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# Smart grid-aware radio engineering in 5G mobile networks

Wael Labidi

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# Smart grid-aware radio engineering in 5G mobile networks

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Thèse présentée et soutenue à Paris, le 21/03/2019, par

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# Abstract

The energy demand in mobile networks is increasing due to the emergence of new technologies and new services with higher requirements (data rates, delays, etc). In this context, the Mobile Network Operator (MNO) has to provide more radio and processing resources in its network leading for higher financial costs. The MNO has no choice but to implement energy saving strategies in all the parts of its infrastructure and especially at the Radio Access Network (RAN).

At the same time, the electrical grid is getting smarter including new functionalities to balance supply and demand by varying the electricity prices, allowing some aggregators to be part of the supply process and signing demand response agreements with its clients. In the context of reliable smart grid, the MNO having thousands of evolved NodeB (eNB) spread over all the country, has to play major role in the grid by acting as a prosumer able to sell electricity. In African Sub-Saharan countries however, the grid may be not reliable or even non existent, the MNO has no choice but to deploy a Virtual Power Plant (VPP) and rely partially or totally on it.

In this thesis, we study the interactions between the network operator and the grid either reliable or not in both developed and developing countries. We investigate both long term and short term optimal energy related management, with the aim of minimising the operator's Total Cost of Ownership (TCO) for energy per base station which is the sum of its Capital Expenditure (CAPEX) and Operational Expenditure (OPEX) while satisfying the growing needs of its user traffic in the cell.

The long term study enables us to make semestral based investment decisions for the battery and renewable energy sources dimensioning considering equipment performance degradation, predictions on users traffic growth and electricity market evolution over a long period of time counted in years.

In the case of being powered by a reliable smart grid, the short term policy helps the operator to set on a daily basis, an optimal battery management strategy by performing electricity arbitrage or trading that takes advantage of the electricity prices hourly fluctuations in order to minimize the MNO daily energy bill while respecting some rules on the usage of its equipments.

In the case of a non reliable or off-grid environment, the operator is powered by hybrid sources coupling storage, diesel generators, solar power and the grid if the latter is operational. Here, we define a fixed order of priority on the use of these sources that extends the battery lifetime and maintain its performance.

# Résumé

La demande en énergie dans les réseaux mobiles augmente en raison de l'émergence de nouvelles technologies et de nouveaux services aux exigences de plus en plus élevées. Dans ce contexte, l'opérateur de réseau mobile (ORM) doit fournir davantage de ressources entraînant ainsi des coûts énergétiques plus élevés. L'ORM n'a pas d'autre choix que de mettre en œuvre des stratégies d'économie d'énergie, notamment au niveau du réseau d'accès radio (RAN).

En parallèle, le réseau électrique devient plus intelligent, avec de nouvelles fonctionnalités pour équilibrer l'offre et la demande en faisant varier les prix de l'électricité, permettant ainsi à certains agrégateurs d'énergie de faire partie du processus d'approvisionnement et en signant des accords de réponse à la demande avec ses clients les plus importants. Dans le contexte d'un réseau électrique intelligent et fiable, l'ORM doit jouer un rôle majeur dans le réseau en agissant en tant que consommateur potentiel capable de vendre de l'électricité. Toutefois, dans les pays d'Afrique subsaharienne, le réseau électrique peut ne pas être fiable, voire même inexistant, l'ORM n'a d'autre choix que de déployer une centrale électrique virtuelle qui l'alimente partiellement ou totalement.

Dans cette thèse, nous étudions les interactions entre l'opérateur de réseau et le réseau électrique, qu'il soit fiable ou non, dans les pays développés comme dans les pays en cours de développement. Nous étudions la gestion optimale de l'énergie à long et à court termes, dans le but de minimiser le coût total de possession (TCO) en énergie de l'opérateur, qui correspond à la somme de ses dépenses d'investissement (CAPEX) et de ses dépenses opérationnelles (OPEX), en assurant la satisfaction des besoins croissants en trafic de ses utilisateurs.

L'étude à long terme nous permet de prendre des décisions d'investissement semestrielles pour le dimensionnement de la batterie et des sources énergies renouvelables, en tenant compte de la dégradation des performances des équipements, des prévisions de la croissance du trafic des utilisateurs et de l'évolution du marché de l'électricité sur une longue période de temps.

Dans le cas où il est alimenté par un réseau intelligent fiable, la politique à court terme aide l'opérateur à définir quotidiennement une stratégie de gestion optimale de la batterie assurant l'arbitrage et/ou le trading d'électricité afin de minimiser la facture énergétique journalière de l'ORM.

Dans le cas d'un réseau électrique non fiable ou complètement inexistant, l'opérateur est alimenté par des sources hybrides couplant stockage, générateurs diesel, énergie solaire et le réseau électrique si ce dernier est opérationnel. Ici, nous définissons un ordre de priorité pour l'utilisation de ces sources qui vise à étendre la durée de vie de la batterie et maintenir ses performances.

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# Abbreviations

3GPP: 3rd Generation Partnership Project  
AC: Alternative Current  
CAPEX: Capital Expenditure  
CMDP: Constrained Markov Decision Process  
DC: Direct Current  
DOD: Depth of Discharge  
DP: Dynamic Programming  
DR: Demand Response  
eNB: evolved NodeB  
EPEX: European Power Exchange  
FIFO: First In First Out  
GA: Genetic Algorithm  
KWH: KiloWatt Hour  
LFP: Lithium Fer Phosphate  
LP: Linear Programming  
LTE: Long Term Evolution  
MDP: Markov Decision Process  
MNO: Mobile Network Operator  
MWH: MegaWatt Hour  
OPEX: Operational Expenditure  
P2P: Peer-to-Peer  
PA: Power Amplifier  
PV: PhotoVoltaic  
QoS: Quality of Service.  
RAN: Radio Access Network  
RF: Radio Frequency  
SOC: State of Charge  
TCO: Total Cost of Ownership  
TRX: Transceiver  
VPP: Virtual Power Plant  
VRLA: Valve Regulated Lead acid

# Chapter 1

## Introduction

As global energy demand keeps increasing, the answer cannot be just to build new infrastructures and open up markets, the electricity grid needs to be optimized to meet the demands of sustainable development. The “smart grid” concept has been proposed as a solution to the problem of matching electricity supply and demand. Smart grids are expected to experience a tremendous growth in the upcoming years with the objective of progressively abandoning fossil and nuclear energy production in favour of distributed renewable energy production where consumers adapt their energy consumption to the state of the energy generation in the grid.

This evolution coincides with the definition of the fifth generation of mobile networks and the deployment of LTE-Advanced networks, calling for a native integration of these networks into the smart grid. These telecommunication networks should be constantly powered by the grid in order to ensure their operations and serve their user demands with no interruption. Their needs in term of energy are growing from one year to another driven by the volume of the wireless traffic in the cells.

This thesis explores the possible interactions between mobile network operators and smart grid operators and sets strategies that take advantage of the electricity grid fluctuations and the users traffic growth in both developed and developing countries characterised by reliable versus non reliable grids, respectively.

### 1.1 Motivation and context

The network operator has an infrastructure allowing it to satisfy its increasing users traffic demands [1]. This infrastructure (eNB’s, backhaul, etc) needs to be continuously powered to ensure its operation. The mobile applications at the users terminals need higher data rates and computational resources forcing the operators to increase their capacity and bandwidth which makes them consume more energy and so increases their electricity bill.

In developed countries, the grid is assumed to be totally reliable and the MNO can be constantly linked to the grid to ensure its operations without deploying its own power sources. The energy provider produces electricity to respond to its customers needs (houses, factories, etc) [2]. The

electricity prices change during the day hours depending on demand and supply. The operator cannot put its eNBs in standby or delay its traffic and so has no other choice but to pay the bill fixed by the energy provider even at high electricity price periods.

On the other hand, most of the operator's eNB sites are endowed with batteries used for backup in case of power failure in the grid [3]. However, these non expected events happen seldomly during the year. Even if these batteries are mandatory, they are typically used very few times before being removed when they reach the end of their lifetime. Our proposal is to use this battery to take advantage of the electricity prices fluctuations by performing electricity arbitrage and trading in order to minimize the network operator's energy expenditure [4].

In developing countries, the grid may be completely non-existent or not reliable suffering from multiple power failures during the day [5]. The MNO cannot trust completely the grid and should rely at least partially on its own sources in order to be powered. In this context, the operator may deploy both storage and energy production units in order to ensure its continuous operation [6]. The MNO should set an energy management strategy combining many power sources (battery, Photovoltaic (PV) plant, Diesel generator, wind turbine, grid if it is operating, etc) taking into account renewable power production distribution and grid availability in order to ensure its energy autonomy with the lowest costs.

In both scenarios, in order to set this layer of interaction with the grid, the MNO should invest in storage and energy production devices that have different usage constraints, lifetimes, efficiencies and capital expenditure (CAPEX). The choice of the right equipments characteristics should be decided in advance in order to minimize the Total Cost of Ownership (TCO) for energy and defined as the sum of the operational expenditure (OPEX) and capital expenditure (CAPEX). Equipment dimensioning should be done based on predictions on the long term of the traffic growth in the cells, the electricity market evolution and should also consider equipment long term degradation.

## 1.2 Interactions between the mobile network and the grid

In this thesis, we aim at modeling a layer of interactions between the mobile network operator and the grid in both developed and developing countries. This relationship should allow the MNO to take advantage of the opportunities given by the grid (pricing, Demand Response (DR), availability, etc) in order to minimize its energy expenditure.

The most direct relationship between these two players is that the mobile network entities (eNodeB, data centers, offices) are linked physically to the grid in order to get the needed power to ensure its operations.

We focus on the Radio Access Network (RAN). It is the entity that ensures the communication with the mobile users terminals. We assume that this entity should be constantly powered and cannot be turned off for long periods in order to to serve its users traffic demands.

### 1.2.1 In developed countries

In developed countries, world-wide research initiatives have just started to transform the old and unintelligent power grid into a new grid, called smart grid. As part of this transformation the underlying information and communication technology is expected to contribute significantly to improving the quality, reliability, security and efficiency of the power grid [7]. Smart grids has 4 principle functionalities [8] that are strongly dependent of each other as shown in fig. 1.1:

- Power generation: A variety of facilities generate electricity, including coal, natural gas, burning power plants, hydroelectric dams, nuclear power plants, wind turbines, and solar panels.
- Power transmission: to carry high-voltage electricity over long distances and connect electricity generators with electricity consumers.
- Power distribution: the system of wires that picks up where the transmission lines leave off starting from the transformers to the homes.
- Consumers load: It represents the demand in electricity. The grid should setup connections for reporting and management of these loads.

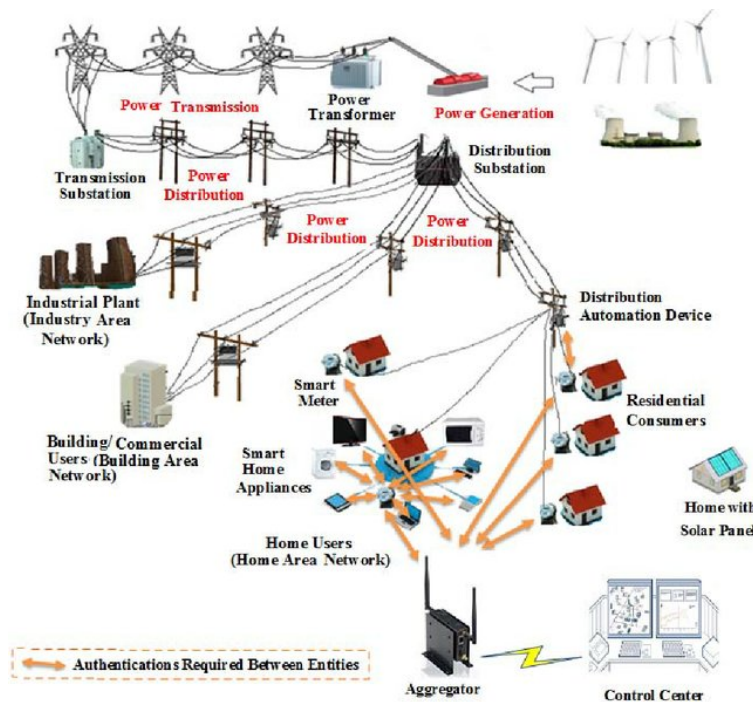


Figure 1.1: Smart grid architecture

The critical function of an electric power grid is to balance the supply and demand of electricity at any instance; either if demand exceeds supply, or supply exceeds demand, both these situations seriously threaten the stability of the grid, and therefore power generation must follow load accurately.

The smart Grid is a data communications network integrated with the electrical grid that collects and analyzes data captured in near-real-time about power transmission, distribution, and consumption [9]. Based on these data, the smart grid provides predictive information and recommendations to utilities, their suppliers and their customers on how to manage power best.

The smart grid network has more requirements to meet and new characteristics to attain. It has to manage systems, devices, applications, or components allowing them to exchange information in as secure manner in order to optimize the electricity operations and reduce energy wastes [10].

### **MNO acting as a simple consumer**

The grid offers electricity to all its consumers with a certain price. These prices change during the day hours, from one day to another, and over the years depending on the country policy for energy generation, the importance of renewable energy in the supply, the population dispersion over the territory, etc [11].

The MNO equipment run using the power delivered by the grid. We assume that the MNO cannot delay its traffic or turn off its base stations and so it has to pay the amounts consumed at the prices fixed by the energy provider in the grid.

The eNBs are currently endowed with backup batteries in order to prevent possible power failures that may occur in the grid [3]. In developed countries these events happen seldomly making the usage of these batteries very rare. The idea is to use these batteries more often as an alternative to the grid in the time periods when the electricity prices are high. We propose in this thesis, an hourly based strategy that alternates between the usage of the grid and the storage in order to minimize the electricity bill of the operator [12]. This technique is called electricity arbitrage [13]. It's only applicable when the electricity prices fluctuates: There is no financial gain to apply it in cases where the consumers sign a "flat prices" contract with the grid.

### **MNO acting as a prosumer**

Traditionally, power system participants have been strictly producers or consumers of electricity. Today, distributed renewable energy sources, storage, and demand response, allow the consumer to produce and to store energy. Thanks to the communication layer offered by the smart grid network, these new entities can take part in the electricity market and can help balance supply and demand in the grid. This new emerging entity is called the "prosumer" [14], an economically motivated entity that can:

1. Consume, produce, and store power
2. Operate or own a power grid, small or large, and hence transport electricity.
3. Optimize the economic decisions regarding its energy utilization.

Physically, the prosumer consists of a combination of components: energy sources, electricity loads, storage equipment and a small scale distribution network allowing it to sell electricity back to the grid or to some neighboring facilities [16]. In our model, we believe that the main function



of the MNO is to carry users data. Thus, we assume that the MNO can play the role of a prosumer only on a small scale.

In developed countries, the MNO may not have enough surface to deploy large arrays of PV panels close to its eNBs located in dense areas. Thus, we assume that the eNBs are only endowed with a storage battery without any production unit and so can sell only the energy stored in their battery back to the grid. To ease the model, we assume also that the conventional grid cannot decline the offers of the MNO. To do so, the MNO should be endowed with a DC/AC inverter [15] in order to be able to convert the DC power stored in the cells and inject the AC power on the transmission lines.

At high electricity peak hours when demand is very high, selling electricity stored in the battery can be very beneficial to the MNO [17]. In this context, the MNO promoted to the role of prosumer can be considered as an energy trader in the grid.

### **MNO part of demand response program**

Peak power usage during hot summer (or cold winter) days is one of the biggest concerns in electric power systems, and to meet the peak demand, high marginal costs are incurred to maintain stand-by power sources. However, in addition to the high investment and running cost, stand-by generators are mostly based on fossil fuel, and thus increase the carbon footprint. Hence, rather than increasing the physical power generation facilities, the grid can solicit demand response strategies where electricity customers can actively participate in balancing the supply and demand curves [18].

Demand response (DR) is a tariff or contract established to motivate changes in electric use by end-use customers in response to changes in the price of electricity over time, or to give incentive payments designed to induce lower electricity use at times of high market prices or when grid reliability is jeopardized.

Under demand response, end-use customers may voluntarily reduce their non critical application electric power consumption (water heater, thermostat, pool pump, etc) based on real-time pricing or incentive price signals.

With the usage of storage, the MNO can be part of this process by balancing its power consumption on the batteries when the grid requests it like residential consumers in [19].

There are several mechanisms to realize demand response:

- The simplest one is direct load control where the utility controls the customer's load based on advanced contracts [18]. We cannot apply this mechanism in our case: Communication is a very critical service and the MNO should maintain its total control on it. We assume that the MNO has always the possibility to decline grid requests when we do not have enough energy stored in the battery.
- Another mechanism of demand response is based on time-dependent prices where electricity price changes over time so that customers can adapt their usage to minimize their total electricity bill. This consists of performing electricity arbitrage in our case.

- Incentive based demand response provides more deterministic load reduction by exploiting bidding and bargaining processes, i.e., market-based mechanism; customers submit their bids (the amount of load reduction and desired incentive price), or alternatively, the utility offers an incentive price to encourage customers to commit their load reductions [20].

In our model, we assume that the MNO signs a yearly contract with the grid and gets a fixed reward thanks to it. The energy provider submits its requests (should not exceed a certain average value per year) and the MNO may accept or decline this request. If the offer is accepted, everything is perfect. If it is declined, the MNO should pay back a fixed penalty to the grid.

### 1.2.2 In developing countries

In developing countries, the electricity supply is managed in a traditional way. Some of the regions, especially in African Sub-Saharan countries, may be out of the electrical grid or even if they have one, the latter may suffer from multiple power failures during the day. These power failures are caused by the disequilibrium between supply and demand as these countries rely a lot on renewable energy especially solar power [5].

In this context, the MNO has no other choice but to act as a prosumer. It should invest in storage facilities and both fossil and renewable power equipment to generate enough energy to secure a continuous operation of its base stations towers [21]. In this case, the MNO can be in the position to sell own-generated renewable energy to the energy distributor.

In our case, we assume that the MNO will not sell electricity to other consumers and will generate power for its own usage. The objective is to dimension well its energy production and storage power ensuring continuous power supply with the lowest costs [22].

### 1.2.3 MNO needed infrastructure

To summarize, in developed countries we assume that the operator sites are endowed with batteries that can store energy from the grid and can be used to power the eNB operations. The MNO can also sell the exceeding electricity to the grid when it is allowed to by investing in a DC/AC inverter to do so. It may also be included in an incentive based demand response program for which it has the choice to stop consuming from the grid when the latter asks it to [4]. In this scenario, the battery allows the operator, using some knowledge of the upcoming electricity prices and subscribers traffic load to set an optimal energy storage strategy that can be coupled with some non-critical traffic scheduling policies that reduce the expenses of the MNO on energy on the short and long terms.

While in developing countries, the MNO is operating in environments in which the grid, if it exists may suffer from multiple anomalies. The operator has to be endowed with some energy production and storage units to ensure its continuous energy autonomy when power failures occur in the grid. We will study two principle cases: a case completely off-grid and a case in which the grid exists but is not reliable. In this scenario, the battery allows the operator to store excess renewable energy production to be used later and so reduce the costs of producing the needed energy using costly fuel generator.

## 1.3 Main objectives

Our main objective is to minimize the total cost of ownership (TCO) of the operator for energy on a long period of time counted in years. This is done by taking advantage of the relationship between the MNO and the grid in both developing and developed countries.

In developed countries where the grid is smart and reliable, this optimization is hierarchical.

- On a daily basis, we will minimize the MNO energy bill when performing electricity arbitrage and trading and being part of DR program. The MNO should respect the constraints of serving all the users traffic load and performing a preferential usage of the battery allowing it to carry also its functionality of backup.
- On a long period of time, on the order of 10 years, we will minimize the return on investment of the MNO for energy by deciding the type, size and long term cycling strategy of the battery on a semestral basis. This optimization is based on predictions of traffic growth and electricity prices evolution and takes into account the long term battery performance degradation.

In African Sub-Saharan countries where the grid may be totally nonexistent or suffering from multiple power failures putting into questions the continuous supply of the eNB components, the MNO should deploy its own storage and production units in order to prevent grid non availability. The optimization is only on the long term aims at ensuring the continuous power supply with the lowest possible TCO.

- On a daily basis, we will define a power source priority aggregating several facilities for powering the eNB that ensures its energy autonomy for the whole day while extending the battery lifetime.
- On a long period of time, on the order of 12 years for instance, we will minimize the return on investment of the MNO for energy equipment by finding a tradeoff between the sizes of storage and power production units on a semestral basis. This optimal equipment dimensioning plan is based on predictions of traffic growth, grid reliability evolution and takes into account the long term battery performance degradation.

## 1.4 Thesis Organization

In this thesis, we propose a new way to dimension energy storage and production units at the eNB level allowing it take advantage of the fluctuations of the grid in both developed and developing countries to minimize its long term expenditure on energy. The structure of the remainder this thesis is organized as follows:

In **Chapter 2**, we recall basic notions on the power consumption model at the base stations and we give the characteristics of the battery used in this study. Then, we present the mathematical tools that helped us model the optimization problems and the algorithms used for solving them. In particular, the policy iteration and primal dual optimization algorithms will be used in order to solve the short term optimization problems and the linear programming solution will be devised in order to achieve the optimal MNO investment strategy on the long term.

**Chapter 3** presents the formulation of the short term problem for minimizing the MNO daily energy bill. In this chapter, we study 3 different problems: First, we treat the problem of an MNO that may act as a simple consumer or as a prosumer in the grid performing electricity arbitrage and trading while respecting a preferential usage of its battery. Section 2 treats the case when the MNO is a part of an incentive based demand response and we show how to devise the optimal battery management strategy that allows it to take advantage of this program. In section 3, we add a layer of complexity to the energy management strategy by assuming that the MNO acts as a simple consumer in the grid and is able to save more money by delaying some of the non-critical traffic for some hours under some delay constraints. Finally, we recall the main achievements of our policies and we establish the link between them and the long term optimization problem.

In **Chapter 4**, we formulate and solve the long term problem aiming at minimizing the MNO TCO for energy by deciding the dimensions and the long term usage of the equipment. This chapter is composed of 2 main sections: The first one studies the case of an MNO powered by a reliable smart grid in European countries. The objective is to optimally decide the size, type and long term cycling of the battery and whether it is interesting to act as a prosumer injecting electricity back in the grid. This work is based on the short term optimization in the previous chapter. In the second section, we aim to define an optimal trade-off between the sizes of the battery and PV panels that minimizes the return on investment ensuring the continuous operation of the base stations located in environments where the grid may suffer from multiple power failures. Finally, section 3 recalls the achievements obtained from these 2 use cases and discusses the feasibility of our dimensioning methods in real use cases.

Finally, **Chapter 5** presents the conclusion and the perspectives.

## 1.5 Publications

Published:

- [1] W. Labidi, T. Chahed, S.E. Elayoubi, "*Optimal battery management strategies in mobile networks powered by a smart grid*", IEEE Transactions on Green Communications and Networking, 2018.
- [2] W. Labidi, T. Chahed, S.E. Elayoubi, "*Optimal battery management strategies in mobile networks powered by a smart grid*", IEEE International conference on Communications (ICC), pp. 1-6, 2017.
- [3] W. Labidi, T. Chahed, S.E. Elayoubi, "*Battery Management for Demand-Response in Mobile Networks Powered by a Smart Grid*", IEEE International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC), 2018.
- [4] U. Hashmi, W. Labidi, A.Busic, S.E. Elayoubi, T. Chahed, "*long term Revenue Estimation for Battery Performing Arbitrage and Ancillary Services*", IEEE International Conference on Communications, Control, and Computing Technologies for Smart Grids (SmartGridComm), 2018.

To be submitted:

- [1] W. Labidi, T. Chahed, S.E. Elayoubi, "*Energy total cost of ownership minimization for mobile networks powered by a smart grid*", 2019.
- [2] W. Labidi, T. Chahed, S.E. Elayoubi, "*Optimal battery management, including its aging effect, for smart grid operated mobile network*", 2019.
- [3] W. Labidi, T. Chahed, S.E. Elayoubi, "*Optimal dimensioning of energy storage and production for a mobile network in unreliable grid regions*", 2019.
- [4] W. Labidi, T. Chahed, S.E. Elayoubi, "*Optimal joint battery management and traffic scheduling in a mobile network powered by a smart-grid*", 2019.

# Chapter 2

## Preliminaries

In this chapter, we present the characteristics of the batteries deployed at the eNB level, the model of consumption of the latter and the mathematical tools for optimization used to achieve the objectives of this work.

### 2.1 Technical aspects

#### 2.1.1 Energy consumption at the eNB level

The base station, named evolved NodeB (eNB) in 4G 3GPP specifications, is the key element in the radio access network. It connects via wireless waves the users terminals to the MNO backhaul network composed of the servers where the computational resources and the services are physically located.

The eNB consumes a fixed part of energy due to some traffic independent features and a variable part which is traffic dependent [23]. Multiple wireless access technologies can be co-located at the eNB level. Even with the emergence of 5G networks, all the other technologies should be maintained: 2G to carry voice, 3G and 4G to carry data for users with non eligible mobile terminals or who do not meet the 5G QoS requirements in the macro cell.

A macro base station consists of multiple transceivers (TRXs), each one of them serving one transmit antenna element. The number of TRXs is the product of the number of antennas per sector and the number of sectors which is for instance 3 in order to cover all the area with 120° antenna coverage angle.

A TRX comprises a power amplifier (PA), a radio frequency (RF) small-signal TRX module, a baseband engine including a receiver (Uplink) and transmitter (Downlink) sections. These elements power consumptions are correlated with the traffic generated in the cell. The traffic independent power consumption is due to the DC-DC power supply, an active cooling system and an AC-DC unit (main supply) used for connection to the electrical power grid [24]. From [23], we can establish the following macro-BS energy consumption  $E_{cons}$ :

$$E_{cons} = n_{tx} \cdot T_c \cdot (P_0 + \Delta_p \cdot P_{out} \cdot U) \quad (2.1)$$

where:

- $n_{TX}$  is the number of transceivers in the eNB.
- $T_c$  is the number of co-located technologies at the eNB.
- $P_0$  is the power consumed for traffic independent features.
- $\Delta_p$  is the slope of load dependent power consumption. It is the conversion rate between the irradiated power and the consumed power due mainly to the amplification gain.
- $P_{out}$  is the irradiated power by the eNB's antennas.
- $U$  is the users traffic load in the cell.

### 2.1.2 Batteries characteristics

A battery is a device that produces electrons through electro-chemical reactions, and contains positive (+) and negative (-) terminals. It consists of one or more cells, which transform stored chemical energy into electrical energy in order to power a facility. When an external load connects to a battery, electrons cross from the negative to the positive terminal, creating an electrical current [25].

Batteries are widely used in the telecommunication field: They are one of the most important elements in users terminals and the unique technology available to support the subscribers mobility. They are also used at the eNB sites: In developed countries, they present a backup solution to overcome possible power failures in the grid. In developing countries, where the grid is not reliable, they are more solicited as they ensure the storage of renewable solar power and the backup function for more frequent and longer periods of power failures in the grid.

Batteries convert electrical energy into chemical energy while charging and chemical energy into electrical energy while discharging. These conversions are not completely efficient, incurring charging and discharging losses in short time frames. On a longer time horizon, batteries degrade because of time and operational cycles, providing us with distinct calendar and cycle lives that depends on the battery type and usage. A typical battery is described by the following metrics [26]:

- Capacity or Nominal Capacity: The coulometric capacity, the total Amp-hours available when the battery is discharged at a certain discharge current (specified as a C-rate) from 100 percent state-of-charge to the cut-off voltage (The minimum allowable voltage. It is this voltage that generally defines the “empty” state of the battery). Capacity is calculated by multiplying the discharge current (in Amps) by the discharge time (in hours) and decreases with increasing C-rate. In this thesis, we will call it also the battery size.
- State of Charge (SOC): An expression of the present battery capacity as a percentage of maximum capacity. SOC is generally calculated using current integration to determine the change in battery capacity over time.

- Depth of Discharge (DOD): The percentage of battery capacity that has been discharged expressed as a percentage of maximum capacity. A discharge to at least 80 % DOD is referred to as deep discharge. A fully charged battery has a SOC equal to 100% which 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%.
- Discharging and charging rates: They are often normalized to the battery capacity. The discharging rate is a measure of the rate at which a battery is discharged relative to its maximum capacity. A 1C rate means that the discharge current will discharge the entire battery in 1 hour. For a battery with a capacity of 100 Amp-hrs, this is equal to a discharge current of 100 Amps. A 5C rate for this battery would be 500 Amps, and a C/2 rate would be 50 Amps. Similarly, the charging rate describes the rate of which the battery is charged relative to its capacity.
- Calendar aging: The battery calendar life is the elapsed time before a battery becomes unusable whether it is in active use or inactive. There are two key factors influencing calendar life: temperature and time. Thus, in order to operate the battery in a safe operating area even with high temperature, high charge/discharge currents should be avoided.
- Cycle aging: Battery cycle life is defined as the number of completed charge-discharge cycles a battery can perform before its nominal capacity falls below 80 % of its initial rated capacity. Key factors affecting cycle life are the number of completed charge-discharge cycles and DOD performed at each cycle. In order to extend the battery cycle life, we will show later the ideal operating range of SOC that is recommended.

In addition to capacity degradation, the battery witnesses energy losses during its operations due to heating. These losses increase with time due to the battery cycle and calendar aging.

- Charging energy efficiency: It is the ratio between the energy stored in the battery and the energy delivered from the source: the grid or PV solar panels in our case.
- Discharging energy efficiency: It is the ratio between the energy delivered for the facility to be powered (eNB components) and the energy discharged from the battery.

We consider in this study three types of batteries:

- Lithium iron phosphate battery (LFP): It is an Ion-Lithium battery that uses  $\text{LiFePO}_4$  as a cathode material, and a graphitic carbon electrode with a metallic current collector grid as the anode. It has a longer cycle life compared to other ion-Lithium batteries and can present a very stable discharge voltage until it is discharged. It experiences a slower rate of capacity loss over time and has better thermal and chemical stability, which improves battery safety. The only drawbacks are its higher costs and the fact that they are not fitted to high temperature environments [27]. Thus, we consider them only in the case of developed countries when the MNO is powered by a reliable smart grid.



- Lead acid battery: Is the oldest type of rechargeable battery. Large-format lead–acid designs are widely used for storage in backup power supplies in cell phone towers. Compared to ion-Lithium batteries, these batteries have lower charge and discharge rates. On the long term, the capacity degradation rate is higher than LFP batteries and so the cycle life. Lead acid presents a risk of explosion and also have a very bad environmental impact. They have the advantage of being easily recyclable (99% of the batteries are recycled in the US) and can operate in very high temperature environment. Despite their lower performances, we study the potential of these batteries in sites linked to smart grid networks as they have lower CAPEX [28].
- Valve regulated Lead acid (VRLA) battery: called also gel cell. VRLA cells consist of two plates of lead, which serve as electrodes, suspended in an electrolyte consisting of diluted sulfuric acid. The battery can be mounted in any position, since the valves only operate on over-pressure faults. VRLA batteries do not require constant maintenance except cleaning and testing. Compared to conventional Lead acid batteries, they have shorter recharge time and are more environmental friendly but can be very sensitive to overcharging and have shorter cycle life [29]. They are fitted for off grid scenarios as they do not require constant maintenance. So, we will study their potential gain in the African Sub-Saharan scenario.

For all of these batteries, with respect to the scenario studied (in the context of non reliable grid or a smart grid), we will derive on the short term a battery management strategy that minimizes the daily energy expenditure under a preferential usage of the battery. This usage shall extend the battery lifetime and maintains a good energy efficiency during charge and discharge processes. To do so, we set limitations on the charge/discharge rates and the battery SOC. These limitations are based on results obtained by our partners in Soogreen Celtic-plus project based on tests done on field [30]. The authors in [31] confirms also these experimental results.

- For classic Lead-acid battery, we assume that the battery SOC should remain between 50% and 100% of the battery capacity. The operator cannot discharge or charge by more than 50% of the battery capacity during 1 hour. The charge and discharge efficiencies are equal to 86% when the battery is new and deteriorats with use to reach 80% at the end of the battery lifetime. This degradation is linear relative to the number of performed cycles [31].
- For Lithium battery, we assume that the battery SOC has to be maintained between 20% and 90% of the battery capacity. The operator cannot discharge or charge by more than 70% of the battery capacity during 1 hour. We can assume that the charge and discharge efficiencies are equal to 96% when a new battery is deployed and 92% at the end of its lifetime. The degradation is also assumed to be linear relative to the number of cycles performed [31].
- For VRLA battery, we assume that the SOC should be maintained between 50% and 90%. The operator cannot discharge or charge by more than 40% of the battery capacity during 1 hour. We assume that the charge and discharge efficiencies are equal to 85% when a new battery is deployed and 70% at the end of its lifetime. The degradation is also assumed to be linear relative to the number of performed cycles [31].

We summarize in the table below the long term characteristics of the batteries to be studied:

	Lead-acid	Lithium	VRLA
cycle life $L_{cy}$	1800 (50 % DOD)	3060 (70 % DOD)	1440 (40 % DOD)
calendar life $L_{cl}$	6 years	8 years	4 years
Price $P_b$	160 €/KWh	350 €/KWh	150 €/KWh
Operation environment	smart grid	smart grid	non reliable grid

Table 2.1: Batteries long term characteristics

## 2.2 Mathematical tools

### 2.2.1 Markov Chain

When we study a system that can change over time, we need a way to keep track of these changes. A Markov chain is a particular model for tracking systems that change according to given probabilities. A Markov chain may allow us to predict future events, but the predictions become less useful for events farther into the future.

This process has the property that the probability of moving from some state  $s_t$  to another state  $s_{t+1}$  is independent of the states visited prior to  $s_t$ . Formally we define this as  $P(X_{t+1} = s_{t+1} | X_t = s_t, X_{t-1} = s_{t-1}, \dots, X_1 = s_1, X_0 = s_0) = P(X_{t+1} = s_{t+1} | X_t = s_t)$  and we say that a process which has this property is Markovian.

A state is any particular situation that could be taken by the system. The term Markov chain refers to any system with a certain number of states and probabilities that the system moves from any state to another. If a Markov chain consists of  $k$  states, the transition matrix is the  $k$  by  $k$  matrix (a table of numbers) whose entries record the probability of moving from one state to another [32].

Let  $p_{ss'}^n$  denote the probability of moving from  $s$  to  $s'$  in  $n$  time-steps. Whenever  $p_{ss'}^n > 0$  for some number of time steps  $n > 0$  we say that  $s'$  is accessible from  $s$ , and if two states are accessible to each other they are said to communicate. If all states communicate the chain is said to be irreducible. The regular properties of probabilities imply that  $p_{ss'} \geq 0$ ,  $\sum_{s'=0}^{\infty} p_{ss'} = 1$ . In other terms, there is no absorbing state in the chain.

A state in a Markov chain is said to be periodic if the system can return to some state  $s$ , while starting in  $s$ , only under some multiple  $d(s)$  of steps, where  $d$  is a positive integer satisfying  $d > 1$ . If instead  $d = 1$  we say that the state is aperiodic. States that are both aperiodic and recurrent are said to be ergodic [33]. This propriety has an implication in finding an optimal solution for the Markov Decision Process (MDP) presented next.

### 2.2.2 Markov Decision Process (MDP)

A Markov decision process (MDP) is a discrete time stochastic control process. It provides a mathematical framework for modeling decision making in situations where outcomes are partly

random and partly under the control of a decision maker [34].

Assume that we have an ordinary Markov chain, at each time-step  $t$  we introduce a set of actions to be taken at each state. Thus, instead of having a process that transitions by itself, we now have a decision-making agent moving through the process. For each state  $s_t$ , we have a finite set of feasible actions  $a_i \in \Omega(s_t)$ . We call each pair  $(a_1, s_t), (a_2, s_t), \dots, (a_n, s_t)$ , a state-action pair.

After an action has been taken by the agent, the system moves to a new state according to some probability distribution  $P_{ij}^a$  dependent on the action taken and some randomness, for which the Markovian property holds:

$$P_{ij}^a = P(s_{t+1} = j | s_t = i, a_t = a, \dots, s_0 = i_0, a_{t_0} = a_0) = P(s_{t+1} = j | s_t = i, a_t = a) \quad (2.2)$$

Furthermore, the agent is rewarded with some bounded value  $r_{ss'}^a$  for entering state  $s'$  from  $s$  under action  $a$ . We call a process having these properties a Markov decision process [35].

The rewards are setup so as to make the agent solve a given problem. In our case, we want the system to take an action at each state for a finite time horizon. Each subset of actions through the states from starting state to the terminal state forms a policy denoted by  $\mu$ . The problem for the agent comes down to finding a path in a randomized environment that maximizes the rewards received while following this policy. If some policy is better or equally good than all the other feasible policies achieving a given objective, we say that it is an optimal policy, and denoted by  $\mu^*$ .

Under the conditions that the Markov chain is irreducible and that the Markov chain is not periodic, we can be sure that the MDP can be solved using dynamic or linear programming algorithms [36]. These methods will devise the optimal policy  $\mu^*$  that can be deterministic or randomized and solves the optimization problem on a predefined finite time scale.

We will formulate all our optimization problems as MDP having the following four components:

- State space  $s\mathcal{S}$ : It describes the states  $s_t$  that the system can reach at time slot  $t$ . This space can be finite or infinite but has to be well defined and countable.
- Action space  $a\mathcal{A}$ : It describes the actions  $a_t$  that the decision maker (agent) can perform at time slot  $t$  when the system reaches the state  $s_t$ .
- Transitions probabilities  $p_t(s_{t+1}|s_t, a_t)$ : They refer to the probability of reaching state  $s_{t+1}$  at time slot  $t + 1$  knowing that the system was in state  $s_t$  at time slot  $t$  and performed a known action  $a_t$ . The state transitions follow the Markov property.
- Reward  $r_t(s_t, a_t)$ : Is the immediate outcome that the system gets after performing action  $a_t$  at state  $s_t$  in time slot  $t$ .

Our MDP runs on finite time scale, indexed with time-step  $t \in [0, 1, \dots, N - 1]$ . The optimal policy can be expressed as a vector  $\bar{\mu}^*$  of subjective functions that defines at each time step and each state a unique action to be executed:  $\bar{\mu}^* = (\mu_0, \mu_1, \dots, \mu_{N-1})$  [37].

$\bar{\mu}^*$  has to achieve an objective averaged on a finite time horizon on all reward functions to verifies the following relationship:

$$\bar{\mu}^* = \underset{\bar{\mu}}{\operatorname{argmin}} E^{\bar{\mu}} \left( \sum_{t=0}^{N-1} r_t(s_t, a_t) \right) \quad (2.3)$$

We see in the following two subsections how this can be done using dynamic and linear programming techniques. For the solutions to be tractable, we need perfect knowledge of the transition probabilities and the immediate reward.

### 2.2.3 Dynamic programming for short term optimization

The dynamic programming technique uses stochastic optimization algorithms to restrict the search for the optimal policy that solves the MDP. The aim is to compute a policy which describes how to act optimally in the face of uncertainty. It consists in breaking a complex problem into sequential sub-problems, solve them individually and combine their solutions to achieve the global one [37]. In each stage, dynamic programming makes decisions based on all the decisions made in the previous stages, and may reconsider the previous stage's algorithmic path to the solution.

The dynamic programming algorithm can be applied on the ergodic and non periodic MDP to achieve a deterministic, offline policy, denoted by  $\bar{\mu}$ , which, at each time slot  $t$  and each state  $s$  defines an unique action  $a$  to perform among all possible actions  $\Omega_t(s)$  in that state. This policy is performed at the beginning of each time slot on a whole finite horizon optimization period.

$\bar{\mu}$  denotes a mapping between the state and action spaces and can be expressed as:

$$\bar{\mu} = (\mu_0, \mu_1, \dots, \mu_{N-1}) \quad \text{with} : \mu_t : \mathcal{S} \rightarrow \mathcal{A} \quad \text{as} \quad a = \mu_t(s).$$

The goal of this algorithm is to find for an ergodic and aperiodic finite horizon Markov chain an optimal, offline and deterministic policy denoted by  $\bar{\mu}^*$  which solves the following average cost problem:

$$\bar{\mu}^* = \underset{\mu}{\operatorname{argmin}} \frac{1}{N} \sum_{t=0}^{N-1} r_t(s_t, \mu_t(s_t)) \quad (2.4)$$

The optimization is based on solving iteratively Bellman optimality equations which compute the optimal path to follow for any initial state distribution at  $h = 0$ . This method is known as the backward induction-algorithm [38].

The objective is to find at each step  $t \in [0, \dots, N - 1]$  the optimal value function  $V^{(t)}(s)$  that defines the optimal cost to go from any state  $s \in \mathcal{S}$  [39].

$$V^{(t)}(s) = \min_{\bar{\mu}} E^{\bar{\mu}} \left( \frac{1}{N - k} \sum_{k=t}^{N-1} r_k(s, \mu_k(s)) \right) \quad (2.5)$$

For  $s_0$  denoting the initial state at  $t = 0$ ,  $J^* = V^{(0)}(s_0)$  is the optimal cost to go from the initial state over  $N$  steps of the finite horizon Markov chain.  $J^*$  could be found by applying backward

recursion assuming that  $V^{(N)}(s) = r_N(s)$ , where  $r_N$  is the end cost that we have at step  $N$ . In the algorithm, we took it null for all the states.

Now we apply policy iteration technique [40]. The optimal policy  $\bar{\mu}^*$  is obtained by computing, through backward recursion, the following two relationships:

- Policy improvement equation: It consists at finding at each slot  $t$  and for each state  $s \in \mathcal{S}$  the optimal action  $a$  to perform which minimizes the cost to go for the remaining  $N - k$  transitions:

$$\mu_t(s) = \operatorname{argmin}_{a \in \Omega_t(s)} \left[ r_t(s, a) + \sum_{s' \in \mathcal{S}} p(s'/s, a) \cdot V^{(t+1)}(s') \right] \quad (2.6)$$

- Policy evaluation equation: It consists at evaluating the cost to go at each state  $s \in \mathcal{S}$  from step  $t$  to  $N$  after choosing the policy  $\mu_t$  to perform:

$$V^{(t)}(s) = r_t(s, \mu_t(s)) + \sum_{s' \in \mathcal{S}} \mathcal{P}(s'/s, \mu_t(s)) \cdot V^{(t+1)}(s') \quad (2.7)$$

The obtained optimal policy  $\bar{\mu}^* = (\mu_0, \mu_1, \dots, \mu_{N-1})$  is deterministic as at each state  $s$  there is only one unique action  $a$  to be executed. It minimizes  $V^{(0)}(s_0)$  regardless of the choice of the initial state  $s_0$  [41].

## 2.2.4 Linear Programming for long term optimization

The MDP optimization can be easily converted to a constrained linear programming problem that can be solved by a classical linear optimization tool. We can use for this, the function 'linprog' in MATLAB for instance.

The linear programming algorithm aims at finding a randomized policy that solves the average cost problem corresponding to the MDP. In fact, the average cost problem could be converted to a linear expression for which we have to find the occupation measures of all the state action couples  $(s, a)$  at each time step  $t \in [0, \dots, N - 1]$  [42].

The occupation measure of a couple  $(s, a)$  defines the amount of time that the system will be in state  $s$  and execute action  $a$  during a process [43]. As we are in a finite horizon case, the duration of the process is  $N$  time steps. If we restrict the calculation in a certain time step  $t$ , the occupation measure will refer in this case to the probability that the system will visit state  $s$  and execute action  $a$  during time slot  $t$ .

Having an initial distribution  $\alpha$  at time slot  $t = 0$ , we have to find, at each step  $t \in [0, \dots, N - 1]$ , the occupation measures  $\beta$  of all the states and actions that minimize the objective function. The solution given by linear programming is optimal.

The Linear optimization can be expressed as follow:

$$\min_{\beta} \frac{1}{N} \sum_{t=0}^{N-1} \sum_{(s,a)} \beta_t(s, a) \cdot R_t(s, a) \quad (2.8)$$

s.t.

$$\forall t \in [0, \dots, N-1] \quad \sum_{(s,a)} \beta_t(s,a) = 1 \quad (2.9)$$

$$\forall s' \in \mathcal{S} \quad \sum_{a'} \beta_{t+1}(s',a') = p_t(s'/s,a) \beta_t(s,a) \quad (2.10)$$

$$\forall t \in [0, \dots, N-1] \quad \beta_t(s,a) = 0 \quad \text{if } a \notin \Omega_s^t \quad (2.11)$$

$$\forall s \in \mathcal{S} \quad \sum_a \beta_0(s,a) = \alpha(s) \quad (2.12)$$

- Equation (2.8) is the objective function averaged on the whole optimization period  $N$ .
- Equation (2.9) is a basic condition which ensures the fact that the sum of all the occupation measures at each semester  $t$  is equal to 1.
- Equation (2.10) is a constraint that sets a relationship between the occupation measures and the transition probabilities of the Markov chain.
- Equation (2.11) defines the actions that cannot be done at each state  $s$  at each time slot.
- Equation (2.12) ensures that the initial state distribution  $\alpha$  is respected by the optimal solution during semester 0.

Having at each time step  $t \in [0, \dots, N-1]$  the optimal occupation measures  $\beta_t(s,a)$ , we can devise a randomized optimal policy  $\bar{\mu}^*$ . It gives  $\forall t \in [0, \dots, N-1]$  and  $\forall s \in \mathcal{S}$ , the probability  $\rho_s^t(a)$  of doing an action  $a$  when the system reaches state  $s$  at time slot  $t$  [43]. This probability can be expressed as follows:

$$\rho_s^t(a) = \frac{\beta_t(s,a)}{\sum_a \beta_t(s,a)} \quad (2.13)$$

### 2.2.5 Constrained MDP and primal dual optimization

In many situations in optimizing dynamic systems, a single utility for the optimizer might not suffice to describe the real objectives involved in the sequential decision making. A natural approach for handling such cases is to perform one optimization of one objective while respecting constraints on the other ones.

A Constrained Markov Decision Process (CMDP) can be seen as a classic non constrained MDP having a reward function composed of the objective function and the different constraint functions that the agent should find the right tradeoff between them. In the case of constrained MDPs, one can devise directly a so called primal dual DP based algorithm by using a Lagrangian approach, and then apply some minmax theorem. Indeed, the Lagrangian approach allows us to transform a constrained control problem into an equivalent minmax non-constrained control problem [37]. If a saddle point property is shown to hold, then the problem is transformed into a maxmin problem, which can be solved using DP. It requires the convexity of the average cost reward toward the policy [43].

The primal dual optimization problem aims to find for an ergodic finite horizon Markov chain an optimal deterministic policy  $\bar{\mu}^*$  which solves the constrained average cost problem [44]:

$$\min_{\bar{\mu}} E^{\bar{\mu}} \left( \sum_{t=0}^{N-1} r_t(s_t, a_t) \right) \quad (2.14)$$

$$s.t \quad E^{\bar{\mu}} \left( \sum_{t=0}^{N-1} C_t(s_t, a_t) \right) \leq \bar{C} \quad (2.15)$$

Its objective is to minimize the objective function in Eqn. (2.14) while the average constraint in Eqn. (2.15) should remain under a predefined threshold  $\bar{C}$ .

The CMDP has the same state and action spaces and the same transition probabilities as the non constrained one. The only difference between them is the fact that we adopt for the CMPD a new instantaneous reward function that relates the objective in Eqn. (2.14) to the average constraint in Eqn. (2.15) using the Lagrange multiplier denoted by  $\lambda$ . The Lagrange multiplier sets the weight of the constraint to the objective function. The new instantaneous reward can be expressed as follows:

$$L_t(s_t, a_t, \lambda) = r_t(s_t, a_t) + \lambda \cdot (C_t(s_t, a_t) - \bar{Q}) \quad (2.16)$$

where:

- $r_t(s_t, a_t)$  is the instantaneous reward of the objective function.
- $C_t(s_t, a_t)$  is the cost describing the variable considered as the constraint.
- $\bar{Q}$  is the threshold to respect.

Let  $\bar{L}$  denote the average Lagrange function:

$$\bar{L}(\bar{\mu}, \lambda) = E^{\bar{\mu}} \left( \sum_{t=0}^{N-1} L_t(s_t, \mu_t(s_t), \lambda) \right) \quad (2.17)$$

Using the Lagrange formulation, the constrained problem is converted to an unconstrained one. The devised optimal policy minimizes the objective function while respecting the imposed constraint. As the problem is convex, optimality is reached when the average constraint is equal to the threshold [43].

The optimal policy  $\bar{\mu}^*$  is obtained by applying dynamic programming algorithm for the optimal Lagrange multiplier denoted by  $\lambda^*$  and achieves the following relationship:

$$\bar{\mu}^* = \operatorname{argmin}_{\bar{\mu} \in \Omega} \bar{L}(\bar{\mu}, \lambda^*) = \operatorname{argmin}_{\bar{\mu} \in \Omega} E^{\bar{\mu}} \left( \sum_{t=0}^{N-1} L_t(s_t, \mu_t(s_t), \lambda^*) \right) \quad (2.18)$$

If the average reward to optimize is convex relative to the policy and concave relative to the Lagrange multiplier, the optimal couple  $(\lambda^*, \bar{\mu}^*)$  is a saddle point for the Lagrange function. The

following saddle point condition holds [37]:

$$L(\bar{\mu}^*, \lambda) \leq L(\bar{\mu}^*, \lambda^*) \leq L(\bar{\mu}, \lambda^*) \quad (2.19)$$

To solve the problem, a primal dual optimization [44] based on two hierarchical relations is computed:

- The primal optimization: it consists at finding the optimal Lagrange multiplier  $\lambda^*$ . It is obtained using gradient descent iterations.
- The dual optimization: it consists at finding the optimal policy for any particular Lagrange multiplier  $\lambda$ . It's is based on a classic dynamic programming optimization.

This primal dual optimization aims at finding:

$$(\lambda^*, \bar{\mu}^*) = \underset{\lambda > 0}{\operatorname{argmax}} \underset{\bar{\mu}}{\operatorname{argmin}} \bar{L}(\bar{\mu}, \lambda) \quad (2.20)$$

For a known  $\lambda$ , the **dual optimization** is handled by solving iteratively dynamic programming equations. It uses the policy iteration technique presented in subsection 2.2.3 for any particular Lagrange multiplier  $\lambda$ .

The policy improvement and policy evaluation equations are now written as follow:

- Policy improvement equation:

$$\mu_k^\lambda(s) = \underset{a \in \Omega_k(s)}{\operatorname{argmin}} \left[ L_k(s, a, \lambda) + \sum_{s' \in \mathcal{S}} p_k(s'/s, a) \cdot V_\lambda^{(k+1)}(s') \right] \quad (2.21)$$

- Policy evaluation equation:

$$V_\lambda^{(k)}(s) = L_k(s, \mu_k^\lambda(s), \lambda) + \sum_{s' \in \mathcal{S}} p_k(s'/s, \mu_k^\lambda(s)) \cdot V_\lambda^{(k+1)}(s') \quad (2.22)$$

The optimal policy for a given Lagrange multiplier  $\lambda$  is denoted by  $\bar{\mu}_\lambda^* = (\mu_0^\lambda, \dots, \mu_{N-1}^\lambda)$  and minimizes  $V_\lambda^{(0)}(s_0)$  regardless of the choice of the initial state  $s_0$ .

The **primal optimization** is computed using the gradient descent iterations after applying the optimal policy  $\bar{\mu}_\lambda^*$  for a given Lagrange multiplier  $\lambda$ .

Knowing the initial distribution of the system states  $\beta_0^\lambda$  at time slot  $k = 0$ , we can find the occupation measures of all the states in the system for each time slot  $k \in [1, \dots, N]$  [43]. The occupation measure  $\beta_k^\lambda(s)$  is the probability that the system will be in a given state  $s$  in a time slot  $t$ . The occupation measures are calculated iteratively using the following relation:

$$\beta_{k+1}^\lambda(s') = \sum_{s \in (\mathcal{S})} p_t(s'/s, \mu_k^\lambda(s)) \cdot \beta_k^\lambda(s) \quad (2.23)$$



Then, based on the occupation measures, we devise respectively the objective function average cost and the constraint average cost using the following two relationships:

$$\bar{R}^\lambda = \frac{1}{N} \cdot \sum_{k=0}^N \sum_{s \in \mathcal{S}} \beta_k^\lambda(s) \cdot r_k(s, \mu_k^\lambda(s)) \quad (2.24)$$

$$\bar{C}^\lambda = \frac{1}{N} \cdot \sum_{k=0}^N \sum_{s \in \mathcal{S}} \beta_k^\lambda(s) \cdot C_k(s, \mu_k^\lambda(s)) \quad (2.25)$$

The Lagrange multiplier is approximated by comparing the average constraint function  $\bar{C}_\lambda$  to the imposed threshold  $\bar{C}$  using gradient descent iterations until convergence is reached:  $\lambda_{m+1} = \lambda_m = \lambda^*$

$$\lambda_{m+1} = \lambda_m + \Phi(m) \cdot (\bar{C}_{\lambda_m} - \bar{C}) \quad (2.26)$$

with  $\Phi$  is a small iteration step  $\Phi > 0$ .

## Chapter 3

# Optimal battery management strategy on the short term

In this chapter, we consider the interactions between the MNO and the smart grid. Our main objective is to minimize the daily energy expenditure of the operator (OPEX). The operator should take advantage of the electricity prices fluctuations, the users traffic load distribution and the incentive based demand response program by setting an optimal battery management strategy allowing it to perform electricity arbitrage/trading in the grid [45].

The MNO has to decide whether it is beneficial for it to be powered by the grid which is assumed in this case to be completely reliable and whether it should rely on its battery and if so the amounts of energy charged/discharged to/from it. This policy should take into account some restriction on the battery usage in order to maintain its performance and extend its lifetime.

This daily battery management strategy will be devised for all the roles that the MNO could play in the smart grid: a simple electricity consumer, an electricity prosumer able to sell energy back to the grid and when it is a part of an incentive based demand response program with the energy provider.

We will also add a layer of complexity in which the MNO can delay some non-critical traffic such as software updating and peer-to-peer (P2P) communications, to be treated in the hours when the electricity is cheaper. In this case, the MNO should define a joint battery management and traffic scheduling strategies that aim at minimizing the MNO daily electricity bill while respecting an average traffic queuing delay constraint.

These problems will be formulated as MDP and CMDP and will be solved using dynamic programming techniques: policy iteration for instance. The MNO needs a day ahead knowledge of the distribution of the electricity prices and the user traffic in order to be able to devise the optimal policy. These policies are deterministic as they define a unique action to perform in each state that may be visited by the system at each decision time which in our case set to be one hour.

This time step makes the prediction of the traffic and electricity price easier for the operator. Based on heuristic data, the MNO can predict the day-ahead average traffic in the cell on an hourly basis [46]. For the electricity prices, with the emergence of new players in the market, some entities

called stockholders manage the power exchange between countries and between intervenients within the same country [47]. These markets are organized by an auction process, matching once a day supply and demand curves and thus fixing day-ahead hourly prices for these exchanges. We call spot-prices the electricity value for inter-countries exchanges and retail prices for the internal exchanges between electricity aggregators and consumers in the grid [48]. The MNO, based on these day ahead hourly prices, can predict with better accuracy the electricity real prices for the upcoming day and devise the optimal battery management strategy based on it.

Moreover, the choice of an hourly time step for the decisions is driven by the internal characteristics of the battery. The cells have limitations on the speed of the charging and discharging processes known as C-rate [26]. This makes the effect of these operations on very short time step (minutes) with no big implication on the battery state of charge making the fact of performing electricity arbitrage or trading on these short time periods with no significant effect on the daily energy bill saving.

The remainder of this chapter is organised as follows:

In **Section 1**, we present the optimal electricity arbitrage/trading strategy for an MNO acting as a consumer or a prosumer in the smart grid. In this context, we aim to minimize the MNO operational expenditure for energy under constraints on the battery usage.

**Section 2** aims at setting an optimal battery management strategy allowing the MNO to be part of an incentive based demand response allowing it to respond to the requests of the grid to stop consuming from it at high electricity peak periods.

In **Section 3**, a joint battery management and traffic scheduling is proposed in order to minimize the OPEX of the MNO on energy. In this scenario, the operator can queue some non critical traffic to be treated with respect to the prices fluctuations and energy availability at the eNB battery.

Finally, we present the conclusions of this chapter in **Section 4** and we introduce the link between this chapter and the following one.

## 3.1 MNO acting as a consumer/prosumer in the smart grid

In this section, we consider a wireless network powered by a smart grid. The base stations are endowed with a backup battery in order to prevent possible power failures in the grid. We propose to use it for arbitrage purposes wherein the operator can purchase electricity from the grid with a certain price and store it in order to use it later when prices go up. Our aim is to design, on a daily basis, an optimal energy storage strategy, taking into account the electricity prices and users traffic load fluctuations in order to reduce the operator's daily energy acquisition costs while satisfying the users traffic requirements. We add a constraint on the maximal number of cycles to be performed by the battery per day in order to extend its lifetime. This optimal policy is devised using MDP formulation and by applying a dynamic programming algorithm to solve it.

### 3.1.1 Context and related works

The MNO in this context can act as a simple consumer in the smart grid or may be a prosumer able to sell electricity already stored in its battery back to the grid using a DC/AC inverter [16].

The MNO can be powered with no interruption using a reliable smart grid that offers electricity with a fixed price that changes over the day hours. We suppose that the eNBs are endowed also with a backup battery in order to prevent possible power failures that happen seldomly in the smart grid. Our proposal is to use this storage as a way of performing electricity arbitrage and trading by devising an optimal usage allowing the MNO to take advantage of the electricity prices based on prior knowledge of the environment while ensuring the backup functionalities.

Battery degrades with usage and time [26]. By taking advantage of the changing electricity prices to perform electricity arbitrage/trading, the operator can reduce its energy bill but this will shorten the battery lifetime compared to the case when the storage is only used for backup. Thus, the battery management that we propose should respect a preferential usage that extends the battery cycle life and maintain its performance [49, 50].

Many works in the literature proposed solutions to reduce the electricity bill by performing arbitrage and trading using storage equipment when operating in dynamic electricity prices environment. The authors in [51] propose an Enhanced Frequency Response policy based on day ahead prices forecasting that consists of using batteries for arbitrage purposes in real time pricing environment based on signal exchanged with the grid. In [52], the authors propose a time scheduling of the charge/discharge processes of the battery in intraday electrical market and evaluate the potential daily gain of the system including renewable energy sources. In [53], a linear optimization method was given for electricity arbitrage based on day ahead pricing and evaluated later under real time pricing including uncertainties. These works proposed battery management solutions for electricity bill minimization that took into account certain characteristics of the battery and predictions over electricity prices based on the day-ahead markets. The problem of these studies is that they did not consider the constraints on the battery usage especially when it comes to cycling. Arbitrage allows to minimize the daily expenditure on the short term but should also take into account battery lifetime and performances on the long term.

Battery cycling was considered in the following papers for the purpose of evaluating the potential gain of these strategies on a long time period. The authors in [54] optimize the charge/discharge decisions for a battery operating in a dynamic pricing environment that can perform 1 or 2 cycles per day and evaluate the gain per cycle. In [55], the authors evaluate the impact of cycle and calendar lives on the gain achieved by arbitrage in smart grid networks for both Lead-acid and Lithium batteries. In [56], the authors propose a linear programming algorithm to optimize the charge and discharge decisions for battery performing regulation and evaluate the return on investment considering the battery performance degradation due to the aging effect.

Unlike the approach of [55] and [56] which consider the load to be deterministic, we assume here a stochastic model for both daily prices and eNB energy consumption profiles and we propose a more general solution based on dynamic programming that can be applicable for other distributions of the system dynamics.

In our study, we assume that the time series of the electricity prices and the user traffic requests are modeled as a Markov chain allowing for an implementation of a dynamic programming algorithm. The aim of this algorithm is to design on a daily basis an optimal energy storage strategy, satisfying the users requirements and minimizing the operator’s daily energy acquisition costs under a maximal number of cycles to be performed by the battery per day.

Following this policy, the MNO decides at each hour of the day and each state of the Markov chain whether to operate its network on the grid or on its own battery and the amounts of energy to buy/sell from/to the smart grid. We compare the daily expenditure of the MNO to the one when it is exclusively powered by the grid for many sites configurations (battery type, size and cycling constraints) and under different markets (Denmark and Europe EPEX zone).

### 3.1.2 System specifications on short term

The MNO can be constantly powered by the grid and has also its own storage devices as a alternative power source as seen in Fig. 3.1

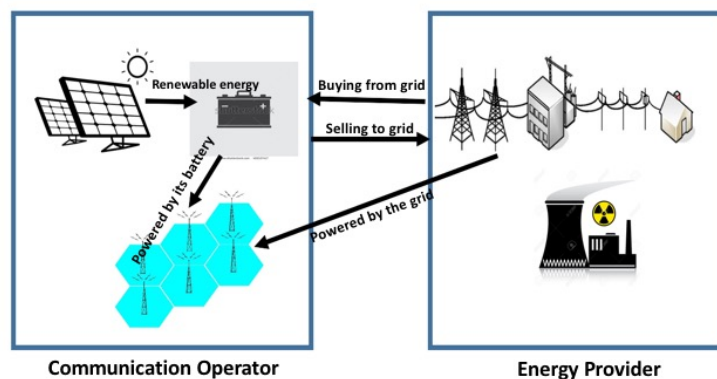


Figure 3.1: MNO acting as a prosumer in the smart grid

We assume that the electricity price changes from one hour to another and that its value is

fixed by the energy provider. The real electricity prices are denoted by  $F_h$  and can be predicted by the network operator with high accuracy based on the day ahead spot and retail prices mentioned earlier.

User traffic demand changes during the day hours. It depends on the users density in the covered area and the type of requested services. Let  $U_h$  denote the ratio in time slot  $h$ <sup>1</sup> between the actual traffic demand and the maximal traffic that could occur in the cell. We suppose that the operator uses all its available capacity to serve its users when  $U_h = 1$ .  $U_h$  is a random variable chosen based on real statistics in [23]. The network operator has to ensure that all its user requests are satisfied; no request could be delayed or not served.

The optimization is done on a time horizon of  $N$  hours with  $N = 24$ . At each hour  $h$  of the day, the operator equipment can be run using two types of power sources:

- It can be powered directly by the smart grid. The network operator pays its consumption following the price fixed by the energy provider.
- It can be powered by its own battery if it has enough reserves to sustain completely its consumption for the upcoming hour. We assume that the use of the battery has no financial cost for the operator.

The operator can also store in its own battery the energy bought from the electricity provider. We assume that when the battery is charging, the network operator cannot use it to power its components. Thus, its infrastructure has to be powered directly by the smart grid.

The operator may also sell energy stored in its battery back to the grid when it is allowed to after converting it to an Alternative Current (AC) using a DC/AC inverter. We assume that the energy provider would not decline any offer of the operator.

We assume that the battery State of Charge (SOC) denoted by  $B_h$ , is discretized into finite values in:  $[SOC_{min}, SOC_{min} + \frac{B_{max}}{M}, \dots, SOC_{max}]$  with  $B_{max}$  is the size of the battery,  $M$  a constant and  $SOC_{min}$  and  $SOC_{max}$  denotes the minimum and maximum SOC allowed for a specific type of battery (Lithium or Lead-acid). Setting SOC limitations extends the battery lifetime allowing it to perform more cycles on the long terms with higher energy efficiency.

In developed countries, power failures happen seldomly in the grid and when they do, they do not last for long periods. We propose to allocate only a fraction of the battery capacity for backup and use the remaining capacity for arbitrage/trading as shown in Fig. 3.2.

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<sup>1</sup> $h$  stands for hour

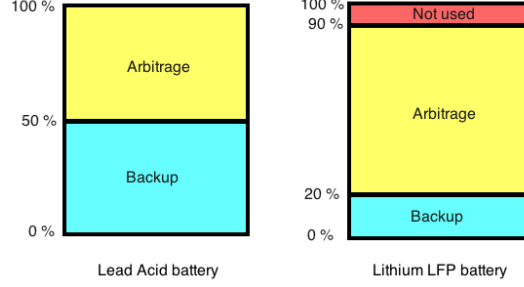


Figure 3.2: Batteries proposed usage

The choice of the fractions is made so as to be compliant with the presented preferential use of the battery (SOC limitations). The backup function will be solicited very few times a year, so we can assume that only electricity arbitrage/trading is the source of long term battery degradation.

- If the operator is powered by its battery and selling electricity back to the grid.

The battery SOC evolution in time can be expressed as:

$$B_{h+1} = B_h + \frac{1}{\gamma_d} \cdot c_h \cdot B_{max} - \frac{1}{\gamma_d} \cdot n_{TX} \cdot T_c \cdot d_h \cdot (P_0 + \Delta_p \cdot P_{out} \cdot U_h) \quad (3.1)$$

where:

- $\gamma_d$  is the discharge energy efficiency.
- $c_h \cdot B_{max}$  is the amount of energy that the operator could buy or sell from or to the grid.  $c_h \leq 0$  when the operator sells electricity back to the grid and positive when it charges its battery from the grid.
- $n_{TX}$  is the number of transceivers in the eNB.
- $T_c$  is the number of co-located technologies at the eNB.
- $d_h$  is the action of switching between the battery and the smart grid.  $d_h = 1$  when the MNO is powered by the battery and 0 when powered by the grid.
- $P_0$  is the power consumed for traffic independent features.
- $\Delta_p$  is the slope of load dependent power consumption.
- $P_{out}$  is the irradiated power by the eNB's antennas.
- $U_h$  is the users traffic load in the cell.

The money spent by the MNO during hour  $h$  is given by:

$$r_h = F_h \cdot c_h \cdot B_{max} \quad (3.2)$$

where  $F_h$  is the electricity price at hour  $h$ .

- If the operator is powered by the grid ( $d_h = 0$ ) and charges its battery ( $c_h \geq 0$ ).

The SOC can be expressed as:

$$B_{h+1} = B_h + c_h \cdot B_{max} \quad (3.3)$$

and the hourly energy expenditure is:

$$r_h = F_h \left[ \frac{1}{\gamma_c} \cdot c_h \cdot B_{max} + T_c \cdot n_{TX} (P_0 + \Delta_p \cdot P_{out} \cdot U_h) \right] \quad (3.4)$$

where  $\gamma_c$  is the charge energy efficiency

We can see from equation (3.1) that the operator needs more energy from its battery when using it to power its infrastructure and selling electricity back to the grid, due to the discharge energy efficiency  $\gamma_d$ .

From equation (3.4), we note that the operator spends more money when it charges its battery from the grid. This is due to its charge energy efficiency  $\gamma_c$ .

During its operation, the battery can experiment three different operation states denoted by  $Y_h$ :

- Charging state: The operator buys energy from the smart grid to be stored in its own batteries.
- Discharging state: In this case the battery is powering the operator infrastructure and selling electricity to the grid.
- Neutral state: When the operator runs its infrastructure using the grid without charging its battery.

$Y_h$  is equal to -1 when the battery is discharging and 1 when the battery is charging. When the battery is in neutral cycle, we take  $Y_h = Y_{h-1}$  during time slot  $h$ .

We define the battery state transition as the transition between the charge and discharge states and vice-versa [26]. When the operator infrastructure is powered by the grid (neutral state), we suppose that no battery state transition happens. At time slot  $h$ , let  $G_h$  denotes the battery state transition. It can be expressed as:  $G_h = 1$  if  $Y_h \neq Y_{h-1}$  and  $G_h = 0$  otherwise. A battery cycle can be defined as two consecutive battery state transitions. Then, the number of cycles achieved by the battery during the day can be expressed as:  $\bar{C} = \frac{1}{2} \cdot \sum_{h=1}^N G_h$ .

### 3.1.3 MDP formulation of the short term problem

The system can be seen as an ergodic finite horizon Markov chain leading to a Markov Decision Process (MDP). Our aim is to minimize the operator daily expenditure for energy while respecting all the users traffic demand and the conditions set in order to extend the battery life. This is achieved by respecting: first, the battery preferential use that takes into account the SOC lower and upper limits and the maximal charge and discharge rates and second, the imposed constraint on the maximal number of battery cycles  $\Gamma_c$  to be performed per day and imposed by the long term optimal investment plan as will be seen later.

We define the following components of this MDP:

**State space:** It denotes the possible states  $s_h$  the system can be in, at any time slot  $h$ . The state space is finite and discrete. It is expressed as follows:  $s_h = (B_h, U_h, F_h, Y_h, H_h)$ , where  $B_h$



is the battery SOC,  $U_h$  is the percentage of the infrastructure occupancy due to the user traffic demand,  $F_h$  the unitary price of electricity and  $Y_h$  the battery operating state during the previous time slot  $h - 1$ .  $H_h$  refers to the still tolerated number of battery state transitions till the end of the day.  $H_h$  takes its value in  $[0, \dots, 2\Gamma_c]$  with  $\Gamma_c$  refers to the constraints on the maximal number of battery cycles to be performed per day.

We set at  $h = 0$ ,  $H_0(s) = 2\Gamma_c \forall s \in S$ .  $H_h$  decreases over the day hours once  $G_h = 1$  but has to respect the condition that  $H_h \geq 0 \forall h \in [1, \dots, N]$  in order to meet the constraint imposed on the maximal number of cycles performed by the battery during the day.

**Action space:** It represents the actions that the operator could perform at the beginning of each time slot  $h$ . At each decision time, the operator can choose from a finite space of possible actions  $a_h \in \Omega_h(s_h)$  with respect to the state  $s_h$  in which it is, the quantity of energy  $c_h$  to buy or sell from or to the smart grid and the decision  $d_h$  of switching the power source between the battery and the grid.

**Transition probabilities:** They correspond to the probabilities of reaching state  $s_{h+1}$  knowing that the system was in the previous slot in state  $s_h$  and that it performed action  $a_h$ .

$$\mathcal{P}(s_{h+1}/s_h, a_h) = \mathcal{P}(B_{h+1}/s_h, a_h) \times \mathcal{P}(U_{h+1}/s_h, a_h) \times \mathcal{P}(F_{h+1}/s_h, a_h) \times \mathcal{P}(Y_{h+1}/s_h, a_h) \times \mathcal{P}(H_{h+1}/s_h, a_h) \quad (3.5)$$

The battery SOC at the beginning of slot  $h + 1$  denoted  $B_{h+1}$  is completely known if we know the state  $s_h$  and the action  $a_h$  taken at time slot  $h$ . Thus the battery SOC transition probability can be expressed:

$$\mathcal{P}(B_{h+1}/s_h, a_h) = \begin{cases} 1 & \text{if } B_{h+1} = B_h + \frac{1}{\gamma_d} \cdot \mathbf{1}_{(c_h < 0)} \cdot c_h \cdot B_{max} - \frac{1}{\gamma_d} n_{TX} \cdot T_c \cdot d_h \cdot (P_0 + \Delta_p \cdot P_{out} \cdot U_h) \\ 0 & \text{otherwise} \end{cases}$$

The energy price and the traffic load are independent and non-correlated in time, thus:

$$\mathcal{P}(F_{h+1}/F_h, a_h) = \mathcal{P}(F_{h+1}) \text{ and } \mathcal{P}(U_{h+1}/U_h, a_h) = \mathcal{P}(U_{h+1})$$

The battery operating state  $Y_{h+1}$  is deterministic and depends only on the action  $a_h$  that the operator chooses to perform during the previous time slot  $h$ .

The distribution of the still tolerated number of battery state transitions is deterministic.  $H_{h+1}$  depends on previous tolerated number of transitions  $H_h$ , the previous battery operating state  $Y_h$  in time slot  $h - 1$ , and the action that the operator chooses to perform  $a_h$  at time slot  $h$ .  $H_h$  can be considered as a variable that defines some restrictions on the possible actions to be performed. In fact, if  $H_h > 0$ , then the operator can charge or discharge its battery in the next slot. If  $H_h = 0$ , then the operator has to stay in the same mode (charge/discharge) or to opt for the neutral mode till the end of the day.

**The instantaneous reward:** It corresponds to the money that the network operator earns or spends with respect to the state  $s_h$  in which it is and the action  $a_h$  it chooses to perform at time slot  $h$ . It is denoted by  $r_h(s_h, a_h)$  and its value depends on the operator's choice for the source of

energy  $d_h$  following Equations (3.2) and (3.4).

The objective of the algorithm can be expressed as follows:

$$\min_{\mu} E^{\mu} \left( \sum_{h=0}^{N-1} r_h(s_h, a_h) \right) \quad (3.6)$$

$$s.t. \quad \forall h \in [1, \dots, N], \quad SOC_{min} \leq B_h \leq SOC_{max} \text{ and } H_h \geq 0 \quad (3.7)$$

Equation (3.6) represents the objective function which is the average money spent by the operator on the whole day for energy acquisition. This value is an expectation over all the transitions between the states of the Markov chain following the policy  $\bar{\mu}$ .

Equation (3.7) represents the imposed constraints which have to verify that the number of the battery cycles during the day has to be under a certain threshold  $\Gamma_C$  as  $H_h \geq 0$  and that the battery state of charge has to remain between an upper and lower bands ( $SOC_{max}$  and  $SOC_{min}$  respectively) relative to the battery type.

With this MDP formulation, we converted the constrained problem in equations (3.6) and (3.7) to an unconstrained one that can be easily solved using dynamic programming tools.

The objective is to define, based on a perfect knowledge of the rewards and probability of transitions, an optimal deterministic policy that for each state of the system  $s \in \mathcal{S}$  and each time slot  $h \in [0, \dots, N - 1]$  decides one unique action defining the source of energy  $d_h$  and the amounts of energy  $c_h$  charged or discharged from the battery [37].

### 3.1.4 Algorithm solving

The MDP presented before verifies the conditions of ergodicity: No absorbing states and no periodicity criteria for the return time of all the states. To devise the optimal deterministic policy, we apply policy iteration technique presented in subsection 2.2.3 that consists at solving iteratively Bellman optimality equations. Then, we devise the occupation measures at each state to calculate the MNO daily expenditure and the average number of cycles performed per day.

Before devising the optimal policy considering the constraint on the maximal number of cycles, we should first calculate the optimal number of cycles performed on average by the battery for the unconstrained problem. To do so, we apply the dynamic programming algorithm described below for an unconstrained MDP having the state space  $s_h = (B_h, F_h, U_h, Y_h)$  and the same action space, transition probabilities and instantaneous reward. In other terms, we just neglect the constraint on  $H_h$  and obtain the minimum possible expenditure which may require more cycles to be performed per day..

Then, if  $H_h$  is lower than this optimal number of cycles  $\Gamma_{op}$ , we can devise the optimal battery management strategy considering the constraint on the maximal number of cycles to be performed per day by the battery.

---

**Algorithm 1** Optimal battery management strategy for electricity arbitrage/trading

---

Calculate the optimal battery number of cycles  $\Gamma_{op}$  using the same algorithm below when  $s_h = (B_h, F_h, U_h, Y_h)$  and  $a_h = (d_h, c_h)$  (no constraint on  $H_h$ )

**IF**  $\Gamma_c \leq \Gamma_{op}$

**Inputs:**  $B_{max}$ ,  $\bar{F}$ ,  $\bar{U}$ ,  $s_h = (B_h, F_h, U_h, Y_h, H_h)$ ,  $a_h = (d_h, c_h)$ ,  $p_h(s_{h+1}/s_h, a_h)$ ,  $\Gamma_c$

**Function:** Policy iteration for optimal battery management under maximal cycles constraints

**Initialize:**  $V_N = r_N = 0$ ,  $V_h(s_h) = 0$ ,  $h=N-1$  and  $\beta_0(s) = \phi(s_0)$

- 1: **while**  $h \geq 0$  **do**
- 2:  $\forall s \in \mathcal{S}, \forall a \in A$   
Calculate  $r_h(s_h, a_h) = F_h \cdot \left[ (1 - d_h) \cdot T_c \cdot n_{TX} (P_0 + \Delta_p \cdot P_{out} \cdot U_h) + \frac{1}{\gamma_c} c_h \cdot B_{max} \right]$
- 3:  $\Omega_h(s) : \{a \text{ has to be compliant with } Y \text{ if } H_h = 0\}$
- 4: Policy improvement step:  $\mu_h(s) = \underset{a \in \Omega_h(s)}{\operatorname{argmin}} \left[ r_h(s, a) + \sum_{s' \in \mathcal{S}} p_h(s'/s, a) \cdot V^{(h+1)}(s') \right]$
- 5: Policy evaluation step:  $V_\lambda^{(h)}(s) = r_h(s, \mu_h) + \sum_{s' \in \mathcal{S}} p_h(s'/s, \mu_h(s)) \cdot V^{(h+1)}(s')$
- 6:  $h \leftarrow h - 1$
- 7: **end while**
- 8: **for**  $k=0:N-1$  **do**
- 9: Calculate the occupation measures:  $\beta_{k+1}(s) = \sum_{s' \in \mathcal{S}} p_t(s/s', \mu_k(s')) \cdot \beta_k(s')$
- 10: Calculate the average battery SOC at each time slot:  $\bar{B}_{k+1} = \sum_{s \in \mathcal{S}} \beta_{k+1}(s) \cdot B_s(k)$
- 11: Calculate the MNO average hourly expenditure:  $\bar{r}_{k+1} = \sum_{s \in \mathcal{S}} \beta_{k+1}(s) \cdot r_s(k)$
- 12: **end for**
- 13: Calculate the daily expenditure of the operator:  $\bar{R} = V_0(s_0)$
- 14: Calculate the average number of cycles:  $\bar{C} = \Gamma_c - \frac{1}{2} \sum_{s \in \mathcal{S}} \beta_N(s) \cdot H_N(s)$

**ENDIF**

---

### 3.1.5 Numerical applications

In our simulations, the time is divided into slots of 1 hour each.

The MNO have the choice between either Lead acid or Lithium batteries. Each one of them have a preferential use:

- For Lead acid battery, we assume that the battery SOC should remain in the range:  $0.5B_{max} \leq B_h \leq B_{max}$  and that the energy efficiency during charge/discharge processes is  $\gamma_c = \gamma_d = 83\%$  [62].  $c_h$  takes values in  $\{0, 0.1, \dots, 0.5\}$  when the operator is not able to sell energy back to the grid and in  $\{-0.5, -0.4, \dots, 0.4, 0.5\}$  when selling is allowed.
- For Lithium battery, we assume that the battery SOC should remain between  $0.2B_{max} \leq B_h \leq 0.9B_{max}$  when doing arbitrage/trading and we take the charge and discharge energy efficiencies to be equal to  $\gamma_c = \gamma_d = 94\%$  [63].  $c_h$  takes values in  $\{0, 0.1, \dots, 0.7\}$  when energy selling is not allowed and in  $\{-0.7, -0.6, \dots, 0.7\}$  when the operator is capable to sell energy back to the grid.

The battery size  $B_{max}$  can take 3 different values in  $\{16, 32, 48\}$  KWh.

The battery has  $L = \frac{(M-1)(SOC_{max} - SOC_{min})}{B_{max}}$  possible values.

We choose  $M = 21$  for 16 KWh battery which makes  $L = 11$  for Lead acid and  $L = 15$  for Lithium battery.  $M = 41$  for 32 KWh battery making 21 states for Lead acid and 29 for Lithium.

While for 48 KWh battery, we choose  $M = 61$  which makes  $L = 31$  for Lead acid and  $L = 43$  for Lithium battery.

At the beginning of each time slot, after calculating the new battery state of charge using Equations (3.1) and (3.3), we make a projection on the battery state space following the rule below:

$$\begin{aligned}
 \text{If } B_{h+1} \in \text{SOC}_{min} + [(2\alpha-1) \cdot \frac{B_{max}}{2 \cdot (M-1)}, (2\alpha+1) \cdot \frac{B_{max}}{2 \cdot (M-1)}] &\rightarrow B_{h+1} = \text{SOC}_{min} + \alpha \cdot \frac{B_{max}}{(M-1)} \quad \forall \alpha \in [1, \dots, L-2] \\
 \text{If } B_{h+1} \in [\text{SOC}_{min}, \text{SOC}_{min} + \frac{B_{max}}{2 \cdot (M-1)}] &\rightarrow B_{h+1} = \text{SOC}_{min} \\
 \text{If } B_{h+1} \in [\text{SOC}_{max} - \frac{B_{max}}{2 \cdot (M-1)}, \text{SOC}_{max}] &\rightarrow B_{h+1} = \text{SOC}_{max}
 \end{aligned}$$

We study 2 cases: European EPEX based market and Danish market. We take into account the seasonality of the prices.

- The Danish spot and retail electricity prices were taken from energiteknik.dk which is the main Transmission system operator in Denmark. It is responsible for setting the framework for a well-functioning electricity market that ensures fair prices for both consumers and producers and promotes climate-friendly energy solutions [58].
- The European electricity prices were taken from EPEX SPOT SE which is a European trading market for electricity which indicates the day-ahead spot and retail energy prices connecting demand and supply curves in order to allow intervenients to make their bids for electricity. EPEX connects markets representing 85% of the European power consumption to set an auction-based market for power exchange between the European countries and inside each one of them [47].

Danish electricity supply relies with 42% on wind turbine power, fossil energy and waste [59]. While in EPEX zone, only 13% of energy is generated using solar and wind making these countries rely mainly on combustible fuels and nuclear power with different proportions between the countries [60]. The renewable energy production is not controllable, it may differ between the hours of the day. This makes the variance between the electricity prices taken at different day hours higher in countries like Denmark compared to countries like France which relies mainly on nuclear power. With this prices dispersion, these countries push their consumers to reduce their consumption at low renewable power production.

The electricity average prices are taken as expectations based on the electricity spot and retail markets in both Denmark and EPEX zone. The expectation is calculated by multiplying the daily day ahead electricity retail prices by the average electricity price in these zones during summer and winter [61]. Then, we take the average hourly prices on all the days of the semester to derive what we call a typical day hourly electricity price.

We assume that the real electricity prices follow a trinomial distribution with one trial. The probability that the real price is equal to the expected value is 0.5 and the probabilities to be equal to the value below or to the value above are equal to 0.25 each.

The average user traffic model is taken from the model presented in [23]. We assume that the traffic at each hour follows also a trinomial distribution with one trial. The probability that the user traffic is equal to the average value is 0.6 and the probabilities to be equal to the value below or to the value above are equal to 0.2 each.

The energy consumption model of the macro base stations is taken also from [23]. We assume that the fixed power consumption  $P_0 = 118.7W$ , the conversion factor between the radiated and consumed powers set to be  $\Delta_p = 5.32$ , the eNB has 3 sector with 2 antennas each  $n_{TX} = 6$  and that the eNB is carrying  $T_c = 5$  wireless technologies and transmitting with its maximal power  $P_{out} = 20W$ . Following this model, the macro base station consumes about 6.5 KWh at maximal capacity and about 3.5 KWh when there is no traffic at all.

As we mentioned before, if  $c_h > 0$  and  $d_h = 0$ , the operator has to switch off its battery and be powered exclusively by the smart grid while its battery is charging and  $Y_h = 1$ .

If  $c_h = 0$  and  $d_h = 0$  then the battery is in neutral state and  $Y_h = Y_{h-1}$ .

Otherwise, if  $c_h \geq 0$  and  $d_h = 1$  then the battery is in discharge mode and  $Y_h = -1$ .

At  $h = 0$ , we suppose that the battery is empty so that it was in a discharge state in the time slot before ( $Y_0 = -1$ ). When the battery cycle constraint  $\Gamma_c$  is set to 0, means that we force the mobile network not to use its battery and use exclusively the grid during all day hours.

We devise the optimal policy for the Danish and EPEX zone cases when the MNO is allowed to sell electricity to the grid and when it is not. The MNO may be endowed with either Lithium or Lead acid battery having a maximal capacity taken in  $\{16,32,48\}$  KWh. For each case, after calculating the optimal number of cycles  $\Gamma_{op}$ , we do not find any case in which the MNO performed more than 3 cycles. This is due to the 2 peaks structure of the electricity prices. So, following the rule of  $\Gamma_c \leq \Gamma_{op}$ , we only impose constraints of 1 or 2 cycles per day and then evaluate the average battery SOC evolution and the savings compared to the case when the MNO is powered exclusively by the grid in a typical week day in summer and winter.

### Danish case

For the danish case, we consider only the case of an MNO acting as a simple electricity consumer in the grid.

In Fig. 3.3, we plot the average battery SOC evolution over the hours of the day, in a typical summer week-day in Denmark for both 32 KWh Lead acid and Lithium batteries while varying the constraint on the number of cycles to be performed per day. This value is an average over all possible values that the electricity prices and the user traffic demands could take during each hour of the day. The average daily energy prices and the average users traffic demand are shown at the top of the figure, to ease illustration.

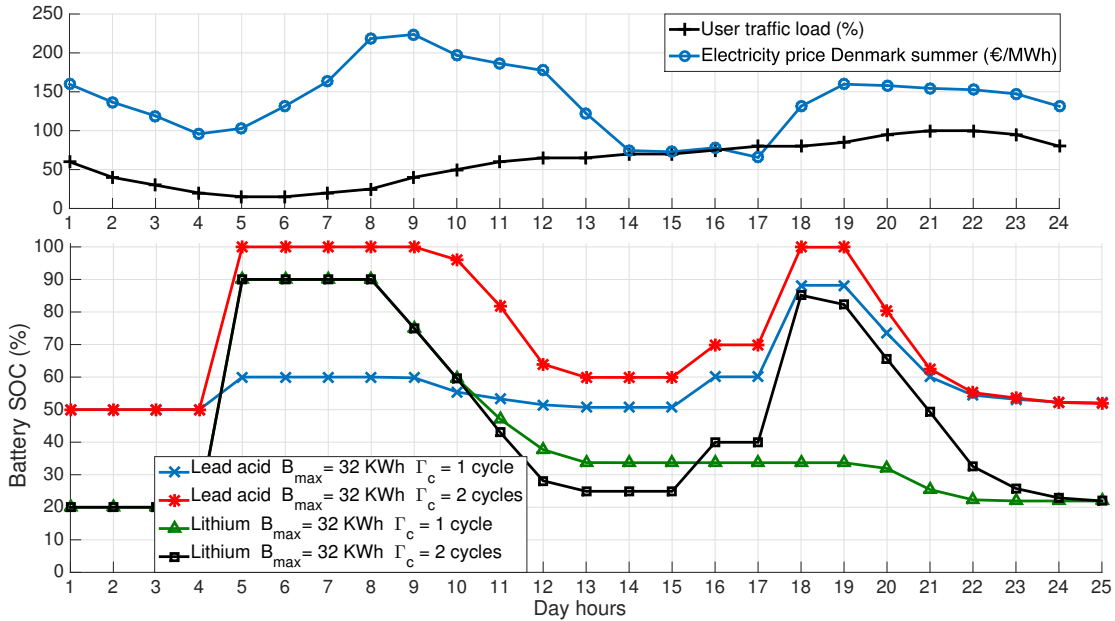


Figure 3.3: The battery SOC daily evolution in Denmark during summer for both 32 KWh Lead acid and Lithium batteries when the MNO is a consumer

We can see clearly that the obtained policy respected perfectly the constraints imposed on the battery SOC limitations and the charge and discharge rates for both Lead acid and Lithium batteries. We can also note that the constraints on the maximal number of cycles are perfectly matched in all cases. The operator charges its battery when the prices are in local minima (4 am and 5 pm) and uses its battery depending on its size during hours when the electricity price is the highest trying to minimize the number of battery transitions. Due to the difference in the energy charge/discharge efficiencies, we can note that there is a difference in the preference of hours for battery charge and discharge. For Lead acid, making one cycle during night time was more financially beneficial for the network operator, while for Lithium battery, the MNO preference is during the morning.

In Fig. 3.4, we present the average SOC for Lead acid battery under different cycle constraints when varying the battery size in  $\{16, 48\}$  KWh during a typical week day in winter in Denmark.

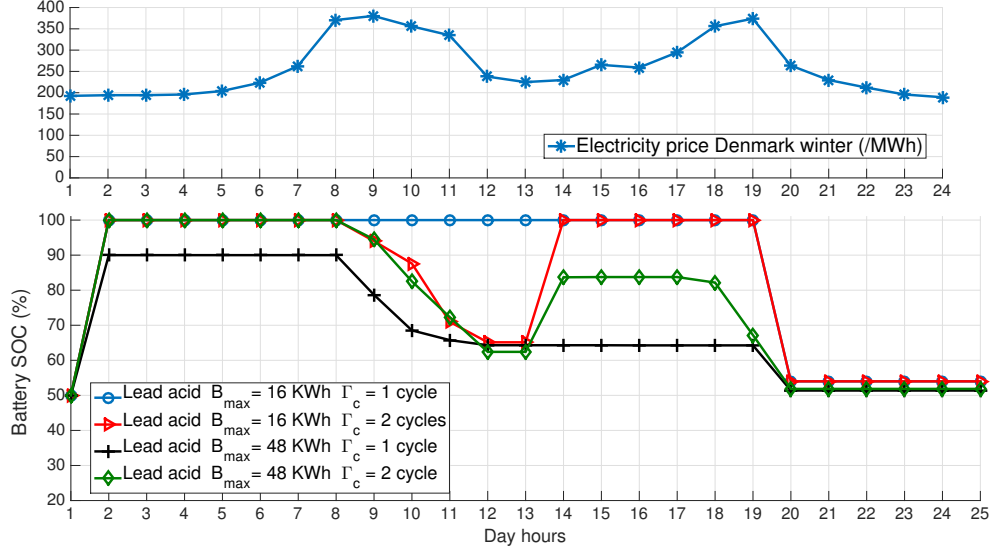


Figure 3.4: The Lead acid battery SOC daily evolution in Denmark during winter for different battery sizes and constraints on the battery cycling

From Fig. 3.4, we note that as we are using the same battery type (Lead acid), the charging and discharging decisions happen in the same hours of the day independently of the battery size. In all the cases, we can see clearly that the operator chooses to charge its battery at 1 am when the price is the lowest, then used the grid for few hours as the price level is still low and then relies on its reserves on the battery with respect to its cycle constraint: When the constraint was 1 cycle, the operator waited until 7 pm to discharge it and when the constraint was 2 cycles, it discharged the first time at 8 am and then another cycle was performed later (charging at 1 pm and discharging at 7 pm). However, the size of the battery has a significant affect on the amount of energy charged by the battery. Having a large battery allows the operator to sustain more hours in energy autonomous mode, and as we assumed that during one hour the operator can only use one source of energy, we can see that when the battery size is 16 KWh, the operator was forced to charge its battery to the maximum in order to be able to use its reserves later.

In Figs. 3.5 and 3.6, we show the average daily expenditure saving for energy for the operator for all the possible battery sizes  $\{16, 32, 48\}$  KWh while varying the constraint on the maximal number of cycles to be performed per day for both winter and summer. This saving is relative to the case when the operator has to be powered exclusively by the grid ( $\Gamma_c = 0$ ).

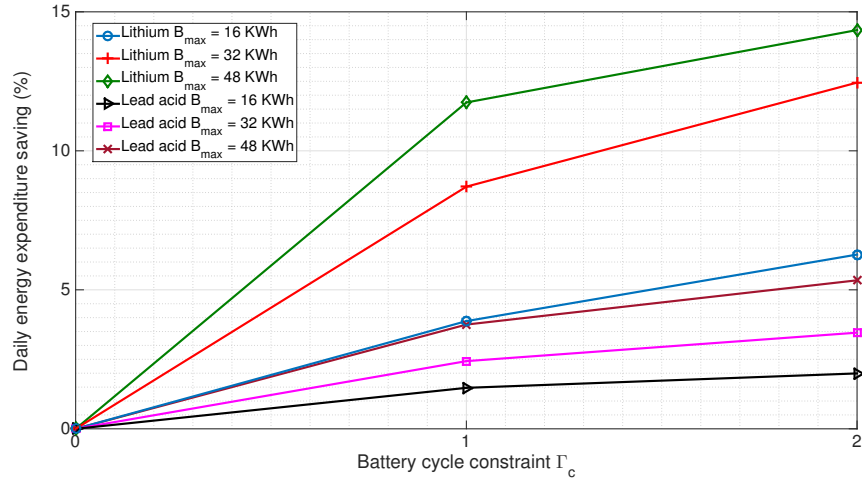


Figure 3.5: The daily energy expenditure saving for an MNO acting as consumer in Denmark during winter

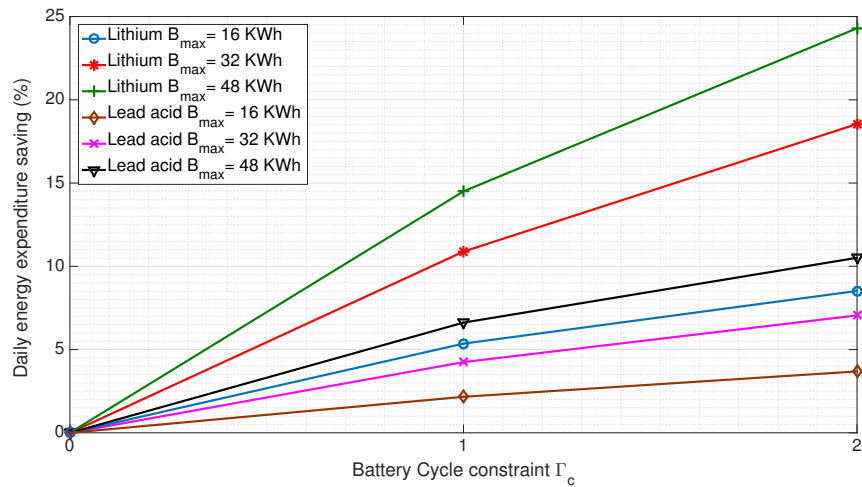


Figure 3.6: The daily energy expenditure saving for an MNO acting as consumer in Denmark during summer

From both figures above, we can see clearly that Lithium battery achieves better gains compared to Lead acid due to its higher energy efficiencies and also for the fact that it allows the MNO to perform cycles with deeper DOD and higher charging rate. It is also trivial that the larger the battery the greater the saving as it can give the MNO more flexibility and allows it to stay for longer periods in energy autonomous mode.

We notice also that the percentage of saving is higher during summer than in winter even if electricity in winter is more expensive. This comes from the fact that the deviation between the maximal and minimal prices is more important during summer. In fact, in summer the minimum is 70% lower than the maximum price, while in winter the difference is only 50%. This is not the case when we compare the nominal values of the saving as the nominal prices in winter are twice higher.



If we look at the price structure during summer, there are two main max peaks: the first one is around 9 am and the second around 7 pm, this makes the fact of performing 2 cycles per day have a good financial income for the operator especially for Lithium batteries in summer.

### Europe EPEX case

In European EPEX zone, we consider the cases when the MNO may act as a prosumer and when it acts as a simple consumer in the smart grid.

In Fig. 3.7, we plot the average 48 KWh Lead-acid battery SOC when selling is enabled and when it is not under different battery cycles constraints in a typical winter day. The average daily energy prices and the average users traffic demand are shown at the top of the figure, to ease illustration.

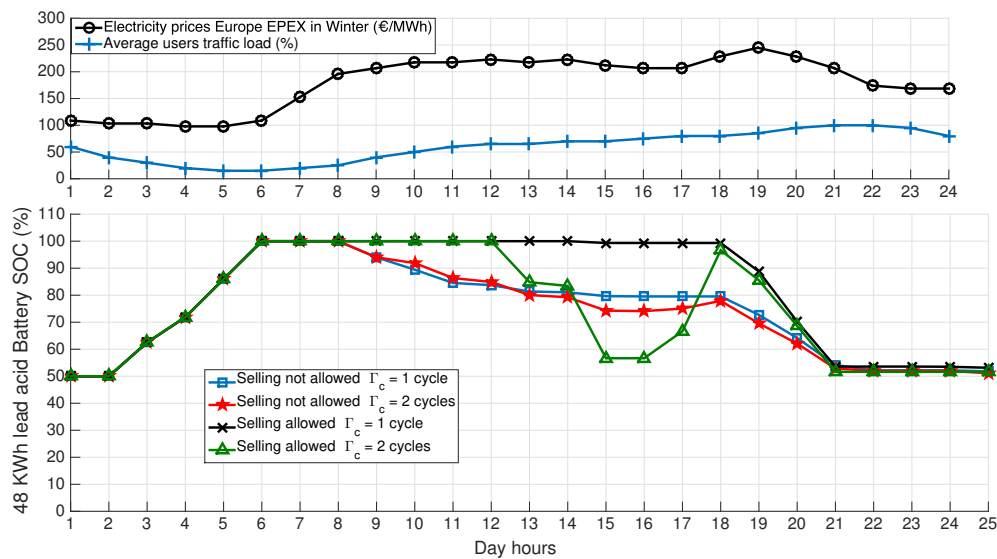


Figure 3.7: The battery SOC daily evolution in Europe during winter for 48 KWh Lead acid battery

When selling is not allowed, even for a constraint on the battery cycles of 2 cycles per day, the battery performed on average only 1 cycle. This is due to the price variation structure and the high battery energy losses which makes the fact of performing more than one cycle have no financial income. On the other hand, when selling is allowed in the grid, under a constraint of 2 cycles maximum, the battery performed on average exactly 2 cycles. In this case, the operator can take advantage of the maximal electricity prices to sell all the excess energy to the grid and so make more money than the case when selling not allowed.

Now, we present in Fig. 3.8 the same results for the case of a 48 KWh Lithium battery in a typical summer week day when the MNO is a consumer and when it acts as a prosumer.

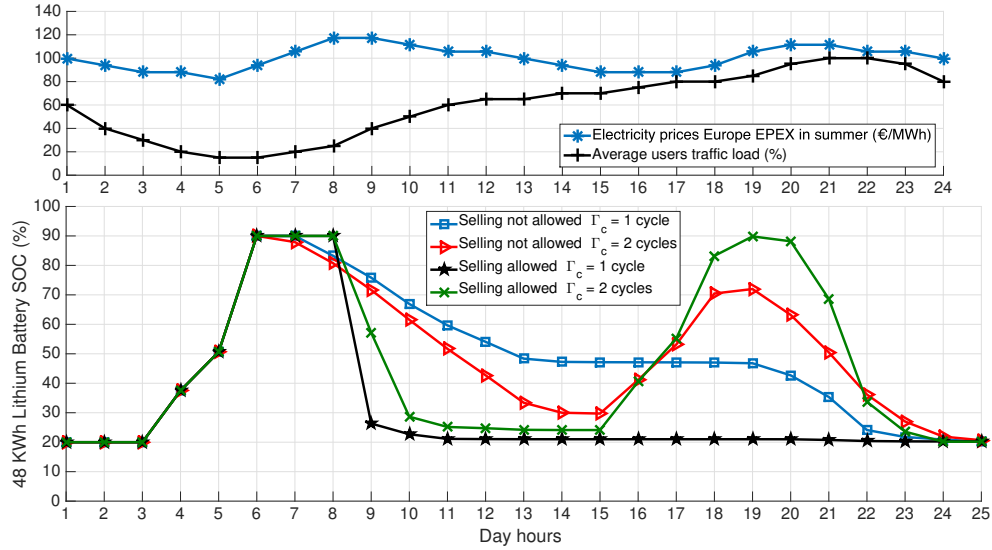


Figure 3.8: The battery SOC daily evolution in Europe during summer for 48 KWh Lithium battery

In the case when selling is not enabled and when the constraint is fixed to 2 cycles, contrary to the Lead acid, we see that the Lithium battery performed on average 2 cycles. Lithium has better energy efficiency which makes energy trading have a good financial gain compared to Lead acid. Moreover, we can notice that when selling is allowed, the MNO makes cycles with higher DOD when acting as prosumer. In fact, it has to store the maximal possible energy reserves to be used later when the prices are in local maxima to sell it back to the grid.

In Fig 3.9, we plot the average daily energy expenditure saving for Lead acid battery when selling is allowed and when it is not in a winter day in Denmark.

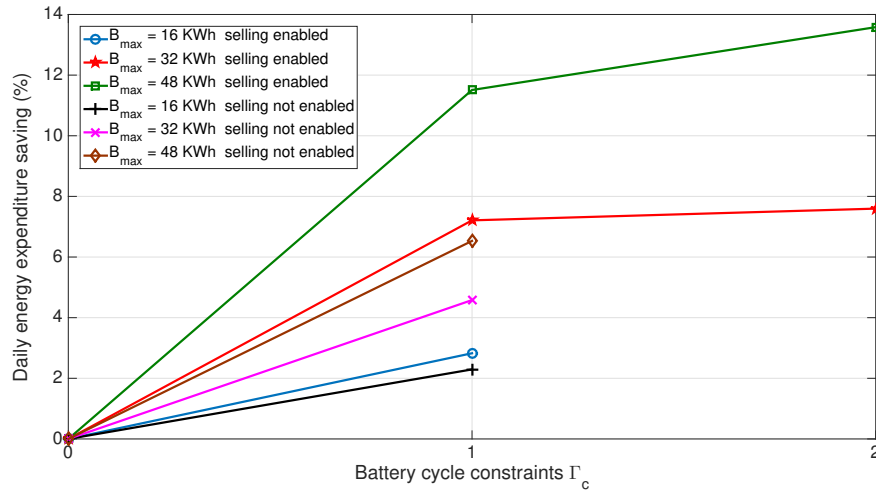


Figure 3.9: The daily energy expenditure saving in Europe during winter for both consumer and prosumer having Lead acid battery

We can see from Fig. 3.9 that enabling energy selling encourages the MNO to perform more cycles during the day especially for larger lead-acid batteries (32 and 48 KWH). When the battery size is 16 KWh, the MNO has no gain in performing more than one cycle per day. Moreover, the saving due to the second cycle is more important when the battery size is higher as the MNO has more reserves to be sold and so make more financial gain.

In Fig. 3.10, we present the saving for Lithium for different battery sizes and when acting as a prosumer or as a simple consumer.

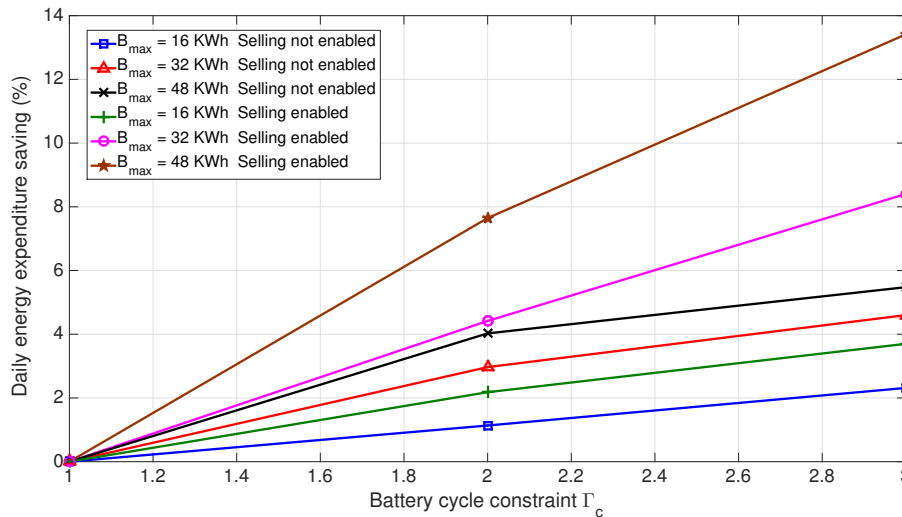


Figure 3.10: The daily energy expenditure saving in Europe during summer for both consumer and prosumer having Lithium battery

In the case of Lithium, being able to sell electricity back to the grid, can have even greater impact on the energy expenditure compared to Lead acid. In all cases, performing a second cycle brings more saving for the operator but we can see that its impact is greater when selling electricity was enabled.

It is clear from the results above that performing more cycles per day allows the operator to reduce more its daily energy bill but should on the other hand, lowers the battery lifetime and may lead to more CAPEX on the long term. Deciding the optimal battery size and cycling strategy on the long term is a primordial step in order to minimize the MNO return on investment for energy which is the objective of the next chapter.

### 3.1.6 Main findings

In this section, we addressed the issue of energy management strategies for a telecommunication operator, equipped with a storage battery, and powered with a smart grid. The aim of the operator is to optimally use its battery both for backup and for arbitrage/trading in order to minimize its expenses for energy when acting as a simple consumer or as a prosumer.

Both strategies should respect the constraints imposed on the battery maximal number of cycles while following a preferential use of the battery that sets limitations on the charge and discharge rates and the battery SOC lower and upper limits. Our results demonstrate that the proposed strategy optimizes the energy expenditures for the operator compared to the case when it is exclusively powered by the grid. The operator opts to charge its battery or power its equipments by the smart grid when the energy prices are low. Conversely, the operator uses its own energy reserves or sell some of it back to the grid when energy prices are high.

On the other hand, performing more cycles, even if it may reduce significantly the MNO daily energy expenditure, reduces the battery cycle life and so forces the MNO to replace it before reaching its calendar life. We will analyze in the next chapter the long term revenue of performing electricity arbitrage and trading in the context of an MNO powered by a smart grid taking into account electricity market and users traffic evolution and batteries long term characteristics. This section's results will be used as input for the overall long term optimization problem in section 1 of the following chapter helping the MNO decide the size, the type and the long term cycling strategy of its battery.

## 3.2 MNO included in demand-response program

We consider in this section the case when the network operator signs an incentive based demand response contract with the energy provider, in which case the former should stop using the grid if the latter tells it to do so, typically in periods of high energy consumption. The operator gets in this case a premium, for instance in the form of a discount on its energy bill. However, if the operator fails to comply with the energy reduction requests, it would pay a penalty. Here too, we formulate the problem using MDP and apply DP algorithm to devise an optimal offline policy which minimizes the network operator energy expenditure, by indicating to it when to buy energy and when to operate its network on the smart grid or on its own energy storage. We also show how the operator should manage its battery in order to respond to the energy provider's requests to stop consuming from the grid at high electricity load.

### 3.2.1 Context and related works

With the evolution of the smart grids, the balance between supply and demand is managed so as to favor more sustainable energy generation and a more responsible energy consumption. Some electricity load peaks could occur during the day. The energy providers need to protect their networks from overload so they can ask their consumers and may ask their consumers to lower or delay (some of) their load and hence their energy demand [10]. The energy provider can sign a so-called demand response contract with big consumers giving them some incentives in order to involve them in this process.

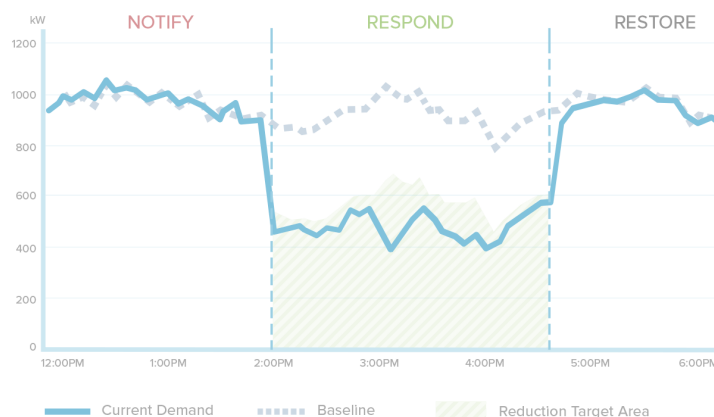


Figure 3.11: Consumer load adaptation under Demand-Response

An incentive based demand response contract is an agreement between a consumer and the grid so that the former stops using the latter when it is asked to do so [20]. At the signing of the contract, the consumer gets a certain amount of money from the grid. Each time it is asked to stop consuming from the grid and it fails to do so, it should pay a penalty to the energy provider.

The network operator, as one of the biggest energy consumers in the grid, has also an interest

to be involved in this demand response strategy [64]. In order to do so, one of the solutions is to equip the network, and especially the eNodeB (eNB), with batteries which can be charged directly from the smart grid and which are able to provide the operator with some self autonomy, when the energy prices are very high or because the grid asks it to stop using it [12].

Energy storage techniques with demand response feature have been widely studied in the literature with the aim of lightening the demand on the grid and minimizing the consumers' energy bills.

In [65], the authors proposed an optimization for the use of non critical services in smart households and a battery management strategy under changing prices and incentive-based demand response program. The house has to respond to the grid requests to reduce its consumption at critical hours by postponing some services (heating, washing machine, etc) or relying on its battery reserves and is subject to some penalties if it does not curtail its consumption.

The authors in [66] and [67] for instance proposed a hierarchical optimization method to manage the battery of an industrial facility powered by the grid. A day ahead Genetic Algorithm (GA) is proposed to define the periods in which the battery is allowed to charge or discharge taking into account the energy price profile as part of a demand response strategy while respecting a maximal number of cycles in order to extend the battery lifetime. A linear optimization algorithm on a shorter time scale is also proposed to optimize the battery power achieving the minimum energy fees while satisfying the industrial facility needs for energy.

In the context of DR with real time pricing, these works focused on the adaptation of the load using shifting and peak shaving to maintain it under a peak power consumption value fixed by the grid by relying partially on the battery to sustain part of the consumption. In the case of incentive based demand response, the consequences of not respecting the requests of the grid are more serious and the traffic shifting cannot be applicable in the case of the eNB. Our proposal to stop consuming from the grid requires a complete usage of the battery as an alternative source of energy when DR requests are triggered.

Our goal in this section is to devise a battery management strategy that minimizes the daily energy expenditure of the network operator taking into account the electricity load of the grid and the demand-response requests, while ensuring Quality of Service (QoS) of the operator's users. We formulate this problem as a Markov Decision Process (MDP). Then, using dynamic programming tools, we investigate offline solutions to find the optimal battery storage policy based on prior knowledge of network subscribers traffic load and unitary electricity prices, as well as deterministic versus probabilistic knowledge of energy provider requests to the operator to stop using the grid.

### **3.2.2 System specifications for short term problem**

In this section, the MNO and the energy provider are both part of a demand response agreement as described in 3.12:

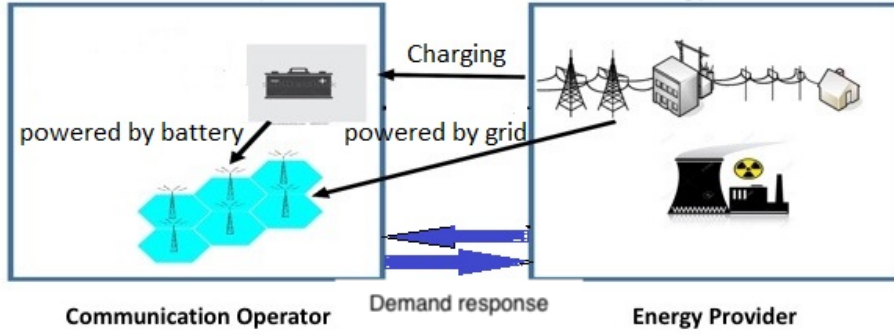


Figure 3.12: Interactions between the MNO and the grid in DR context

We consider the case of incentive demand response program when the operator signs a yearly demand response contract with the grid and gets a reward in the form of a fixed amount of money at the beginning of the year [64]. Let  $rw$  denote the amount of the reward earned by the MNO per hour.

With this agreement, the energy provider can ask the operator to stop consuming from the grid and be powered exclusively by its own battery during the next hour. We call this event blocking request and is denoted by  $K_h$ :  $K_h = 1$  when the grid asks the operator to stop consuming and  $K_h = 0$  when it does not. We assume also that  $K_h$  follows Bernoulli law with a probability that changes at each hour of the day depending on the electricity load.

Telecommunications are a very critical service that cannot be not delivered or postponed. The MNO has the choice to respond favorably or decline the requests of the grid. If the operator does not respect the blocking request, it has to pay a fixed penalty, denoted by  $pe$ .

We assume that the MNO is linked to the smart grid and so can be powered by the electricity purchased from the energy provider or using its own storage battery. Conversely to the case presented in section 1, we assume this time that there are no constraints on the battery SOC limits or on the number of cycles to be performed per day. The MNO can use all the available capacity offered by its storage equipment. All its concern is to satisfy its users load while responding if possible to the requests of the grid to stop consuming.

We assume the same eNB energy consumption (Equation 2.1) and the same battery SOC evolution models (Equations (3.1) and (3.3)) as before considering the case of an MNO acting as a simple consumer in the smart grid. T

As the eNB should operate with no interruption, the usage of the battery in this case, is the only way for the MNO to be part of the DR program to be able respond to the requests of the grid. Based on different levels of knowledge of the blocking requests, we set the optimal battery management strategy in order to take advantage of the incentive based DR program and reduce significantly the operator daily expenses for electricity.

### 3.2.3 MDP formulation

Our aim is to devise an offline deterministic policy which minimizes the operator daily expenditure for energy. We do so using an unconstrained MDP formulation which can be solved using dynamic programming. We study two cases: when the blocking requests sent by the grid are deterministically known in advance by the operator and when they are known probabilistically.

#### Demand response with deterministic knowledge of blocking requests

In this case, the MNO is informed by the energy provider at the beginning of the hour if it has to stop consuming from the grid or not. Based on this, the operator will take two decisions: one when a request occurs and when there is no request. At each time slot, the operator will decide the source of power and the amount of energy to charge the battery taking into account its battery SOC, the energy prices, the users traffic load and the request of the grid. We define the following components of this MDP :

**State space:** State  $s_h = (B_h, U_h, F_h, K_h)$ , where  $B_h$  is the battery state of charge,  $U_h$  is the ratio between the actual user traffic load and the maximal one,  $F_h$  is the unitary price of energy and  $K_t$  is a Boolean variable which is equal to 1 if the grid asks the operator to stop consuming and 0 otherwise. All these values are discrete and finite which makes the whole system state space finite.

**Action space:** Action  $a_h = (c_h, d_h)$  with  $c_h$  the amount of energy to buy from the smart grid and  $d_h$  the decision of switching the power source between the battery and the smart grid. The MNO knows perfectly if the grid requests will occur or not and so has one unique decision in each case.

#### Transition probabilities:

$$\mathcal{P}(s_{h+1}/s_h, a_h) = \mathcal{P}(B_{h+1}/s_h, a_h) \cdot \mathcal{P}(U_{h+1}/s_h, a_h) \cdot \mathcal{P}(F_{h+1}/s_h, a_h) \cdot \mathcal{P}(K_{h+1}/s_h, a_h) \quad (3.8)$$

The battery state of charge at the beginning of time slot  $h + 1$ , denoted by  $B_{h+1}$ , is completely known if we know state  $s_h$  and action  $a_h$  taken at time slot  $h$ . Thus the battery transition probability is deterministic and can be expressed as follows:

$$\mathcal{P}(B_{h+1}/s_h, a_h) = \begin{cases} 1 & \text{if } B_{h+1} = B_h + c_h \cdot B_{max} - n_{TX} \cdot T_c \cdot d_h \cdot (P_0 + \Delta_p \cdot P_{out} \cdot U_h) \\ 0 & \text{otherwise} \end{cases}$$

The energy price, user traffic load and the blocking requests are assumed to be independent and non-correlated in time. Thus:  $\mathcal{P}_h(F_{h+1}/F_h, a_h) = \mathcal{P}_h(F_{h+1})$ ,  $\mathcal{P}_h(U_{t+1}/U_h, a_h) = \mathcal{P}_h(U_{h+1})$  and  $\mathcal{P}_h(K_{t+1}/K_h, a_h) = \mathcal{P}_h(K_{h+1})$

**Instantaneous reward:** It refers to the money that the network operator spends or earns (thanks to the DR reward) at time slot  $h$ .



If the grid asks the operator to stop consuming energy for the next hour ( $K_h = 1$ ), the operator has two choices:

- To be powered by its own battery ( $d_h = 1$ ). The reward in this case is:

$$r_h(s_h, a_h) = -rw \quad (3.9)$$

- To be powered by the grid ( $d_h = 0$ ). The operator pays a penalty to the energy provider in addition to its energy consumption fees. The reward is in this case:

$$r_h(s_h, a_h) = F_h \cdot \left[ T_c \cdot n_{TX} (P_0 + \Delta_p \cdot P_{out} \cdot U_h) + \frac{1}{\gamma_c} \cdot c_h \cdot B_{max} \right] + pe - rw \quad (3.10)$$

where:

- $F_h$  is the electricity unitary price during hour  $h$ .
- $T_c$  is the number of co-located technologies at the eNB.
- $n_{TX}$  is the number of transceivers in the eNB.
- $P_0$  is the power consumed for traffic independent features.
- $\Delta_p$  is the slope of load dependent power consumption. It is the conversion rate between the irradiated power and the consumed power due mainly to the amplification gain.
- $P_{out}$  is the irradiated power by the eNB's antennas.
- $U_h$  is the users traffic load in the cell.
- $\gamma_c$  is the charge energy efficiency.
- $c_h \cdot B_{max}$  is the amount of energy purchased from the grid and stored in the battery.
- $pe$  is the value of the penalty paid by the MNO when it does not respond favorably the requests of the grid.
- $rw$  is the value of the reward per hour after signing the DR annual contract.

If the energy provider does not ask for energy blocking ( $K_h = 0$ ), the operator pays the normal price:

$$r_h(s_h, a_h) = F_h \cdot \left[ (1 - d_h) \cdot T_c \cdot n_{TX} (P_0 + \Delta_p \cdot P_{out} \cdot U_h) + \frac{1}{\gamma_c} \cdot c_h \cdot B_{max} \right] - rw \quad (3.11)$$

### **Demand response with probabilistic knowledge of blocking requests**

In this subsection, we treat the case when the network operator knows only the probability of blocking requests  $\mathcal{P}(X = K_h)$ . The MNO decides at the beginning of the hour one action and assumes the consequences of it. If it receives a request of the grid, it pays the penalty and pays nothing if no request occurs. The MDP in this case can be expressed as follows:

**State space:** The blocking request variable is not counted in the state space. The state is denoted by  $s_h = (B_h, U_h, F_h)$

**Action space:** The action  $a_h = (d_h, c_h)$  is the same as before. In this case, the actions are chosen without being sure if the grid request will occur or not. The MNO will execute the action and assumes the consequences if there is a penalty to pay.

**Transition probabilities:**

$$\mathcal{P}_h(s_{h+1}/s_h, a_h) = \mathcal{P}_h(B_{h+1}/s_h, a_h) \cdot \mathcal{P}_h(U_{h+1}/s_h, a_h) \cdot \mathcal{P}_h(F_{h+1}/s_h, a_h) \quad (3.12)$$

All state variables have the same transition probabilities as in the case of deterministic knowledge of the blocking requests.

**Instantaneous reward:** The hourly operator expenditure for energy is expressed as follows:

- If the operator uses its battery:

$$r_h(s_h, a_h) = -rw \quad (3.13)$$

- If the operator is powered by the grid:

$$r_h(s_h, a_h) = F_h \cdot [T_c \cdot n_{TX}(P_0 + \Delta_p \cdot P_{out} \cdot U_h) + c_h \cdot B_{max}] - rw + pe \cdot P(K_h = 1) \quad (3.14)$$

In this case, the blocking probability appears only in the instantaneous reward and is not taken into account in the state space and transition probabilities.

### 3.2.4 MDP solving

Both MDPs can be solved using the same policy iteration technique in subsection 2.2.3 when including the corresponding input parameters: state space, action space, transition probabilities and the instantaneous reward as described before.

They have both the same objective of minimizing the daily energy expenditure:

$$\min_{\mu} E^{\mu} \left( \sum_{h=0}^{N-1} r_h(s_h, a_h) \right) \quad (3.15)$$

Here, there is no constraints on the battery usage or on the its cycling strategy.

---

**Algorithm 2** Case of deterministic knowledge of blocking probabilities

---

**Inputs:**  $B_{max}, \bar{F}, \bar{U}, \bar{P}_{bl}, s_t = (B_H, F_h, U_h, K_h), a_h = (d_h, c_h), p(s_{h+1}|s_h, a_h)$

**Function:** Optimal battery management plan in case of deterministic knowledge

**Initialize:**  $V_N = r_N = 0, V_t(s_t) = 0, h=N-1$  and  $\beta_0(s) = \alpha(s_0)$

- 1: **while**  $h > 0$  **do**
  - 2:    $\forall s \in S, \forall a \in A$
  - 3: Calculate  $r_h(s_h, a_h) = F_h \cdot (1 - d_h) [T_c \cdot n_{TX}(P_0 + \Delta_p \cdot P_{out} \cdot U_h) + c_h \cdot B_{max}] + 1_{K_h=1} \cdot pe - rw$
  - 4:   Policy improvement step:  $\mu_h(s) = \underset{a \in \Omega_h(s)}{\operatorname{argmin}} [r_h(s, a) + \sum_{s' \in S} p_h(s'/s, a) \cdot V^{(h+1)}(s')]$
  - 5:   Policy evaluation step:  $V_\lambda^{(h)}(s) = r_h(s, \mu_h) + \sum_{s' \in S} p_h(s'/s, \mu_h(s)) \cdot V^{(h+1)}(s')$
  - 6:    $h \leftarrow h - 1$
  - 7: **end while**
  
  - 8: **for**  $k=0:N-1$  **do**
  - 9:   Calculate the occupation measures:  $\beta_{k+1}(s) = \sum_{s' \in (S)} \mathcal{P}_k(s/s', \mu_k(s')) \cdot \beta_k(s')$
  - 10:   Calculate the average battery SOC at each time slot:  $\bar{B}_{k+1} = \sum_{s \in S} \beta_{k+1}(s) \cdot B_s(k)$
  - 11:   The MNO average hourly expenditure:  $\bar{r}_k = \sum_{s \in S} \beta_k(s) \cdot r_k(s, \mu_k(s))$
  - 12: **end for**
  - 13: Calculate the daily expenditure of the operator:  $\bar{R} = V_0(s_0)$
- 

---

**Algorithm 3** Case of probabilistic knowledge of blocking probabilities

---

**Inputs:**  $B_{max}, \bar{F}, \bar{U}, \bar{P}_{bl}, s_t = (B_t, F_t, U_t), a_t = (d_t, c_t), p(s_{t+1}/s_t, a_t)$

**Function:** Optimal battery management plan in case of probabilistic knowledge

**Initialize:**  $V_N = r_N = 0, V_t(s_t) = 0, h=N-1$  and  $\beta_0(s) = \alpha(s_0)$

- 1: **while**  $h > 0$  **do**
  - 2:    $\forall s \in S, \forall a \in A$
  - 3: Calculate  $r_h(s_h, a_h) = F_h \cdot (1 - d_h) [T_c \cdot n_{TX}(P_0 + \Delta_p \cdot P_{out} \cdot U_h) + c_h \cdot B_{max}] + P(K_h = 1) \cdot pe - rw$
  - 4:   Policy improvement step:  $\mu_h(s) = \underset{a \in \Omega_h(s)}{\operatorname{argmin}} [r_h(s, a) + \sum_{s' \in S} p_h(s'/s, a) \cdot V^{(h+1)}(s')]$
  - 5:   Policy evaluation step:  $V_\lambda^{(h)}(s) = r_h(s, \mu_h) + \sum_{s' \in S} p_h(s'/s, \mu_h(s)) \cdot V^{(h+1)}(s')$
  - 6:    $h \leftarrow h - 1$
  - 7: **end while**
  
  - 8: **for**  $k=0:N-1$  **do**
  - 9:   Calculate the occupation measures:  $\beta_{k+1}(s) = \sum_{s' \in (S)} p_k(s/s', \mu_k(s')) \cdot \beta_k(s')$
  - 10:   Calculate the average battery SOC at each time slot:  $\bar{B}_k = \sum_{s \in S} \beta_k(s) \cdot B_s(k)$
  - 11:   The MNO average hourly expenditure:  $\bar{r}_k = \sum_{s \in S} \beta_k(s) \cdot r_k(s, \mu_k(s))$
  - 12: **end for**
  - 13: Calculate the daily expenditure of the operator:  $\bar{R} = V_0(s_0)$
- 

### 3.2.5 Numerical applications

The time is divided into slots of 1 hour each and the optimization is done on a daily basis  $N = 24$ . We take  $M = 21$  states of battery charge. We consider here a Lithium battery with a capacity  $B_{max} \in \{16, 32, 48\}$  KWh.

At the beginning of each time slot, we make a projection of the SOC on  $[0, \frac{B_{max}}{M-1}, \dots, B_{max}]$

following the rule below:

$$\begin{aligned}
& \text{If } B_{h+1} \in \left[ (2\alpha - 1) \frac{B_{max}}{2(M-1)}, (2\alpha + 1) \frac{B_{max}}{2(M-1)} \right[ \text{ then } B_{h+1} = \alpha \cdot \frac{B_{max}}{(M-1)} \quad \forall \alpha \in [1, M-2] \\
& \qquad \text{If } B_{h+1} \in \left[ 0, \frac{B_{max}}{2(M-1)} \right[ \text{ then } B_{h+1} = 0 \\
& \qquad \text{If } B_{h+1} \in \left[ B_{max} - \frac{B_{max}}{2(M-1)}, B_{max} \right] \text{ then } B_{h+1} = B_{max}
\end{aligned}$$

In these simulations, we assume that the MNO can use all the capacity available in its battery (no SOC limitations) and that there is no restrictions on the number of cycles to be performed by the battery per day. With respect to the results in [63], as we execute deep cycles discharge with the battery, the charge/discharge energy efficiencies are taken to be equal to ( $\gamma_c = \gamma_d = 0.9$ ).

The SOC consideration presented in section 1 are not taken into account in this model. In fact, reducing the capacity allocated for energy supply using the battery, will be fatal for the MNO expenses as the value of the penalty is chosen to be 10 times higher that of the reward. Thus, we decided to allocate 100% of the battery capacity allowing it to sustain the consumption of the eNB for longer periods of time and avoid paying the penalty even if this will shorten its lifetime.

We assume that the distribution of the electricity real prices follows a trinomial distribution with 1 trial. We base our model on European trading market EPEX type of pricing for electricity which indicates an estimated price of energy one day ahead based on demand and supply. We take the italian use case in [68]. As this day-ahead price might differ from the actual one, we added 0.15 probability for it to be a little higher or a little lower.

The same argument holds for user traffic. The average traffic load is taken from the model in [23]. We assume that the probability that the user traffic is equal to the average value is 0.5 and the probabilities to be equal to the value below or to the value above are equal to 0.25 each.

Our algorithm is nevertheless optimal for any distribution which respects the Markov criteria and the ergodicity of the Markov chain (no absorbing states and no periodicity in states transitions).

The energy consumption model of the macro base stations is taken also from [23]. We suppose that  $P_0 = 118.7W$ ,  $\Delta_p = 5.32$ ,  $n_{trx} = 6$ ,  $T_c = 5$  and that the eNB is transmitting with its maximal power  $P_{out} = 20W$ .

The operator can buy energy from the grid with predefined portions:  $c_h \in [0, 0.2, 0.4, 0.6, 0.8, 1]$ . If  $c_h \geq 0$  and  $d_h = 0$ , the operator is powered by the grid and can also buy energy to charge its battery. If  $c_h = 0$  and  $d_h = 1$ , the operator is using its own battery.

We take the penalty  $pe$  to be equal to 1 € if the operator does not respond to the requests of the grid and an hourly income  $rw$  of 10 cents of euros thanks to the contract signed at the beginning of the year. This makes the contract value equal to 857 euros per year for one eNB site.

We consider a case with high blocking request probabilities, with an average blocking time period of 6.4 hours per day and we compare the cases with no demand response, with a deterministic one and a probabilistic one.

The case with no DR is simulated by setting the reward  $rw = 0$  and the probability of grid requests  $P(K_h = 1) = 0$  for all day hours  $h \in [0, \dots, N - 1]$ .

Fig. 3.13 shows the evolution of the average battery SOC for a battery size of 16 KWh for the cases of demand response with deterministic and probabilistic knowledge and without demand response. The average daily energy prices, the average users traffic demand and the high blocking requests daily profiles are shown at the top of the figure, to ease illustration.

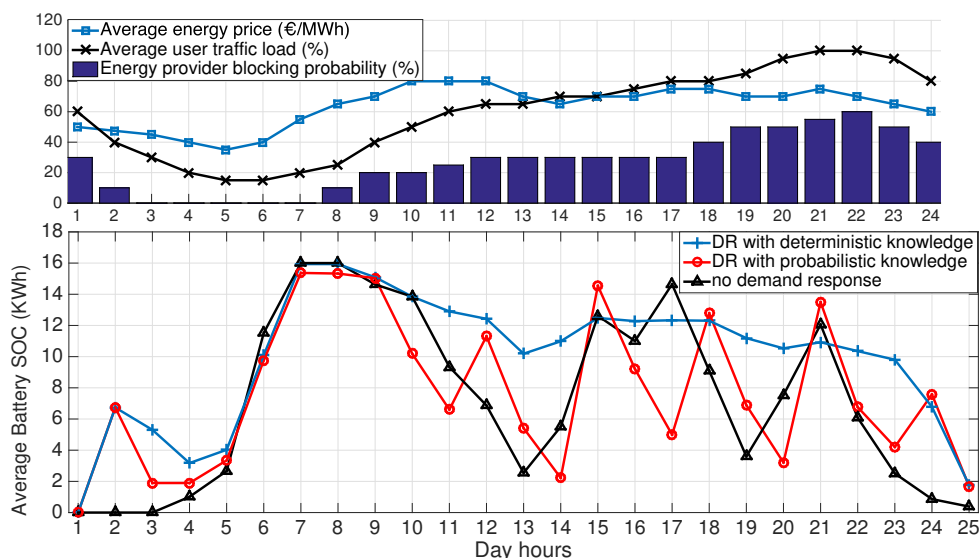


Figure 3.13: The impact of the knowledge on the average SOC evolution for 16 KWh battery size

We observe in Fig. 3.13 that the shapes of the curves of the average battery state of charge evolution during the day differ a lot between the cases listed before. This is due to the small battery size which does not allow long hours of energy self autonomy.

Due to the high value of the penalty compared to the actual consumption fees, the main observed tendency in case of demand response is to avoid paying the penalty. That is why, we note that at 1 am, as the battery is empty and even if the electricity price is higher than at 2 am, the operator chooses in both cases of demand response (with deterministic and probabilistic knowledge) to charge its battery in order to use it for one hour and so avoid paying the penalty.

For a battery size of 16 KWh, energy self autonomy can last between 2 and 3 hours during the day. When demand response does not hold, we note that the operator takes advantage of the energy unitary prices by being powered by the grid while charging its battery at low electricity prices and relies on its own storage when the prices go high.

In the case of demand response with deterministic knowledge, the MNO, thanks to its perfect knowledge of the blocking requests, manages to fill its battery to the maximum when the grid does not ask it to stop consuming and relies on it when blocking occurs which explains why the battery average SOC stays above a certain level. At the end of the day, between 10 pm and midnight, blocking is the highest, the MNO relies exclusively on its battery to empty it at the end of the day.

We note that the operator, in the case of probabilistic knowledge demand response, tries to limit the number of times it uses the grid. When the battery cannot sustain the infrastructure consump-

tion, the operator always charges it to the maximum during one hour in order to stay in energy self autonomous mode as long as possible (2 to 3 hours in this case) and avoid paying the penalty. We note also that the operator chooses the hours in which the blocking is in a local minimum to charge its battery. The effect of the energy price in this case becomes negligible as the value of the penalty is much higher than the energy consumption fees.

In Fig. 3.14, we produce the same curves for the case when the operator is endowed with a large battery size equal to 48 KWh.

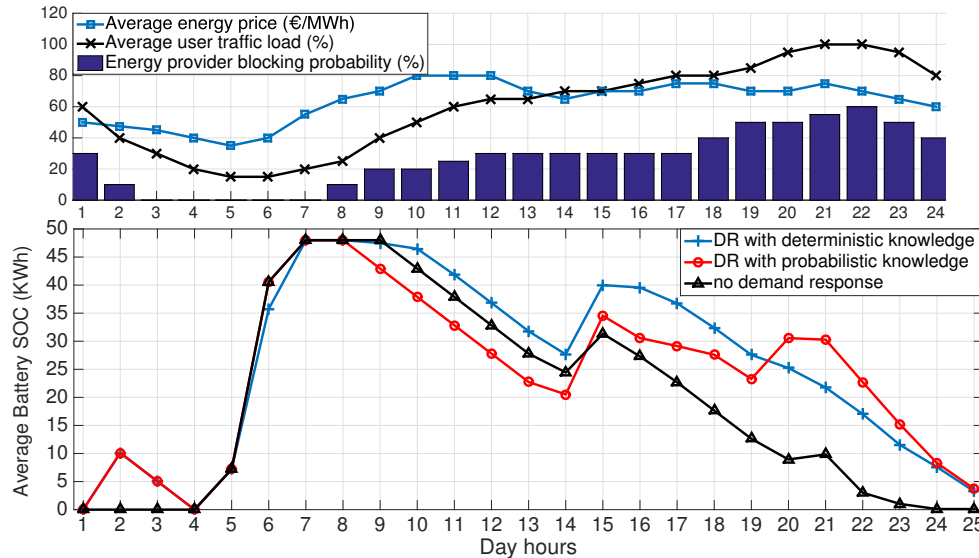


Figure 3.14: The impact of the knowledge on the average SOC evolution for 48 KWh battery size

For the battery size of 48 KWh, we observe that the curves of the average battery state of charge have the same shapes independently from the knowledge and even compared to the case when demand response does not hold. We can see clearly in this case that having a large battery size allows the operator to stay for a long period of time in energy self-autonomous mode (between 8 and 10 hours) and so it can rely on its reserves when the blocking probability becomes important and so avoids paying the penalty which was not possible when  $B_{max} = 16$  KWh.

In fact, as the blocking probabilities and the energy prices have a close distribution over the day, the operator, even if it is not eligible to demand response, will try to charge its battery at low prices and avoid using the grid when the prices get higher taking advantage of its large battery reserves.

When the operator has a perfect knowledge of the blocking requests, it charges its battery when there are no blocking requests and when the prices are in local minima at 5 AM and 2 PM and then relies mainly on its battery till the end of the day.

Having a large battery size allows the operator, even under probabilistic knowledge, to anticipate the future blocking requests as it can stay in self autonomous mode for a long period of time and so respects almost all the requests of the grid to stop the consumption when needed. In fact, after 8 AM, it solicited the grid only 2 times: at 2 PM and 7 PM when the prices were in two local minima,

to charge its battery. That was enough for it to be able to satisfy its own demand until the end of the day when the blocking probability and energy prices got higher.

In Figs. 3.15 and 3.16, we vary the blocking request distribution and we compare the daily energy bill saving by the network operator in the three cases stated above. This saving is relative to the case when the operator is not a part of demand response feature and has no battery and so it is forced to be powered exclusively by the smart grid during the whole day.

We consider two cases: low and high blocking request probabilities, with an average blocking of 3.2 hours per day in the first case and 6.4 hours per day in the second. For the case of low blocking probability presented in Fig. 3.15, the operator has to respond favorably to more than 31% of the grid blocking requests to be able to gain money thanks to demand response contract. In the second case presented in Fig. 3.16, the operator has to respect more than 62% of the requests in order to save money compared to the case when demand response does not hold.

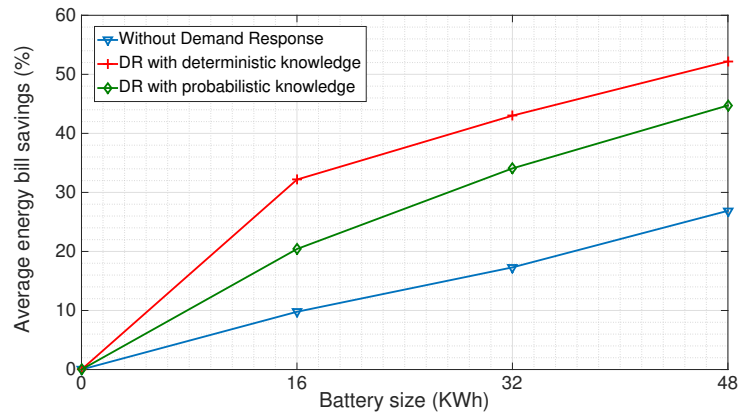


Figure 3.15: The impact of the knowledge on the average energy expenditure of the MNO at low blocking probability

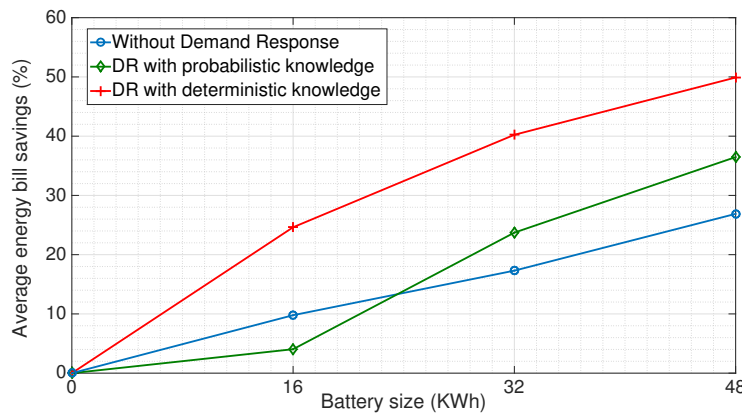


Figure 3.16: The impact of the knowledge on the average energy expenditure of the MNO at high blocking probability

From Fig. 3.15, we can see trivially that the deterministic knowledge case gives the best performance. As the blocking probability is low, the operator was able to well anticipate the requests and so take advantage of demand response even with probabilistic knowledge to reduce its energy bill. We can note also that the larger the battery, the smaller the gap between the gain achieved by the two demand response policies compared to the case when the operator is powered exclusively by the grid.

At high blocking probability, we can see from Fig. 3.16 that having a battery size of 16 KWh does not allow the operator to take advantage of demand response with probabilistic knowledge. The small size of the battery prevents the operator from anticipating the blocking requests as it cannot stay in self autonomous mode for a long period of time forcing it at a certain point to use the grid and pay the penalty. Higher battery sizes are more fitted to demand response case even with probabilistic knowledge. The operator can have enough energy to support long hours of autonomy when the energy provider is undergoing high electricity load.

### **3.2.6 Main findings**

In this section, we addressed the issue of energy management strategies for a MNO part of an incentive based demand response agreement with the grid. The MNO has to respect the requests of the energy provider to stop consuming from the grid at high electricity peak loads.

We treated the cases when the operator has a deterministic, a prior knowledge of the requests that the energy provider could make in the following hours and the case when it only knows the distribution of these requests and we compared the average financial savings that could be achieved in both cases.

We saw that the demand response feature, even with probabilistic knowledge, can be very beneficial to the operator especially if it is equipped with a large battery allowing it to be in self autonomous mode for a long period of time and so be able to respond to the requests of the energy provider and avoid paying the penalties when the request is not respected.

The value of the demand response contract, the smart grid DR requests distribution are important parameters that make the operator decide on the long term if it is beneficial to invest in storage devices and if it has to be involved in demand response program with the energy provider.



### 3.3 Joint battery management and traffic scheduling strategy

In this section, we aim to implement a strategy allowing the MNO to adapt its traffic with respect to the smart grid dynamics. Many works are done in order to save energy at low traffic load periods: The MNO can turn off some technologies (3G, HSDPA, etc), decrease the transmission power or the downlink bandwidth or yet implement some sleep mode schemes. All these strategies are only correlated with the traffic in the cell and have no link with the grid. If we can apply them, it is only under the condition of maintaining an acceptable QoS whether the electricity prices are low or high. The MNO can nevertheless implement some traffic rescheduling techniques for traffic that tolerates delays such as P2P at the network level or the software update at users terminals level with their approval.

For this, we address joint battery management and traffic scheduling problem for a MNO linked to a smart grid. As considered before, the eNB can be powered either by the electricity purchased from the grid or by its reserves stored in its own battery. The operator has to satisfy all its subscribers traffic demands. This traffic is categorized in 2 main types: A delay sensitive traffic that has to be processed instantaneously and a delay tolerant traffic that can be processed after some hours when the eNB has enough energy and processing capacity. The problem can be seen as a Constrained Markov Decision Process (CMDP) for which we can apply a primal dual optimization algorithm based on both Lagrange formulation and DP in order to devise a deterministic offline joint battery management and traffic scheduling strategy. Our aim is to minimize the operator's daily expenses for energy while respecting on average the queuing delay constraints on the users traffic demand.

#### 3.3.1 Context and related works

The MNOs are facing a growing need in mobile applications requiring higher data rates and processing capabilities [1]. This increases the eNB energy consumption and the operational expenditure of the operator driving us to the need to deploy alternative power sources and to set traffic scheduling strategies compliant with the dynamics of the smart grid environment.

Here too, the eNB is endowed with a battery and is powered by a smart grid and experiencing time-varying electricity prices and dynamic traffic loads with variable delay constraint applications at the users terminals.

The fluctuations of the energy prices are visible on an hourly basis. On the other hand, the average duration of most services is about some minutes and has to be treated shortly in time. In our case, we call delay tolerant the traffic that the operator can delay for some hours without affecting the users experience [69].

In this scenario, we investigate joint dynamic optimization that aims at minimizing the communication operator energy costs under constraints on the delivery delay of the services provided to its clients. To do so, the operator has to take advantage of the fluctuations of the electricity prices fixed by the grid and optimally schedule the traffic with respect to the energy available in its battery and to the service delay constraint.

The authors in [71], proposed for instance a traffic calendaring strategy based on packets active queue management with respect to its priority ensuring that the packet loss remains under a certain threshold.

We set in this section a joint battery management and non-critical traffic scheduling strategy that aims at minimizing the MNO energy expenditure. Therefore, the non-critical traffic scheduling and battery charge/discharge decisions are adapted to the time-varying electricity prices and user traffic load in order to reduce the average daily energy bill under average delivery delay constraints. We formulate this problem as a Constrained Markov Decision Problem (CMDP). Then, using dynamic programming tools and Lagrange formulation, we investigate offline solutions to find the optimal deterministic strategy that solves this convex optimization problem.

### 3.3.2 System model

As stated above, the users in the cell could require two types of traffics:

- A delay sensitive traffic which cannot be delayed and has to be processed in a very short time by the operator. This includes voice, internet browsing, video streaming, etc. We assume that the traffic has a fixed hourly load known on average by the operator. It depends on the users' density in the covered area and the type of requested services. Let  $U^i$  denote the ratio in time slot  $h$  between the actual instantaneous traffic demand and the maximal load at peak hours. In peak hours When  $U^i = 1$ , we assume that the operator cannot treat any additional traffic.
- A delay tolerant traffic such as software updating and P2P communications. This traffic can be delayed and processed later by the eNB, allowing the MNO to alleviate the load on the network at peak hours. This traffic can be delayed to be served later in periods in which the energy reserves are high and electricity prices are low. We split this traffic into packets of equal sizes. Let  $C^d$  denote the ratio between 1 packet of delay tolerant applications and the load at peak hour. We assume that  $A^d$  users' packets arrive and that the eNB will process  $U^d$  packets. The packets arrival is randomized and follows a Poisson process with an average arrival rate equal to  $\bar{a}_d$ .

The delay sensitive traffic has the priority to be treated. The operator can only use the remaining radio/processing capacity to treat its delay tolerant requests. If the remaining capacity does not allow it to, the communication operator enqueues the user requests in a FIFO buffer [72] with maximal size  $Q_{max}$  packets as shown in Fig. 3.17.

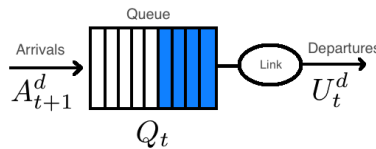


Figure 3.17: Non critical traffic FIFO queue evolution

We assume that time is divided into equal epochs indexed by  $h$ . We take  $h$  as 1 hour in the numerical applications. The buffer length evolution in time is expressed as follow:

$$Q_{h+1} = \min(Q_{max}, Q_h + A_{h+1}^d - R_h^d) \quad (3.16)$$

where:

- $A_{h+1}^d$  is the packets arriving to the queuing buffer at the beginning of the time slot  $h + 1$ .
- $R_h^d$  is the number of delayable packets processed during time slot  $h$ .

The average queuing delay for these applications has to be under a certain threshold  $\bar{D}$ . If we were in an infinite time horizon system, following Little law [73], the average queuing delay can be see as a constraint on the average buffer length that can be expressed as:  $\bar{Q} = \bar{a}^d \times \bar{D}$ .

As we are in the case of a finite horizon of  $N$  hours, we impose that the average queue length of the delay tolerant applications should remain under a threshold equal to  $\bar{Q}$  packets with minimal packet loss.

We assume in this section that the MNO is a simple consumer and does not sell electricity back to the grid. We assume that the eNB can be powered using two possible power sources:

- The electricity purchased from the grid.
- Its reserves already stored in the battery.

We do not consider the constraints on the SOC limitations and the maximal number of cycles performed by the battery. The battery state of charge (SOC) is discretized into finite values in  $[0, \dots, B_{max}]$ . Its evolution in time can be expressed as follows:

$$B_{h+1} = B_h + c_h \cdot B_{max} - \frac{1}{\gamma_d} \cdot n_{tx} \cdot d_h \left( P_0 + P_{out} \cdot \Delta_p \cdot (A_h^i + C^d \cdot R_h^d) \right) \quad (3.17)$$

where:

- $c_h \cdot B_{max}$  is the amount of energy that the operator could buy from the grid.
- $\gamma_d$  is the discharge energy efficiency.
- $n_{TX}$  is the number of transceivers in the eNB.
- $d_h$  is the action of switching between the battery and the smart grid.  $d_h = 1$  when the MNO is powered by the battery.
- $P_0$  is the power consumed for traffic independent features.
- $P_{out}$  is the irradiated power by the eNB's antennas.
- $\Delta_p$  is the slope of load dependent power consumption.
- $A_h^i$  is the delay sensitive traffic load.

We consider the case of Lithium battery. We assume that the operator can use all the available battery capacity and charge and discharge its battery by a rate of 1 C. We assume furthermore that the battery, with this usage, operates with a charge and discharge efficiencies  $\gamma = \gamma_c = \gamma_d = 94\%$ .

### 3.3.3 Constrained Markov Decision Process formulation

Our objective is to minimize the daily expenditure of the MNO to purchase energy from the smart grid under the constraints that the average queue length of the non-critical applications does not exceed a certain threshold  $\bar{Q}$  and that the buffer overflow is kept minimal. Let  $\bar{\mu}^*$  denote this optimal policy. It is a sequence of control decisions that specify, at the beginning of each hour of the day, if MNO has to be powered by the grid or by its own battery, the amounts of energy to be bought from the grid and the number of non-critical traffic packets to be treated by the eNB.

The system can be seen as an ergodic Markov chain leading to a CMDP and could be solved using dynamic programming tools. We can define the following components of this CMDP :

**State space:** At each time slot  $h$ , the system states are denoted by  $s_h = (B_h, U_h^i, Q_h, F_h)$ ; with  $B_h$  the battery state of charge,  $U_h^i$  the instantaneous traffic load that has to be treated at each time slot,  $Q_h$  the buffer length of the delay tolerant traffic not treated yet and  $F_h$  the unitary electricity price. All these variables are finite and discretized which makes the state space finite too.

**Action space:** It represents the actions that the operator has to perform at the beginning of each time slot  $h$ , which are denoted by  $a_h = (d_h, c_h, R_h^d)$ .  $d_h$  is the decision of being powered by the smart grid or by its own battery,  $c_h$  denotes the amount of energy to buy from grid and  $R_h^d$  is the number of delayed packets treated by the eNB at each time slot. The operator has no choice on the priority traffic. All the packets arriving to the operator have to be treated instantaneously thus, we do not consider it in the action space.

**Transition probability:** They represent the probability of reaching state  $s_{h+1}$  at time slot  $h + 1$  when the system was in state  $s_t$  and when the action performed is  $a_h$  at time slot  $h$ . The system state action space is an ergodic Markov chain  $p(s_{h+1}/s_h, a_h, \dots, s_0, a_0) = p(s_{h+1}/s_h, a_h)$ .

All the state space variables are independent of each other thus:

$$p(s_{h+1}/s_h, a_h) = p(B_{h+1}/s_h, a_h) \times p(U_{h+1}^i/s_h, a_h) \times p(F_{h+1}/s_h, a_h) \times p(A_{h+1}^d/s_h, a_h) \quad (3.18)$$

$$\text{with: } \mathcal{P}(B_{h+1}/s_h, a_h) = \begin{cases} 1 & \text{if } B_{h+1} = B_h + c_h \cdot B_{max} - \frac{1}{\gamma_d} \cdot d_h \cdot n_{tx} \cdot (P_0 - \Delta_p \cdot P_{out} \cdot (A_h^i + C^d \cdot R_h^d)) \\ 0 & \text{otherwise} \end{cases}$$

and

$$p(A_{h+1}^d/s_h, a_h) = p(A_{h+1}^d = Q_{h+1} - (Q_h - U_h^d))$$

The energy price and the traffic load are independent and non-correlated in time, thus:

$$\mathcal{P}(F_{h+1}/F_h, a_h) = \mathcal{P}(F_{h+1}) \text{ and } \mathcal{P}(U_{h+1}/U_h, a_h) = \mathcal{P}(U_{h+1})$$

**Instantaneous reward:** It represents the money spent by the operator for energy for the next hour knowing that the system is in state  $s_h$  and that it performed action  $a_h$ .

$$r_h(s_h, a_h) = F_h \cdot \left( \frac{1}{\gamma_c} \cdot c_h \cdot B_{max} + (1 - d_h) \cdot n_{tx} \cdot (P_0 + P_{out} \Delta_p (A_h^i + C^d \cdot R_h^d)) \right) \quad (3.19)$$

Our objective can be expressed as follows:

$$\min_{\bar{\mu}} E^{\bar{\mu}} \left( \sum_{h=0}^{N-1} (r_h(s_h, a_h)) \right) \quad (3.20)$$

$$s.t. \quad E^{\bar{\mu}} \left( \frac{1}{N+1} \cdot \sum_{h=0}^N Q_h \right) \leq \bar{Q} \quad (3.21)$$

$$and \quad E^{\bar{\mu}} \left( \frac{1}{N} \cdot \sum_{h=0}^{N-1} \max(Q_{h+1} - Q_{max}, 0) \right) = \min_{\bar{\mu}} E^{\bar{\mu}} \left( \frac{1}{N} \cdot \sum_{h=0}^{N-1} \max(Q_{h+1} - Q_{max}, 0) \right) \quad (3.22)$$

Eqn. (3.20) represents the objective function which consists of minimizing the average money spent by the operator on the whole day for energy acquisition. This value is an expectation over all the possible transitions between the states of the Markov chain following policy  $\bar{\mu}$ .

Eqn. (3.21) represents the constraint that verifies that average queue length of the non-critical traffic has to remain lower than a certain threshold  $\bar{Q}$  packets.

Eqn. (3.22) represents the constraint that verifies that average buffer overflow is equal to the minimum possible value  $\bar{O}^*$  over all possible policies.  $\bar{O}^*$  may or not be equal to 0 due to the fact that the number of treated packets is limited by the remaining capacity at the eNB after serving the delay non-tolerant traffic. It can be easily calculated by assuming that the MNO at each hour will treat exactly the minimum between the number of packets in its queue and the maximum number of packets that can be served with respect to its remaining capacity.

The average constraints in Eqn. (3.21) and (3.22) are both convex relative to the number of processed packets  $R_h^d$ . The objective function in Eqn. (3.20) is also convex relative to  $R_h^d$  [74]. Thus, we can convert our constrained problem to a non-constrained one using Lagrange formulation.

The modified non-constrained MDP has the same state and action spaces and the same transition probabilities as the constrained one. The only difference compared to the original one is the fact that we adopt a new instantaneous reward function that relates the objective in Eqn. (3.20) to the average constraints in Eqn. (3.21) and (3.22) using two Lagrange multipliers denoted by  $\lambda_1$  and  $\lambda_2$ . The Lagrange multiplier sets the weight of the instantaneous reward relative to the constraints on the queuing delay and the buffer overflow. The new instantaneous reward is expressed as:

$$L_h(s_h, a_h, \lambda_1, \lambda_2) = F_h \left( \frac{1}{\gamma_c} \cdot c_h \cdot B_{max} + (1 - d_h) \cdot n_{tx} \left( P_0 + P_{out} \Delta_p (A_h^i + C^d \cdot R_h^d) \right) \right) + \lambda_1 (Q_h - \bar{Q}) + \lambda_2 \cdot (\max(Q_{h+1} - Q_{max}, 0) - \bar{O}^*) \quad (3.23)$$

Let  $\bar{L}$  denote the averaged Lagrange function:

$$\bar{L}(\bar{\mu}, \lambda_1, \lambda_2) = E^{\bar{\mu}} \left( \sum_{h=0}^{N-1} L_h(s_h, \mu_h(s_h), \lambda_1, \lambda_2) \right) \quad (3.24)$$

As the problem is convex, the optimality is reached when the average queue length is equal to the constraint  $\bar{Q}$  and when the average buffer overflow is equal to  $\bar{O}^*$  [43].

The optimal policy  $\bar{\mu}^*$  is obtained by applying the primal dual algorithm and verifies the following relationship for the optimal Lagrange multipliers  $\lambda_1^*$  and  $\lambda_2^*$ :

$$\bar{\mu}^* = \underset{\bar{\mu} \in \Omega}{\operatorname{argmin}} \bar{L}(\bar{\mu}, \lambda_1^*, \lambda_2^*) = \underset{\bar{\mu} \in \Omega}{\operatorname{argmin}} E^{\bar{\mu}} \left( \sum_{h=0}^N L_h(s_h, \mu_t(s_h), \lambda_1^*, \lambda_2^*) \right) \quad (3.25)$$

### 3.3.4 Primal dual optimization algorithm

The goal of this algorithm is to find for this CMDP an optimal deterministic policy which solves the constrained average cost problem in Eqn. (3.20), (3.21) and (3.22) [37].

The average reward to optimize is convex relative to the policy and concave relative to the Lagrange multipliers. The optimal triplet  $(\lambda_1^*, \lambda_2^*, \bar{\mu}^*)$  is obtained in 2 steps as explained in algorithm 4 and represents a saddle point for the Lagrange function.

The primal dual optimization is based on two hierarchical relationships:

- The primal optimization: it consists of finding the optimal Lagrange multiplier to the following problem. It is obtained using gradient descent iterations.
- The dual optimization: it consists of finding the optimal policy for any particular Lagrange multiplier. It's based on a classic dynamic programming optimization.

For a known  $\lambda_1$  and  $\lambda_2$ , the **dual optimization** is handled by solving iteratively dynamic programming equations. The **primal optimization** is computed using the gradient descent iterations after applying the optimal policy  $\bar{\mu}_{\lambda_1, \lambda_2}^*$  for given Lagrange multipliers  $\lambda_1$  and  $\lambda_2$ . The Lagrange multipliers are approximated using gradient descent iterations by comparing the average queuing delay and the average buffer overflow to the constraints imposed until convergence is reached  $\lambda_{m+1,1} = \lambda_{m,1} = \lambda_1^*$  and  $\lambda_{m+1,2} = \lambda_{m,2} = \lambda_2^*$  with  $m$  the iteration index.

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#### Algorithm 4 Joint optimal battery management and traffic scheduling policy

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**Inputs:**  $B_{max}$ ,  $\bar{F}$ ,  $\bar{A}^i$ ,  $\bar{A}^d$ ,  $\bar{Q}$ ,  $s_h = (B_h, F_h, A_h^i, Q_h)$ ,  $a_h = (d_h, c_h, R_h^d)$ ,  $p(s_{h+1}/s_h, a_h)$

**Function:** Primal dual optimization for CMDP

**Initialize:**  $\lambda_{n,1} = 0$ ,  $\lambda_{n,2} = 0$  when  $n = 0$  and calculate the minimum possible buffer overflow  $\bar{O}^*$

```

1: while ( $\lambda_{n+1,2} - \lambda_{n,2} > 0$ ) do
2:   while ( $\lambda_{n+1,1} - \lambda_{n,1} > \epsilon$ ) do
3:     Initialize:  $V_{\lambda_{n,1}, \lambda_{n,2}}^N = r_N = 0$ ,  $V_{\lambda_{n,1}, \lambda_{n,2}}^h(s_h) = 0$ ,  $h=N-1$  and  $\beta_{\lambda_{n,1}, \lambda_{n,2}}^h(s) = \alpha(s_0)$ 
4:     while  $h \geq 0$  do
5:       dual optimization  $\forall s \in S, \forall a \in A$ 
6:       Calculate  $L_h(s_h, a_h, \lambda_{n,1}, \lambda_{n,2})$  from Eqn. (3.23).
7:       Policy improvement:  $\mu_h(s) = \operatorname{argmin}_{a \in \Omega_h(s)} [L_h(s, a, \lambda_{n,1}, \lambda_{n,2}) + \sum_{s' \in S} p_h(s'/s, a) \cdot V_{\lambda_{n,1}, \lambda_{n,2}}^{h+1}(s')]$ 
8:       Policy evaluation:  $V_{\lambda_{n,1}, \lambda_{n,2}}^h(s) = L_h(s, \mu_h(s), \lambda_{n,1}, \lambda_{n,2}) + \sum_{s' \in S} p_h(s'/s, \mu_h(s)) \cdot V_{\lambda_{n,1}, \lambda_{n,2}}^{h+1}(s')$ 
9:        $h \leftarrow h - 1$ 
10:    end while
11:   for  $h = 0 : N - 1$  do
12:     Calculate the occupation measures:  $\beta_{\lambda_{n,1}, \lambda_{n,2}}^{h+1}(s) = \sum_{s' \in (S)} p_h(s/s', \mu_h(s')) \cdot \beta_{\lambda_{n,1}, \lambda_{n,2}}^h(s')$ 
13:   end for
14:   Calculate the average queue length:  $\bar{Q}_{\lambda_{n,1}} = \frac{1}{N} \cdot \sum_{h=0}^N \sum_{s \in S} \beta_{\lambda_{n,1}, \lambda_{n,2}}^h(s) \cdot Q_s(h)$ 
15:   Calculate the average buffer overflow:  $\bar{O}_{\lambda_{n,2}} = \frac{1}{N} \cdot \sum_{h=0}^N \sum_{s \in S} \beta_{\lambda_{n,1}, \lambda_{n,2}}^h(s) \cdot \max(Q_s(h+1) - Q_{max}, 0)$ 
16:   primal optimization gradient descent equation for  $\lambda_{n,2}$ :  $\lambda_{n+1,2} = \lambda_{n,2} + \Phi_2(n)(\bar{O}_{\lambda_{n,2}} - \bar{O}^*)$ 
17:   primal optimization gradient descent equation for  $\lambda_{n,1}$ :  $\lambda_{n+1,1} = \lambda_{n,1} + \Phi_1(n)(\bar{Q}_{\lambda_{n,1}} - \bar{Q})$ 
   where:  $\Phi_1(n) = 0$  if  $\bar{O}_{\lambda_{n,2}} - \bar{O}^* > 0$  and  $0 < \Phi_1(n) \ll \Phi_2(n)$  if  $\bar{O}_{\lambda_{n,2}} = \bar{O}^*$ 
18:    $n \leftarrow n + 1$ 
19:   end while
20: end while

```

---

### 3.3.5 Numerical applications

In our simulations, the time is divided into equal slots of 1 hour each. The optimization is done over a period of one day thus  $N = 24$ . The operator has two possible choices on the size of Lithium batteries to be deployed: 4 and 8 KWh. The operator can use all the available capacity of the battery.

The battery is discretized into finite values  $[0, \frac{B_{max}}{M-1}, \dots, B_{max} - \frac{B_{max}}{M-1}, B_{max}]$  with  $M$  a value taken with respect to the battery size:  $M = 21$  when  $B_{max} = 4$  KWh and  $M = 41$  if  $B_{max} = 8$  KWh.

The electricity day ahead average prices are taken from the Italian energy provider [68]. We assume that prices at each hour follow trinomial distribution with one trial: the probability that the real prices are equal to the day ahead prices is about 0.7 and the probabilities to be equal to the value below or above are equal to 0.15 each.

The energy consumption model of the macro base stations is taken from [23]. We assume that  $P_0 = 118.7$  Wh,  $\Delta_p = 5.32$ ,  $n_{tx} = 6$  and that the eNB is transmitting with a power  $P_{out} = 20$  W. Following this model, the eNB consumes about 1.3 KWh at maximal capacity and about 0.7 KWh when there is no traffic.

As we mentioned before, if  $c_h = 0$  and  $d_h = 1$ , the operator infrastructure runs in this case using its own battery. If  $c_h > 0$  and  $d_h = 0$ , the operator has to switch off its battery and be powered exclusively by the smart grid while its battery is charging. If  $c_h = 0$  and  $d_h = 0$  then the MNO is operating its system using the grid without charging its battery.

The average user delay sensitive traffic model is taken from [23]. The traffic follows a trinomial distribution with one trial. The probability that the real traffic is equal to the average is 0.5 and the probability to be equal to the value above or below is 0.25 each.

The load of non-critical traffic is expressed in packets of equal sizes. It arrives to the eNB following a Poisson distribution with an average arrival rate  $\bar{a}_d$  expressed in packets per hour. We assume that one packet of delayable traffic represents around  $C_d = 20$  % of the load at peak hour. The non-critical traffic that cannot be treated is queued in a buffer to be processed later. The buffer is FIFO and its maximal size is  $Q_{max} = 10$  packets.

In the simulations, we choose two possible values for the non-critical traffic arrival rate: 0.5 to 1 packets/hour corresponding to 10 % and 20 % of the whole system capacity. The instantaneous traffic consumes on average 60 % of the whole system capacity on a whole day. The remaining capacity allows the eNB to treat at maximum a non-critical traffic with an arrival rate of 1.54 packets/hour in case if we do not consider overflow constraint and arrival rate of 1.32 packets/hour if we do not tolerate any packet loss. The traffic independent features consume about 0.712 KWh. The eNB needs 0.383 KWh on average to treat the instantaneous traffic.

Having a delayable traffic with an arrival rate of 0.5 packets/hour represents about 12.5 % of the total traffic making the eNB consume about 0.0638 KWh in order to serve it which represents 5.5 % of the eNB total power consumption. When the arrival rate is 1 packets/hour, it is 25 % of the total traffic and needs about 0.1276 KWh which represents 10.45 % of the eNB consumption.

We devise using primal dual algorithm the optimal policy combining battery management and

traffic scheduling under different scenarios. Results show that the devised strategy respects the queuing delay constraints of users traffic and that there were no packet losses.

In the first experiment, we devise the average daily money saved by the operator while varying the queue length constraint of the non-critical traffic. This saving is relative to the case when the non-critical traffic has to be treated instantaneously while applying the same energy management strategy. We present the curves for 2 battery sizes of 4 and 8 KWh and an average non-critical traffic arrival rate of 1 packet/hour.

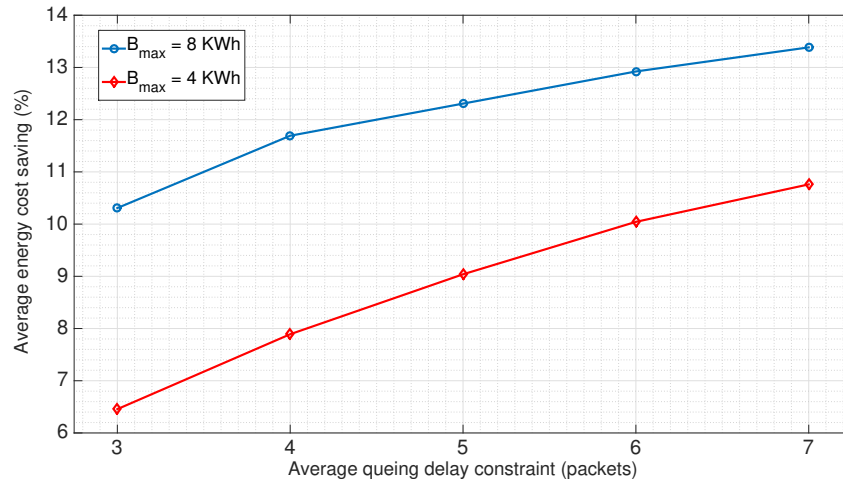


Figure 3.18: The average energy expenditure saving for different buffer length queuing constraints

Fig. 3.18 confirms the convexity of our problem. In fact, as we alleviate the constraint on the average queue length, the operator expenses for energy decrease and the operator saves more money compared to the case when this additional non-critical traffic has to be processed instantaneously. In fact, by alleviating this constraint on the queuing delay of the packets, we give the operator more time to take advantage of the right moments to process this traffic powered by the grid when the electricity prices are low or by its battery when there are enough reserves.

We note also that when the battery is large, the fact of delaying traffic yields higher financial gain for the operator. In fact, thanks to the storage, it will be able to have enough energy to process both instantaneous and delayable traffic in the right moments and so avoid purchasing electricity from the grid.

In Fig. 3.19, we compare the operator's expenses increase when increasing the traffic for the cases when the traffic is delayed and the case when it is not. We consider two battery sizes of 4 and 8 KWh and we impose a queuing constraint of 4 packets having initially 4 packets in the buffer while varying the arrival rate in  $\{0.5, 1\}$  packets/hour.



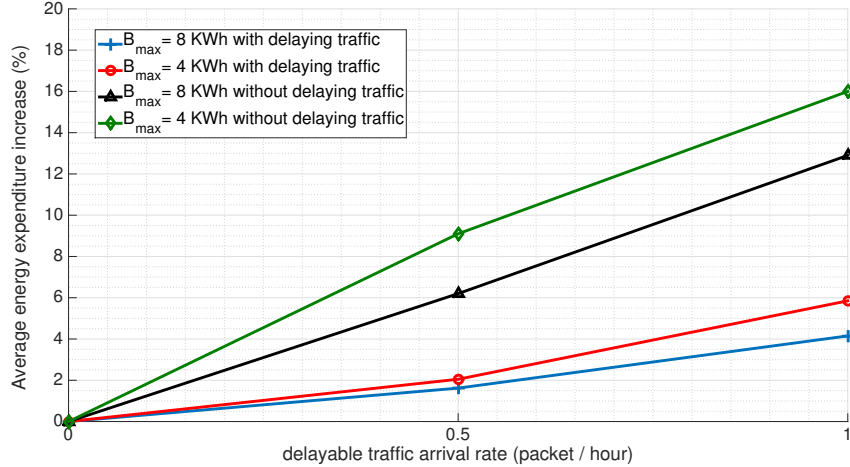


Figure 3.19: The effect of the additional traffic on the energy expenditure

We notice that when the operator cannot delay traffic, the raise in expenses is higher than the raise on average energy needed to treat this additional traffic. When the arrival rate was 0.5, the operator, equipped with a battery size of 4 KWh, spent 6.5% more for only 5.5% additional energy needed. This gap increases for higher battery size and higher arrival rate. On the other hand, having the possibility to delay traffic allows the operator to spend less money than the energy needed. For example, only 6 % of additional fees for 10.5 % of additional energy were needed to process the additional traffic when the battery size is 4 KWh at 1 packet/hour arrival rate. This proves that the devised traffic scheduling policy succeeded to optimally manage the hours in which the non-critical traffic should be treated in order to reduce the MNO expenditure for energy.

In Fig. 3.20, we present the evolution of the average battery SOC and the average non-critical traffic queue length for a battery size of 8 KWh and an arrival rate of 1 packet/hour.

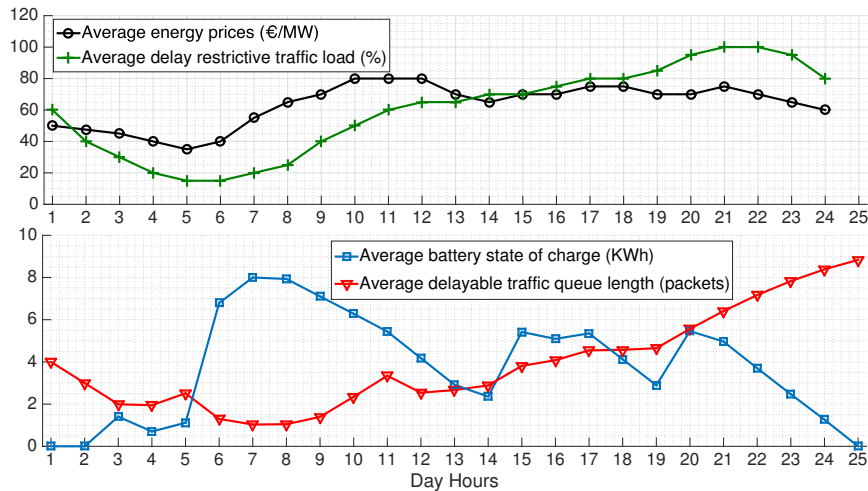


Figure 3.20: Average battery SOC and the average queue evolution in time

From the average SOC evolution, we note that the operator fills completely its battery around 5 am when the electricity prices are the lowest and then tries to profit from prices fluctuations to optimize its expenditure by buying electricity and storing it at local minima (2 pm and 7 pm) and using its battery reserves when the prices get higher.

On the other hand, the evolution of the delayable traffic queue length confirms that there were no packets losses during the day hours as the average queue length remains under the maximal possible value  $Q_{max} = 10$ . Moreover, we see that the operator processes the maximum number of packets in the first hours of the day when the instantaneous traffic is not important, and the energy prices are low. After 8 am, due to the high electricity prices and the lack of processing resources due to the delay sensitive traffic, the operator was forced to alternate between sending small portions of traffic (1 packet in maximum) or queuing more traffic in the buffer until the end of the day.

### 3.3.6 Main findings

In this section, we addressed the issue of a joint energy management and traffic scheduling strategy for a telecommunication operator endowed with a storage battery and powered with a smart grid. The aim of the operator is to minimize its energy bill while serving its customers' requests. We divided these requests into two types: a traffic that should be served immediately and a traffic that could be delayed for a certain number of hours and served later.

We modeled the problem as CMDP for which we proposed a primal dual optimization algorithm that devises an optimal offline strategy that can benefit from the prior knowledge of the users traffic requests and electricity unitary prices distributions in order to minimize the MNO daily energy expenditure while serving all the users traffic load within a constraint on the average queuing length of delay tolerant services.

For the battery management side, the operator can therefore opt to recharge its battery or power its equipment by the smart grid when the energy prices are low. Conversely, the operator might decide to use its own energy reserves when energy prices are high. Concerning the traffic scheduling strategy, we showed that the operator achieved a good energy cost savings compared to the case when it cannot delay traffic. The policy devised, with respect to the available processing capability at the eNB level, chooses the right hours when the electricity prices are low or when the battery reserves are high enough to process the non-critical traffic.

### 3.4 Conclusion

In this chapter, we have set a layer of interactions between the network operator and the smart grid. The objective is to implement some strategies at the eNB side allowing the MNO based on collected data, to take advantage of the dynamics of the smart grid environment in order to minimize its energy bill while satisfying all its user traffic demand and some constraints on the battery usage depending on its type (lead-acid or Lithium).

In this context where the grid is completely reliable, we treated the cases when the operator performs electricity arbitrage when acting as a simple consumer and electricity trading when it acts as an active prosumer able to sell electricity back to the grid. We also analyzed the possibility using the batteries to be part of an incentive based DR program in which the MNO may respond to the requests of the grid to stop consuming in electricity load peak hours. Another layer of complexity was added by defining a joint battery management and non-critical traffic scheduling techniques that minimize the expenditure for energy while respecting the services average queue length constraint.

Our contribution is to define for each eNB site an optimal usage of its battery by taking advantage of the electricity prices fluctuations. The MNO will decide at each hour of the day if it should be powered by the grid or by its own energy storage unit and the amounts of energy to be charged or discharged from the battery while respecting some constraints on battery cycling and SOC limitations. These usage constraints allow to extend the cells lifetime and maintain their performance for longer periods.

The dynamic programming driven policies in all these cases achieved a great financial gain compared to the case when the MNO is exclusively powered by the grid. In this context, batteries that are already deployed at the eNB sites as backup solution in case of power failures that happens seldomly in nowadays reliable smart grids, are also used as an alternative power source used during high electricity prices periods allowing the MNO to reduce significantly its energy daily bill.

However, performing these operations of DR and electricity arbitrage and trading requires higher battery activity compared to backup and so may reduce on the long term its lifetime and deteriorate its performances forcing the MNO to replace it before reaching its calendar life and so leads to higher CAPEX on the long term. Thus, in the next chapter, We propose to evaluate the total cost of ownership when performing these operations. The MNO has to decide the optimal dimensioning of energy storage and production units in both smart grid and non reliable grid environments. The long term optimization in smart grid context is presented in section 1 of chapter 4 and was based on the OPEX evaluation in section 1 of this chapter. While in African Sub-Saharan countries, the usage of the battery is very different of what presented in this section as the grid cannot be trusted. It will be modeled in section 2 of the following chapter.

## Chapter 4

# Long term optimization: minimizing total cost of ownership

In the previous chapter, we defined an optimal battery charge/discharge strategy and energy source switching for an MNO powered by a smart grid that may act as a prosumer or as a simple consumer in the grid. We evaluated the daily costs of energy for many eNB sites for various battery sizes and different electricity prices distributions.

However this cost evaluation cannot be the same from one day to another, from one season to another and from one year to another due to many factors. In fact, we can easily notice a big variation of the electricity prices between the week days and the weekends. The prices also have a seasonality trend due to users consumption profiles and power generation difference between summer and winter. Reports confirm that the average electricity prices in Europe will be 50% higher by 2030 [75] with many differences on the daily prices profiles from one country to another due to the power generation disparity between the countries.

Another point to consider in the future is the exponential growth of the traffic worldwide (44% on average per year) [1]. This traffic growth trend may also differ from one site to another due to the population growth and the urban development trend of the covered areas. The MNO in this context has no choice but to deploy more eNBs with higher capacity (bandwidth, antenna arrays, densification, etc) which may cause a huge increase in the MNO energy consumption and so its electricity bill [76].

Using the backup battery as an electricity arbitrage/trading tool showed great efficiency in nowadays environments with the actual consumption and price model but should also be evaluated in the future where many parameters may change. The dimensioning of the equipment should also be correlated to the increase of the eNB consumption in the future [77]. Thus, a Total Cost of Ownership (TCO) <sup>1</sup> evaluation on a long time period counted in years that copes with battery lifetime and long term performance evolution is mandatory in order to evaluate the efficiency of our battery management solutions. Moreover, deciding the size and the type of battery to be deployed

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<sup>1</sup>TCO is the cost of the life cycle of a product. It is the sum of the capital expenditure (cost of the initial investment in the product) and the operational expenditure (cost of running the product)

should be studied taking into account its long term and short term characteristics.

In African Sub-Saharan countries where the grid may be completely non-existent or not reliable, the MNO has no choice but to act as a prosumer endowed with a Virtual Power Plant (VPP) that takes advantage of the huge potential of solar power to generate the energy needed to maintain the eNB operations. In these countries, driven by the urban expansion and the high population growth, the average traffic increase is huge and can be estimated to 64% per year [1]. The storage units in these countries may suffer from faster deterioration due to the high temperatures but could also be less solicited in the future due to the reliability improvement of the grid and the emergence of new private power aggregators in these energy markets [78, 79]. In this context, deploying batteries and renewable power sources can be a source to reduce the expenses on energy as well as a mandatory solution to ensure continuous operations when recurrent power failures may affect the grid [80].

The remainder of this chapter is organised as follows:

In **Section 1**, we present the TCO optimization problem for the case of an MNO acting as a simple consumer or as prosumer in the smart grid. This is done by defining on a long period of time an optimal battery dimensioning and cycling strategy allowing it to optimally perform the electricity arbitrage and trading in the grid and ensure simultaneously its functionality of backup as described in the previous chapter.

**Section 2** presents the long term optimal dimensioning plan of storage and energy production units in the context of African Sub-Saharan countries where the grid can be nonexistent or, if it exists, suffers from multiple power failures during the day.

Finally, conclusions are given in **Section 3**.

## 4.1 MNO acting as a consumer/prosumer in a smart grid

### 4.1.1 Context and related works

Due to the MNO increasing needs in electricity and the changes in the energy market in the future, the MNO has no choice but to predict this evolution and take in advance the right decisions on the dimensioning of both its network and energy storage units.

The grid in developed countries is reliable, the battery will be rarely solicited to ensure backup. With the usage fixed in section 1 of the previous chapter, we have set an optimal battery management strategy allowing to ensure both functionalities of backup and electricity arbitrage/trading in order to reduce the MNO daily electricity bill. In fact, the operator can buy electricity from the energy provider at low prices and store it in its battery in order to use it later or sell it back to the grid when prices get higher.

Many works in the literature evaluated the long term financial potential of the batteries considering their lifetime and performance degradation. In [81], the authors evaluated the TCO when performing electricity arbitrage using Lithium on a period equal to its calendar life assuming the same energy load and prices structure and taking into account battery degradation model. The authors in [82] proposed a joint arbitrage and operating reserve scheduling using batteries considering limitations on the SOC usage. The authors evaluate the cycles performed by the battery year per year and the annual revenues of both techniques for a fixed battery capacity until it reaches its lifespan. In [83], the authors evaluated the OPEX achieved per year by performing electricity arbitrage under changing electricity prices for different battery sizes in the context of households.

Conversely to the previous works which only evaluated the TCO of a fixed battery capacity, we want in this section to control also the long term cycling strategy of the battery and be able to choose the exact time to install it in order to make the maximal profit of the arbitrage potential. This financial gain may grow in the future driven by the growth in the prices variations within the day if the battery has enough capacity to sustain the eNB consumption in the future.

By performing electricity arbitrage/trading, the MNO battery will execute more cycles during the day. This can reduce significantly the energy bill on the short term but at the same time shorten the battery cycle life which leads to more capital expenditure as the operator will find itself forced to replace its existent battery by a new one before reaching its calendar life. Thus, we have to carry a technical-economical study on the long term in order to evaluate the return on investment of the operator.

In this section, we propose an optimal battery cycling and dimensioning plan for an MNO powered by a reliable smart grid that can allow it to act as a prosumer. Based on the OPEX evaluation carried in section 1 of chapter 3, we propose a linear programming based optimization algorithm that allows the MNO to minimize its TCO for energy on the long term in 2 cases: When the grid allows it to sell electricity back to the grid and when electricity selling is not allowed.

The idea is to decide, on a semestral basis, if the MNO should keep its actual battery or replace it by a new one and if so, the optimal size of its battery. The MNO has to decide also the maximal number of cycles to be performed by the battery per day taking into account the storage lifetime

and performance degradation and if it should invest or not in a DC/AC inverter allowing it to sell electricity back to the grid. The objective is to minimize on the long term the MNO expenditure for energy facing a growing user traffic load and a changing electricity market over the years.

#### 4.1.2 System specifications for long term optimization problem

The MNO is linked with the smart grid to be powered with no interruption. It is also endowed with a battery allowing it to perform arbitrage/trading: It can store the energy purchased from the grid and power the infrastructure when requested. In order to be able to sell electricity back to the grid, the MNO has to be also equipped with a DC/AC inverter [15]. We assume also that the operator is endowed also with a backup battery in case of power failure in the grid used only for that purpose [84].

The battery allocated for electricity arbitrage/trading is characterized by [26]:

- A maximal capacity denoted by  $B_{max}$  expressed in KWh.
- A cycle life before being considered unusable expressed in cycles, denoted by  $L_{cy}$ .
- A calendar life expressed in years and denoted by  $L_{cl}$ .
- A calendar age denoted by  $A_{cl}$  and counted from the date when it becomes operational.
- A number of executed cycles denoted by  $A_{cy}$  from the date when it becomes operational.
- Charging and discharging energy efficiencies  $\gamma_c$  and  $\gamma_d$ , respectively, depending on its age.
- A price denoted by  $I_b$  and expressed in euros per KWh. It depends on the battery type.
- A yearly maintenance cost  $M_b$  independent of the battery capacity or type.

Note that the charge/discharge energy efficiencies deteriorate with the cycle and calendar lives due to the internal impedance of the battery and the DC/AC commutations when the MNO sells energy back to the grid. In this study, we consider two types of batteries: Lead-acid and Lithium.

For each of these batteries, we impose a preferential use in order to extend their lifetime and maintain their performances. This is done by setting limitations on the charge/discharge rates and the battery SOC as explained in section 1 of the previous chapter.

- For Lead acid battery, the State of Charge SOC has to remain between  $0.5 B_{max}$  and  $B_{max}$ . We assume that the charge and discharge efficiencies are equal to 86% when the battery is new and deteriorates with use to reach 80% at the end of the battery cycle life. This degradation is linear.
- For Lithium LFP battery, the SOC remains between  $0.2 B_{max}$  and  $0.9 B_{max}$  and the charge and discharge efficiencies are equal to 96% when a new battery is operating and 92% at the end of the battery lifetime.

This usage allows us also to provide the MNO by an additional backup capability: 50 % of the battery size in case of Lead-acid and 20 % in the case of Lithium and so reduce the initial investment

costs of the MNO for backup solution. As the power failures in the grid occur rarely, only electricity arbitrage will have an effect on the battery lifetime.

If the MNO is allowed to sell electricity to the neighbouring facilities, it has to deploy a DC/AC inverter that converts the DC power stored in the battery to an AC power [15]:

- A maintenance cost each year denoted by  $M_c$ .
- A price denoted by  $I_c$  and expressed in euros.

Our objective is to find an optimal investment plan for the operator over a certain number of years which takes into account projections on the energy unitary prices and the user traffic load. The MNO has to decide the best dimensioning of its equipment in order to have the best return on investment for energy. The decisions are taken at the beginning of each semester considering the seasonality of the electricity prices. The MNO has also to define a battery cycling strategy that considers the battery lifetime.

Again, our aim is to minimize the TCO for energy which is, as stated earlier the sum of the CAPEX and OPEX [85].

In our case, the capital expenditure (CAPEX) includes the equipment installation cost: the battery and DC/AC inverter.

The operational expenditure (OPEX) includes the operators daily expenses for energy when performing electricity arbitrage. If the operator chooses to stay without a battery or use the grid all the time even if its battery is deployed, this cost will only depend on the prices fixed by the energy provider with respect to the eNB consumption.

In order to decide the optimal investment (equipment dimensioning) and battery long term management (battery cycling) plan, we have to forecast the expected costs of purchasing energy on a time period of let say 10 years taking into account the evolution of the electricity prices in the market and user traffic growth including the investment that the operator has to make. It relies on 2 hierarchical steps:

- First, we evaluate on the short term using section 1 of chapter 3, for all the sites configurations (battery type and size, cycle constraint, selling enabled or not), the daily energy expenditure for the MNO after setting an optimal battery management strategy applied in all the days of the season. This is set by deciding the source of energy to power the eNB and the amount of energy to be charged and discharged from the battery with respect to the constraint on the maximal number of cycles to be performed by the battery.
- Then, we use this optimized daily expenditure as an input for a long term investment plan to decide the size of the battery, its cycling strategy and if we have to invest in a DC/AC inverter to be able to sell energy back to the grid. This takes into account the evolution of the electricity prices, the increase of the user traffic load and the battery lifetime and performance degradation model.



### 4.1.3 MDP formulation for long term optimization problem

In this part, we will treat two cases:

1. First, when the MNO is a simple consumer and has no possibility to sell electricity back to the grid. All the amounts of energy purchased and stored in the battery are intended for its own consumption. In this case, the MNO has only to be endowed with a battery.
2. Second, when the MNO acts as prosumer and is allowed to sell its energy reserves to the energy provider in the grid. The MNO in this scenario has to be, in addition to storage, equipped with a DC/AC inverter that inverts the DC electricity in the battery to an AC current that can be conducted in the power connection lines to be sold.

#### MNO having no possibility to sell energy

Our objective is to minimize the operator's TCO for energy counting the operational costs of purchasing electricity from the grid and the equipment investment costs on a period of say 10 years.

The investment decisions are taken at the beginning of each semester indexed by  $t$  on a time period of  $L$  semesters. The operator chooses between installing a new battery or keep using the operating one. The operator has also the choice to remain exclusively powered by the grid all the time even if it is endowed with a storage battery. When the operator opts to install a new battery, it has to choose its size and the number of cycles to be performed per day. When it opts to maintain the existent one, it has to decide only the number of cycles per day to perform. The followed cycling strategy has to take into account the battery cycle and calendar lives and the battery charge/discharge energy efficiencies.

This investment decision plan can be seen as an MDP having the following elements:

**State space:** The state is denoted by  $s_t$ . It describes the energy storage infrastructure already deployed on the operator's site at the beginning of the semester  $t$ .  $s_t = (B_{max}(t), A_{cy}(t), A_{cl}(t))$  with  $B_{max}(t)$  the size of the battery,  $A_{cy}(t)$  its cycle age (the remaining cycles that can be performed before considering that the battery is unusable) and  $A_{cl}(t)$  the calendar age of the battery expressed in years. If the operator has a new battery then  $A_{cy}(t) = L_{cy}$  and  $A_{cl}(t) = 0$ . Conversely, when  $A_{cy}(t) = 0$  or  $A_{cl}(t) = L_{cy}$  the battery is considered unusable in the future and has to be removed from the site.

We assume that the energy prices, the users traffic demands daily profiles and the battery degradation are deterministic and known in advance for all the upcoming semesters for the whole optimization period. Thus, we choose to not include them in the state space.

If  $(B_{max}(t), A_{cy}(t), A_{cl}(t)) = (0, 0, 0)$ , then we assume that the operator's site is not equipped with a battery and is powered exclusively by the grid.

**Action space:** The actions are denoted by  $a_t = (\alpha(t), \Gamma(t))$ ; where  $\alpha(t)$  specifies the size of the battery to deploy and  $\Gamma(t)$  denotes the maximal number of cycles allowed per day.

- If  $\alpha(t) = 0$ , then we suppose that the operator does not make any investment.
- If  $\alpha(t) > 0$ , then the operator decides to install a new battery with size  $\beta(t)$  taken from a finite set of possibilities.
- If  $\Gamma(t) = 0$ , then the operator decides to keep its battery but prefers to not use it and relies on the grid all the time. In this case, the MNO has to pay the maintenance costs of the battery and the consumption fees from the grid.
- If  $\Gamma(t) > 0$ , then we suppose that the operator decided to use its battery with a fixed constraint on the daily cycles  $\Gamma(t)$ .

$\Gamma(t)$  has to be integer and has to be under the optimal number of cycles which minimizes the average daily operator's expenses  $\Gamma_{op}$ . The choice of  $\Gamma(t)$  has to respect the remaining number of cycles before considering the battery unusable:  $A_{cy}(t) - 180.\Gamma(t) \geq 0$ . Where 180 refers to the number of days per semester.

**Transition probabilities:** All the state variables are deterministic, non-correlated in time and independent of each other. Thus, state  $s_{t+1} = (B_{max}(t+1), A_{cy}(t+1), A_{cl}(t+1))$  is perfectly known if we know state  $s_t$  and action  $a_t$  performed at the previous semester  $t$ . The transition probability can be expressed as follows:

$$p(s_{t+1}/s_t, a_t) = p(B_{max}(t+1)/s_t, a_t) \cdot p(A_{cy}(t+1)/s_t, a_t) \cdot p(A_{cl}(t+1)/s_t, a_t) \quad (4.1)$$

In the next equations (4.2) and (4.4),  $\parallel$  denotes "logic disjunction" (or) ;  $\&$  denotes "logical conjunction" (and).

$$\begin{aligned}
& * \text{ If } (\alpha(t) = 0) \ \& \ \left[ (B_{max}(t) = 0) \ \parallel \ \left[ (B_{max}(t) \neq 0) \ \& \ [(A_{cy}(t) - 180.\Gamma(t) = 0) \ \parallel \ (A_{cl}(t) + \frac{1}{2} = L_{cl})] \right] \right] \\
& \quad \text{ then } (B_{max}(t+1) = 0), (A_{cy}(t+1) = 0) \ \text{ and } (A_{cl}(t+1) = 0) \\
& * \text{ If } \left[ (\alpha(t) = 0) \ \& \ (B_{max}(t) \neq 0) \ \& \ (A_{cy}(t) - 180.\Gamma(t) > 0) \ \& \ A_{cl}(t) + \frac{1}{2} < L_{cl} \right] \\
& \quad \text{ then } (B_{max}(t+1) = B_{max}(t)), (A_{cl}(t+1) = A_{cl}(t) + 1/2) \ \text{ and } (A_{cy}(t+1) = A_{cy}(t) - 180.\Gamma(t)) \\
& * \text{ If } (\alpha(t) > 0) \ \text{ then } (B_{max}(t+1) = \alpha(t)), (A_{cl}(t+1) = \frac{1}{2}) \ \text{ and } (A_{cy}(t+1) = L_{cy}(t) - 180.\Gamma(t))
\end{aligned} \quad (4.2)$$

**Outcome:** It refers to the money spent by the operator during the semester. It is composed of the money spent for energy during the semester for which the daily cost is denoted by  $D$  which depends on the existing infrastructure (battery performances), the investment to make and the constraint imposed on the maximal number of cycles per day, the investment cost given the equipment installed denoted by  $I$  and the maintenance costs during the semester denoted by  $M$ .

$$R_t(s_t, a_t) = 180.D(s_t, a_t) + I(a_t) + M(s_t, a_t) \quad (4.3)$$

$$D(s_t, a_t) = \begin{cases} D_b^t(s_t, a_t) & \text{if } [(B_{t+1} > 0) \ \& \ (\Gamma(t) > 0)] \\ D_{og}^t & \text{if } [(B_{t+1} = 0) \ || \ (\Gamma(t) = 0)] \end{cases} \quad (4.4)$$

where:

- $D_b^t$  is the daily expenditure for energy for a known battery characteristics. It is based on the work done in the short term optimization for OPEX calculation in section 1 of chapter 3 for the case of an operator who cannot sell energy back to the grid and has to satisfy a maximal number of cycles per day  $\Gamma(t)$ . It depends on the battery size  $B_{max}$ , the charge discharge energy efficiencies  $\gamma_c$  and  $\gamma_d$  due to the battery age  $A_{cy}(t)$  expressed as the number of remaining cycles that the battery can perform before being considered unusable, the electricity prices and user traffic daily profiles  $\bar{F}_t$  and  $\bar{U}_t$ . We also imposed constraints on the battery SOC allowing it to present an additional capacity for backup.
- $D_{og}^t$  is the money spent by the operator if it is powered exclusively by the smart grid. It depends only on the electricity prices and user traffic load profiles  $\bar{F}_t$  and  $\bar{U}_t$ .  $D_{og}^t$  is calculated by averaging the cost of buying electricity from the grid on the possible values of electricity prices and user traffic.

When the operator opts to install a new battery, it pays an investment cost for a battery equal to  $I_b \cdot \alpha(t)$ . It depends on its size  $\alpha(t)$  and  $I_b$  the battery price per KWh which differs between Lead acid and Lithium. It has also to take into account the maintenance costs of its battery denoted by  $M_b$ . If the battery is still usable ( $A_{cy}(t) > 0$ ) but the MNO made the choice to use the grid all the time ( $\Gamma(t) = 0$ ), it has to pay the maintenance costs.

### MNO having the possibility to sell energy

In this case, the operator is allowed to sell energy back to the grid or to some neighboring facilities in order to make profit. To do so, the operator has to be equipped, in addition to its battery, with a DC/AC inverter to be able to inject the energy collected in its battery in the transmission lines of the smart grid. We assume that the selling prices  $\bar{W}_t$  and the purchase prices  $\bar{F}_t$  follow the same trend and have a linear relationship:  $\bar{W}_t = \xi \bar{F}_t$  with  $\xi \leq 1$ . We assume that the selling prices are lower than the purchase prices as the grid is totally reliable and can alone sustain its consumers needs. We assume also that all the amounts of energy that the operator wants to sell are accepted by the energy provider

This investment decision plan can be seen as an MDP similar to the previous one with some additional variables related to the energy selling activity:

**State space:** The state here is denoted by  $s_t = (B_{max}(t), A_{cy}(t), A_{cl}(t), b_s(t))$ , with  $b_s(t)$  a Boolean value equal to 1 if the operator is endowed with a DC/AC inverter to sell energy to the grid and 0 otherwise.

**Action space:** Actions here are denoted by  $a_t = (\alpha(t), \Gamma(t), \eta(t))$ , with  $\eta(t) = 1$  if the operator invests in a DC/AC inverter to sell energy back to the grid and 0 otherwise.

**Transition probabilities:** All the state variables are deterministic, independent of each other. Thus, state  $s_{t+1}$  is perfectly known if we know state  $s_t$  and action  $a_t$  performed at the previous semester  $t$ . The transition probability can be expressed as follows:

$$p(s_{t+1}/s_t, a_t) = p(B_{max}(t+1)/s_t, a_t) \cdot p(A_{cy}(t+1)/s_t, a_t) \cdot p(A_{cl}(t+1)/s_t, a_t) \cdot p(b_s(t+1)/s_t, a_t) \quad (4.5)$$

with:  $B_{max}(t+1)$ ,  $A_{cy}(t+1)$  and  $A_{cl}(t+1)$  evolution the same as the case when electricity selling is not allowed.

In the next equations (4.6) and (4.8),  $\parallel$  denotes "logic disjunction" (or) ;  $\&$  denotes "logical conjunction" (and).

$$b_s(t+1) = \begin{cases} 1 & \text{if } (b_s(t) = 1) \parallel (\eta(t) = 1) \\ 0 & \text{otherwise} \end{cases} \quad (4.6)$$

**Outcome:**

$$R_t(s_t, a_t) = 180 \cdot D(s_t, a_t) + I(a_t) + M(s_t, a_t) \quad (4.7)$$

where:

$$D(s_t, a_t) = \begin{cases} D_{b,s}^t(s_t, a_t) & \text{if } [(B_{t+1} > 0) \& (\Gamma(t) > 0)] \& [(b_s(t) = 1) \parallel (\eta(t) = 1)] \\ D_b^t(s_t, a_t) & \text{if } [(B_{t+1} > 0) \& (\Gamma(t) > 0)] \& [(b_s(t) = 0) \& (\eta(t) = 0)] \\ D_{og}^t & \text{otherwise } [B_{t+1} = 0] \parallel [\Gamma(t) = 0] \end{cases} \quad (4.8)$$

with  $D_{(b,s)}^t$  the daily cost for energy with a predefined infrastructure when the operator is able to sell energy back to the grid. It depends on the battery size  $B_{max}(t)$ , the charge/discharge energy efficiencies  $\gamma_c$  and  $\gamma_d$  due to the battery cycle age  $A_{cy}(t)$ , the electricity purchase prices  $\bar{F}_t$ , user traffic profiles  $\bar{U}_t$ , the rate between the electricity selling and buying prices  $\xi$  and the constraints on SOC limitations and on the maximal number of cycles to be performed by the battery per day.

The investment and maintenance costs per semester are expressed as:

$$I(a_t) = I_b \cdot \alpha(t) + \eta(t) \cdot I_c \quad \text{and} \quad M(s_t, a_t) = M_b \cdot 1_{B_{max}(t+1) > 0} + M_c \cdot b_s(t+1) \quad (4.9)$$

with  $I_c$  the investment cost paid by the operator to install an DC/AC inverter and  $M_c$  its maintenance cost per semester.

#### 4.1.4 Algorithm solving

To solve this MDP, we developed a linear programming algorithm as presented in subsection 2.2.4. The aim of this algorithm is to devise the optimal occupation probabilities of all the couples states/actions. Based on this we can easily derive an optimal randomized policy that defines for

each state a set of possible actions to perform with a fixed probability [43].

As all the transition probabilities between the system states are deterministic the policy derived by linear programming will be deterministic too.

In order to obtain the optimal occupation measures, we use linprog function of MATLAB to obtain a vector of all these probabilities that can be used to devise all the probabilities of doing an action at each state that may be visited by the system.

Algorithm 5 presented below can be used for both cases: when selling is allowed and when it is not. We have just to specify the corresponding state and action spaces of the MDP as described previously. we have just to add the variable describing the fact of having a DC/AC inverter in the state space and the corresponding action of installing one in the action space.

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**Algorithm 5** Optimal investment plan for MNO acting as consumer in the smart grid

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**Inputs:**  $\bar{F}(t)$ ,  $\bar{U}(t)$ ,  $\gamma(A_{cl})$ ,  $s_h = (B_{max}, A_{cl}(t), A_{cy}(t))$ ,  $a_t = (\alpha(t), \Gamma(t))$ ,  $p_t(s_{t+1}/s_t, a_t)$

**Function:** Linear programming algorithm

- 1: **Initialize:**  $\beta(s, a) = 0 \forall s \in \mathcal{S}$  and  $a \in \mathcal{A}$
  - 2: **while**  $t > 1$  **do**
  - 3: Calculate based on short term optimization the optimal battery number of cycles  $\Gamma_{op}$   
 $\forall s \in \mathcal{S}, \forall a \in \mathcal{A} \Gamma_{op}$  The action  $a_t = (\beta(t), \Gamma(t))$  should ensure that  $\Gamma(t) \leq \Gamma_{op}$
  - 4: Calculate based on short term optimization the daily expenditure  
 $\forall s \in \mathcal{S}, \forall a \in \mathcal{A} D_b^t(B_{max}(t+1), \gamma(A_{cl}(t)), \bar{F}(t), \bar{U}(t))$  or  $D_{og}^t(\bar{F}(t), \bar{U}(t))$
  - 5: Calculate the semestral expenditure of the MNO:  
 $R_t(s_t, a_t) = 180.D(s_t, a_t) + I(a_t) + M(s_t, a_t)$
  - 6: Solve using 'Linprog' on MATLAB to find  $\beta_t(s, a) \forall s \in \mathcal{S}, \forall a \in \mathcal{A}$ :
  - 7: Objective function:  $\min_{\beta} \frac{1}{L} \sum_{t=1}^L \sum_{(s,a)} \beta_t(s, a).R_t(s, a)$
  - 8: Constraint 1:  $\forall t \in [1, \dots, L] \sum_{(s,a)} \beta_t(s, a) = 1$
  - 9: Constraint 2:  $\forall s' \in \mathcal{S} \sum_{a'} \beta_{t+1}(s', a') = p_t(s'/s, a)\beta_t(s, a)$
  - 10: Constraint 3:  $\forall t \in [1, \dots, L] \beta_t(s, a) = 0$  if  $a \notin \Omega_s^t$
  - 11: Constraint 4  $\forall s \in \mathcal{S} \sum_a \beta_1(s, a) = \phi(s)$
  - 12: **end while**
  - 13: **for**  $t = 1 : L$  **do**
  - 14: Devise the randomized policy actions probability:  $\rho_s^t(a) = \frac{\beta_t(s, a)}{\sum_a \beta_t(s, a)}$
  - 15: Devise the optimal TCO  $\bar{R} = \sum_{t=1}^L \sum_{s,a} \beta_t(s, a).R_t(s, a)$
  - 16: **end for**
- 

- The objective function represents the average expenditure of the MNO counting the OPEX and CAPEX on the whole optimization period of  $N$  years.
- Constraint 1 is a basic condition which ensures that the sum of all the occupation measures at each semester  $t$  is equal to 1.
- Constraint 2 is a constraint that sets a relationship between the occupation measures and the transition probabilities of the Markov chain.
- Constraint 3 defines the actions that cannot be done at each state  $s$  at each semester: like imposing a constraint on the battery cycle higher than the optimal battery cycle.
- Constraint 4 ensures that the initial state distribution  $\phi$  is respected by the optimal solution during semester 1.

### 4.1.5 Numerical applications

The optimization is done on a period of 10 years ( $L = 20$  semesters). The decisions are made at the beginning of each semester. Summer ( $t$  is an odd number) is taken between 01/04 and 30/09 and winter ( $t$  is an even number) is between the 01/10 and 31/03. We assume that each semester is composed of 180 days, in which we apply the same battery management strategy on short term horizon (1 day) which makes the operator assumed to spend the same amount of money at all days.

We assume also that the average electricity purchasing and selling prices daily profiles are known in advance for each semester based on projections done by the MNO and that their daily profiles change over the years [86]. We consider 2 cases: Europe (EPEX) and Denmark. We assume that in both scenarios, the electricity will be 60% costlier on average after 10 years.

In figures (4.1) and (4.2), (resp. (4.3) and (4.4)), we show 5 samples of the yearly growing electricity prices daily profiles during summer and winter in Europe (resp. Denmark).

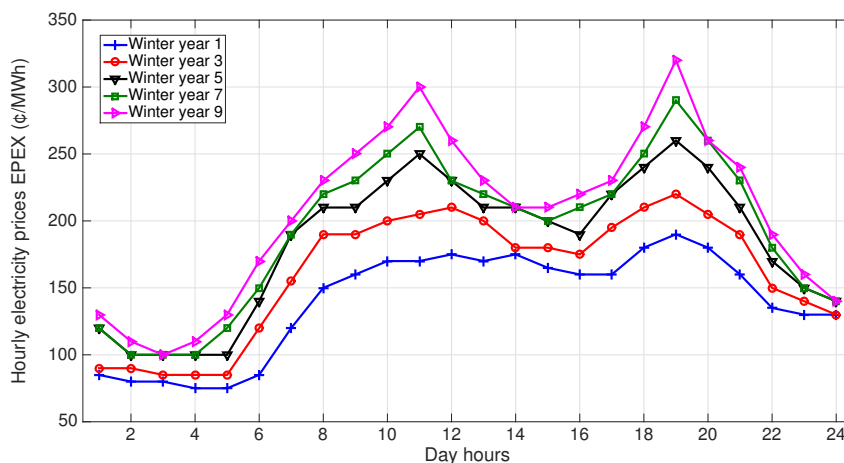


Figure 4.1: Electricity prices evolution in winter in Europe EPEX zone

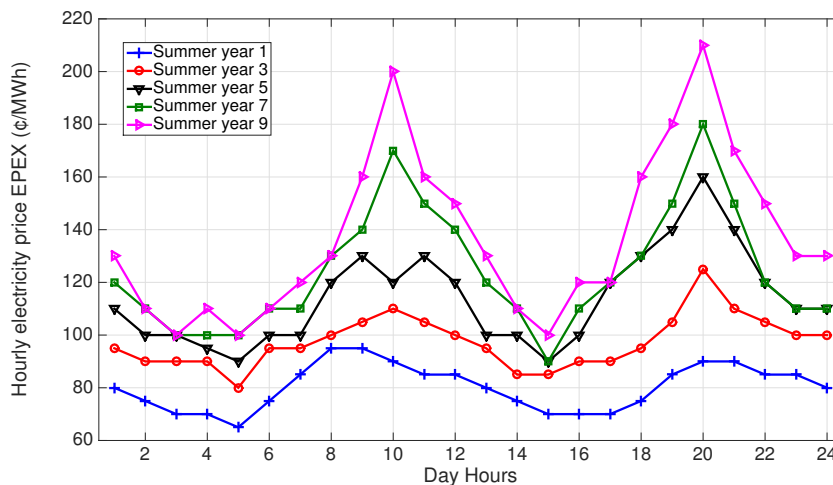


Figure 4.2: Electricity prices evolution in summer in Europe EPEX zone

For the European (EPEX) case, the electricity price growth is visible during all the hours of the day in both winter and summer, but it is assumed to be higher during peak hours which makes the standard deviation between the prices within the day in the future years higher than the actual one (blue curve). This can be explained by the nature of the power supply in these countries which, even if the trend is to give more importance to renewable sources in the future, is still dependent on nuclear and fossil power plants. This makes the increase in the average electricity price due mainly to the increase in demand and not in the variation of the supply [87].

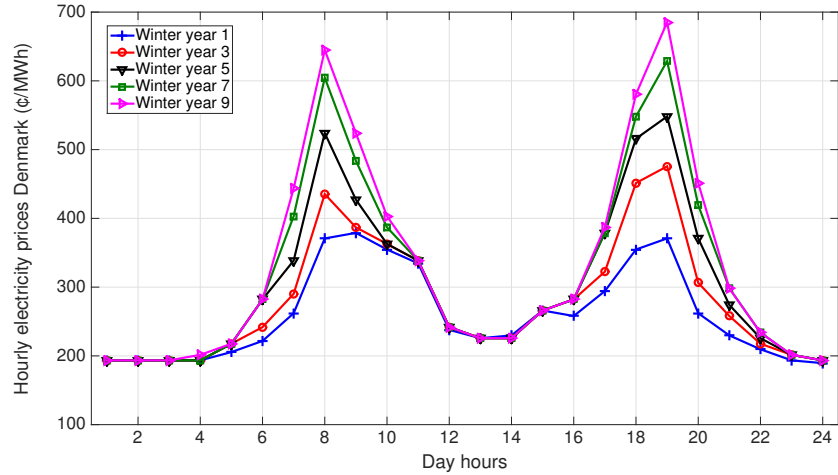


Figure 4.3: Electricity prices evolution in winter in Denmark

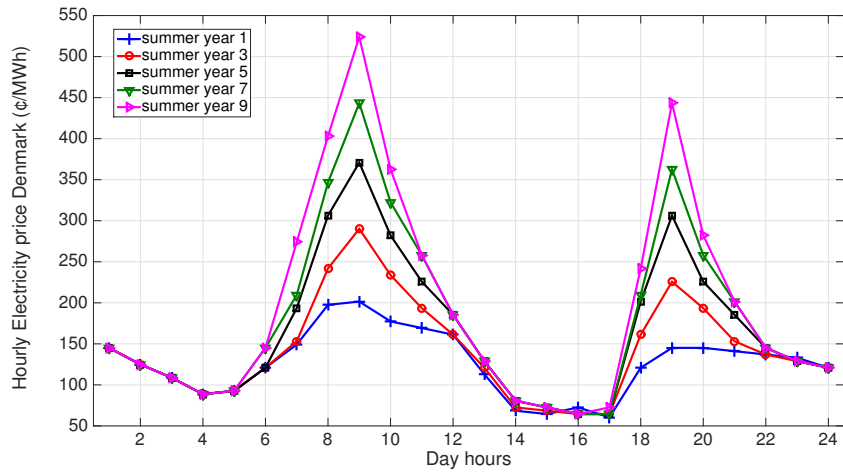


Figure 4.4: Electricity prices evolution in summer in Denmark

In Denmark, we note that the electricity prices growth is concentrated mainly during peak hours. In fact, Denmark is one of the leading countries worldwide in the use of renewable energy and mainly wind turbines [88]. The problem of this energy is that it cannot be stored or increased in order to balance instantaneously the peak hours consumption. The government has to increase the prices mainly at the peak hours to give consumers incentives to shift their electric consumption [89].

For the user traffic load, we take the case of urban environment where the traffic growth remains under the average expected one and we make some projections on its evolution over the semesters. We assume that on average the traffic generated in the cells increases approximately by a factor of 6 in 10 years [1]. We consider in our numerical applications 2 possible traffic growth models based both on results in [23] during the first semester of the first year (summer):

- The exponential traffic growth: This model is more convenient for telecommunication sites in which the activity is maintained at the same level (very slow growth) in the first years and explodes after some years lead by both high population growth and the increase of requirements of users experience.

$$\forall t \in [2, 20], \quad \forall h \in [1, 24], \quad U(t, h) = (1 + 0.01 \cdot (t - 1)) \cdot U(t - 1, h) \quad (4.10)$$

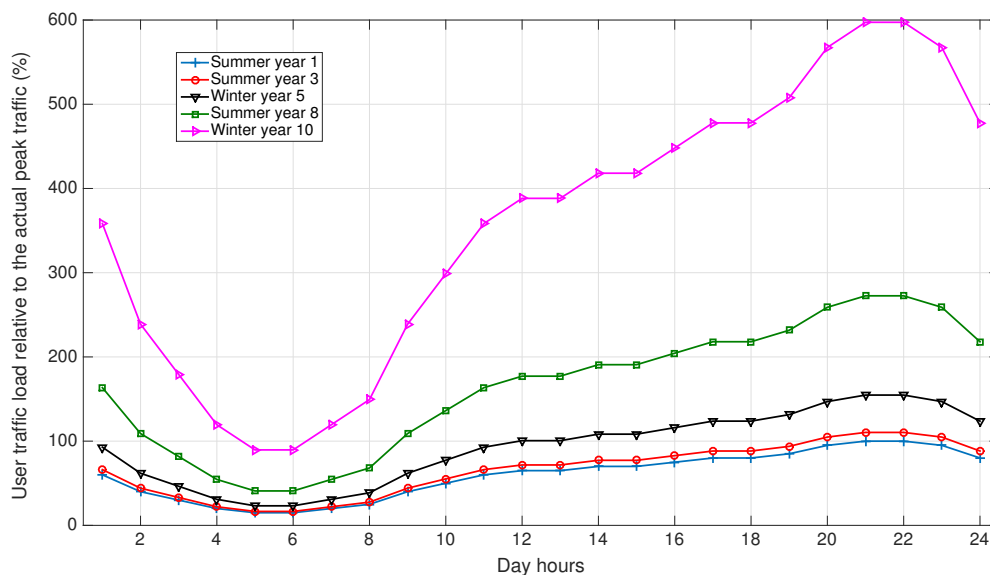


Figure 4.5: Exponential traffic growth

- The incremental traffic growth: It is applicable for sites in which the activity is in constant growth, which is not due to the population growth but mainly to the evolution of the users' applications requiring higher data rates in the future.

$$\forall t \in [2, 20], \quad \forall h \in [1, 24], \quad U(t, h) = 1.1 \cdot U(t - 1, h) \quad (4.11)$$



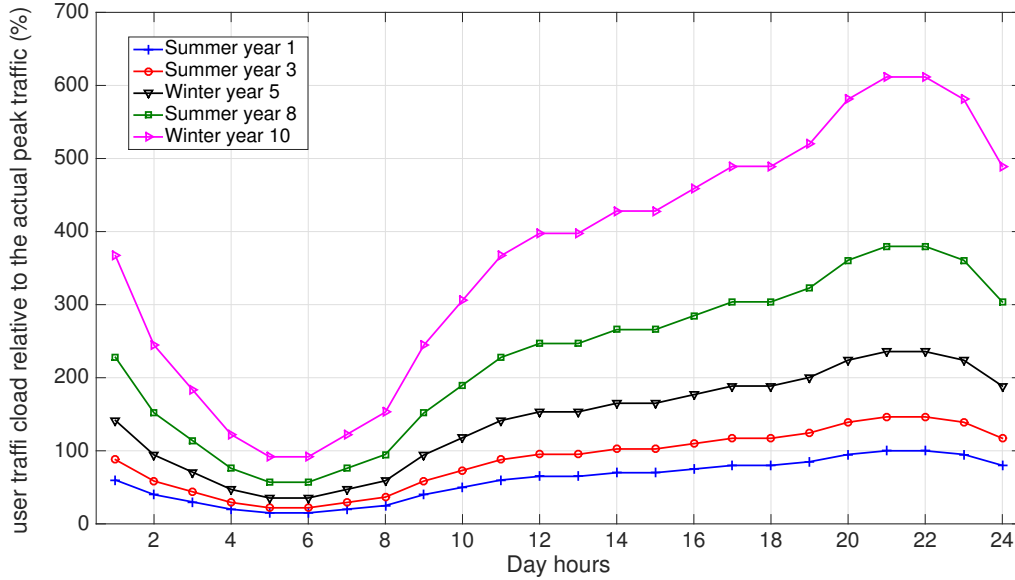


Figure 4.6: Incremental traffic growth

We assume that the operator has the choice over 3 possible battery sizes: {48, 64, 80} KWh. It can install only one type of battery Lead acid or Lithium. The choice of these values due to the high growth of the traffic leading for higher consumption at the eNB level. In fact, in the last semester of the 10th year, the operator may need approximately 21.5 KWh to satisfy the traffic demand at peak hour. So, if the operator wants to use its battery during this hour, counting its energy efficiency loss, it needs to discharge its battery by around 22.4 KWh for a freshly installed Lithium battery and by 24 KWh for a new Lead acid battery. As the Lead acid battery is allowed to do cycles of maximum 50% DOD, only batteries of more than 48 KWh is able to power the infrastructure during this peak hour.

We assume that the Lead acid battery has a cycle life of  $L_{cy} = 1800$  cycles at 50% DOD [90]. For Lithium, the battery can perform  $L_{cy} = 3060$  cycles at 70% DOD [91]. The cycle age  $A_{cy}$  decreases from one semester to another depending on the decision of the operator on the maximal number of cycles performed per day during the 6 months. When it reaches 0, the battery is considered unusable. The operator in this case can replace it by a new one or stay without battery and be powered exclusively by the grid during the whole semester. We assume also that the battery calendar life for both Lithium and Lead acid is equal to 10 years, and so the battery remains operational during the whole optimization period as long as the cycle life does not expire. This assumption, even if it does not cope with the real values (6 years for Lead acid and 8 for Lithium), will allow us to remove the variable  $L_{cl}$  from the state space and so reduce the computation time of our solution [31].

	Lead-acid	Lithium
cycle life $L_{cy}$	1800 (50 % DOD)	3060 (70 % DOD)
calendar life $L_{cl}$	10 years	10 years
Price $P_b$	160 €/KWh	350 €/KWh
$\gamma_c = \gamma_d$ evolution	86 % to 80 %	96 % to 92 %

Table 4.1: Batteries long term characteristics considered in developed countries

We assume that the battery charge and discharge efficiency degradation model is only dependent on the total number of performed cycles. On the short term usage as explained in section 1 of chapter 3, we imposed limitations on the battery SOC and on the number of cycles to be performed per day to be under 2. This can maintain the battery good operation and slow down its performance deterioration. For the Lead acid battery, this degradation is linear varying between 86% and 80% relative to the cycles completed by the battery. For Lithium battery, the charge/discharge energy efficiencies degradation models are also assumed to linear varying between 96% and 92% relative to the number of cycles [31].

The battery investment cost depends on its type. We assume that the operator pays 160 € per KWh for Lead acid battery and 350 € per KWh for Lithium battery. The maintenance cost for both batteries was assumed to be equal to 0 [92]. We assume also that the DC/AC inverter costs 1000€ and that it does not require any maintenance [93].

When selling is allowed, we will produce the results for the cases when the factor between the electricity selling and purchase prices  $\xi$  can take values in  $\{0.6, 0.8, 1\}$ .

We present in the next tables 4.2, 4.3, 4.4 and 4.5 the money spent by the operator per semester when it is exclusively powered by the grid on the whole optimization period in both EPEX zone and Denmark when traffic growth is exponential and when it is incremental. We show only the OPEX without counting the investment costs of the backup battery.

**Europe EPEX with exponential traffic model:** Money spent during 10 years = 107 660 €

year	1	2	3	4	5	6	7	8	9	10
Expenditure summer (€)	1902	2096	2405	2707	3138	3596	4141	5057	6423	8267
Expenditure winter (€)	3412	3692	4134	4742	5326	6037	7020	8439	10797	14331

Table 4.2: MNO expenditure in Europe EPEX under exponential traffic model when powered exclusively by the grid

**Europe EPEX with incremental traffic model:** Money spent during 10 years = 124 550 €

year	1	2	3	4	5	6	7	8	9	10
Expenditure summer (€)	1902	2227	2701	3190	3844	4510	5220	6257	7561	8924
Expenditure winter (€)	3524	4047	4776	5721	6633	7635	8817	10236	12233	14595

Table 4.3: MNO expenditure in Europe EPEX under incremental traffic model when powered exclusively by the grid

**Denmark with exponential traffic model:** Money spent during 10 years = 164 440 €

year	1	2	3	4	5	6	7	8	9	10
Expenditure winter (€)	2997	3273	3526	3853	4467	5012	5854	7001	8748	11279
Expenditure summer (€)	6153	6460	7008	7611	8500	9612	11211	13347	16689	21836

Table 4.4: MNO expenditure in Denmark under exponential traffic model when powered exclusively by the grid

**Denmark with incremental traffic model:** Money spent during 10 years = 189 540 €

year	1	2	3	4	5	6	7	8	9	10
Expenditure winter (€)	2997	3475	3951	4526	5448	6259	7349	8624	10262	12160
Expenditure summer (€)	6346	7075	8063	9138	10531	12094	14017	16138	18876	22234

Table 4.5: MNO expenditure in Denmark under incremental traffic model when powered exclusively by the grid

Next, we present the MNO battery dimensioning and cycling strategies for different cases.

For each case, we present in a first table the optimal investment plan of the operator and the TCO and the percentage of the money saved compared to the case when it is exclusively powered by the grid and endowed with a battery used only for backup. This gain is compared to 2 cases: The first when the battery deployed for arbitrage will not serve as a backup solution. Second, when a portion of this battery will be used for backup (20 % for Lithium and 50 % for Lead acid) with respect with the usage presented in section 1 of the previous chapter.

Then, in the following tables of each case, we present semester by semester the decisions made by the operator and the money spent during each period. This expenditure includes the operational costs and the costs of installing the battery and the DC/AC inverter that ensure the electricity trading and arbitrage. We will not include the cost of purchasing the backup battery in the first semester of the first year.

In the case when the battery has to ensure both arbitrage and backup functionalities, we assume that the lower SOC portion can be used for the backup (20 % for Lithium and 50 % for lead-acid). This portion can be subtracted from the initial Lead acid battery capacity that should be initially deployed to ensure backup. With respect to the maximal traffic that could occur in the cell after 10 year, the MNO needs 21.5 KWh in order to serve it. We assume that we can use 100% of the capacity of the backup battery that we deploy and that it should allow the MNO to sustain 2 hours in energy autonomous mode in case of power failure. Counting the energy efficiency loss of the battery, its size should be around 50 KWh.

The TCO saving in each of these cases is compared to the scenario in which the MNO endowed with 50 KWh backup Lead acid battery and powered during all day hours by the smart grid.

### Selling not allowed in Europe (EPEX)

In these simulations, we first consider the real prices of the batteries in the case of European EPEX based market. The optimal investment plan devised, with respect to these values, gives that the best option for the operator is to not deploy any battery and remain exclusively powered by the grid during the whole optimization period of 10 years. Thus, we made more simulations to obtain the upper limit for the battery unitary price making the fact of investing in storage devices seen as a better option for the MNO. Simulations gave us that the operator should negotiate a price of 90 €/KWh for Lead acid and 210 €/KWh for Lithium batteries when the energy selling is not allowed in Europe. The optimal investment plan and TCO evaluation in all these scenarios are given in table 4.6.

Battery	exponential traffic	incremental traffic
Lead acid (160 €/KWh)	Decision: use the grid all the time Money spent = 115 660 € Savings = 0%	Decision: use the grid all the time Money spent =132 550 € Savings = 0%
Lithium (350 €/KWh)	Decision: use the grid all the time Money spent = 115 660 € Savings = 0%	Decision: use the grid all the time Money spent =132 550 € Savings = 0%
Lead acid (90 €/KWh)	Decision: Install a battery of 48 KWh in the winter of the 1st year and use it until the end of its calendar and cycle lives TCO (arbitrage only) = 115 520 € Savings = 0.12% TCO (arbitrage + Backup) =111 680 € Savings = 3.44%	Decision: Install a battery of 80 KWh in the winter of the 1st year and use it until the end of its calendar and cycle lives TCO (arbitrage only) = 132 390 € Savings = 0.12% TCO (arbitrage + Backup) =125 990 € Savings = 4.949%
Lithium (210 €/KWh)	Decision: Install a battery of 64 KWh in winter of the 1st year and use it until the end of its cycle and calendar lives TCO (arbitrage only) =115 060 € Savings = 0.52% TCO (arbitrage + Backup) =113012 € Savings = 2.29%	Decision: Install a battery of 64 KWh in winter of the 1st year and use it until the end of its cycle and calendar lives TCO (arbitrage only) =131 650 € Savings = 0.68% TCO (arbitrage + Backup) =129 602 € Savings = 2.224%

Table 4.6: TCO evaluation under different scenarios when selling is not allowed in EPEX zone

In Europe, the variation of the electricity prices even after some years is not high enough to make the gain issued from performing arbitrage high enough to cover the initial costs of installing equipment. When considering lower battery prices (90 € per KWh for Lead acid and 210 € per KWh for Lithium) and assuming that the battery that we use is only intended for electricity arbitrage, we achieved a TCO equal to the one when the MNO is powered exclusively by the grid on the whole period of 10 years.

We can note that when considering the possibility to use these batteries as an additional backup solution to the existent battery, we can achieve a considerable gain compared to the case when powered exclusively by the grid even if the variation between the maximal and minimal prices is

not that important. In this scenario, even if the OPEX gain generated when performing electricity arbitrage by Lithium battery is much higher than the one using Lead-acid, the higher backup capability offered by Lead acid makes it a better option in this scenario. It may not be the case in other scenarios where the variation between electricity prices is higher making arbitrage financially very beneficial for the MNO.

Now, we show in tables 4.7, 4.8, 4.9 and 4.10 the optimal battery dimensioning and cycling and the OPEX per semester in the cases when we considered batteries with lower CAPEX (90 € for Lead acid and 210 € for Lithium) when the MNO has to serve an exponential and incremental growing traffic models.

year	1	2	3	4	5	6	7	8	9	10
battery installed summer (KWh)	0	48	48	48	48	48	48	48	48	48
battery installed winter (KWh)	48	48	48	48	48	48	48	48	48	48
cycles performed per day summer $\Gamma(t)$	0	0	0	0	0	0	0	0	0	1
cycles performed per day winter $\Gamma(t)$	1	0	1	1	1	1	1	1	1	1
cycle life in summer $A_{cy}$ (cycles)	0	1620	1620	1440	1260	1080	900	720	540	360
cycle life in winter $A_{cy}$ (cycles)	1800	1620	1620	1440	1260	1080	900	720	540	180
Expenditure summer (€)	1902	2096	2405	2707	3138	3596	4141	5057	6423	8038
Expenditure winter (€)	7424	3692	3781	4293	4892	5592	6555	7912	10273	13604

Table 4.7: The investment and cycling plan in case of MNO in EPEX zone acting as a simple consumer, endowed with Lead acid battery (90 €) with exponential traffic

year	1	2	3	4	5	6	7	8	9	10
battery installed summer (KWh)	0	80	80	80	80	80	80	80	80	80
battery installed winter (KWh)	80	80	80	80	80	80	80	80	80	80
cycles performed per day summer $\Gamma(t)$	0	0	0	0	0	0	0	0	0	0
cycles performed per day winter $\Gamma(t)$	1	1	1	1	1	1	1	1	1	1
cycle life in summer $A_{cy}$ (cycles)	0	1620	1440	1260	1080	900	720	540	360	180
cycle life in winter $A_{cy}$ (cycles)	1800	1620	1440	1260	1080	900	720	540	360	180
Expenditure summer (€)	1902	2227	2701	3190	3844	4510	5220	6257	7561	8924
Expenditure winter (€)	10239	3600	4106	4908	5803	6893	8050	9418	11360	13678

Table 4.8: The investment and cycling plan in case of MNO in EPEX zone acting as a simple consumer, endowed with Lead acid battery (90 €) with incremental traffic

From tables 4.7 and 4.8, we can note that the MNO did not use the same sizes for Lead acid batteries in order to perform arbitrage: 48 KWh when the traffic have an exponential growth and 80 KWh when the growth is assumed to be incremental. In fact for the first case, the traffic remains not important until a certain number of years and so there is no need to deploy a huge battery to be able to sustain it and perform arbitrage. That is not the case when traffic is incremental as it may need an important amount of energy in order to be treated, just after few years and so makes the MNO forced to deploy larger batteries.

Moreover, from tables 4.7 and 4.8, we can see that the battery cycling strategy is very similar in both cases. The MNO exploited completely the cycle life offered by its battery. We can also detect a

clear tendency to perform arbitrage with one cycle per day during winter days and remain powered by the grid during summers. This is due to the fact that the variation between the maximal and minimal prices is higher during winter making arbitrage have a better financial gain.

year	1	2	3	4	5	6	7	8	9	10
battery installed summer (KWh)	0	64	64	64	64	64	64	64	64	64
battery installed winter (KWh)	64	64	64	64	64	64	64	64	64	64
cycles performed per day summer $\Gamma(t)$	0	0	0	0	0	1	1	1	1	2
cycles performed per day winter $\Gamma(t)$	1	1	1	1	1	1	1	1	1	2
cycle life in summer $A_{cy}$ (cycles)	0	2880	2700	2520	2340	2160	1800	1440	1080	720
cycle life in winter $A_{cy}$ (cycles)	3060	2880	2700	2520	2340	1980	1620	1260	900	360
Expenditure summer (€)	1902	2096	2405	2707	3138	3206	3751	4633	5809	7238
Expenditure winter (€)	16212	2980	3221	3659	4193	4865	5804	7302	9516	12510

Table 4.9: The investment and cycling plan in case of MNO in EPEX zone acting as a simple consumer, endowed with Lithium battery (210 €) with exponential traffic

year	1	2	3	4	5	6	7	8	9	10
battery installed summer (KWh)	0	64	64	64	64	64	64	64	64	64
battery installed winter (KWh)	64	64	64	64	64	64	64	64	64	64
cycles performed per day summer	0	0	0	0	0	1	0	1	2	2
cycles performed per day winter	1	1	1	1	1	1	1	1	1	2
cycle life in summer $A_{cy}$ (cycles)	0	2880	2700	2520	2340	2160	1800	1620	1260	720
cycle life in winter $A_{cy}$ (cycles)	3060	2880	2700	2520	2340	1980	1800	1440	900	360
Expenditure summer (€)	1902	2227	2701	3190	3844	4094	5520	5772	6663	7887
Expenditure winter (€)	16242	3212	3830	4577	5585	6616	7594	8960	10821	12709

Table 4.10: The investment and cycling plan in case of MNO in EPEX zone acting as a simple consumer, endowed with Lithium battery (210 €) with incremental traffic

From tables 4.9 and 4.10, we note that the MNO chooses to deploy a 64 KWh Lithium battery in both cases. The battery cycle life was fully exploited. Concerning the battery cycling strategy, we detect also the same tendency of performing arbitrage in winter as the MNO waited to the 6th year to start to do so in summer. Lithium batteries have higher cycling potential which makes the operator able to perform 2 cycles per day in the last years driven by the two peak structure of the electricity prices and the increase of its variation. Comparing between the MNO expenditure semester per semester for each battery type confirms the advantage that have Lithium in reducing the OPEX compared to Lead acid even if it has lower size due to its better charge/discharge energy efficiencies.

### Selling enabled Europe (EPEX)

From table 4.11, we notice that in this case too, after considering the real battery prices, we have found that the best for the MNO is to do not invest in any battery and stay exclusively powered by the grid for the whole optimization period. In order to achieve a minimal financial gain when performing electricity trading, the MNO should buy a Lead-acid battery with 100 e/KWh and Lithium for 250 e/KWh when selling is allowed assuming also that the DC/AC inverter cost is free of charge and that the selling/purchase electricity prices ratio  $\xi = 1$ .

Battery	exponential traffic	incremental traffic
Lead acid (160 €/KWh) AC/DC inverter 1000 €	Decision: use the grid all the time TCO = 115 660 € Savings = 0%	Decision: use the grid all the time TCO =132 550 € Savings = 0%
Lithium (350 €/KWh) AC/DC inverter 1000 €	Decision: use the grid all the time TCO = 115 660 € Savings = 0%	Decision: use the grid all the time TCO =132 550 € Savings = 0%
Lead acid (100 €/KWh) AC/DC inverter 0 € selling/purchase price ratio = 1	Decision: Install a battery of 80 KWh in winter of the 1st year and use it until the end of its cycle and calendar life. The energy selling is enabled also in the winter of the 1st year till the end of the optimization period TCO (arbitrage only)=115 420 € Savings = 0.21% TCO (arbitrage+Backup)=109 020 € Savings = 5.74%	Decision: Install a battery of 80 KWh in winter of the 1st year and use it until the end of its cycle and calendar life. The energy selling is enabled also in the winter of the 1st year till the end of the optimization period TCO (arbitrage only)=132 470 € Savings = 0.06% TCO (arbitrage+Backup)=126 070 € Savings = 4.89%
Lithium (250 €/KWh) AC/DC inverter 0 € selling/purchase price ratio = 1	Decision: Install a battery of 80 KWh in winter of the 1st year and use it until the end of its cycle and calendar life. The energy selling is enabled also in the winter of the 1st year till the end of the optimization period TCO (arbitrage only)=114 980 € Savings = 0.59% TCO (arbitrage+Backup) =112 420 € Savings = 2.8%	Decision: Install a battery of 80 KWh in winter of the 1st year and use it until the end of its cycle and calendar life. The energy selling is enabled also in the winter of the 1st year till the end of the optimization period TCO (arbitrage only)=132 250 € Savings = 0.226% TCO (arbitrage+Backup) =129 690 € Savings = 2.158%

Table 4.11: TCO evaluation under different scenarios when selling is allowed in EPEX zone

Results in table 4.11 show that the gain achieved when performing electricity trading in EPEX zone considering real equipment prices is not high enough to cover the initial units installation costs. When we consider lower equipment prices, we see, conversely to the case when selling is not enabled, that the MNO chooses in all cases to install a battery with the maximal allowed capacity (80 KWh). In fact in the case when selling is enabled, the MNO does not care that much of traffic distribution as all the amounts that exceed its own energy consumption could be sold back to the grid. So having a larger battery allows it to have enough reserves to sell and so make a good financial operation when prices get higher. Moreover, encouraged by the good selling/purchase electricity prices rate

and by the fact that the AC/AC inverter installation was free of charge, the MNO choose to enable selling as soon as it install its battery and so take advantage of the electricity trading potential.

In the tables 4.12, 4.13, 4.14 and 4.15, we can see similarly to the case when selling is not allowed that the MNO favors to perform arbitrage during winter more than in summer except for the last 2 years of the optimization period when the electricity prices variations are higher in summer. In case of Lithium battery, the MNO chooses even to perform electricity trading two cycles per day in summer and only 1 in winter as it gives it better financial income. There is also something very appealing when you follow the evolution of the OPEX in summer over the years especially when it is endowed with Lithium. In fact, as soon as the MNO start performing trading or increases the number of cycles performed when doing so, we can observe that the expenditure decreases in that season compared to the year before (summers 5 and 6 with exponential traffic and summers 6 and 7 with incremental traffic as the MNO start doing trading) or even if it increases, the increase is very small (summers 8 and 9 in both traffic growth models when it starts performing 2 cycles per day instead of 1) despite the fact that the average electricity prices and eNB energy consumption grow. This proves the gain that may bring such operations, even in the case of Europe EPEX zone where the variation of the prices is not that important due to the energy generation policy followed by these countries.

year	1	2	3	4	5	6	7	8	9	10
battery installed summer (KWh)	0	80	80	80	80	80	80	80	80	80
battery installed winter (KWh)	80	80	80	80	80	80	80	80	80	80
cycles performed per day summer	0	0	0	0	0	0	0	0	0	0
cycles performed per day winter	1	1	1	1	1	1	1	1	1	1
cycle life in summer $A_{cy}$ (cycles)	0	1620	1440	1260	1080	900	720	540	360	180
cycle life in winter $A_{cy}$ (cycles)	1800	1620	1440	1260	1080	900	720	540	360	180
Expenditure summer (€)	1902	2096	2405	2707	3138	3596	4141	5057	6423	8257
Expenditure winter (€)	10757	3066	3422	4006	4551	5170	6114	7599	9692	13313

Table 4.12: The investment and cycling plan in case of MNO in EPEX zone acting as a prosumer ( $\xi = 1$ ), endowed with Lead acid battery (100 €) with exponential traffic

year	1	2	3	4	5	6	7	8	9	10
battery installed summer (KWh)	0	80	80	80	80	80	80	80	80	80
battery installed winter (KWh)	80	80	80	80	80	80	80	80	80	80
cycles performed per day summer	0	0	0	0	0	0	0	0	0	0
cycles performed per day winter	1	1	1	1	1	1	1	1	1	1
cycle life in summer $A_{cy}$ (cycles)	0	1620	1440	1260	1080	900	720	540	360	180
cycle life in winter $A_{cy}$ (cycles)	1800	1620	1440	1260	1080	900	720	540	360	180
Expenditure summer (€)	1902	2227	2701	3190	3844	4510	5220	6257	7561	8924
Expenditure winter (€)	10887	3487	4082	4879	5803	6893	8050	9272	11175	13607

Table 4.13: The investment and cycling plan in case of MNO in EPEX zone acting as a prosumer ( $\xi = 1$ ), endowed with Lead acid battery (100 €) with incremental traffic



year	1	2	3	4	5	6	7	8	9	10
battery installed summer (KWh)	0	80	80	80	80	80	80	80	80	80
battery installed winter (KWh)	80	80	80	80	80	80	80	80	80	80
cycles performed per day summer	0	0	0	0	0	1	1	1	2	2
cycles performed per day winter	1	1	1	1	1	1	1	1	1	1
cycle life in summer $A_{cy}$ (cycles)	0	2880	2700	2520	2340	2160	1800	1440	1080	540
cycle life in winter $A_{cy}$ (cycles)	3060	2880	2700	2520	2340	1980	1620	1260	720	180
Expenditure summer (€)	1902	2096	2405	2707	3138	2945	3462	4355	4883	6474
Expenditure winter (€)	22210	2589	2868	3274	3936	4542	5339	6701	8993	12158

Table 4.14: The investment and cycling plan in case of MNO in EPEX zone acting as a prosumer ( $\xi = 1$ ), endowed with Lithium battery (250 €) with exponential traffic

year	1	2	3	4	5	6	7	8	9	10
battery installed summer (KWh)	0	80	80	80	80	80	80	80	80	80
battery installed winter (KWh)	80	80	80	80	80	80	80	80	80	80
cycles performed per day summer	0	0	0	0	0	0	1	1	2	2
cycles performed per day winter	1	1	1	1	1	1	1	1	1	2
cycle life in summer $A_{cy}$ (cycles)	0	2880	2700	2520	2340	2160	1980	1620	1260	720
cycle life in winter $A_{cy}$ (cycles)	3060	2880	2700	2520	2340	2160	1800	1440	900	360
Expenditure summer (€)	1902	2227	2701	3190	3844	4510	4457	5609	6005	7292
Expenditure winter (€)	22422	2920	3581	4330	5173	6033	7120	8560	10441	11937

Table 4.15: The investment and cycling plan in case of MNO in EPEX zone acting as a prosumer ( $\xi = 1$ ), endowed with Lithium battery (250 €) with incremental traffic

### Selling not allowed in Denmark

In the case of Denmark, as shown in table 4.16, we have found that performing arbitrage is a good option in all cases (Lithium or Lead acid, exponential or incremental growth traffic modem) using the real prices of batteries.

Battery	exponential traffic	incremental traffic
Lead acid (160 €/KWh)	Decision: Install a battery of 80 KWh in winter of the 5th year and use it until the end of its cycle life. The battery does not reach its calendar life. TCO(arbitrage only)=167 770 € Savings = 2.71% TCO(arbitrage+backup)=161 370 € Savings = 6.42%	Decision: Install a battery of 80 KWh in winter of the 4th year and use it until the end of its cycle life. The battery does not reach its calendar life. TCO(arbitrage only)=193 260 € Savings = 2.66% TCO(arbitrage+backup)=186 860 € Savings = 5.88%
Lithium (350 €/KWh)	Decision: Install a battery of 64 KWh in winter of the 4th year and use it until the end of its cycle life The battery does not reach its calendar life. TCO(arbitrage only)=161 830 € Savings = 6.15% TCO(arbitrage+Backup)=159 782 € Savings = 7.34%	Decision: Install a battery of 64 KWh in winter of the 3rd year and use it until the end of its cycle life. The battery does not reach its calendar life. TCO(arbitrage only)=184 820 € Savings = 6.91% TCO(arbitrage+Backup)=182 772 € Savings = 7.94%

Table 4.16: TCO evaluation under different scenarios when selling is not allowed in Denmark

We notice from Table 4.16, that performing arbitrage was in all cases a good solution for the MNO in order to optimize its return on investment. We note also that Lithium outperforms clearly Lead acid battery even when considering the backup functionality. The MNO chooses to deploy only 64 KWh Lithium battery with respect to the consumption model of the eNB. Thanks to its better battery energy efficiency and higher DOD when ensuring arbitrage, Lithium allowed the MNO to take advantage of the high variance of the electricity unitary prices and so reduce significantly the OPEX compared to Lead acid to cover its high installation costs.

In tables 4.17 to 4.20, we show the optimal battery strategy and OPEX in all these cases.

year	1	2	3	4	5	6	7	8	9	10
battery installed summer (KWh)	0	0	0	0	0	80	80	80	80	80
battery installed winter (KWh)	0	0	0	0	80	80	80	80	80	80
cycles performed per day summer	0	0	0	0	0	0	0	1	1	2
cycles performed per day winter	0	0	0	0	1	1	1	1	1	1
cycle life in summer $A_{cy}$ (cycles)	0	0	0	0	0	1620	1440	1260	900	540
cycle life in winter $A_{cy}$ (cycles)	0	0	0	0	1800	1620	1440	1080	720	180
Expenditure summer (€)	2997	3273	3526	3853	4467	5012	5854	5488	6894	8321
Expenditure winter (€)	6153	6460	7008	7611	19923	7775	9533	11459	14814	19348

Table 4.17: The investment and cycling plan in case of MNO in Denmark acting as a simple consumer, endowed with Lead acid battery (160 €) with exponential traffic

year	1	2	3	4	5	6	7	8	9	10
battery installed summer (KWh)	0	0	0	0	80	80	80	80	80	80
battery installed winter (KWh)	0	0	0	80	80	80	80	80	80	80
cycles performed per day summer	0	0	0	0	0	0	1	1	1	1
cycles performed per day winter	0	0	0	1	0	1	1	1	1	1
cycle life in summer $A_{cy}$ (cycles)	0	0	0	0	1620	1620	1440	1080	720	360
cycle life in winter $A_{cy}$ (cycles)	0	0	0	1800	1620	1620	1260	900	540	180
Expenditure summer (€)	2997	3475	3951	4526	5448	6259	5821	7067	8322	10299
Expenditure winter (€)	6346	7057	8063	20547	10513	10622	12261	14465	16974	20227

Table 4.18: The investment and cycling plan in case of MNO in Denmark acting as a simple consumer, endowed with Lead acid battery (160 €) with incremental traffic

year	1	2	3	4	5	6	7	8	9	10
battery installed summer (KWh)	0	0	0	0	64	64	64	64	64	64
battery installed winter (KWh)	0	0	0	64	64	64	64	64	64	64
cycles performed per day summer	0	0	0	0	1	1	1	1	2	2
cycles performed per day winter	0	0	0	1	1	1	1	1	2	2
cycle life in summer $A_{cy}$ (cycles)	0	0	0	0	2880	2520	2160	1800	1440	720
cycle life in winter $A_{cy}$ (cycles)	0	0	0	3060	2700	2340	1980	1620	1080	360
Expenditure summer (€)	2997	3273	3526	3853	3155	3555	4259	5073	4977	7268
Expenditure winter (€)	6153	6460	7008	28297	6602	7685	8780	10951	13029	16934

Table 4.19: The investment and cycling plan in case of MNO in Denmark acting as a simple consumer, endowed with Lithium battery (350 €) with exponential traffic

year	1	2	3	4	5	6	7	8	9	10
battery installed summer (KWh)	0	0	0	64	64	64	64	64	64	64
battery installed winter (KWh)	0	0	64	64	64	64	64	64	64	64
cycles performed per day summer	0	0	0	0	0	1	1	2	2	2
cycles performed per day winter	0	0	1	1	1	1	1	1	1	2
cycle life in summer $A_{cy}$ (cycles)	0	0	0	2880	2700	2520	2160	1800	1260	720
cycle life in winter $A_{cy}$ (cycles)	0	0	3060	2880	2700	2340	1980	1440	900	360
Expenditure summer (€)	2997	3475	3951	4526	5448	4637	5388	5162	6552	7833
Expenditure winter (€)	6346	7057	28901	7460	8555	10034	11597	12271	16047	17486

Table 4.20: The investment and cycling plan in case of MNO in Denmark acting as a simple consumer, endowed with Lithium battery (350 €) with incremental traffic

In the tables 4.17, 4.18, 4.19 and 4.20, we see that the MNO waited for some years powered exclusively by the grid before installing its battery which allows it to take advantage of the high variance of the electricity prices that grows significantly at the end of the optimization window making arbitrage has more financial benefits in the future than in the few upcoming years. In this case, we can note that the followed cycling strategy gives more equity between summer and winter seasons than the EPEX case but still favors winter over summer to perform electricity arbitrage.

### Selling allowed in Denmark

In table 4.21, we consider real equipment prices when varying the electricity selling/purchase ratio  $\xi$  in  $\{0.6, 0.8, 1\}$  for both battery types under different traffic growth models (exponential and incremental).

Battery	exponential traffic	incremental traffic
Lead acid (160 €/KWh) AC/DC inverter 1000 € selling/purchase price ratio = 1	Decision: Install a 1st battery of 80 KWh in winter of the 4th year and use it until the end of its cycle life. Selling is enabled also in the same time. A 2nd 80 KWh battery is deployed in the winter of the 8th year and used until the end of its cycle life TCO(arbitrage only)=160 930 € (6.67% saving) TCO(arbitrage+backup)=154 530 € (10.38% saving)	Decision: Install a 1st battery of 80 KWh in winter of the 4th year and use it until the end of its cycle life. Selling is enabled also in the same time. A 2nd 80 KWh battery is deployed in the winter of the 8th year and used until the end of its cycle life. TCO(arbitrage only)=186 080 € (5.8% saving) TCO(arbitrage+backup)=179 680 € (9.05% saving)
Lead acid (160 €/KWh) AC/DC inverter 1000 € selling/purchase price ratio = 0.8	Decision: Install a battery of 80 KWh in winter of the 6th year and use it until the end of its cycle life. Selling is enabled in the same time TCO(arbitrage only)=166 870 € (3.23% saving) TCO(arbitrage+backup)=160 470 € (7% saving)	Decision: Install a battery of 80 KWh in winter of the 4th year and use it until the end of its cycle life. Selling is enabled in the same time TCO(arbitrage only)=192 160 € (2.72% saving) TCO(arbitrage+backup)=185 760 € (5.96% saving)
Lead acid (160 €/KWh) AC/DC inverter 1000 € selling/purchase price ratio = 0.6	Decision: The MNO does not invest in a DC/AC inverter. It does the same investment and battery cycle management decisions as the case when selling is not allowed. TCO(arbitrage only)=167 770 € (2.71% saving) TCO(arbitrage+backup)=161 370 € (6.42% saving)	Decision: The MNO does not invest in a DC/AC inverter. It does the same investment and battery cycle management decisions as the case when selling is not allowed. TCO(arbitrage only)=193 260 € (2.66% saving) TCO(arbitrage+backup)=186 860 € (5.88% saving)
Lithium (350 €/KWh) AC/DC inverter 1000 € selling/purchase price ratio = 1	Decision: Install a 1st battery of 80 KWh in winter of the 1st year and use it until the end of its cycle life. Selling is enabled also in the same time. A 2nd 80 KWh battery is deployed in winter of the 6th year and used until the end of its cycle life. TCO(arbitrage only)=135 480 € (21.43% saving) TCO(arbitrage+backup) = 132 920 € (22.91% saving)	Decision: Install a 1st battery of 80 KWh in winter of the 1st year and use it until the end of its cycle life. Selling is enabled also in the same time. A 2nd 80 KWh battery is deployed in winter of the 6th year and used until the end of its cycle life. TCO(arbitrage only)=160 580 € (18.7% saving) TCO(arbitrage+backup) = 158 020 € (20% saving)
Lithium (350 €/KWh) AC/DC inverter 1000 € selling/purchase price ratio = 0.8	Decision: Install a battery of 80 KWh in winter of the 4th year and use it until the end of its cycle life. Selling is enabled in the same time. TCO(arbitrage only)=153 930 € (11.73% saving) TCO(arbitrage+backup)=151 370 € (12.22% saving)	Decision: Install a battery of 80 KWh in winter of the 4th year and use it until the end of its cycle life. Selling is enabled in the same time. TCO(arbitrage only)=178 130 € (9.82% saving) TCO(arbitrage+backup)=175 570 € (11.12% saving)
Lithium (350 €/KWh) AC/DC inverter 1000 € selling/purchase price ratio = 0.6	Decision: The MNO does not invest in a DC/AC inverter. It does the same investment (64 KWh) and battery cycle management decisions as the case when selling is not allowed. TCO(arbitrage only)=161 830 € (6.15% saving) TCO(arbitrage+backup)=159 270 € (7.34% saving)	Decision: The MNO does not invest in a DC/AC inverter. It does the same investment (64 KWh) and battery cycle management decisions as the case when selling is not allowed. TCO(arbitrage only)=184 820 € (6.91% saving) TCO(arbitrage+backup)=182 260 € (7.94% saving)

Table 4.21: TCO evaluation under different scenarios when selling is allowed in Denmark

From Table 4.21, we can see clearly that enabling selling in Denmark allows the MNO to set an optimal energy trading strategy and hence reduce significantly its TCO for energy. The TCO savings confirm that Lithium outperform clearly Lead acid for this purpose. In all cases, the MNO chooses to install a DC/AC inverter at the same time with the battery in order to act as a prosumer

in the grid when  $\xi = \{1, 0.8\}$ . Conversely, when  $\xi = 0.6$ , the MNO chooses to not invest in a DC/AC inverter and makes the same decisions as the case when it cannot sell electricity back to the grid. When  $\xi = 1$ , the gain achieved on a daily basis was very important pushing the MNO to invest in 2 batteries during these 10 years to perform electricity trading. These batteries were both replaced by a new one before the end of their calendar life but using all their cycling potential.

year	1	2	3	4	5	6	7	8	9	10
battery installed summer (KWh)	0	0	0	0	80	80	80	80	80	80
battery installed winter (KWh)	0	0	0	80 <sub>(1)</sub>	80	80	80	80 <sub>(2)</sub>	80	80
cycles performed per day summer	0	0	0	0	1	1	2	2	2	2
cycles performed per day winter	0	0	0	1	1	1	1	2	2	2
cycle life in summer $A_{cy}$ (cycles)	0	0	0	0	1620	1260	900	360	1440	720
cycle life in winter $A_{cy}$ (cycles)	0	0	0	1800	1440	1080	540	1800 <sub>(2)</sub>	1080	360
Expenditure summer (€)	2997	3273	3526	3853	2945	3306	2375	3586	4534	6644
Expenditure winter (€)	6153	6460	7008	20766	6621	7641	9151	22306	12871	17915

Table 4.22: The investment and cycling plan in case of MNO in Denmark acting as a prosumer ( $\xi = 1$ ), endowed with Lead acid battery (160 €) with exponential traffic

year	1	2	3	4	5	6	7	8	9	10
battery installed summer (KWh)	0	0	0	0	0	0	80	80	80	80
battery installed winter (KWh)	0	0	0	0	0	80	80	80	80	80
cycles performed per day summer	0	0	0	0	0	0	1	1	1	2
cycles performed per day winter	0	0	0	0	0	1	1	1	1	1
cycle life in summer $A_{cy}$ (cycles)	0	0	0	0	0	0	1620	1260	900	540
cycle life in winter $A_{cy}$ (cycles)	0	0	0	0	0	1800	1440	1080	720	180
Expenditure summer (€)	2997	3273	3526	3853	4467	5012	5274	5374	6720	7236
Expenditure winter (€)	6153	6460	7008	7611	8500	20575	9333	11402	14814	19348

Table 4.23: The investment and cycling plan in case of MNO in Denmark acting as a prosumer ( $\xi = 0.8$ ), endowed with Lead acid battery (160 €) with exponential traffic

From Table 4.22, the MNO invested in two Lead acid batteries and performed with each one of them the maximal number of cycles allowed. The arbitrage and energy trading is more interesting at the end of the optimization window. Thus, the MNO waited for the 4th year before installing the first battery and the second one was installed in the 8th year and performed 2 cycles per day and so lasted only 2 years and a half.

From Table 4.23, when  $\xi = 0.8$ , the MNO invested only in one battery installed in winter of 6th year. We can note also that when the MNO start performing 2 cycles per day using the same battery (summer of year 7 when  $\xi = 1$  for example), it can achieve an OPEX that is even lower than the year before although the electricity prices and user traffic are increasing.

year	1	2	3	4	5	6	7	8	9	10
battery installed summer (KWh)	0	80	80	80	80	80	80	80	80	80
battery installed winter (KWh)	80 <sub>(1)</sub>	80	80	80	80	80 <sub>(2)</sub>	80	80	80	80
cycles performed per day summer	0	1	2	2	2	2	1	2	2	2
cycles performed per day winter	1	1	2	2	2	2	2	2	2	2
cycle life in summer $A_{cy}$ (cycles)	0	2880	2520	1800	1080	360	2700	2160	1440	720
cycle life in winter $A_{cy}$ (cycles)	3060	2700	2160	1440	720	3060	2520	1800	1080	360
Expenditure summer (€)	2997	1941	687	917	928	1403	4276	2480	3308	4554
Expenditure winter (€)	33462	4942	4159	4616	5334	33739	7071	9229	11690	14850

Table 4.24: The investment and cycling plan in case of MNO in Denmark acting as a prosumer ( $\xi = 1$ ), endowed with Lithium battery (350 €) with incremental traffic

year	1	2	3	4	5	6	7	8	9	10
battery installed summer (KWh)	0	0	0	0	80	80	80	80	80	80
battery installed winter (KWh)	0	0	0	80	80	80	80	80	80	80
cycles performed per day summer	0	0	0	0	0	1	1	2	2	2
cycles performed per day winter	0	0	0	1	1	1	1	1	2	2
cycle life in summer $A_{cy}$ (cycles)	0	0	0	0	2880	2700	2340	1980	1440	720
cycle life in winter $A_{cy}$ (cycles)	0	0	0	3060	2880	2520	2160	1620	1080	360
Expenditure summer (€)	2997	3475	3951	4526	5448	3887	4852	3521	4565	5882
Expenditure winter (€)	6346	7057	8063	35840	7630	9442	10942	12723	12951	16029

Table 4.25: The investment and cycling plan in case of MNO in Denmark acting as a prosumer ( $\xi = 0.8$ ), endowed with Lithium battery (350 €) with incremental traffic

From Table 4.24, when  $\xi = 1$ , the MNO invested also in 2 Lithium batteries performing both the maximal number of cycles allowed. The batteries performed mostly 2 cycles per day during its usage period due to the big variance of the electricity prices making the energy trading operations have a great financial gain for the MNO. From Table 4.25, when  $\xi = 0.8$ , the MNO invested in only one battery installed in winter of 4th year using all its cycling potential.

#### 4.1.6 Main findings and further insights

In this section, we addressed the issue of energy management strategies for a telecommunication operator, equipped with a storage battery, and powered with a smart grid. The MNO can be a simple consumer in the grid or a prosumer able to sell electricity back to the grid using a DC/AC inverter. The aim of the operator in this chapter, is to optimally use its storage battery for electricity arbitrage/trading in order to minimize its energy expenditure on the long term. Based on electricity prices and user traffic forecasting, the operator has to decide the size and type of the battery to be deployed on the long term and sets an optimal cycling strategy that defines constraints on the number of cycles to be performed by the battery on a daily basis. It has also to decide if it has to invest in a DC/AC inverter allowing it to sell electricity back to the grid while respecting the characteristics of the battery usage (SOC limitations and charge/discharge rates).

On the long term, with respect to the battery characteristics, the electricity prices and user traffic load growth, the MNO chooses the right battery size allowing it to have enough reserves to perform both arbitrage and backup functionalities in order to minimize its TCO for energy. It may also decide to do not invest in any storage and remain powered by the grid during all the optimization window. Our results show that Lithium battery presents a better solution when performing arbitrage/trading thanks to its higher charge and discharge rates and energy efficiency. However, in some cases in Europe EPEX zone where the prices variations are not that high, even with lower cycle life, Lead acid can be on the long term a better option when considering its higher backup capability.

When selling is enabled, the MNO chooses all the time to deploy the largest possible battery in order to have enough energy reserves to be sold later when the prices get higher. Conversely, when selling is not allowed, the MNO makes its choice on the size with respect to the traffic load distribution and the usage fixed for the battery (SOC limitations).

This optimal policy defines also a battery cycling strategy by defining an upper constraint on the cycles to be performed by the battery per day at each season. Our results show that in all cases even if in some cases the calendar life was not reached, the MNO uses all the cycling capacity of its battery before replacing it by a new one despite the decrease of its charge/discharge energy efficiencies. With respect to the price model assumed in this work, the MNO favors winter season when performing arbitrage due to the higher variance between maximal and minimal prices. We note also that the MNO in the Danish case, does not invest in any battery in the first years and remains powered exclusively by the grid waiting for the prices variance to become high enough allowing it to save enough money by performing arbitrage/trading to cover the equipment installation costs.

When selling is enabled, as we assumed that the electricity selling and buying prices are correlated linearly with a factor  $\xi$ , this ratio will be one of the key variables in defining the MNO investment strategy. The energy selling was considered as a good option only if  $\xi$  is higher than a certain value (0.75 in the case of Denmark). We saw in Denmark, when the electricity prices are equal to the buying prices, that the MNO can even choose to invest in 2 batteries during the 10 years and performs almost 2 cycles per day with them. Even if the battery was removed early

before its calendar life, the financial potential of performing energy trading in this scenario is high enough to make the MNO save money up to 22% compared to the case when it remains exclusively powered by the grid using its battery only for backup.

In order to improve the robustness of the developed methods, the MNO has to make these steps for each eNB site to run the long term and short term policies on a real use case:

- Forecast the electricity prices on the whole optimization period: It can be based on mathematical models such as Mean reversion with jump diffusion for the electricity daily prices or on predictions including some knowledge of the electricity supply and demand evolution in a predefined region [94]. These predictions have to take into account some events like: building of new power plants, change in the country power generation policy, population growth due to a new real estate project, etc.
- Based on the predicted electricity prices, we should make classification on the days of the semester and define classes for which we have to define a typical day energy price profile (we can use K-means algorithm for instance to do so) [95]. For each typical day price model of each class, we apply the short term optimization in order to calculate the OPEX in the semester.
- Compute the short term non-constrained optimization and calculate the optimal number of cycles  $\Gamma_{op}$  that reduces the operator daily expenses for each class.
- Compute the long term optimization using linear programming: In this case, the action space will be composed of the investment to make (battery, DC/AC inverter) and a vector of the maximal number of cycles performed by the battery for each electricity price based day class.
- After obtaining the optimal investment and battery cycling strategy, we calculate the occupation measures and the TCO gain compared to the case when powered by the grid.
- We make a risk analysis taking into account the volatility of the prices and the user traffic demand per day and define the comfort zone for which the operator is sure that if it invests in batteries, it will be saving money compared to the case when powered exclusively by the grid [96]. If the operator finds itself in the comfort zone, it has to apply the optimal investment plan on the long term. If the risk is too high and the expected gain is not that important, the MNO should keep its backup battery and remain powered exclusively by the grid.
- After having a clear view of the battery dimensioning and cycling plan, the MNO should apply the optimal battery management strategy indexed by the short term optimization. On a daily basis, the operator has to check the day ahead electricity spot and retail prices, predict the real prices and identify the day class and the maximal number of cycles to be respected and apply the corresponding short term optimization algorithm to obtain the optimal daily battery management strategy.
- At the end of each semester, the MNO should test its battery efficiency and evaluate the remaining battery cycles and recompute the long term optimization for a shorter time period if there is a big gap between the real battery measurements and expected values given by the optimization.



## 4.2 MNO acting as a prosumer in non-reliable grid environment

### 4.2.1 Context and related works

In most African countries, where the electric grid is neither ubiquitous nor reliable, the mobile network operator (MNO) has to deploy its own energy sources coupled with energy storage capabilities on the mobile network radio sites in order to be constantly powered to satisfy its subscribers traffic [97]. The MNO in this context can buy electricity from the energy provider when the grid is available and may generate it thanks to its own power sources. The battery is used for storing the exceeding renewable energy production to be used later in case of power shortage [98].

We focus in this section on optimal dimensioning for storage capabilities and solar energy production units for an MNO powered by a non-reliable electrical grid suffering from multiple power failures during the day but gaining reliability over time. The MNO has to find, on the long term, an optimal trade-off between the sizes of its battery and photovoltaic (PV) panels in order to take more advantage of solar energy and so reduce the costs of purchasing electricity from the grid or producing it using its Diesel generator.

Many works in the literature focused on optimizing the dimensioning of batteries and PV panels to ensure the operations of a facility or reduce its electricity bill. In [99] for instance, the authors developed a linear optimization approach to find the most cost-effective battery sizing in residential context that matches a fixed load demand and local PV generation profiles. The authors compared the economical potential of 3 battery types taking into account their degradation models in a case of a reliable grid. The authors in [100] presented a genetic algorithm that calculates the optimal size of PV panels that power a house in a rural area with no access to the conventional grid. The objective is to be energy autonomous ensuring that the loss of load probability remains under a certain threshold. The authors in [101] derived the size of the battery for a fixed PV array capacity in order to power the eNB in off-grid context under a constraint ensuring the the power outage probability of the base station does not exceed a certain threshold.

Similarly to the previous works, we consider in this section an energy storage/production dimensioning problem in dynamic environment. Unlike the approach of [100] and [99] which considers the load to remain unchanged over time, we consider here a case in which the eNB consumption grows over time, driven by the users' traffic growth, and in which the electricity prices profile changes from one season to another and from one year to another. Both storage and PV should be re-scaled periodically, conversely to the work in [101], in order to ensure that the site is continuously powered and able to face the growing needs of the operator in energy.

We carry a technical-economical study allowing the operator to scale up its energy storage and production units at the eNBs located in non-reliable grid environment, with respect to its users traffic growth and electricity market evolution. This equipment dimensioning has as objective to ensure that the eNB is powered with no interruption while reducing the MNO expenses for energy on a long time period counted in years, taking into account the equipment short term usage constraints and performance degradation on the long term. Based on these investment decisions, we define an efficient usage of these equipment, on a daily basis which satisfies all the subscribers traffic demands

while extending the battery lifetime.

### 4.2.2 System specifications

In this context, the MNO is operating in an environment in which the grid suffers from multiple power failures and has to be equipped with its own energy storage and production units in order to ensure its continuous operation as shown in Fig. 4.7.

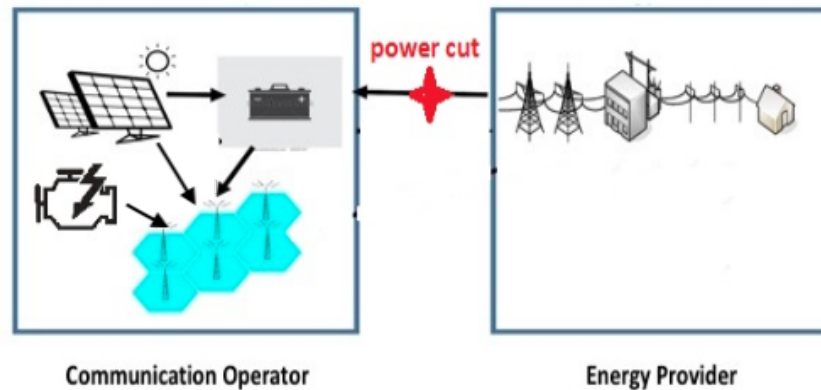


Figure 4.7: Interactions between the MNO and the grid in African Sub-Saharan countries

We can identify two main roles that the MNO can play in the context of African Sub-Saharan countries:

- Prosumer: the rise of prosumers refers to the partial decentralization of energy production, enabled by the increasing affordability of local and small-scale energy generators such as small wind turbines, rooftop solar panels or micro combined heat and fossil power generators [102].
- Virtual power plants (VPP): A VPP is essentially an aggregation of electricity flows coming from small-scale distributed energy generators or energy storage facilities. The MNO can participate to distributed generation for himself and act as prosumer. It may have renewable energy sources on his base station sites. The MNO in this context helps to regulate and mitigate grid imbalance resulting from distributed generation. The MNO can use its base stations as storage facilities [103].

In most African countries, the grid cannot be totally trusted. There is always some power failures due to the bad balancing between generation and demand [104]. The MNO in this context has no choice but to act as a prosumer and to generate the necessary energy for powering its eNB equipment. We will not consider in this work the possibility to sell electricity back to the grid.

In this work, we focus on the case when the operator invests in renewable and non-renewable energy sources and storage facilities to ensure its own operations. We devise the optimal investment strategy to be followed by the MNO in both cases:

1. The grid is nonexistent: The MNO relies completely on its energy storage and production units.
2. The grid exists but is not completely reliable suffering from multiple power failures that may occur during the day: The MNO can purchase electricity from the grid when the latter is operational.

In the case when the grid exist, we assume that it can experiment multiple power failures during the day. These incidents may last for many consecutive hours [5]. The MNO does not know in advance when these power cut-offs may occur but knows their distribution over the day hours. However, we assume that the grid is gaining reliability in time. Thus, the probability of power failures decreases from one year to another [105]. The completely off-grid case can be easily simulated based on the previous one by setting the probability of power failures equal to 1 at all hours of the day.

In order to be constantly powered, the operator has to be endowed with its own renewable (PV panels) and non-renewable (Diesel generator) energy sources and a battery as a storage facility. The eNB components can be powered, in addition to its own energy sources and battery, by the grid, when the latter is operational.

During the day, the MNO equipment can be run using these power sources with the following order of priority:

- Energy produced by its own PV plant: When the production exceeds the actual consumption, the exceeding amount of energy is stored in the battery to be used later.
- Energy stored in the battery: If the PV panels production is lower than the eNB needs, the operator has to power its infrastructure using the battery if it is not empty.
- When the grid is operational and there is no energy left in the battery, the operator can be powered by the cheapest source between the electrical grid and its own Diesel engine.
- When there is a power failure in the grid and the battery is empty, the operator has no choice but to produce the needed energy using its engine.

All the amounts of energy purchased from the grid or produced by the Diesel engine are exclusively intended to power the eNB infrastructure and cannot be stored in the battery. In fact, energy produced by the engine has the same cost in all day hours as the fuel price does not change, so there is no point to store this energy in the battery as there is no financial gain of storing it to be used later. Conversely, the MNO can save money if it stores the electricity purchased from the grid when prices are low to use them when prices get higher but, it will make it perform more battery cycles and so shorten its lifetime.

We assume that the operator is endowed with a Valve regulated Lead Acid (VRLA) battery as a storage facility. This type of battery shows a good efficiency in off-grid context and is characterized by its cheap installation cost and maintenance fees [29].

In our model, we fix a preferential use of the battery by setting limitations on the allowed State of Charge (SOC) and the charge and discharge rates in order to extend its lifetime [79]. The VRLA battery is characterized by:

- A size denoted by  $B_{max}$  expressed in KWh.
- A minimum and maximum allowed SOC:  $SOC_{min} = 0.5 B_{max}$  and  $SOC_{max} = 0.9 B_{max}$
- A charge and discharge rates of 0.4 C
- A cycle life before being considered unusable expressed in cycles  $L_{cy}$ .
- A number of executed cycles denoted by  $A_{cy}$  from the date when it becomes operational.
- A calendar life  $L_{cl}$  after which it should be removed.
- A calendar age expressed in years denoted by  $A_{cl}$ .
- Charging and discharging energy efficiencies  $\gamma_c$  and  $\gamma_d$  depending on the battery calendar age.
- A price denoted by  $I_b$  and expressed in euros per KWh which includes the shipping fees.
- A maintenance cost each semester  $M_b$ .

Africa has abundant renewable energy resources. The continent is increasingly turning to solar photovoltaic to bolster energy security and support rapid economic growth in a sustainable manner [5]. Given the pressing need across Africa to address the low rates of access to electricity and poor-quality electricity supply, the ability to rapidly scale up solar PV is a significant benefit especially for network operators [106]. The PV panels are characterized by:

- A surface in  $m^2$  denoted by  $S_{PV}$ .
- A maintenance (cleaning) cost each semester denoted by  $M_{PV}$  and independent of the surface.
- A price per  $m^2$  denoted by  $I_{PV}$ .
- A calendar life of say 12 years.
- We assume that the PV panel losses do not increase with its age.

Diesel generator is an internal-combustion engine in which air is compressed to a sufficiently high temperature to ignite diesel fuel injected into the cylinder, where combustion and expansion actuate a piston. It converts the chemical energy stored in the fuel into electrical energy, which can be used to power many features in off-grid regions including eNB's [107]. The Diesel generator is characterized by:

- A maintenance cost each year  $M_e$ .
- A price denoted by  $I_e$ .
- A fuel consumption rate denoted by  $\omega$  expressed in liters per KWh.
- A calendar life of say 7 years.
- We assume that the generator efficiency does not decrease with respect to the equipment age.

Here too, the aim is to minimize TCO for energy which is again the sum of the operational expenditure (OPEX) and the Capital expenditure (CAPEX):

- The CAPEX includes the costs of storage and energy production units to install on the eNB site (long term investment).
- The OPEX calculates the daily costs for energy for a given site configuration. It is the sum of the costs of purchasing electricity from the grid when the latter is operational and the costs of producing energy using the Diesel engine added to the cost of the equipment maintenance.

In order to optimize the TCO, the PV plant and battery sizes have to be compliant with each other to avoid the waste of renewable energy and so minimize the operational costs due to the non renewable energy usage while taking into account the lifetime and performance degradation of the battery [100].

### 4.2.3 OPEX evaluation

The grid can experiment multiple power failures during the day. We assume these events to follow a Bernoulli distribution that changes from one hour to another following probability  $P_{bl}(h)$ . With respect to the power source usage priority that we presented above, we calculate in this part, the MNO daily costs for energy under all possible configurations of PV plant surface and battery size and age. This daily energy expenditure will be used later as an input for the long term optimization problem.

The battery SOC at the beginning of hour  $h + 1$  is denoted by  $B_{h+1}$  and can be expressed as follows [23]:

- When the renewable energy production is higher than the eNB consumption: The operator stores the exceeding energy produced by the PV panels in its battery.

$$B_{h+1} = \min(SOC_{max}, B_h + \gamma_c \cdot (S_{PV} \cdot P_h - T_c \cdot n_{tx} \cdot (P_0 + \Delta_p P_{out} U_h))) \quad (4.12)$$

where:

- $P_h$  is the energy produced by 1  $m^2$  of PV panel. It counts the losses and the AC/DC inverter efficiency rate.
  - $T_c$  is the number of wireless technologies co-located at the base station level.
  - $n_{tx}$  is the number of sector.
  - $P_0$  is the traffic independent power consumption.
  - $\Delta_p$  is the slope of load power consumption.
  - $P_{out}$  is the irradiated power.
  - $U_h$  is the users traffic load ratio compared to the peak hour load at hour  $h$ .
- When the renewable energy production is lower than the actual eNB needs: The operator uses the remaining battery reserves to power its infrastructure.

$$B_{h+1} = \max(SOC_{min}, B_h - \frac{1}{\gamma_d} \cdot (T_c \cdot n_{tx} \cdot (P_0 + \Delta_p P_{out} U_h) - S_{PV} \cdot P_h)) \quad (4.13)$$

The operator spends money on energy only if the sum of the energy produced by the solar panels with that discharged from the battery does not cover the eNB needs. The remaining energy in that case should be produced by the Diesel generator or purchased from the grid if the latter is operational. We can express the money spent by the operator during hour  $h$  denoted by  $r_h$  as follows:

- When there is a power failure in the grid: the MNO produces the remaining energy using the generator.

$$r_{h,1} = \max(0, \omega \cdot P_F \cdot [T_c \cdot n_{tx} \cdot (P_0 + \Delta_p \cdot P_{out} \cdot U_h) - S_{PV} \cdot P_h - \frac{1}{\gamma_d} (B_h - SOC_{min})]) \quad (4.14)$$

with  $P_F$  the price of 1 liter of fuel and  $F_h$  the electricity unitary price at hour  $h$ ; we assume that the operator signs a yearly contract with the energy provider in the grid and that the electricity prices are well known by the MNO in advance.

- When the grid is operational: the MNO chooses the cheapest source, between the generator and the grid, to provide the power still needed by the infrastructure.

$$r_{h,2} = \max(0, \min(F_h, \omega \cdot P_F) \cdot [T_c \cdot n_{tx} \cdot (P_0 + \Delta_p \cdot P_{out} \cdot U_h) - S_{PV} \cdot P_h - \frac{1}{\gamma_d} (B_h - SOC_{min})]) \quad (4.15)$$

The daily energy expenditure is calculated with respect to the distributions of the renewable energy production, the user traffic demand and the grid failure probability as follows:

$$D = \sum_{h=1}^{24} \sum_{P_h \in \mathcal{P}} \sum_{U_h \in \mathcal{U}} [P_{bl}(h) \cdot r_{h,1} + (1 - P_{bl}(h)) \cdot r_{h,2}] \cdot p(P_h) \cdot p(U_h) \quad (4.16)$$

We calculate the money spent by the operator for energy under all combinations of PV plant surfaces and the battery sizes and ages taking into account the constraints imposed on the battery usage (SOC limits, C-rate and DOD limitations) that extends the battery lifetime. With respect to the fixed power source priority rule, the operator's battery will perform either 1 or 0 cycles per day. This extends the battery cycle life and maintains acceptable charge/discharge energy efficiencies. The daily expenditure and the number of battery cycles performed per day will be used as input for the long term optimization problem.

#### 4.2.4 MDP formulation for long term optimization problem

Our objective is to set an optimal investment plan in energy storage and production units that minimizes the MNO expenditure for energy on the long term, taking into account the evolution of the electricity market (grid reliability and electricity prices), users traffic growth and equipment performance degradation over the years.

The system can be seen as an MDP having the following components:

**State space:** The state denoted by  $s_t$ , it describes the energy storage and production infrastructure already deployed on the operator's site at the beginning of the semester  $t$ .

$$s_t = (B_{max}(t), A_{cy}(t), A_{cl}(t), S_{PV}(t), N_e(t), \bar{U}(t), \bar{P}_{bl}(t))$$

with  $B_{max}(t)$  the size of the battery,  $A_{cy}(t)$  its cycle age (expressed as the number of executed cycles from the day it became operational) and  $A_{cl}(t)$  the calendar age of the battery. If the operator has a new battery then  $A_{cy}(t) = 0$  and  $A_{cl}(t) = 0$ . Conversely, when  $A_{cy}(t) = L_{cy}$  or  $A_{cl}(t) = L_{cl}$  then the battery is considered unusable and has to be removed from the site and replaced by a new one.  $S_{PV}(t)$  is the surface of PV panels deployed on site and  $N_e(t)$  is a Boolean value equal to 1 if the operator is endowed with a Diesel generator and 0 otherwise. We assume also that the MNO has to be all the time equipped by a battery and a Diesel engine.

$\bar{U}(t)$  and  $\bar{P}_{bl}(t)$  denote respectively the traffic load and the blocking probability daily profiles. We assume that the solar production daily profile does not change on the long term and that the electricity price evolution over time is known in advance. Thus, we choose not to include them in the state space.

**Action space:** The action specifies the investment that the operator makes at the beginning of the semester  $t$ . It is denoted by  $a_t = (\alpha(t), \theta(t))$ ; where  $\alpha(t)$  specifies the size of the battery to deploy and  $\theta(t)$  denotes the size of the PV panels to add. When the battery reaches its cycle or calendar life, the operator has no choice but to replace it by a new one. In that case, it decides only its size. The same holds for the generator, it has to be replaced by a new one after for instance 7 years.

- If  $\alpha(t) = 0$ , then we suppose that the operator keeps its actual battery. It supposes that the battery did not reach its calendar or cycle life.
- If  $\alpha(t) > 0$ , then the operator decides to install a new battery with size  $\alpha(t)$  taken from a finite set of possibilities.
- $\theta(t)$  is also taken from a finite set of possibilities. We assume that the MNO cannot install more than a maximal surface  $S_{max}$  of PV panels each semester.

**Transition probabilities:** They refer to the probabilities that the system will be in state  $s(t+1)$  at the beginning of semester  $t+1$  knowing that it was in state  $s_t$  in the beginning of the semester  $t$  and that the operator made investment decision  $a_t$ .

In our case, all the state variables related to the equipment installed are deterministic, non-correlated in time and independent of each other.

The randomness in our system comes from the variable related to the environment: the electricity prices, the user traffic and grid reliability evolution over the years. These parameters will change from one site to another due to the urbanization and the governmental investment strategy in

sustainable power. For example, traffic in rural areas does not increase very much, but if a building project emerges, the population will increase and so the traffic will explode in very short time. We propose a model in which the growth can have a finite set of possibilities weighted with different probabilities that change from one site to another and over time.

The transition probability can be expressed as follows:

$$p(s_{t+1}/s_t, a_t) = p(B_{max}(t+1)/s_t, a_t) \times p(A_{cy}(t+1)/s_t, a_t) \times p(A_{cl}(t+1)/s_t, a_t) \times p(S_{PV}(t+1)/s_t, a_t) \\ \times p(N_e(t+1)/s_t, a_t) \times p(\bar{U}(t+1) | \bar{U}(t)) \times p(\bar{P}_{bl}(t+1) | \bar{P}_{bl}(t)) \quad (4.17)$$

State  $s_{t+1}$  is perfectly known if we know state  $s_t$  and action  $a_t$  performed by the MNO at the previous semester  $t$ , thus:

$$B_{max}(t+1) = \begin{cases} B_{max}(t) & \text{if } \alpha(t) = 0 \\ \alpha(t) & \text{if } \alpha(t) > 0 \end{cases}$$

$$A_{cy}(t+1) = \begin{cases} A_{cy}(t) + 180.\bar{C} & \text{if } \alpha(t) = 0 \\ 180.\bar{C} & \text{if } \alpha(t) > 0 \end{cases}$$

$$A_{cl}(t+1) = \begin{cases} A_{cl}(t) + \frac{1}{2} & \text{if } \alpha(t) = 0 \\ \frac{1}{2} & \text{if } \alpha(t) > 0 \end{cases}$$

$$S_{PV}(t+1) = S_{PV}(t) + \theta(t)$$

$$N_e(t+1) = 1 \quad \forall t \in [1, \dots, N]$$

We assume that the user traffic and grid reliability evolution between two consecutive semesters  $p(\bar{U}(t+1) | \bar{U}(t))$  and  $p(\bar{P}_{bl}(t+1) | \bar{P}_{bl}(t))$  follow both a trinomial distribution with one trial that can change from one semester to another.

**Outcome:** It refers to the money spent by the operator during the semester. It depends on the state in which it is at the beginning of semester  $t$  and the action to perform.

$$R_t(s_t, a_t) = 180.D(s_t, a_t) + I(a_t) + M(s_t, a_t) \quad (4.18)$$

where:

- $D(s_t, a_t)$  is the daily expenditure for energy for a given battery and PV plant characteristics following the OPEX calculation in subsection 3 of this section. It depends on the battery size, the charge/discharge energy efficiencies  $\gamma_c$  and  $\gamma_d$  due to the battery cycle age  $A_{cy}(t)$  expressed by the number of executed cycles, the electricity prices and user traffic daily profiles  $\bar{F}_t$  and  $\bar{U}_t$  respectively, the surface of PV panels deployed  $S_{PV}$ , the solar radiation daily profile  $\bar{P}_t$  and the grid failure daily distribution  $\bar{P}_{bl}(t)$ .
- The investment cost  $I$  is equal to the price of the equipment to install:



$$I(a_t) = \alpha(t).I_b + \theta(t).I_{PV} + \epsilon.I_e \text{ with: } \epsilon = 1 \text{ when } \text{mod}(t, 14) = 1.$$

- The maintenance cost  $M(s_t, a_t)$  is the sum of the maintenance fees of the existent equipment, we assume that it is independent of their sizes.

#### 4.2.5 Algorithm solving

We solve this optimal equipment dimensioning plan using linear programming technique in subsection 2.2.4 to obtain a randomized policy [43].

---

##### Algorithm 6 Optimal investment plan in non-reliable grid regions

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**Inputs:**  $\bar{F}(t), \bar{U}(t), \bar{P}_{bl}(t), \gamma(A_{cl}), s_h = (B_{max}, A_{cl}(t), A_{cy}(t), S_{PV}(t), \bar{U}(t), \bar{P}_{bl}(t)), a_t = (\beta(t), \theta(t)), p_t(s_{t+1}/s_t, a_t)$

**Function:** Linear programming algorithm

- 1: **Initialize:**  $\beta = 0 \forall s \in \mathcal{S} \text{ and } a \in \mathcal{A}$
  - 2: **while**  $t > 0$  **do**
  - 3:     Calculate the OPEX:  $\forall s \in \mathcal{S}, \forall a \in \mathcal{A} D_t(B_{max}(t+1), S_{PV}(t), \gamma(A_{cy}(t)), \bar{F}(t), \bar{U}(t), \bar{P}_{bl}(t))$
  - 4:     Calculate the semestral expenditure of the MNO:
  - 5:  $R_t(s_t, a_t) = 180.D_t(B_{max}(t+1), \gamma(A_{cl}(t)), S_{PV}, \bar{F}(t), \bar{U}(t), \bar{P}_{bl}(t)) + I(a_t) + M(s_t, a_t)$
  - 6:
  - 7:     Solve using 'Linprog' on MATLAB to find  $\beta_t(s, a) \forall s \in \mathcal{S}, \forall a \in \mathcal{A}$ :
  - 8:     Objective function:  $\min_{\beta} \frac{1}{L} \sum_{t=0}^{L-1} \sum_{(s,a)} \beta_t(s, a).R_t(s, a)$
  - 9:     Constraint 1:  $\forall t \in [0, \dots, L-1] \sum_{(s,a)} \beta_t(s, a) = 1$
  - 10:     Constraint 2:  $\forall s' \in \mathcal{S} \sum_{a'} \beta_{t+1}(s', a') = p_t(s'/s, a)\beta_t(s, a)$
  - 11:     Constraint 3:  $\forall t \in [0, \dots, L-1] \beta_t(s, a) = 0 \text{ if } a \notin \Omega_s^t$
  - 12:     Constraint 4:  $\forall s \in \mathcal{S} \sum_a \beta_0(s, a) = \phi(s)$
  - 13: **end while**
  - 14: **for**  $h=0:N-1$  **do**
  - 15:     Devise the randomized policy actions probability:  $\rho_s^t(a) = \frac{\beta_t(s,a)}{\sum_a \beta_t(s,a)}$
  - 16:     Devise the optimal MNO expenditure  $\bar{R} = \sum_{n=0}^N \sum_{s,a} \beta_t(s, a).R_t(s, a)$
  - 17: **end for**
- 

- The objective function represents the average expenditure of the MNO including the OPEX and CAPEX on the whole optimization period of  $N$  years.
- Constraint 1 is a basic condition which ensures the fact that the sum of all the occupation measures at each semester  $t$  is equal to 1.
- Constraint 2 is a constraint that sets a relationship between the occupation measures and the transition probabilities of the Markov chain.
- Constraint 3 defines the actions that cannot be done at each state  $s$  in each semester: Staying without a battery when the latter reaches its cycle or calendar life or install more PV panels than allowed.
- Constraint 4 ensures that the initial state distribution  $\phi$  is respected by the optimal solution during semester 0.

### 4.2.6 Numerical applications

In our simulations, the optimization is done on a period of 12 years. The investment decisions have to be taken at the beginning of each semester  $t \in [0, N - 1]$  with  $N = 24$ . We considered that summer season starts in April 1st and finishes at September 30th and winter is from October 1st to March 31st. For  $t \in [0, N - 1]$ , when  $t$  is an odd number, it corresponds to winter and when  $t$  is an even number, it corresponds to summer. We assume also that each season is composed of 180 days in order to ease the calculations.

On the daily basis, let  $h$  denotes the hour of the day. The renewable solar power, the user traffic load ratio, the electricity prices and the grid failure probability have a daily distribution that remain the same during all the 180 days of the semester but may change from one semester to another except for the solar energy production.

The PV panels can operate for a long period of 12 years. We assume that the losses are the same during all the years (14% in our case). We assume also that the MNO cannot install more than  $S_{max} = 60m^2$  of PV panels each semester and that the maximum allowed surface is  $200m^2$  [108].

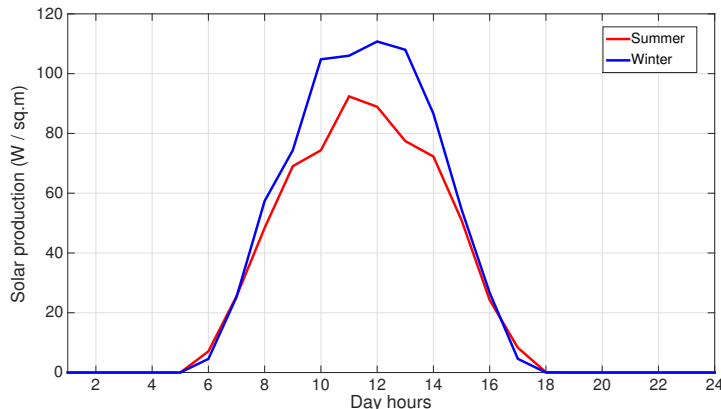


Figure 4.8: Average solar energy production during winter and summer in N'Djamena Chad

We assume that the Diesel generator can last 7 years, that there is no efficiency loss over the years and that it can cover, when requested, all the eNB needs for energy. We assume that the engine has a fuel conversion ratio  $\omega = 0.66$  liters/KWh and that the fuel price is fixed to  $P_F = 0.7$  € per liter for all the years which makes the costs of producing electricity using the Diesel generator fixed around 466 € for 1 MWh [109, 110].

Valve Regulated Lead Acid batteries shows a great performance in off-grid context operating systems powered with hybrid sources [111]. The MNO can install a VRLA battery with a predefined size taken from the following set:  $\{24, 32, 40, 48, 56, 64, 72, 80, 88, 96, 104, 112, 120\}$  KWh. .

In order to extend the battery lifetime and maintain its performances, we adopt the following use: The battery SOC has to remain between 50 % and 90 % of the battery capacity and the charge and discharge rates cannot exceed 0.4 C which makes the battery achieve potentially 1440 cycles [112]. With this predefined usage, if the MNO is endowed with enough PV panels, the battery will execute only 1 cycle per day which makes the cycle life coincides exactly with the calendar life.

The charge and discharge energy efficiencies decrease linearly with respect to the number of executed cycles from 86 % when it becomes operational dropping to 70 % at the end of its lifetime. [79].

The equipment's costs are summarized in the table 4.26 [113–115] :

	Battery	PV panels	generator
Installation cost (€)	150/KWh	100/ $m^2$	2500
Maintenance (€)	50	200	50
Calendar life (years)	4	15	7

Table 4.26: Equipment characteristics in non reliable grid scenarios

We assume that the average traffic growth per semester is linear with an average value of 20% which is equivalent to 44 % yearly growth [1]. We take a case in which the semestral growth has a probability of 0.5 to be equal to the 20 %, a probability of 0.25 to be equal to 10 % and 0.25 % to be equal to 30 %. This distribution has to be evaluated for all the telecommunication sites as it is closely correlated to the urbanism and mobile users applications. On an hourly basis, we assume that traffic follows a trinomial distribution with one trial. Its value has a probability of 0.6 to be equal to the average, 0.2 to be equal to a value 10% more than the average and a probability of 0.2 to be equal to 10% less. In the next figures, the user traffic load ratio is taken by dividing the real traffic by the maximal capacity that is offered by the eNB. In our case, after 12 years, traffic will be 14 times more important than the actual eNB capacity. We assume that the MNO will increase its bandwidth to handle the traffic load ratio between 1 and 4 which increases the eNB variable consumption part while keeping the fixed power consumption part unchanged. Then, when the peak hour traffic becomes higher than 4, we increase the number of antennas which increases both the fixed and variable consumption parts.

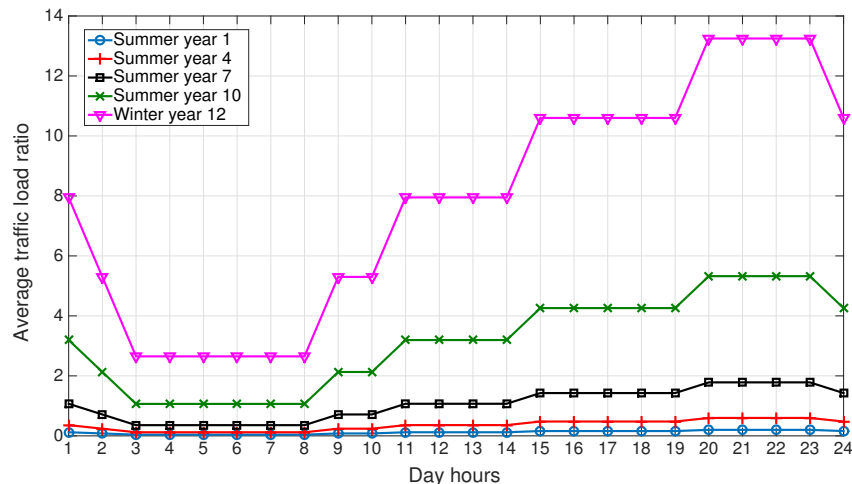


Figure 4.9: Average traffic daily profile growth in African countries

The energy consumption model of the macro base stations is taken from EARTH model [23]. We assume that the fixed power is  $P_0 = 118.7$  Wh, and that the slope of load power consumption

is  $\Delta_p = 5.32$ . We assume that  $T_c = 2$  technologies are co-located at the eNB level and that it is transmitting with power  $P_{out} = 20$  W. From summer of year 1 to summer of year 9, we assume that the eNB has 3 sectors with two antennas in each ( $n_{tx} = 6$ ). Then, from winter of year 9, we increase the number of antennas per sector to be equal to 8 which makes ( $n_{tx} = 24$ ).

When the grid is available, we assume that the electricity prices grow by 10% on average from one year to another as the government has to cover a part of its investments intended to improve the grid reliability. Then after 8 years, we assume that the grid reaches a certain maturity and so the prices will be dropping by 5% on average each year [116]. We assume that the operator signs a yearly contract with the grid and so the prices are unchanged and known in advance during all the days of the year. Within the day, the electricity prices have an off-peak and peak structure as shown in the figure (4.10) below.

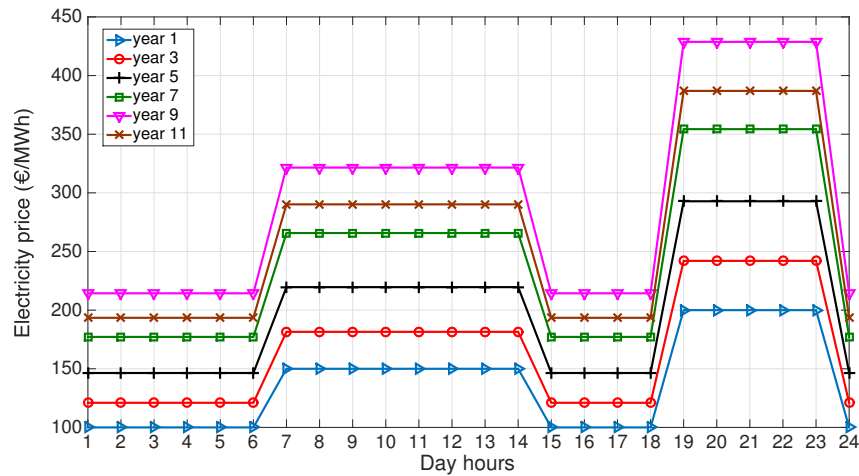


Figure 4.10: Electricity price growth over years in case of a grid gaining reliability

The probability of power failure decreases from one year to another and has different values depending on the season (summer/winter) [116]. We assume that this semestral decrease has a probability of 0.6 to be equal to 10 %, a probability of 0.2 to be equal to 5 % and 0.2 to be equal to 15 %. We assume that this probability decreases linearly by 10% from one year to another. The grid failure probability is higher during summer than in winter as the solar power supply is lower and the electricity consumption is higher due to air conditioning usage.

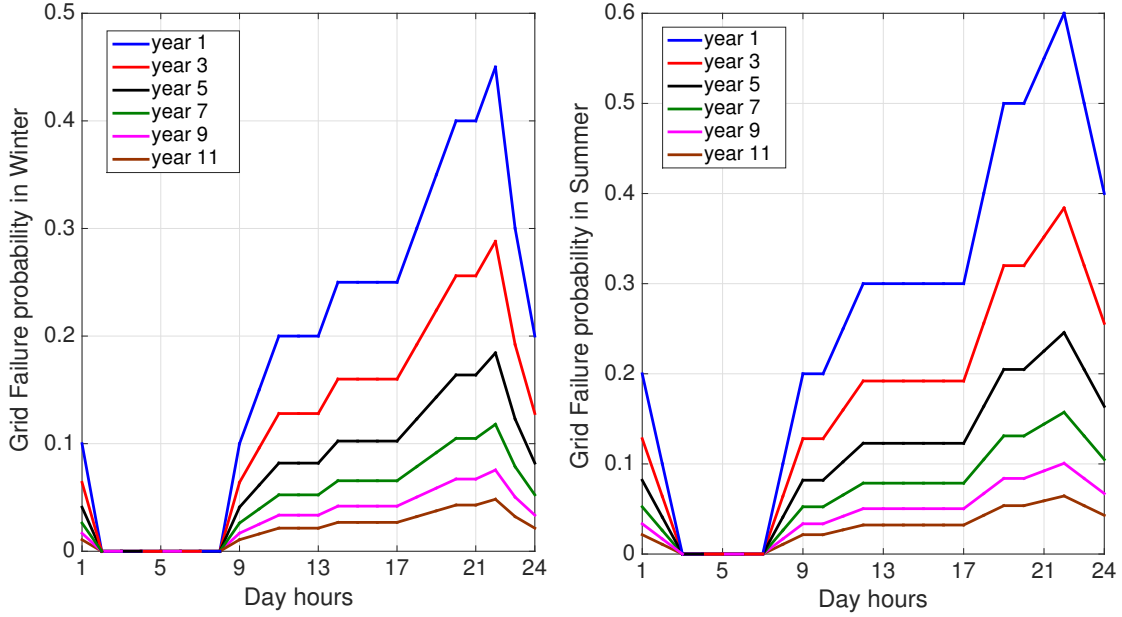


Figure 4.11: Grid failure probability evolution over years in African sub-Saharan countries

Given all these parameters, we devise the optimal investment plan for two cases: The first is when the grid exists and becomes more reliable from one year to another. The second one is in a complete off-grid scenario on the whole period in which the MNO has to rely exclusively on its own energy sources. This case is simulated based on the first one by fixing the grid blocking probability to 100% at all day hours for all the semesters. The TCO evaluation for both cases are given in the tables 4.27 and 4.28 below.

In order to ease the illustration of the results and have one clear equipment dimensioning plan. We assume that the traffic growth and the grid power failure distribution decrease are both deterministic and equal to their average values (20% increase for traffic per semester and 10% decrease for the grid failure probabilities per semester in the case when the grid exists and is gaining in reliability).

#### Case of a grid gaining in reliability

- 1- Install a 40 KWh battery, 60  $m^2$  PV panels and a generator in the first summer of the 1<sup>st</sup> year.
- 2- Install a 56 KWh battery and add 20  $m^2$  PV panels in the summer of 5<sup>th</sup> year and replace the generator by a new one in the summer of 8<sup>th</sup> year.
- 3- Install a 56 KWh battery and add 60  $m^2$  PV panels in the first semester of year 9.

Period (years)	1 to 4	5 to 8	9 to 12
CAPEX (€)	14500	12900	14400
OPEX (€)	3040	11135	52500
Maintenance (€)	2400	2400	2400
TCO (€)	19940	26435	69300

Table 4.27: MNO expenditure on long term in case of a grid gaining reliability

### Case completely off-grid

- 1- Install a 40 KWh battery, 60  $m^2$  PV panels and a Diesel generator in the summer of the 1st year.
- 2- Install a 72 KWh battery and add 40  $m^2$  PV panels in the summer of 5<sup>th</sup> year and a Diesel generator in the summer of the 8<sup>th</sup> year.
- 3- Install a 112 KWh battery and add 60  $m^2$  PV panels in the first semester of year 9 and add 40  $m^2$  PV in the second semester.

Period (years)	1 to 4	5 to 8	9 to 12
CAPEX (€)	14500	17300	26800
OPEX (€)	9309	15576	63561
Maintenance (€)	2400	2400	2400
TCO (€)	26209	35276	92761

Table 4.28: MNO expenditure on long term in off-grid case

We can note from the tables 4.27 and 4.28 that the operator will deploy larger batteries and larger PV panels as its eNB needs in energy grow due to users traffic increase. Having larger storage allows the MNO to store higher amounts of solar power to be used later in night time and so reduce its operational expenditure for the energy produced by the engine or purchased from the grid when the latter is operational.

We can see also that the operator did not replace its battery before it reached its calendar life in order to reduce the CAPEX. This makes the operator match perfectly between the cycle and calendar lives of the battery as it was performing exactly one cycle per day.

After a certain number of years, the MNO needs in energy become very important in order to satisfy the growing traffic demands of its subscribers. As the costs of producing electricity using the Diesel generator in this case will be very important especially for the off-grid case, the need to store renewable energy becomes more crucial. Thus, the MNO has to deploy huge batteries and increase the surface of deployed photovoltaic panels in order to respond to the load.

In the case when the grid is gaining in reliability, the operator can rely more and more on the electricity purchased from the energy provider and so does not have to increase a lot the size of its battery and PV plant.

### 4.2.7 Main findings and further insights

In this section, we investigated the optimal investment plan for the MNO in energy storage devices (battery) and solar energy production units (PV plant). The equipment sizes should be derived jointly in order to minimize the TCO of the MNO on a long period of time, in our case 12 years. We formulated this problem as an MDP and solved it with policy iteration technique that devises an optimal offline and deterministic strategy for the MNO in the case of developing country where the grid may suffer from multiple power failures, if it exists.

On the long term, the operator, based on predictions of the user traffic growth, the grid evolution and its battery performance degradation, will decide at the beginning of each semester if it has to

add some PV panels or replace its existing battery and the best sizes for these units. Based on this investment plan, we defined on a daily basis a power source order of priority and a battery preferential usage (SOC and C-rates limitations) in order to extend its lifetime and maintain its charge/discharge energy efficiencies. Due to the high growth of traffic, the MNO, in order to ensure its energy autonomy, increases proportionally the sizes of the batteries and PV panels deployed on its site. This allows it to take advantage of the free solar energy and so reduce the costs of purchasing electricity from the grid and produce it by the Diesel engine.

As the short term usage of the energy storage and production units is fixed, the robustness of the solution will only improve for the long term optimization problem. To do so, we should follow these steps:

- Forecast the electricity prices and the grid reliability evolution on the whole optimization period. In general, the MNO signs contracts with the grid owner in these countries. The energy prices have a peak, off-peak structure and can be known in advance by the MNO but their value may change in the future as the energy provider can renegotiate these contracts as the grid reliability increases. This reliability described by the distribution of the power failures has also to be forecasted considering the governmental investment plan in the energy generation sector and the urban development in the region.
- The solar power generation can be predicted using machine learning techniques based on heuristic data and solar radiation predictions [117].
- Based on the predicted power failures and solar energy production, we should make classification on the days of the semester and derive classes for which we have to define a typical day power failure and solar power generation profiles (we can use K-means algorithm for instance to do so). For each typical day corresponding to a class, we calculate the daily expenditure and then evaluate the OPEX per semester by integrating all the classes.
- Compute the long term optimization using linear programming and decide the optimal dimensioning of the equipments.
- We apply the optimal investment plan and we evaluate the operational costs and test the battery energy charge/discharge energy efficiencies at each semester. If the battery performances are compliant with the expectations, we keep applying the optimal strategy and if it is not the case, we recompute the linear programming algorithm when considering the tests as the new initial state.

### 4.3 Conclusion

The policies that we derived in this chapter are based on forecasts over a long period of time counted in years of the evolution of the dynamic parameters of the environment: electricity prices and traffic loads in the cell in both developed and developing countries. They allow the operator to decide for each of its eNB sites the optimal dimensioning of its storage and energy production units and the optimal usage of it in order to minimize its TCO for energy on the long term.

This defines a new way for radio site initial setting: In addition to the allocation of the right communication resources in order to satisfy the users traffic load which is also based on some forecasting on the users activity, we defined a new way to enable the eNB, thanks to its batteries deployed mainly to ensure backup, to reduce the MNO electricity bill by acting as prosumer in the grid if possible and performing electricity arbitrage and trading.

The main challenge of our method is that it is based on forecasted data for many parameters that may not correspond to reality in the future. Many non predictable event could happen making the system deviate from the expected states. That is why we proposed in the main findings of sections 1 and 2 of this chapter, a method to follow by the MNO for each of its site, combining offline DP/LP based policies and machine learning techniques for data classification and prediction allowing the operator to make some modifications on the optimal policy to follow in case of a big variation between the expected state of the system and the real measurements.

For the long term optimization, we do not have to push the accuracy of the model to the maximum as the actions are discretized and so a small error in modeling prices or traffic will not have a big effect on the decisions to be taken by the MNO concerning the battery and PV panels sizes or the number of cycles to be performed per day. For the short term optimization, we should always check the day ahead spot and retail prices in order to make the right predictions and well classify the day in order to apply the right battery management strategy.



## Chapter 5

# General conclusion and perspectives

### 5.1 General conclusion

This thesis explores both energy storage and production units at the RAN and the dynamics of the grid in both developed and developing countries to set a layer of interaction between the MNO and the energy provider in the grid. The MNO in the context of smart grid may act as a simple consumer or a prosumer able to sell electricity back to the grid or even be part of demand response program with the energy provider. When the grid is not reliable, the MNO has to be endowed with a small scale virtual power plant in order to sustain its needs when there is a power outage affecting the grid.

Our proposal is to use the batteries that are currently deployed at the eNodeB sites for backup in order to make some savings on the energy bill by performing electricity arbitrage and trading in smart grid networks and be able to sustain the base station own supply in developing countries with the lowest possible costs.

We developed dynamic and linear programming based methods in order to achieve optimal strategies that give for each site configuration a clear investment strategy on the long term and a deterministic battery management strategy on the short term.

These two hierarchical policies take into account expectations on the electricity prices and users traffic growth over the years, the evolution of the grid reliability and the batteries aging effect. We conducted this research based on real test measurements done by our colleagues in **SooGreen Celtic plus** project, for both flooded Lead acid and Lithium batteries in developed countries and valve regulated Lead acid batteries which are more adapted to the off-grid context in developing countries.

In the context of reliable smart grid environment, the main contribution of this work is that it quantifies the expected financial gain compared to the case when powered exclusively by the grid. The policy developed helps the MNO decide if it should invest in additional storage capacity to perform electricity arbitrage/trading in order to minimize its TCO or restrict the usage of its batteries to ensure only backup functionality. The optimal battery management strategy developed on the short term minimizes the operational expenditure of the MNO taking into account the battery

internal characteristics and the cycling strategy decided by the long term optimization.

In the context of African Sub-Saharan countries, our work gives the MNO a clear road map to scale up its investment in storage and energy production units in order to ensure its continuous power supply facing the exponential growth of the traffic in these countries and the anomalies that may affect the grid if it exists. We establish for the MNO the compromise between the battery capacity, solar PV panels surface and the use of Diesel engine allowing it to take advantage of the abundant solar power to reduce its energy bill while maintaining the battery performance facing fast deterioration due to the extreme temperatures.

Our solution can be applied for any utility having a certain energy consumption term and endowed with a battery and energy production units (renewable or non renewable). It can be used in the context of households, manufactures or electric vehicles for example. The usage of MDPs allows the generalisation of the solution to systems which have the Markovian property and which covers a large area of domains.

Our work and proposed solutions have a green footprint. In fact, high electricity prices characterize the periods in which the demand is so high compared to the generation. In this case, the energy provider should respond quickly to these peaks in order to avoid power outage and the most used sources to do that are gas turbines and Diesel engines. Their response is very quick but they are very costly (Electricity cost can reach 1000 €/MW) and very polluting. The fact of being powered by batteries during these time periods allows to reduce the needs in energy and so reduces the CO2 footprint [118].

## 5.2 Future works

The method that we developed is primordial in the setup of eNodeB site's storage and energy production devices. As we mentioned earlier, this dimensioning strategy relies on expectations of many parameters with high volatility, the exact values of which are hard to predict over a long period of time.

We proposed as further insights at the end of each long term optimization problem, a method to improve the accuracy of our method on a real use case. This method requires in turn other methods based on machine learning for electricity prices prediction and clustering.

### 5.2.1 Prediction of electricity prices

Many mathematical models are given in the literature in order to predict the electricity spot prices. One of the most used model is mean reversion with jump diffusion [94]. With this assumption, the electricity spot prices at each day  $t$  in the future can be expressed as:

$$S_t = G(t) \cdot \exp^{Y_t}$$

where:

- $G(t)$  is a deterministic function which accounts for the observed seasonality in power markets. It depends on the market in question. For instance, the seasonality of some electricity markets with a discernible pattern between summer and winter months can be modeled by a sinusoidal function. We can include in this function the weekly correlation of the prices (e.g., the prices on Mondays of all weeks can be similar).
- $Y_t$  is a zero level mean-reverting jump diffusion process for the underlying electricity spot price  $S_t$  that considers the speed of mean reversion, the time dependent volatility, the jump size and the increment of the standard Brownian motion and Poisson processes. The jump size models spikes in the electricity prices and the mean reversion describes the return to the long run average prices.

After having the expected spot prices, we can predict based on them the real electricity prices in the market and consider this model as a baseline for predicting the OPEX over the optimization window.

### 5.2.2 Classification of electricity prices

The data collected after forecasting prices for all days over the whole optimization period is huge and needs huge processing in order to devise the optimal battery management strategy. Clustering the electricity prices in classes which have similar proprieties in terms of variation between the maximal and minimal prices can reduce this complexity as it allows us to define only one policy for each class.

One machine learning algorithm, namely k-means algorithm, consists of exploiting some heuristic data defined as a training set in order to partition the data into  $k$  similar characteristics classes [95]. Each of these classes are characterised by a mean that is adapted iteratively and serves as a benchmark to assign the observations to each one of the clusters using these 2 relationships:

- Assignment step: Assign each observation to the cluster whose mean has the least squared Euclidean distance: In our case the distance can be the variation between the electricity hourly prices.
- Update step: Calculate the new means to be the centroids of the observations in the new clusters. The mean in our case will be the daily energy price averaged on all the days of the cluster.

Based on all the forecasted prices, we build our class partition for different values of  $k$  representing the number of clusters. Then we evaluate for each  $k$  the silhouette function which provides a measure of the clusters separation. Its value varies between  $-1$  and  $+1$ , where  $+1$  denotes clear cluster separation and  $-1$  marks points with questionable cluster assignment. A successful clustering has a mean silhouette value higher than  $0,6$  for all clusters. As this value may not be reached, it can be enough to adopt a clustering partition if we do not obtain a negative mean silhouette value for one of the classes.

After choosing the number of classes  $k$  and the mean for each of the classes, we devise the optimal battery management strategy for each one of them and evaluate the expected OPEX by summing the daily expenditure of the MNO considering the mean of the class multiplied by the number of days considered in each class.

In our case, the classes should take into account week days, weekends, the seasonality of the prices, the months in which the prices are the highest (December and January in Europe for instance) and the change over the years of the daily prices model due to the changes that may affect the energy market in the future.

### 5.2.3 New delay tolerant traffic scheduling

In this problem, we will define a joint optimal battery management strategy and delay tolerant traffic scheduling that aims at minimizing the daily expenditure for energy under a maximal queuing delay of the services. Contrary to what we did in section 3.3, here the threshold  $\bar{D}$  is to be respected by each individual packet. This requires a distinction of the individual waiting time of each packet. Thus, we should define  $\bar{D} + 1$  different virtual waiting queues indexed by  $k \in [1, \dots, \bar{D} + 1]$  which are interconnected. When a packet is in the  $k^{\text{th}}$  queue, it means that it waited already for  $k - 1$  hours. The evolution of these buffers can be characterized as follows:

$$\begin{aligned}
Q_{h+1}^1 &= A_{h+1}^d \\
Q_{h+1}^2 &= Q_h^2 + Q_h^1 - U_{h,2}^d \\
\text{If } 3 \leq k \leq \bar{D} + 1, \quad Q_{h+1}^k &= Q_h^k + (Q_h^{k-1} - U_{h,k-1}^d) - U_{h,k}^d \quad \text{s.t.} \quad \sum_{k=1}^{\bar{D}+1} Q_h^k \leq Q_{max}
\end{aligned}$$

where  $Q_h^k$  is the number of packets in the buffer  $k$  which already waited  $k - 1$  hours at time slot  $h$  and  $U_{h,k}^d$  is the number of packets that already waited  $k - 1$  hours and treated by the eNB at time slot  $h$ .

In order to be sure that each individual packet will respect the constraint imposed on its queuing delay, we have to ensure that the queue length of the virtual buffer indexed by  $k = \bar{D} + 1$  is equal to 0 at each time slot:  $Q_h^{\bar{D}+1} = 0 \quad \forall h \in [0, N - 1]$ .

This system is also an ergodic Markov chain leading to a non-constrained MDP that could be solved using policy iteration algorithm. We can define the following components of this MDP :

**State space:** At each time slot  $h$ ,  $s_h = (B_h, U_h^i, \{Q_h^1, Q_h^1, \dots, Q_h^{\bar{D}+1}\}, F_h)$ ; where  $\{Q_h^1, Q_h^1, \dots, Q_h^{\bar{D}+1}\}$  are the queue lengths of all the individual virtual buffers. In order to respond to the imposed constraint,  $Q_h^{\bar{D}+1}$  should be fixed to 0.

**Action space:**  $a_h = (d_h, c_h, \{U_{h,2}^d, \dots, U_{h,\bar{D}+1}^d\})$ . The MNO has to decide the number of non-critical packets, with respect to their waiting time, to be treated at each time slot  $h$

**Transition probabilities:**

$$p(s_{h+1}/s_h, a_h) = p(B_{h+1}/s_h, a_h) \times p(U_{h+1}^i/s_h, a_h) \times p(F_{h+1}/s_h, a_h) \times p(Q_{h+1}^1/s_h, a_h) \times \dots \times p(Q_{h+1}^{\bar{D}+1}/s_h, a_h)$$

Only the evolution virtual buffer length indexed by  $k = 1$  is stochastic. All the other parameters for buffers indexed by  $k \in [2, \dots, \bar{D} + 1]$  are deterministic if we know the previous state and the action performed.

$$p(Q_{h+1}^1/s_h, a_h) = p(A_{h+1}^d/s_h, a_h) = p(A_{h+1}^d = Q_{h+1}^1)$$

All the arguments for the other state variables still hold.

**Instantaneous reward:** It represents the money spent by the operator for energy for the next hour knowing that the system is in state  $s_h$  and that it performed action  $a_h$ .

$$r_h(s_h, a_h) = F_h \cdot \left( \frac{1}{\gamma_c} \cdot c_h \cdot B_{max} + (1 - d_h) \cdot n_{tx} \left( P_0 + P_{out} \Delta_p(A_h^i + C^d \cdot \sum_{k=2}^{\bar{D}+1} U_{h,k}^d) \right) \right)$$

The new problem formulation is more compliant with the requirements of certain services in wireless networks as it imposes that all packets are to be treated with respect to a fixed delay constraint.

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