorithme proposé (JPARS-SM) sur la qualité de la batterie avec la solution heuristique (SPAEMA) y compris l'usage agressive de la batterie (c.-à-d., sans prendre compte les contraintes pour préserver la durée de vie de la batterie). Nous montrons que, tout en respectant les contraintes de vieillissement de la batterie, nous perdons en moyenne 40% de la capacité initiale de la batterie après un an, contre 75% lorsque ces contraintes sont ignorées. De plus, nous montrons que JPARS-SM permet de réaliser des économies d'énergie plus importantes que les algorithmes de référence. Ceci est dû au fait que JPARS-SM permet d'acheter de l'énergie à l'avance pour pouvoir l'utiliser plus tard (par exemple, achetez de l'énergie lorsque le prix de l'électricité est bas et utilisez-la lorsque le prix est élevé).

Finalement, le Chapitre 5 présente une étude du problème du compromis délai-énergie-échange dans les réseaux cellulaires sans fil dans les niveaux avancés du mode veille. En raison de la complexité des futurs environnements réseau 5G, nous nous appuyons sur des outils intelligents capables d'apprendre et de gérer cette complexité afin de satisfaire les diverses exigences. À cet égard, nous nous appuyons sur l'apprentissage artificiel, et en particulier sur le Q-learning, qui ouvre la voie à l'optimalité en explorant l'environnement et en interagissant avec celui-ci, en nous

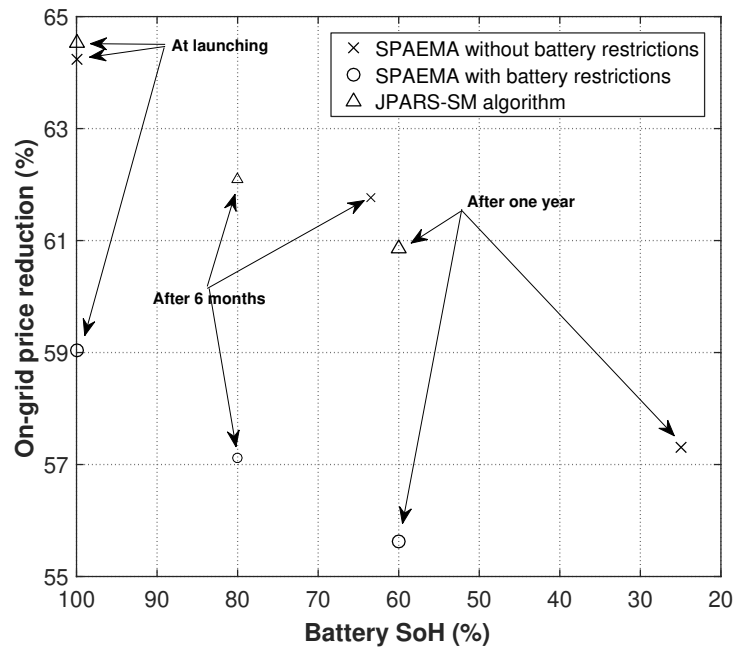


Figure A.2 – Grid energy cost savings with the average evolution of the battery SoH after one year.

fiant uniquement à l'état actuel de la cellule. Contrairement aux approches hors ligne qui requièrent une connaissance totale du système pour résoudre le problème, Q-learning allège les informations système non causales en en faisant une solution prometteuse pour une application en temps réel. Nous fournissons plusieurs contributions dans ce chapitre. Parmi eux, l'étude d'un réseau hétérogène où des petites cellules sont autorisées à passer à différents niveaux de mode veille (SM1, SM2 et SM3) afin d'économiser de l'énergie tout en minimisant le délai de service. Dans Figure A.3, nous rapportons les différentes activités des petites cellules pour différentes valeurs du paramètre de réglage  $w$ . Ce paramètre, qui prend une valeur entre 0 et 1, est un facteur de pondération qui établit une priorité entre la consommation d'énergie et le délai de service. Nous observons que le système a tendance à économiser plus d'énergie lorsque  $w$  approche de zéro en passant au niveau de mode de sommeil le plus profond (SM3) la plupart du temps, tandis qu'un passage progressif au mode actif est observé lors de l'augmentation de  $w$ .

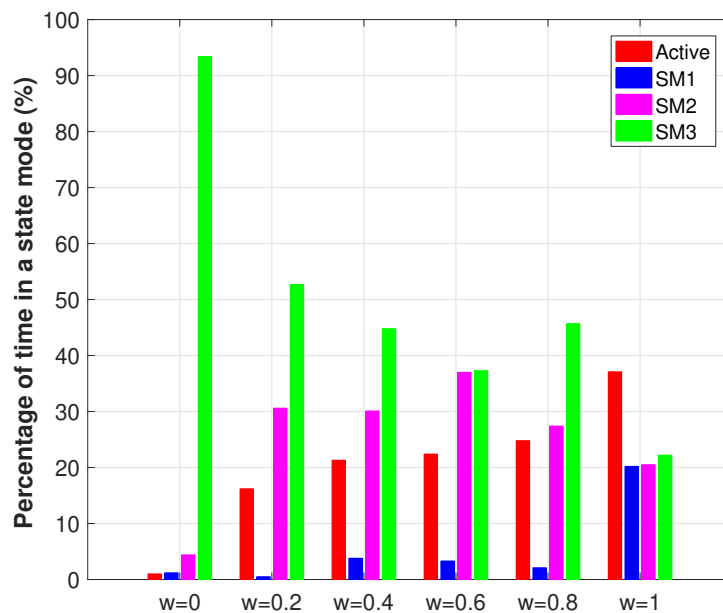


Figure A.3 – Different SM policies as a function of  $w$ .

## A.4 Conclusions et travaux futurs

Le travail effectué dans cette thèse dans les différents domaines des réseaux cellulaires verts peut être considéré comme un pas en avant vers les réseaux 5G pour répondre aux exigences strictes des applications des utilisateurs radios, tout en maintenant une empreinte énergétique réduite. Ce dernier vise plusieurs objectifs, parmi lesquels la réduction des émissions de carbone, la consommation d'énergie du réseau et la facture d'électricité des opérateurs. Tout au long de notre travail, nous avons constaté qu'il y a encore beaucoup de possibilités à explorer. Dans le Chapitre 2, nous avons identifié des différentes pistes de recherche sur les réseaux cellulaires écoénergétiques. En particulier, nous avons mis en évidence quatre axes de recherche principaux: (1) techniques et approches d'efficacité énergétique pour les réseaux 5G, (2) intégration des sources d'énergie renouvelables aux stations de base cellulaires, (3) exploitation de réseaux cellulaires sous l'architecture de réseau intelligent pour inclure l'interaction entre ces deux systèmes et (4) application des outils d'intelligence artificiel pour gérer la complexité croissante de ces systèmes. Dans ce qui suit, nous exposons certaines idées et perspectives que nous considérons comme une extension possible de notre travail.

Notre première contribution qui a étudié les systèmes d'énergie renouvelable partiellement équipés s'est concentrée sur les économies de coûts

d'exploitation pour l'opérateur. Une extension naturelle serait de prendre en compte les coûts d'investissement de ces systèmes. Sachant que l'équipement des sites en énergies renouvelables nécessite un investissement initial, il serait intéressant de disposer d'une étude économique qui montre combien d'investissement en capital est nécessaire pour réaliser les économies de coûts d'exploitation souhaitables. De cette façon, l'opérateur sera conscient de tous les coûts (en capital et opérationnels) lorsqu'il décidera d'investir dans ces systèmes. Par conséquent, il est possible de mettre à jour les KPI proposés dans le Chapitre 3 pour refléter le coût de l'énergie obtenue par les énergies renouvelables.

À la suite de l'étude économique, une idée intéressante serait de ne considérer que les batteries sans récupérateurs d'énergie. En fonction de l'emplacement des stations de base ou des profils d'énergie renouvelable, le choix d'équiper des panneaux solaires ou non peut être étudié. En se basant sur l'interaction avec le réseau intelligent (Smart Grid), la station de base peut fournir des services auxiliaires en augmentant sa consommation d'énergie et en la stockant dans la batterie pour bénéficier des incitations monétaires. Une autre solution consisterait à acheter l'énergie excédentaire et à la stocker lorsque le prix de l'électricité est bas pour l'utiliser plus tard, lorsque le prix augmente, tout en tenant compte des restrictions de la batterie.

Pour exploiter davantage le potentiel des réseaux cellulaires verts et en particulier des systèmes d'énergie renouvelable, de nouvelles architectures doivent être envisagées, telles que les réseaux hétérogènes. Certains travaux ont été déjà commencés dans ce sens [94, 169, 93, 170]. Afin d'économiser de l'énergie, les petites cellules sont éteintes et leurs utilisateurs sont déchargés vers les macro stations de base. Cependant, le compromis entre l'énergie économisée en éteignant ces petites cellules et l'augmentation de l'énergie dans les macro stations de base n'est pas bien étudié, étant donné que le profil de consommation d'énergie de la macro cellule augmente beaucoup plus significativement avec la charge de trafic qu'avec le cas de petites cellules.

Bien que le système cellulaire de 5<sup>ème</sup> génération ait été envisagé comme un opérateur pour les services Internet de tout (IoE), le développement en cours des réseaux 5G expose continuellement les limites de ce système [200]. Avec l'émergence de nouveaux services IoE, tels que les services de réalité augmentée (XR), l'haptique, les véhicules volants, l'interface cerveau-ordinateur et les systèmes autonomes con-

nectés [201], deux questions principales se posent: la 5G peut-elle fournir de tels services? et combien cela coûte-t-il au niveau énergétique? À cet égard, et afin de surmonter ces défis, un système perturbateur de 6ème génération devrait prendre en charge cette variété d'applications. La 6G étendra les tendances passées de la 5G pour inclure de nouveaux services et la révolution récente dans les dispositifs sans fil, l'intelligence artificielle, l'informatique, la détection et la cartographie environnementale en 3D.

La 6G envisagera plusieurs nouvelles tendances du système [201]. L'une des tendances intéressantes va des réseaux auto-organisés (Self-Organizing Network - SON) aux réseaux auto-entretenus (Self-Sustaining Network - SSN). Dans le Chapitre 5, nous avons étudié les réseaux auto-organisés (SONs) dans lesquels le réseau adapte ses fonctions à des états d'environnement spécifiques en fonction de l'apprentissage par renforcement. Dans les SSNs, le réseau doit également pouvoir conserver un indicateur de performance clé élevé dans un environnement dynamique et plus complexe en maintenant son utilisation et sa gestion des ressources, y compris l'utilisation d'énergies renouvelables. Afin de réaliser la vision du SSN, l'IA (en particulier l'apprentissage en profondeur - Deep learning) jouera un rôle crucial dans la création de SSN.

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# B

## **Reinforcement learning: background and preliminaries**

### **B.1 Introduction**

The field of Artificial Intelligence (AI) dates back to the 1950's. However due to the limitation in the computational power in that era, this field failed to be recognized as a promising paradigm. Today and with the advances in computer engineering, AI is emerging with a lot of research activities in both academia and industry. As detailed in Section 2.5 of Chapter 2, machine learning (a subset of AI) is divided into three main categories: supervised learning, unsupervised learning and reinforcement learning.

The term reinforcement learning emerged in the late 1970s as part of a project in the university of Massachusetts, and inspired by control theory and behaviorist psychology [202]. It is based on the simplest idea of a learning system that wants something, and adapts its behavior in order to maximize a numerical performance derived from the environment. Such system is known as a hedonistic learning system, that came later to be known as reinforcement learning. Little by little, the field has evolved and matured in several directions, making reinforcement learning one of the most attractive research areas in ML, AI and neural network.

The idea of learning from the interaction with the environment is a foundation idea underlying nearly all theories of learning and intelligence. With no explicit teacher, the agent (entity to control) interacts with the

environment by means of sensors and motors. This connection results in acquiring information about cause and effect, in other words for each action its consequence, and in learning what to do to achieve the goals set.

## B.2 Reinforcement learning

Reinforcement learning is built around the idea of learning by interaction, or learning by trial-and-error (in its simplest form, i.e., when the environment is model-free) in order to map situations to actions that maximize a numerical reward. A classical setting of a reinforcement learning scenario is depicted in Fig. B.1. An agent senses the environment and receives a system state  $s_t \in \mathcal{S}$  describing the environment at time  $t$ , where  $\mathcal{S}$  is the set of possible states. Then, it decides to take an action  $a_t \in \mathcal{A}(S_t)$ , where  $\mathcal{A}(S_t)$  is the set of actions available in state  $s_t$ . In response to this action, the system receives a numerical reward  $r_t$ , moves to a new state  $s_{t+1}$ , and the cycle is repeated. The process of choosing an action at each state is known as mapping states to actions. This mapping is called the agent's policy and is denoted by  $\pi_t$ , where  $\pi_t(a, s)$  is the probability that the agent will choose action  $a$  at state  $s$ . The goal of reinforcement learning is to learn the best policy  $\pi^*$  to control the system in order to maximize the total reward.

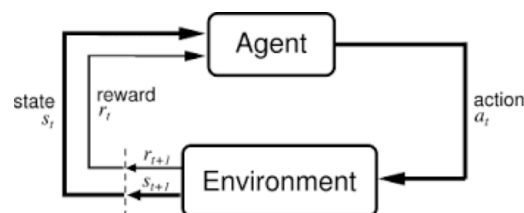


Figure B.1 – Classical reinforcement learning scenario [202].

Based on the description above, we note three characteristics for reinforcement learning problems:

1. **Close-loop problems:** in their essence, reinforcement learning problems are closed-loop problems that rely on feedback to learn the best control policy. This is because the actions taken by the agent influence its later inputs.

2. **No instructions:** the learner does not have direct instructions on what actions to take. However, it must discover the actions that yield to the highest reward by trying them all.
3. **Actions consequences:** in most interesting cases, actions do not only affect the current reward, but also can extend to all subsequent rewards.

## B.3 Elements of reinforcement learning

In reinforcement learning systems, one can identify several main elements. Besides the agent and the environment, we identify the following elements [202]:

1. **Policy:** it is the core of reinforcement learning agent. It defines the way the agent should behave at a given time. In other words, it is a mapping from the states to actions. A policy could be as simple as a lookup table and as computationally expensive as a search process.
2. **Reward:** it defines the goal of the system. At each time, the agent takes an action and receives a reward. The objective of the agent is to maximize this reward. Hence, finding the best policy that maps states to actions. For instance, if an action chosen based on a policy yields to low reward, this policy can be changed to select another action with a higher reward.
3. **Value function:** While the reward gives the instantaneous value of an action, the value function indicates the best policy in the long run. The value evaluated at a given state is the total amount of expected reward an agent can expect to collect over the future, starting from the state.
4. **Model of the environment:** it mimics the behavior of the environment. More generally, it speculates how the environment will behave. We distinguish between two types of approaches: model-based and model-free approaches. In model-based approaches, given an action and a state, the model might predict the next state and next reward. Thus, considering possible future situations before they are actually happening. Model-free approaches do not involve planning and are based on trial-and-error learners.



## B.4 Reinforcement learning framework

Reinforcement learning problems can be best described or formulated under the framework of MDP problems, since they are decision making problems, they share the Markov property (i.e, the future state of the system depends only on the current system's state) and the system to be controlled is in general stochastic. The Markov property is important because decisions and values are assumed to be related only to the current state.

Under the MDP framework, in particular finite MDP (most reinforcement learning fall under this category), one can derive the probability of transition from a state  $s$  to another state  $s'$ , and the reward  $r$  given an action  $a$ :

$$p(s', r|s, a) \triangleq \Pr\{S_{t+1} = s', R_{t+1} = r|S_t = s, A_t = a\} \quad (\text{B.1})$$

From B.1, one can compute anything about the environment, such as the expected reward for state-action pairs, the state-transition probabilities and the expected rewards for the state-action-next-state triples. However, in reinforcement learning similar to MDP problems, the goal is to find the optimal policy that returns the highest expected total discounted reward. Also known as delayed reward, the total discounted reward  $G(t)$  evaluates the present value of future rewards. It is defined as follows:

$$G(t) \triangleq R_t + \gamma R_{t+1} + \gamma^2 R_{t+2} + \dots = \sum_{k=0}^{\infty} \gamma^k R_{t+k} \quad (\text{B.2})$$

where  $\gamma \in [0, 1]$  is called the discount rate.

The above equation highlights the following question: "is a large reward in the future better than a smaller reward now?". A reward received  $k$  time steps in the future is worth  $\gamma^{k-1}$  times if it were received immediately. When  $\gamma$  is closer to 0 (or 1) more emphasis is given to immediate (or future) reward. One way to finding the optimal behavior is to list all possible policies, then choose the one with the highest reward. This method however is not efficient especially if there are too many policies to test, which is the case in most of these problems. A better solution is based on estimating value functions that evaluate how good or bad is to be in a given state, in terms of future expected rewards the agent might receive. Thus, for MDP one can define the value of a state under a policy  $\pi$  as follows:

$$v_{\pi}(s) \triangleq \mathbb{E}_{\pi}[G_t|S_t = s] = \mathbb{E}_{\pi}\left[\sum_{k=0}^{\infty} \gamma^k R_{t+k+1} \middle| S_t = s\right] \quad (\text{B.3})$$

where  $\mathbb{E}_\pi[\cdot]$  denotes the expected value of the random variable when the agent follows policy  $\pi$ .

**Goal:** Learn the optimal policy  $\pi^*$  that maximizes the expected value function  $v^\pi$ .

Similar to the value function in (B.3), in reinforcement learning it is more interesting and useful to define the action-value function, which is defined as the value of taking an action  $a$  in state  $s$  under policy  $\pi$ , denoted by  $q_\pi(s, a)$ . It is defined as follows:

$$q_\pi(s, a) \triangleq \mathbb{E}_\pi[G_t | S_t = s, A_t = a] = \mathbb{E}_\pi \left[ \sum_{k=0}^{\infty} \gamma^k R_{t+k+1} \middle| S_t = s, A_t = a \right] \quad (\text{B.4})$$

One of the main advantages of value functions ((B.3) and (B.4)) is that they satisfy particular recursive relationships. Thus, they can be written to what is known as *Bellman equation*. For instance (B.3) can be written as follows:

$$v_\pi(s) = \sum_a \pi(a|s) \sum_{s', r} p(s', r|s, a) [r + \gamma v_\pi(s')], \quad \forall s \in \mathcal{S} \quad (\text{B.5})$$

Solving Bellman equation leads to finding the optimal policy, and thus to solving the reinforcement learning problem. In doing so, one has to solve a system with  $N$  equations in  $N$  unknowns, where  $N$  is the number of states. However, this solution is not useful for several reasons: (1) the dynamics of the environment needs to be accurately modeled; (2) there should be enough resources to handle the computation of the solution; and (3) the Markov property. For the kinds of problems in which we are interested in, it is difficult to implement this approach because one or more of these assumptions are violated. In particular, the second assumption is a major drawback, since computational resources are limited. In this regard, reinforcement learning settles for approximate solutions.

There exist several methods and approximations to solve the Bellman equation in (B.5), such as Dynamic Programming (DP), Monte Carlo and Temporal Difference (TD). While DP is a powerful tool to derive the optimal policy, it is not useful in reinforcement learning because as previously discussed, it requires full knowledge of the environment and is computationally expensive. On the other hand, Monte Carlo and TD are learning methods that discover optimal policies without a complete knowledge of the environment. They require only experience by interacting with the environment.

With Monte Carlo approach, learning is done in an episode-by-episode sense, and not step-by-step. An episode is an experience that starts at an initial state and always finishes at a terminal state no matter what actions are selected. Thus, different episodes can have different policies, but leading to the same terminal state. Monte Carlo is based on averaging complete returns from different sample episodes starting at a given state. This average becomes an approximation of the state-value, since the value of a state is the expected return.

A central and novel idea in reinforcement learning is TD learning. TD takes the advantage of DP and Monte Carlo. Similar to Monte Carlo, TD approaches do not need a model for the environment dynamics and learn from experience by interaction. Like DP, TD methods bootstrap based on learned estimates without waiting for the final outcome like in Monte Carlo approaches. A common characteristic between DP, Monte Carlo and TD approaches is being recursive.

There exist several variations of TD learning, such as Sarsa and Q-learning. Both rely on the Q-function  $Q(s, a)$  that is the expected maximum discounted cumulative reward starting from state  $s$  and applying action  $a$ .

$$Q(s, a) = \mathbb{E}[r(s, a) + \gamma v^{\pi^*}(q(s, a))] \quad (\text{B.6})$$

The optimal policy  $\pi^*$  corresponds to the action  $a$  that maximizes  $Q(s, a)$ :

$$\pi^*(s) = \underset{a}{\operatorname{argmax}} Q(s, a) \quad (\text{B.7})$$

Using (B.7), (B.6) can be redefined recursively as:

$$Q(s, a) = \mathbb{E}[r(s, a) + \gamma \max_{a'} Q(s', a')] \quad (\text{B.8})$$

## B.5 Q-learning algorithm

Q-learning is an off-policy TD control algorithm that keeps an estimate of the Q-function, defined by:

$$Q(s^t, a^t) \leftarrow Q(s^t, a^t) + \alpha [r^t + \gamma \max_{a' \in A} Q(s^{t+1}, a^{t+1}) - Q(s^t, a^t)] \quad (\text{B.9})$$

where  $\alpha \in [0, 1]$  is the learning rate that represents the speed of convergence.

**Algorithm 8** : Q-Learning Algorithm

---

```

Initialize  $Q(s,a)$  for all  $s \in S, a \in A(s)$ 
repeat(for each episode):
  Initialize  $s$ 
  repeat(for each time  $t$ ):
    Choose  $a^t$  using  $\epsilon$ -greedy policy in (B.10)
    Compute  $r^t$ 
    Update  $Q(s^t, a^t)$  using the update rule in (B.9)
     $s^t \leftarrow s^{t+1}$ 
  until the end of the day
until convergence

```

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As shown in (B.9), the learned action-value function,  $Q$ , directly approximates  $q^*$ , the optimal action-value function, independent of the policy being followed. This has a major impact on the analysis simplification, and ensure early convergence.

**B.5.1 Exploration Vs exploitation**

A major dilemma in all learning control methods is the compromise between exploration and exploitation: how to achieve the optimal policy if it does not explore all the states? How should action  $a$  be selected? One way to alleviate this issue is to consider  $\epsilon$ -greedy policy. In such policy, the action that yields to the highest estimated  $Q$  value is chosen most of the time, but with probability  $\epsilon$  a random action is selected. This will make sure that all the state-action pairs are visited. The  $\epsilon$ -greedy policy can be defined as follows:

$$\alpha^t = \begin{cases} \underset{a \in \mathcal{A}}{\operatorname{argmax}} Q(s^t, a^t), & \text{if } y > \epsilon \\ \operatorname{rand}(\mathcal{A}), & \text{otherwise} \end{cases} \quad (\text{B.10})$$

where  $y$  is a random variable uniformly distributed between 0 and 1. We summarize the procedure of the Q-learning algorithm in Algorithm 8.

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**Titre :** Allocation des ressources radio dans les réseaux cellulaires 5G alimentés par le smart grid et les énergies renouvelables

**Mots clés :** Réseaux cellulaires, efficacité énergétique, 5G, énergie renouvelable, allocation de ressource, intelligence artificielle.

**Résumé :** Nous vivons une révolution numérique où l'Internet est devenu un élément essentiel de notre vie quotidienne. Avec plus de 750 millions de foyers connectés et plus de 6,8 milliards d'abonnés à la téléphonie mobile, les réseaux cellulaires dominent le secteur des Technologies de l'Information et de la Communication (TIC) avec plus de 75%. La tendance est à la hausse et ne semble pas avoir de signe de ralentissement dans un avenir proche en raison des nouveaux services et applications en cours. Cependant, cette augmentation radicale des appareils et services TIC a poussé la consommation d'énergie correspondante et son impact sur l'environnement à croître à un rythme effarant, consommant plus de 5% de l'énergie électrique mondiale et libérant dans l'atmosphère environ 2% des émissions de CO<sub>2</sub>. Étant donné que les stations de base, éléments essentiels de la fourniture d'accès à l'Internet, consomment la plus grande partie de l'énergie des réseaux cellulaires, il est essentiel d'étudier de nouvelles stratégies et architectures afin de prévenir cette pénurie d'énergie.

Cette thèse porte sur le rôle essentiel de l'énergie dans la conception et l'exploitation de futurs réseaux cellulaires. Nous considérons des approches différentes et complémentaires, y compris des techniques d'efficacité énergétique (gestion des ressources radio et systèmes de sommeil), des sources d'énergie renouvelables, le Smart Grid et des outils d'apprentissage basés sur l'intelligence artificielle pour réduire la consommation d'énergie de ces réseaux complexes tout en garantissant une certaine qualité de service adapté aux cas d'utilisation 5G.

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**Title :** Radio resource allocation in 5G cellular networks powered by the smart grid and renewable energies

**Keywords :** Green cellular networks, energy efficiency, 5G, renewable energy, resource allocation, machine learning.

**Abstract :** We live in the digital era where the Internet has become an essential part of our daily lives. With more than 750 million connected households and over 6.8 billion mobile subscribers, mobile networks are dominating the Information and Communication Technology (ICT) sector with more than 75%. The trend is of further increase and appears to have no signs of slowing down in the near future due to the ongoing new services and applications. However, this radical surge of ICT devices and services has pushed corresponding energy consumption and its footprint on the environment to grow at a staggering rate consuming more than 5% of the world's electrical energy and releasing into the atmosphere about 2% of the global CO<sub>2</sub> emissions. Since base stations, the core elements to provide internet access, consume most of the energy in cellular networks, it is essential to study new strategies and architectures in order to deter this energy crunch.

This thesis focuses on the crucial role of energy in the design and operation of future cellular networks. We consider different and complementary approaches and parameters, including energy efficiency techniques (i.e., radio resource management and sleep schemes), renewable energy sources, Smart Grid and tools from machine learning to bring down the energy consumption of these complex networks while guaranteeing a certain quality of service adapted to 5G use cases.