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Intelligent Management of Energy Storage Systems in Buildings

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“Give me a lever long enough and a fulcrum on which to place it,
and I shall move the world”

Archimedes

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Abstract

The usage of electricity, nowadays, suffers from large fluctuations and is inefficient, creating load management issues and a considerable carbon footprint. Within this subject, buildings are one of the main culprits, due to the high percentage of time that people spend within them. In addition, electricity plays a determinant role for the comfort within buildings, creating an intrinsic need for it.

Therefore, due to the occupant's behavioural patterns, inefficiencies occur between electricity's supply and demand. Consequently, to reach ambitious energy efficiency goals, the building sector must undergo through technological innovation enabling a better energy management.

Energy management is nowadays a subject of great importance and complexity, by choosing amongst a set of sources and loads that could minimize the losses and costs. Energy management systems, coupled with energy storage systems, can optimize the electricity usage, making it more efficient.

Accordingly, the goal of this dissertation is to present a system able to, intelligently, manage energy storage systems, user consumptions within buildings and power sources through strictly defined strategies. This system bases itself on a decision system that, while maintaining the security, stability and quality of service of the power network, can enhance how buildings consume electricity, optimizing it and lowering the load management problems.

To conclude, this dissertation aims to develop computer software, a simulator, in order to test this system's viability and if the results globally optimize the electricity usage.

Keywords: Energy management systems; Energy storage systems; Electricity consumption; Buildings; Behavioural patterns; Simulator.

Resumo

Atualmente, o uso de eletricidade sofre de grandes flutuações e é ineficiente, criando problemas de gestão da carga e um considerável peso para o ambiente devido ao carbono libertado na produção. Os edifícios são um dos principais culpados, uma vez que constituem o local onde a maioria das pessoas despende grande parte do seu tempo. Além disso, a eletricidade desempenha um papel determinante para o conforto no interior dos edifícios, criando uma necessidade intrínseca para tal.

Por conseguinte, devido aos padrões de comportamento das pessoas dentro de edifícios, ocorrem algumas ineficiências entre a oferta e a procura da eletricidade. Assim, para alcançar metas de eficiência energética ambiciosas, os edifícios devem ser sujeitos á inovação tecnológica, que permitirá uma melhor gestão de energia.

A gestão de energia, nos dias de hoje, é um assunto de grande importância e complexidade, pois escolhe de entre um conjunto de fontes e cargas que poderiam minimizar as perdas e os custos. Sistemas de gestão de energia juntamente com os sistemas de armazenamento de energia podem otimizar a utilização de eletricidade, tornando-a mais eficiente.

Deste modo, o objetivo desta dissertação é apresentar um sistema capaz de gerir de forma inteligente sistemas de armazenamento de energia, padrões de consumo dentro de prédios e fontes de energia através de estratégias bem definidas. Este sistema tem por base um sistema de decisão que, embora mantendo a segurança, a estabilidade e a qualidade do serviço da rede de alimentação, pode otimizar o consumo de eletricidade dentro dos edifícios e melhorar a gestão da carga elétrica.

Para concluir, esta dissertação visa desenvolver um *software* de computador, um simulador, a fim de testar a viabilidade deste sistema e se os resultados globalmente otimizam a utilização de eletricidade.

Palavras-chave: Sistemas de gestão energética; Sistemas de armazenamento de energia; Consumo de eletricidade; Edifícios; Padrões de comportamento; Simulador.

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Abbreviations List

Abbreviation	Meaning
AC	Alternate current
AGM	Absorbed glass mat
BOP	Balance of plant
DC	Direct current
EDP	Energias de Portugal
ESS	Energy storage system
EU	European Union
GHG	Greenhouse gas
GUI	Graphical user interface
KPI	Key performance indicator
LCoS	Levelised cost of storage
PCS	Power conversion system
QoS	Quality of service
REN	Redes energéticas nacionais
SIC	Specific investment cost
SOC	State of charge
USA	United States of America
VAT	Value-added tax
WACC	Weighted average cost of capital

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1

Introduction

In the following subchapters, the author displays a brief contextualization of the problem that lead to the creation of this dissertation. In addition, the author presents below the motivation, the proposed objectives and a simple explanation of each chapter.

1.1 Context

Electricity consumption worldwide is currently an important topic, due to not only the amount, but also the variations within the day. These factors generate inefficiencies in supply and demand of electricity. Buildings, an important part in people's lives, have a significant share in both amount and fluctuations, in behalf of the occupants' behavioural patterns. Energy storage systems (ESSs) are key technologies to counter this problem by enabling efficient load management. These systems combined with a predictive model of the building occupants' behaviour can improve the load management and optimize the end-user consumption. However, this improvement is only achievable through the creation of strategies that follow a well-defined set of rules.

1.2 Motivation

Energy affects us all. It is a major concern thanks to the greenhouse gas (GHG) emissions impact on the environment and on the dependency of fossil fuels (limited resource) to create energy, a good that most people take for granted. Electricity also participate heavily on human comfort, which enforces a need to optimize its supply-demand balance.

The building sector is an important target to optimize, due to its importance in people's lives. If we take into account work offices, residences and commercial buildings, people generally spend 90% or more of their time indoors (EPA's Green Building Workgroup, 2009). By spending so much time within buildings, these consume electricity actively. This happens to maximize our comfort, creating an intrinsic need for energy. Light, power or mobility are a few examples of electricity's share on human comfort.

The author of this thesis desires to develop a system that has a positive impact on people's lives, through enhancing efficiency between energy suppliers and consumers.

1.3 Objective

In this thesis, the proposed methodology is to manage different energy storage systems within buildings. This procedure means to improve the load management, optimize electricity consumption and minimize the costs without decreasing quality of service (QoS). To fulfil these objectives, this project requires distinctive components: a set of ESSs, a building with access to the power grid, predictive model of human behaviour within buildings and algorithms to resolve the interoperability between these components.

Each energy storage system (ESS) connects with the grid through the building's energy supply, whether it comes from the power grid or local renewable resources. These are capable of energy storage and release whenever required. The above-mentioned have specific operational constraints that differ between individual units such as efficiency, capacity and charging times.

The human behaviour model has its foundation on statistical electricity consumptions (patterns), gathered from trustworthy sources (e.g. REN, Portuguese company that manages the national electrical system), and on-going energy consumption verification.

The algorithms controls the ESSs operational methods (charge and discharge periods) depending on their individual attributes, through implemented strategies. In addition, it decides when to use energy from ESSs or the grid based on the supplied energy characteristics and prices, without the end-user realising any changes (maintain the QoS). In summary, routing, treating and managing all the communications between each component is the algorithm's main purpose, ensuring QoS and minimal cost.

Therefore, to create this, there has to be a decision system with specific strategies that can implement this idea.

To test this decision system, a simulation platform is developed in Java programming language to demonstrate the results of the implementation in different situations.

1.4 Original Contributions

Although chapters 2 and 3 details the information that enabled its creation, the author developed a simulator exclusively for this thesis. This simulator enables the usage of the components required for the objectives by implementing the proposed system. It contains the management system that facilitates the usage of different strategies to obtain results.

1.5 Outline

This dissertation's structure is as follows:

- **Chapter 1 –** Introduction.

  It contains the contextualization of the topic of this dissertation, referring the problems that lead to the creation of this system, the motivation behind it and the original contributions that this project implements.

- **Chapter 2 –** Electricity: the indispensable good.

  This chapter addresses the importance of electricity on human life, its generation, consumption, prices and consequences of its use.

- **Chapter 3** – Energy storage systems.

  An introduction of energy storage systems' definition, their composition and characteristics. Contains a comparison between storage technologies to achieve the best-suited devices for this project.

- **Chapter 4** – Previous work and proposed approach.

  It has a brief description of some projects and designs created within the area of subject and details the architecture and method of operation of the system to implement.

- **Chapter 5** – Implementation.

  An explanation of the components, methodologies and processes that the author implemented for this thesis.

- **Chapter 6** – Validation.

  Contains the demonstration and interpretation of the system's results. Displays multiple simulations for diverse situations.

- **Chapter 7 –** Conclusions and future work.

  This chapter contains the conclusions regarding the dissertation along with some prospects about future work.

2

Electricity: the indispensable good

This chapter emphasizes on the importance of electricity as a consumer item and its impact on human life. It details its generation, consumption, prices and consequences of its use.

2.1 Electricity's share in energy *versus* environment

Energy is an important factor in everyday human lives, whether it is through electricity, usage of fossil fuels for vehicle purposes or heating using natural gas. Its usage has been critical to maintain our comfort, through the majority of its forms, suffering a 49% growth in consumption between 1984 and 2004 (Pérez-Lombard, Ortiz, & Pout, 2008). Consequentially , electricity generation also experienced nearly a quadruple growth between 1973 and 2014 (International Energy Agency, 2016), with prospects of further increase around 43% until 2031 (World Nuclear Association, 2011).

This increase of electricity generation supports the discovery of technologies that enabled its production through renewable resources. However, coal remains as the fuel with the highest share of electricity generation (International Energy Agency, 2016). This creates an environmental impact, supported by the growth of CO_2 (carbon dioxide) emissions by 43% between 1984 and 2004 (Pérez-Lombard et al., 2008), and the fact that it is a limited resource. In addition, electrical energy production is responsible for approximately 37% of the total of global CO_2 emissions (World Nuclear Association, 2011).

The increase of emissions developed into palpable climate changes and an increase worry for the planet's sustainability. According to (Rissman, 2013), "*The limiting factor on humans' fossil fuel use will not be the exhaustion of economically recoverable fossil fuels, but the exhaustion of the Earth's capacity to withstand the harmful by-products of fossil fuel combustion*". This means that even before the drainage of all the planet's fossil fuel reserves, irreversible changes would affect the environment.

Therefore, nowadays, renewable energy resources – any resource that regenerates naturally, over a human timescale, and derived directly or indirectly natural movements and mechanisms of the environment (e.g. sun and wind) – have an important role in global energy production.

2.2 Renewable energy sources: solution or problem?

Renewable energy sources, as clean energy, can help fulfil the end-users demands when the production is not enough, by taking some weight out of conventional energy production and helping with the diminishing of GHG emissions as observed in Figure 2.1

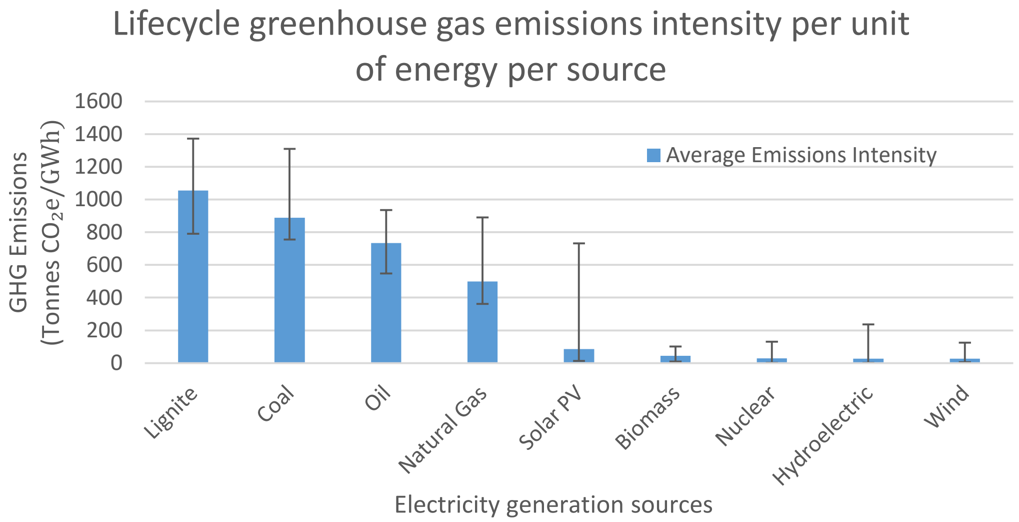


Figure 2.1 – Lifecycle greenhouse gas emissions intensity by energy generation method. The error bars relate to the range between different studies. Adapted from (World Nuclear Association, 2011).

A problem of renewable energy is the investment required for production infrastructures. However, some technologies can achieve prices similar to fossil fuel currently. In 2014, fossil fuel delivered electricity regularly between 0.045 $/kWh and 0.14 $/kWh, with some solar photovoltaic projects capable of reaching prices as low as 0.06 $/kWh and onshore wind reaching 0.05 $/kWh (Irena, 2015). The values presented are in American dollars.

The usage of natural resources, while being environmentally friendly, has some adjacent problems. The most important is the reliability of supply. By depending on climacteric conditions, these sources are dependent on external factors. Any significant change in weather can alter the production of energy and possibly halting it all together. These resources, by not producing based on demand, lead to unnecessary production if not well managed.

The answer to the question: *"Renewable energy sources: solution or problem?"* is solution due to the environmental impact of fossil fuels. However, this solution does intake some problems, due to its unreliability.

Flagged as a solution, the European Union (EU) created a package, known as "2020 climate & energy package", based on three key targets (European Comission, 2016):

- 20% cut in GHG emissions (from 1990 levels);
- 20% of EU energy from renewables;
- 20% improvement in energy efficiency.

Respecting this package, occurred an increase of renewable energy installed capacity as witnessed in Figure 2.2.

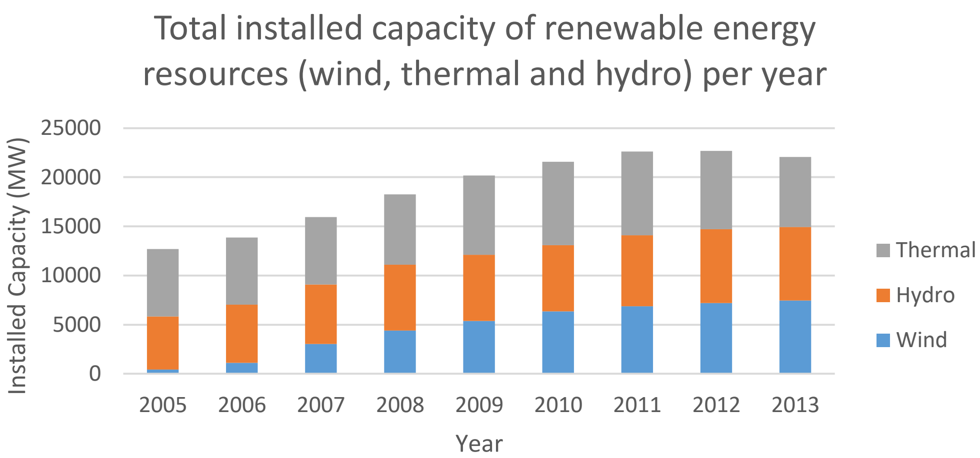


Figure 2.2 – *Energias de Portugal* (EDP) total installed capacity in MW of different types of renewable energy resources between 2005 and 2013 in Belgium, Brazil, France, Portugal, Spain and USA combined. This chart includes both special and conventional regimes. Adapted from (Energias de Portugal (EDP), 2014).

2.3 Electricity: consumption patterns

Electricity is a good that the vast majority of consumers specify as a personal need, with 99,9% of the houses in Portugal having electricity by being connected to the grid by 2010 (INE & DGEG, 2011). Also, by 2012, 84.6% of world population had access to electricity, with the majority of the European countries presenting a share of approximately 100% (The World Bank, n.d.).

Different applications use electricity, like a consumer item, to perform their tasks, such as lighting, heating or cooling, operating appliances and electronic devices. The consumption depend on human behaviour, which differs between seasons, because the consumers have different needs whether it is summer or winter, and between diverse geographic locations. Although it can be predictable on a large timescale, it incorporates an unpredictability factor.

Accordingly, the author displays below aspects of electricity consumption, for Portugal and USA.

2.3.1 Portugal

In Portugal, the day with the highest peak, is usually in the winter. Its consumption peaks reach up to almost twice the value of the lowest demand period (Redes Energéticas Nacionais, 2014), as corroborated by Figure 2.3.

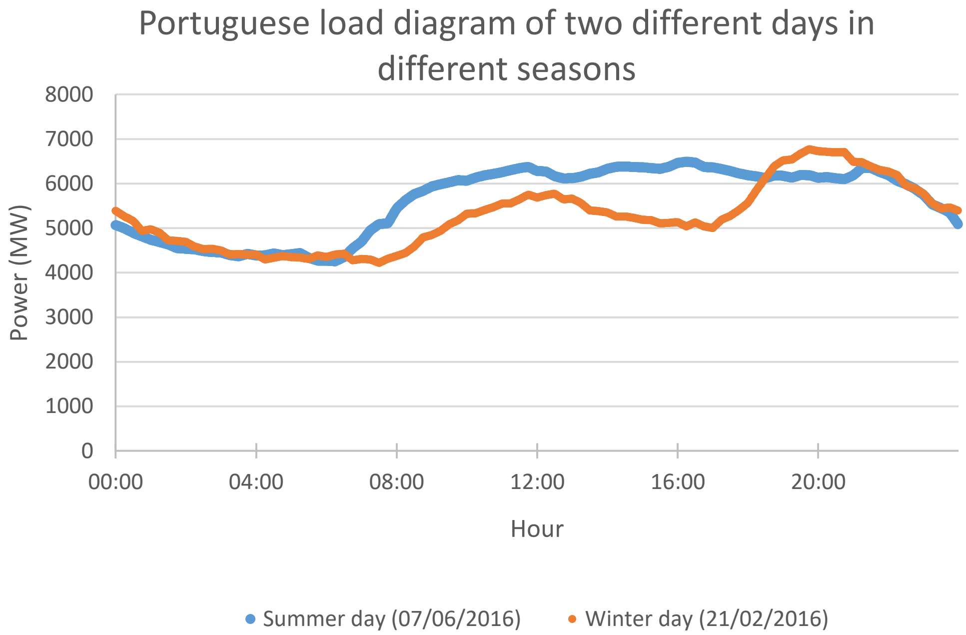


Figure 2.3 – Load diagram of two different days in different seasons. Consumption of the entire country. Adapted from (Redes Energéticas Nacionais, 2016).

Since the electricity fully penetrated the market, its consumption has three main sectors: transport, industry and buildings (residential and commercial).

In Portugal, by 2013, electricity consumption divided itself as follows: industry (37%), services (34%) and domestic purposes (26%) as observed in Figure 2.4. The services share refer, mostly, to electricity usage within commercial or offices buildings (Direção-Geral de Energia e Geologia, 2013). This determines that, building-related expenses are the main reason for the consumption of electricity with near 60% (34%+26%) of its total.

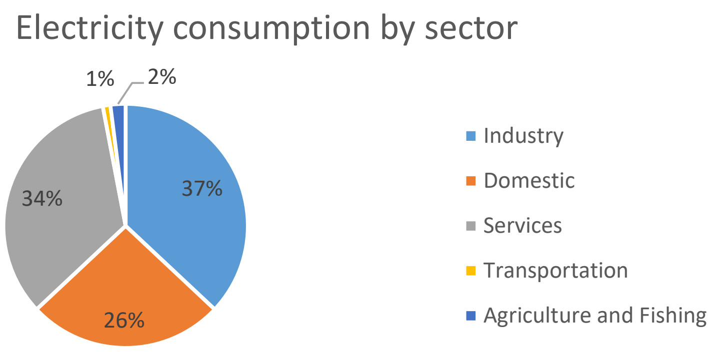


Figure 2.4 – Electricity consumption by sector in Portugal, in 2013. Adapted from (Direção-Geral de Energia e Geologia, 2013).

2.3.2 USA

Changes in electricity demand levels are generally predictable and have daily, weekly and seasonal patterns. Daily fluctuations create consumption peaks, as seen in Figure 2.5, which vary between seasons. Summer and winter months tend to have higher demand levels than fall or spring due to space conditioning (heating or cooling) (U.S. Energy Information Administration, 2011b).

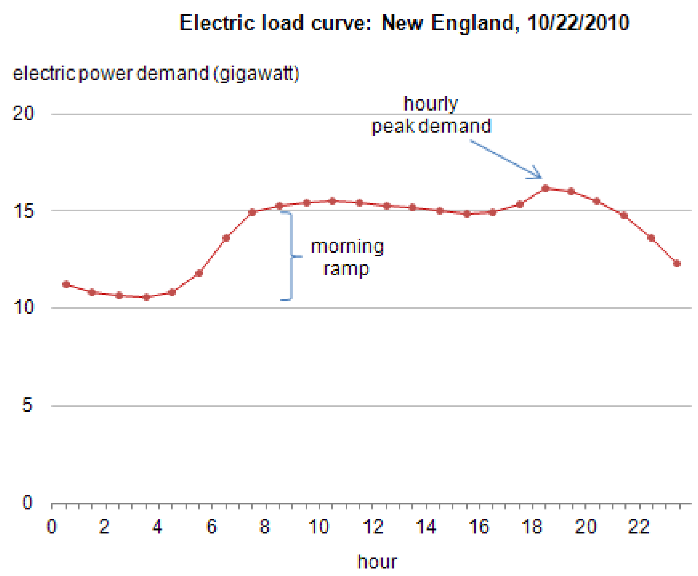


Figure 2.5 – Example of a load diagram in New England, USA on a autumn's day (U.S. Energy Information Administration, 2011a).

In the USA, the residential, or domestic, sector led the total consumption of electricity in 2014 with 36%, followed by commercial purposes with 35%, industry 28% and transportation 0.2% (U.S. Energy Information Administration, 2016). Since the commercial and residential sectors link with buildings, they have a considerable impact on electricity consumption with 71% of its total (36%+35%).

2.4 Buildings: electricity utilization and consequences

As explained in 2.3, buildings have a high share of the total consumption of electricity, which embodies some consequences. Depending on the amount of consumption, it affects the payment bill and influences the load management problem. Both usage and price depend heavily on human behaviour patterns, geographic location and rules associated with said location. Accordingly, buildings represent an opportunity to optimize the load management and general energy efficiency.

2.4.1 Utilization

Concerning buildings' consumption, the average annual consumption of a residence utility customer was 10 932 kWh in 2014, in the USA (U.S. Energy Information Administration, 2015b) and 3 673 kWh in Portugal in 2010 (INE & DGEG, 2011). Dividing equally, between twelve months, results in approximately 911 kWh and 300 kWh, respectively, per month. However, this calculation has an error attached because of significant differences in consumption between seasons, as explained in 2.3.1 and 2.3.2.

For possibility of consumption, the consumer establishes a contract agreement with the service provider for energy and power supply.

2.4.2 Contract conditions

Each contract has specific conditions: power supplied (in kVA) and its attached price per day (in € or $), type of schedule (how many different prices per day) and the various prices per energy (€/kWh or $/kWh).

Electricity's prices depend on several variables. It may be, throughout a specific period, constant or variable, established by a single entity or different between service providers.

Such variables also vary between geographic locations, as displayed further below.

2.4.2.1 Portugal

In Portugal, since the completion of the energy market's liberalization, the previous entity, ensured to enlist the electricity prices, no longer controls it. Thus, each of the provider companies can establish their own prices, respecting the competition rules established and the commercial relations regulation.

Contract agreement's total cost, for the consumer, depends on several variables such as contracted power, type of schedule, method of payment and type of receipt. Contracted power is the maximum power supplied to the consumer and, for households or small companies and offices, it ranges between 1,15 kVA and 41,4 kVA (EDP Comercial, 2016). The type of schedule is the amount of different prices per energy, throughout one day, while the method of payment refers to ATM payment or direct debit. The type of receipt is the choice between physical or virtual receipt.

For example, the price range, listed alphabetically by service providers, for a direct debit with virtual receipt electricity contract (between 1.15 kVA and 41.4 kVA) within different types of schedules can be:

- *EDP Comercial*: Contracted power between 0.0832 and 0.8495 €/day and energy consumption between 0.0805 and 0.3192 €/kWh.
- *ELusa*: Contracted power between 0.1536 and 1.6544 €/day and energy consumption between 0.0696 and 0.3047 €/kWh.
- *ENAT*: Contracted power between 0.0832 and 2.1472 €/day and energy consumption between 0.0756 and 0.3227 €/kWh.
- *ENDESA*: Contracted power between 0.1492 and 1.5242 €/day and energy consumption between 0.0705 and 0.2718 €/kWh.
- *Energia Simples*: Contracted power between 0.0832 and 2.1472 €/day and energy consumption between 0.0750 and 0.3105 €/kWh.
- *GALP Energia*: Contracted power between 0.1261 and 1.9278 €/day and energy consumption between 0.0762 and 0.2967 €/kWh.

The prices shown above are presented without the value-added tax (VAT) and were obtained from the (ERSE, 2016) report. Additionally, above the 41.4 kVA mark, prices are dependent on the situation, requiring a specific contact with the service provider.

The types of schedules used are identical between each provider, dividing up to three different periods the 24-hour cycle. Each of this division has a different price per unit of energy (e.g. €/kWh). There can be one (normal price), two (normal and economic) or three prices per day (normal, economic and super economic). However, the normal price is different between each division.

As an example, Figure 2.6 demonstrates a type of schedule from a specific service provider, *EDP Comercial*. This division may not be equal in different electricity providers.

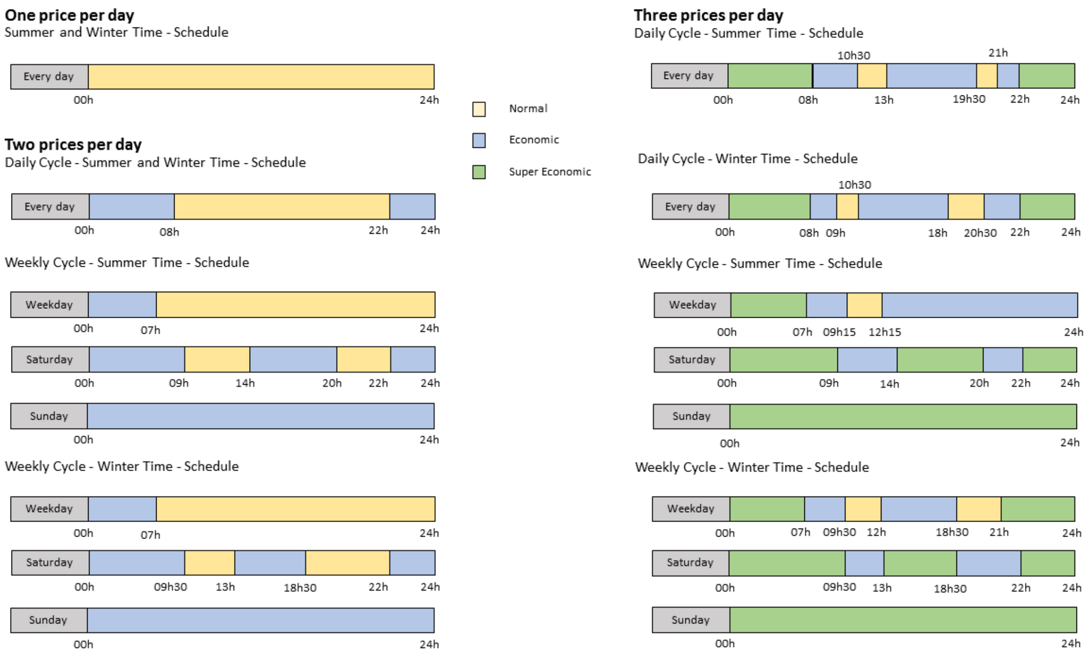


Figure 2.6 - Difference between types of schedules and the respective types of price in a specific energy provider (*EDP Comercial*). Adapted from (EDP Comercial, 2016).

Between the types, which have different price tags during the day, there are also two options: weekly or daily cycle. The consumer chooses the one which best fits his needs.

In every schedule, there is something constant: the attempt for the costumer to use electricity outside peak hours (late afternoon, early evening to beginning of night). This would lighten the demand during those periods, decreasing the demand's fluctuations intensity.

2.4.2.2 USA

In the USA, prices per unit of energy can fluctuate within every minute, depending mostly on the current demand. Whenever the demand is highest, so is the price. This demand is usually higher during the afternoon and early evening (also known as peak hours). In general, these prices are higher in the summer due to the higher demand observed during that season (U.S. Energy Information Administration, 2015a).

During the year of 2014, the average retail price of electricity within the USA was different between sectors with the following:

- Residential: 12,50 cents per kWh;
- Commercial: 10,75 cents per kWh;
- Industrial: 7,01 cents per kWh;
- Transportation: 10,27 cents per kWh;

With these prices, the global average retail price for electricity was 10,45 cents per kWh (U.S. Energy Information Administration, 2015a). All the prices in 2.4.2.2 are in American dollars.

2.4.3 Load management

The increase of global electricity consumption, based on the easy access to electricity and its impact on personal comfort, united with the global human behaviour created fluctuations in its consumption.

During the hours of peak usage, the grid must be able to fulfil the needs of its users. Due to the users' energy demand, the consumption will be continuously fluctuating, creating large differences in energy demand during the day. In order to brace those peaks, the distribution and transmission processes are over-dimensioned. By creating such an empowered energy delivery and transmission system, we acknowledge that, most of the time, the grid is working far from its maximum capabilities, proving the existence of energy inefficiencies. In extreme cases, the ratio between peak and lower power levels in end-user demand, can reach a value of 10 (Ibrahim, Ilinca, & Perron, 2008).

A valid solution to stabilise the energy daily grind and increase the usage efficiency is through load levelling.

Energy load levelling is a method for reducing the large fluctuations that occur in electricity demand. Storing energy during periods of low demand and releasing it later, when there are high demand periods (peaks), is key to implement load levelling as Figure 2.7 demonstrates.

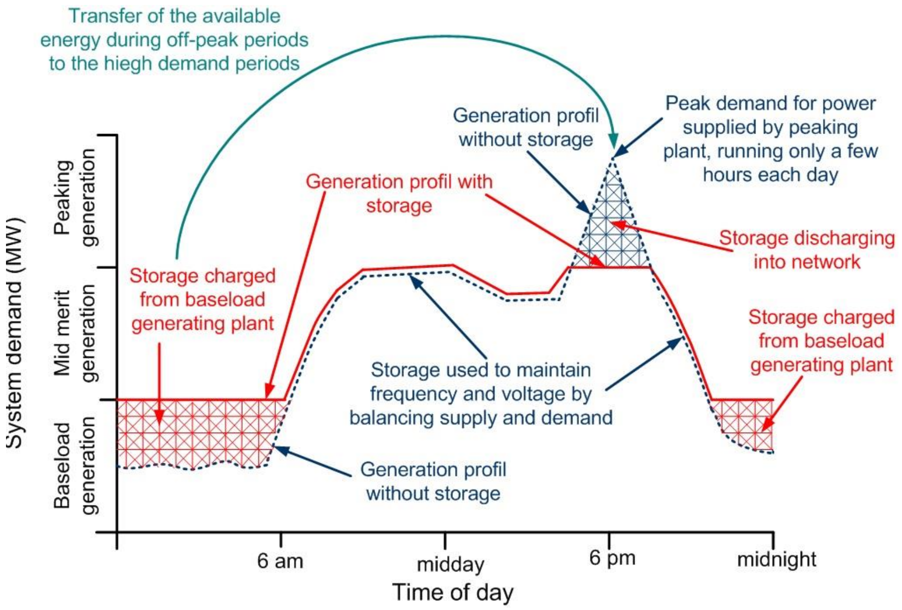


Figure 2.7 – Effects of energy storage on the electricity system demand (Ibrahim & Ilinca, 2013).

However, for load levelling implementation, devices capable of storing energy are required. Energy storage systems are available and the next chapter describes their characteristics and functionalities.

3

Energy storage systems

In this chapter, there is an explanation of the definition, virtues, characteristics and applications of energy storage systems. It also describes a comparison between several devices to discover which are better suited for the purpose of this thesis.

3.1 Overview

Energy storage systems, or ESSs, are devices installed within a power system that can store and release energy received by the power grid.

Inconsistencies in energy consumption-generation balance such as fluctuation in power usage and the unreliability of energy production by virtue of renewable resources created the need to develop such devices.

These devices, would not only enable the implementation of the energy load levelling method, as detailed in 2.4.3, but also ensure the reliability of renewable energy resources and power quality within the network, amongst others, as displayed in Figure 3.1.

Energy storage systems are categorised by the type of stored energy each one utilises. This categorisation is as follows:

- **Chemical energy** → Hydrogen, batteries and flow batteries;
- **Electrical energy** → Capacitors, supercapacitors and superconductors;
- **Mechanical energy** → Flywheels, compressed air and pumped hydroelectric;
- **Thermal energy** → Sensible and latent heat storage, cryogenic storage and pumped heat.

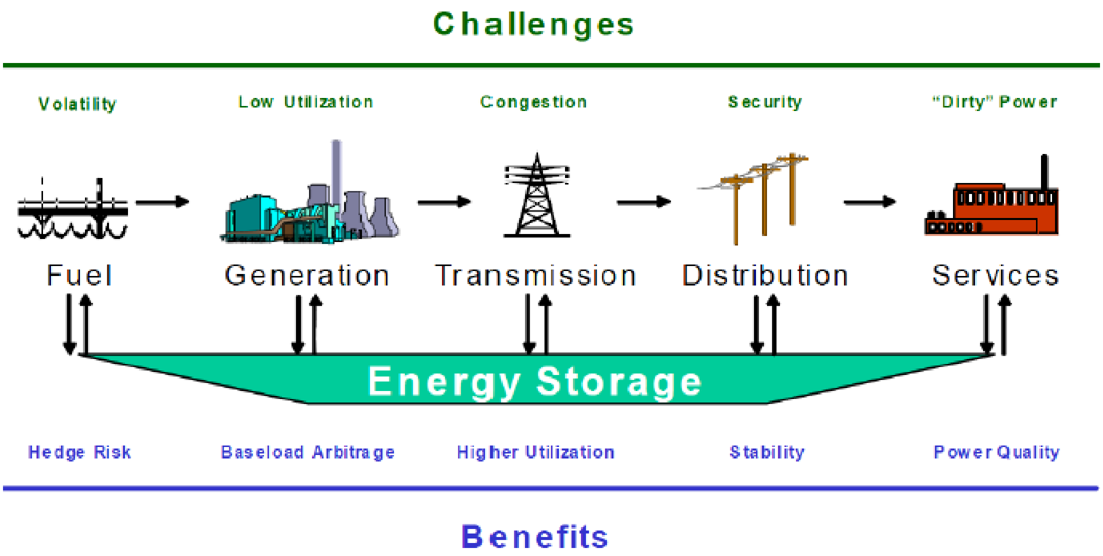


Figure 3.1 – Benefits of energy storage systems (Ibrahim & Ilinca, 2013).

These systems are divided into three primary components: storage medium or energy storage unit, power conversion system (PCS) and balance of plant (BOP) (Schoenung & Hassenzahl, 2003) as Figure 3.2 shows.

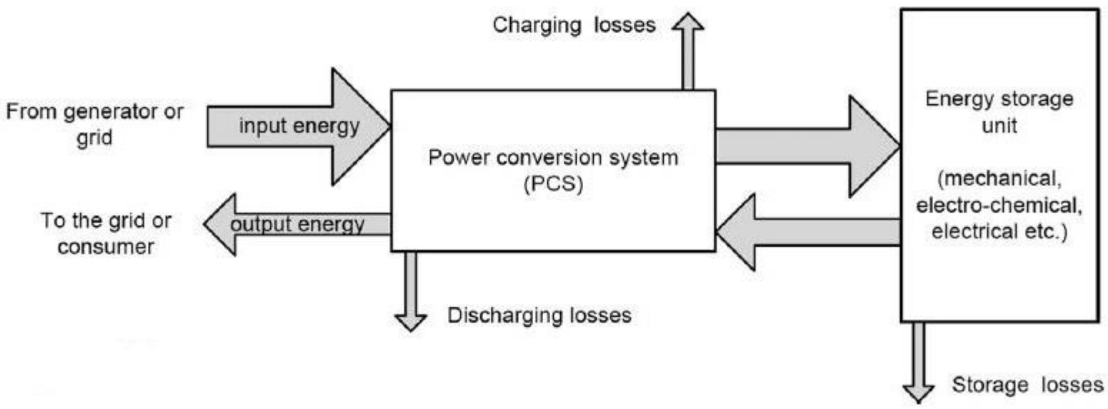


Figure 3.2 – Schematic of a possible composition of a ESS (Zakeri & Syri, 2015). This figure does not include the BOP.

Whilst the storage medium is the physical space where the energy is stored, the PCS is the power electronics required to convert between AC (alternate current) and DC (direct current). PCS operates, also, as a rectifier and an inverter to: enable charge and discharge cycles, and restrain the power during conversion to maintain the safety of the entire system. This component is responsible for 33% to 50% of the entire facility costs because it needs adaptation to each specified ESS (Ibrahim & Ilinca, 2013). Since current can only flow in one direction, the PCS enables the calculation between the required current from the load and the charging current from the grid. The result of this calculation determines if the battery charges (higher current from grid) or discharges (higher current demand from load).

The third component, BOP, is the protection of the system, its physical surrounding. It encloses the equipment, controls the storage facility environment and provides the connection between PCS and the grid.

In recent years, there has been a global attempt to improve the capacity of energy storage capabilities, resulting in the increase of nearly 40 GW in the last 14 years (International Energy Agency, 2015).

3.2 Characteristics

Before analysing in detail the different types of storage systems, the author discloses some concepts regarding these technologies and their respective units, if applicable. Some units are not in tandem with the international system of units for easier manipulation and visualisation.

Power Density (W/m^3) – amount of power per unit of volume.

Energy Density (J/m^3) – amount of energy per unit of volume. Also known as specific energy.

Capacity ($Wh\ or\ Ah$) – amount of available energy after a full recharge. It is the total of energy stored in a specific ESS.

State of charge ($\%\ of\ capacity$) –percentage value of remaining energy within an ESS unit.

Rated Power ($W\ or\ VA$) –value representing the operational power of charge or discharge. Both values are usually different.

Discharge Time ($minutes$) – duration of a complete discharge. It is a relation between capacity and rated output power.

Recharge Time ($minutes$) – duration of a complete charge. It is a relation between capacity and rated input power.

Efficiency (%) – ratio between the energy stored in the ESS and the energy supplied to it. Measures the energy loss by comparing its output with its input.

Durability – number of cycles, or years, the system can withstand. A cycle consists on a charge and a discharge of energy.

Self-discharge ($Wh\ or\ Ah$) – amount of energy dissipated from the system while not in use.

Maturity – whether the technology has developed enough for implementation. Expresses the degree of “technical and commercial readiness”.

Maximum depth of discharge (%) – percentage value of the total capacity that can be discharged. This is usually a recommended value for ideal durability.

Equivalent full-load hours ($hours\ per\ year$) – amount of hours per year an ESS operates to store energy.

Response Time ($seconds$) – time that an ESS takes to react to a given input.

Specific investment cost (SIC) ($€/kW$) –cost value of one kilowatt. Investment cost per installed power.

Levelised Cost of Storage (LCoS) ($€/kWh$) (World Energy Council, 2016) – It is a fictitious average 'net' price that must be received per unit of output (kWh) for storing energy during its entire lifetime, in order to reach a specified financial return. This notion standardises the units of measuring the lifecycle costs of storing energy. It eases the comparison of the cost of storing one unit of stored electric energy by each technology.

LCoS takes into account different characteristics (detailed further in Table 3.1) of the technologies as described in equation 1 and Table 3.1 (World Energy Council, 2016).

$$LCoS = \frac{I_o + \sum_{t=1}^{n} \frac{A_t}{(1+i)^t}}{\sum_{t=1}^{n} \frac{M_{el}}{(1+i)^t}} \tag{1}$$

$$LCoS - Levelised\ cost\ of\ storage\ \left[\frac{€}{kWh}\right]$$

Table 3.1 – Explanation of calculation of LCoS variables (World Energy Council, 2016).

Variables	Definition	Unit
Investment costs(I_o)	Specific investment cost (SIC) * rated power	Euro (€)
Annual total costs in year(A_t)	Operational costs (in %) * investment costs	Euro (€)
Produced electricity in each year(M_{el})	Rated power * Equivalent full-load hours * Efficiency	kWh
Technical lifetime(n)	Durability of a device in years	Years
Year of technical lifetime(t)	"Age" of the specific device	Integer(1,2,3,…n)
Discount rate(i)	Discount rate(WACC)	%

As detailed in Table 3.1, SIC is a part of the investment cost. This parameter describes the investment required per installed discharging capacity (€/kW).

The annual costs are a small part (usually between 1% and 5%) of the total investment costs. In addition, the weighted average cost of capital (WACC) is a tax value used to discount future electricity discharge. This equation assumes that there are no changes in parameters or prices during its lifetime and that there is no input for the price of charging power (can be added later for specific studies) (World Energy Council, 2016).

These concepts will be the basis of an informed decision on which systems are best for this thesis. The next sub-chapter, with these notions, compares different types of ESSs technologies regarding some rules.

3.3 Comparison between ESS technologies: Which are better suited for this project?

Before being able to make a comparison between different energy storage systems, the author developed a review of existent technology to understand their operational process, their composition and their definition. The technologies in comparison are hydrogen energy storage, lead acid batteries, nickel-cadmium batteries, sodium sulphur batteries, sodium nickel-chloride batteries, lithium ion batteries, flow batteries, supercapacitors, superconducting magnetic energy storage, flywheels, compressed air storage, pumped hydroelectric and thermal energy storage.

The comparison uses several characteristics that differentiate the technologies. Size, maturity, environmental impact, efficiency, rated power, discharge time, durability and cost are some specifications that this analogy uses to reach a conclusion on the implementation of an intelligent energy management system within buildings.

3.3.1 Size

Since the project designed is to use these technologies within buildings, size is crucial. Therefore, the devices chosen must have dimensions that a normal building can accommodate. With this in mind, the infrastructures of compressed air energy storage, pumped hydroelectric and thermal technologies, preclude the usage of these devices within residential buildings.

3.3.2 Maturity

The possibility of implementation depends on already developed technologies. Maturity determines which devices are capable of implementation.

As observed in Figure 3.3, research, development, demonstration, deployment and commercialisation are the possibilities regarding maturity. This project does not consider technologies within stages of research and development, due to the lack of guarantees these might provide. Likewise, it only considers technologies in the decreasing part of the curve (capital requirement * technology risk). Through this decision, supercapacitors, superconducting magnetic energy storage, hydrogen technologies, sodium-nickel chloride batteries and flow batteries are not suitable for this project at this time.

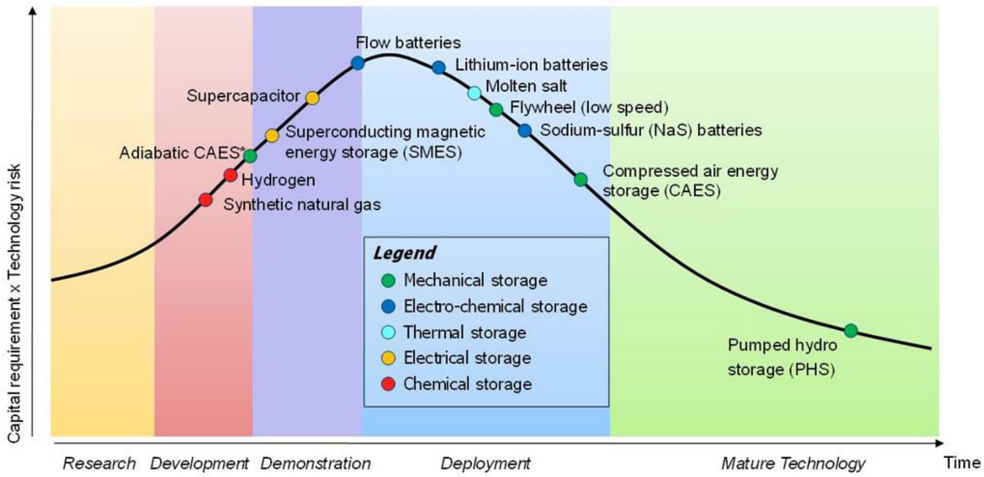


Figure 3.3 – Maturity curve of different ESS technologies (SBC Energy Institute, 2013).

3.3.3 Environmental Impact

The effect on the environment is an important factor on the choice of these technologies. Within the technologies studied, one contained an element that is toxic for the environment (cadmium). Consequently, nickel cadmium batteries are not useful. Although lead acid batteries are hazardous, there are technologies that recycle lead without consequences to the environment, reaching up to a total of 98.25% of lead content recycled (Exide Technologies, 2016).

3.3.4 Performance characteristics

These characteristics are capacity, rated power, discharge time, charging time, durability, efficiency, response time, self-discharge, maximum depth of discharge and operational temperature.

Table 3.2 presents the specifications' values for different energy storage systems. The table show an interval of values for each technology's parameter. However, depending on the usage of each ESS, it tends more to the beginning or end of that interval, depending on the application. For example, if a battery completes two cycles per day, its longevity should be shorter than if it only does it once per day.

From Table 3.2, we can acknowledge that flywheels have the highest power output and fastest recharging time between the technologies compared but also has high self-discharge rate. In addition, the implementation of a sodium sulphur battery is difficult within a building due to the high operating temperature, precluding its use.

Table 3.2 – Performance characteristics of different ESSs for short-term storage. Adapted from (Badwal, Giddey, Munnings, Bhatt, & Hollenkamp, 2014; H. Chen et al., 2009; Hadjipaschalis, Poullikkas, & Efthimiou, 2009; World Energy Council, 2016; Zakeri & Syri, 2015).

Characteristics		**Technologies**			
Parameter	**Unit**	Lithium ion battery	Sodium sulphur battery	Lead acid battery	Flywheel
Rated power	kW	up to 10 000	Up to 34 000	Up to 70 000	Less than 500
Discharge time at rated power	time	Minutes to 10 hours	Seconds to 10 hours	Seconds to 10 hours	Milliseconds to 15 minutes
Recharging time	time	Minutes to hours	~9 hours	8-16 hours	Less than 15 minutes
Efficiency	%	80 - 92	75 - 80	65 - 90	80 - 95
Maximum depth of discharge	%	Up to 90	Up to 90	60 - 70	Up to 100
Self-discharge per day	%	0.1 - 0.3	~20	0.1 - 0.3	100 (20 per hour)
Durability	years	5 - 20	15 - 25	5 - 15	15 - 20
Durability	cycles	1500 - 4500	2500 - 4500	2000-4500	10^5 to 10^7
Response time	seconds	0.18 – 0.3	0.18 – 0.3	0.18 – 0.3	4 - 10
Operating temperature	°C	-10 to 50	300 to 350	-5 to 40	20 to 40

3.3.5 Cost

Cost, regarding ESSs, divides itself between initial investment and annual operational costs. The latter depends on the former and the former depends on the SIC (energy per unit of power). Table 3.3 displays the SIC and operational costs for the different technologies chosen previously.

As displayed, the expectation is a decrease on investment costs until 2030, due to the increasing need and usage of these technologies in the near future. Hand in hand with this usage growth, are expected several developments for every storage technology. This advancement anticipates the average increase of durability, efficiency and maximum depth of discharge (World Energy Council, 2016).

Table 3.3 – Investment and operational costs differences between ESSs technologies in 2015 and its expected evolution until 2030. Adapted from (World Energy Council, 2016).

Characteristics		**Technologies**					
Parameter	**Unit**	Lithium ion battery		Lead acid battery		Flywheel	
Year	--------	2015	2030	2015	2030	2015	2030
Specific investment costs	€/kW	800-3700	300-1700	500-1700	100-600	600-1000	200-300
Operation costs	(%*Investments)	2	2	2	2	2	2

Based on SIC and LCoS notions, a technology financial review was developed in World Energy Council, 2016, which considered different possible implementation of ESSs. It resulted in a range of values for LCoS in 2015 and 2030 visible in Table 3.4 .

Table 3.4 – Levelised cost of storage between ESSs technologies in 2015 and its expected evolution until 2030. Adapted from (World Energy Council, 2016).

Characteristics		**Technologies**					
Parameter	**Unit**	Lithium ion battery		Lead acid battery		Flywheel	
Year	--------	2015	2030	2015	2030	2015	2030
Levelised cost of energy storage (LCoS)	€/kWh	0.15-0.7	0.15-0.19	0.11-0.4	0.06-0.08	0.06-0.09	0.02-0.04

As expected, after examining Table 3.4, the LCoS values decreases until 2030, because of high market penetration.

The calculations required to achieve these values, in Table 3.4, depend on the SIC and LCoS notions explained in 3.2 and Table 3.1. The discount rate (WACC) is 8% and there is no price variations throughout the durability of the system. Plus, the LCoS does not include the cost for input electric energy (World Energy Council, 2016).

Even so, to reach the values presented in Table 3.3 and Table 3.4 , the financial review assumed that the discharge time at rated power is between 1 and 4 hours for lithium ion and lead acid batteries and 0.25 hours (15 minutes) for flywheels (World Energy Council, 2016).

The calculation of LCoS (Table 3.4), for both 2015 and 2030, stipulated the values of equivalent full-load hours, efficiency, maximum depth of discharge and technical lifetime as represented in Table 3.5.

Table 3.5 – Assumptions for LCoS calculations. Adapted from (World Energy Council, 2016).

Characteristics		**Technologies**					
Parameter	**Unit**	Lithium ion battery		Lead acid battery		Flywheel	
Year	-------------	2015	2030	2015	2030	2015	2030
Equivalent full-load hours	Hours/year	365-1460	365-1460	365-1460	365-1460	1825	1825
Efficiency	(%)	85	92	77	82	88	88
Maximum depth of discharge	(% of capacity)	70	80	65	75	100	100
Technical lifetime	years	6	12	5	15	15	15

The results obtained through the LCoS calculation are not perfectly accurate, because it can change depending on its application. It is noteworthy that the BOP is not included in the final cost. Nonetheless, it is a good method for comparing costs between ESSs.

3.3.6 Summarize and conclusions

After the comparison between these ESSs, the results answer the question "*Which are better suited for this project?*" with three different types of technology.

Acknowledging the limitations and specifications of the purpose of this system, the lead acid batteries, lithium ion batteries and flywheels are the better-suited options for implementation.

4

Previous work and proposed approach

This chapter enlists some previous work within the field of this project and specifies the general idea behind this project by enumerating its subparts and explaining its main functionalities.

4.1 Previous work

Several researchers have conducted studies for intelligent management systems in the past few years. Within this field, building simulation tools are the whole-building energy simulation programs that provide users with key building performance indicators, such as energy use, demand and costs. In addition, most of these programs rely on assumptions referring to human behaviour (Robinson, 2006).

In (Crawley, Hand, Kummert, & Griffith, 2008) there is a comparison between twenty simulation programs such as EnergyPlus, which this article considers as the state of the art regarding building energy simulation software. However, these do not support energy storage systems, basing themselves on the optimization of utilities usage within buildings. Another example is (Byun, Hong, & Park, 2012), which proposes intelligent cloud home energy management systems to establish dynamic priorities to household appliances.

However, some designs implement energy storage systems for energy optimization, as in (C. Chen, Duan, Cai, Liu, & Hu, 2011; Cirrincione et al., 2009; Huang, 2010).

The FREEDM system (Huang, 2010), on one hand, attempts to change the entire power network with the help of solid-state transformers and energy storage systems, using renewable energy resources to provide “cleaner” energy with guaranteed stability. The possibility of plug-and-play within the power network is the main objective within this system. It uses management systems throughout the grid for decision-making purposes, in order to achieve distributed generation.

Another proposition is a system able to self-regulate a heterogeneous set of power sources and loads with the help of energy storage systems to optimize cost and efficiency (Cirrincione et al., 2009). It uses a multi-agent system to perform the communication between the load demand, the sources and the grid. Although the strategy is always the same, the researchers are designing new techniques to improve the decision-making and enable the creation of new and more efficient management strategies.

In (C. Chen et al., 2011), a smart energy management system , accompanied by energy storage systems, has application on improving the reliability of photovoltaic modules, in different weather conditions.

Other propositions, as (Hajizadeh & Golkar, 2007; Wai & Jhung, 2013) limits the use of energy storage systems by adopting specific technologies for hybrid distributed generation.

Some studies have also applied this methodology to optimize vehicular energy optimization as (Amjadi & Williamson, 2010; Lukic, Jian Cao, Bansal, Rodriguez, & Emadi, 2008) propose, in order to improve electric propulsion, battery life and overall vehicle efficiency.

4.2 Proposed Approach

This subchapter details the approach, or architecture, of the proposed system to implement, through explanation of its components and respective method of operation.

4.2.1 Components

This project's objective is the development of a system, with methodologies and an algorithm, which enables the interoperability between diverse energy storage systems and optimizes energy consumption in buildings. Such ambition requires different components with dissimilar operational constraints. These components are storage systems, the source that supplies the energy and the energy usage. This system tests its viability through a simulator, employing user interfaces and algorithms to achieve its goals.

Consequentially, Figure 4.1 displays the above-mentioned components and the system's runtime perspective.

Several units of ESSs, with different characteristics, compose the set of storage systems. The mentioned devices store energy received from the grid and release it whenever required. Since most ESSs cannot charge and discharge at the same time (the current can only flow one-way), there is a subtraction between the two currents to discover which is higher and consequentially, which functionality the storage device executes. For storage units, type of technology, capacity, state of charge, discharge and charge times, efficiency, rated power, durability, self-discharge and maximum depth of discharge are important factors. In addition, the building's characteristics influences the choice of the individual ESSs.

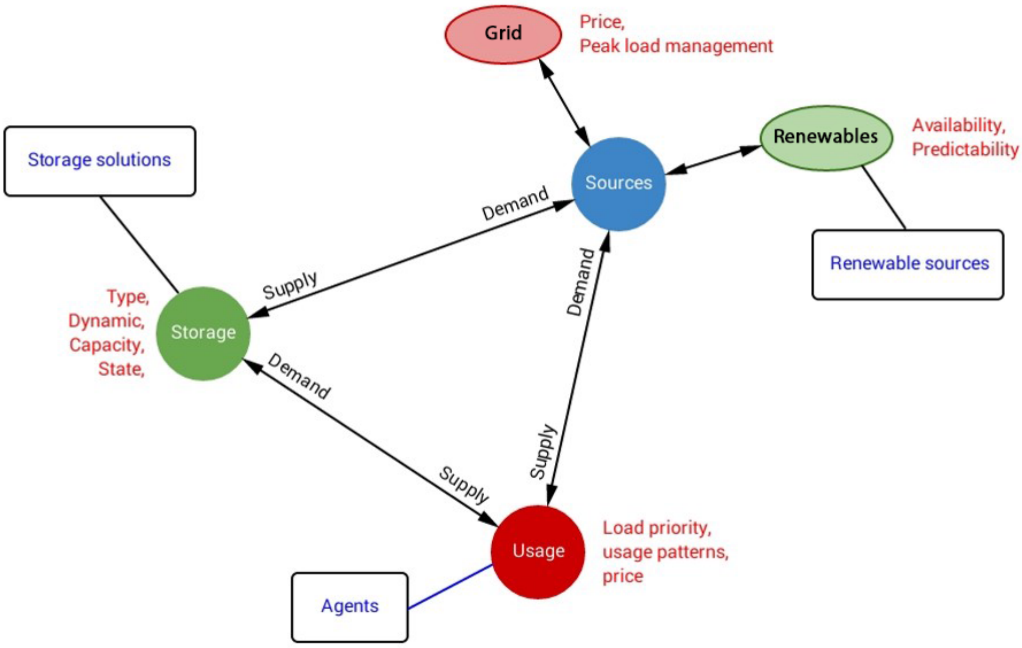


Figure 4.1 – Components of the system and its run-time perspective.

The energy supplier, or source, depends on the contract agreement established between the consumer and the energy provider. It contains the type of schedule and respective energy prices, the contracted power and its price per day. Likewise, renewable sources, connected to the building, can produce energy, possibly precluding the supply from the power grid.

Energy usage depends on human behaviour patterns. These patterns, aligned with predictive models, will allow some predictability on future behaviour. Perfect precision is impossible to achieve due to unpredictable factors, however the models are adaptive to prevent fluctuations between predicted and real patterns.

4.2.2 Algorithm

4.2.2.1 Specifications

As seen in Figure 4.1, each component communicate with each other. This communication requires the creation of algorithms, due to the interoperability between the different components.

Such an algorithm craves specific characteristics, which Figure 4.2 exhibits.

Regarding usage performance, the algorithm defines and maintains a set of key performance indicators (KPIs) to monitor the overall performance of the system both on short-term (e.g. demand response) and long-term (e.g. time between storage shortages). The KPIs depend on the strategies adopted, which have the ability to optimize energy consumption through different methodologies.

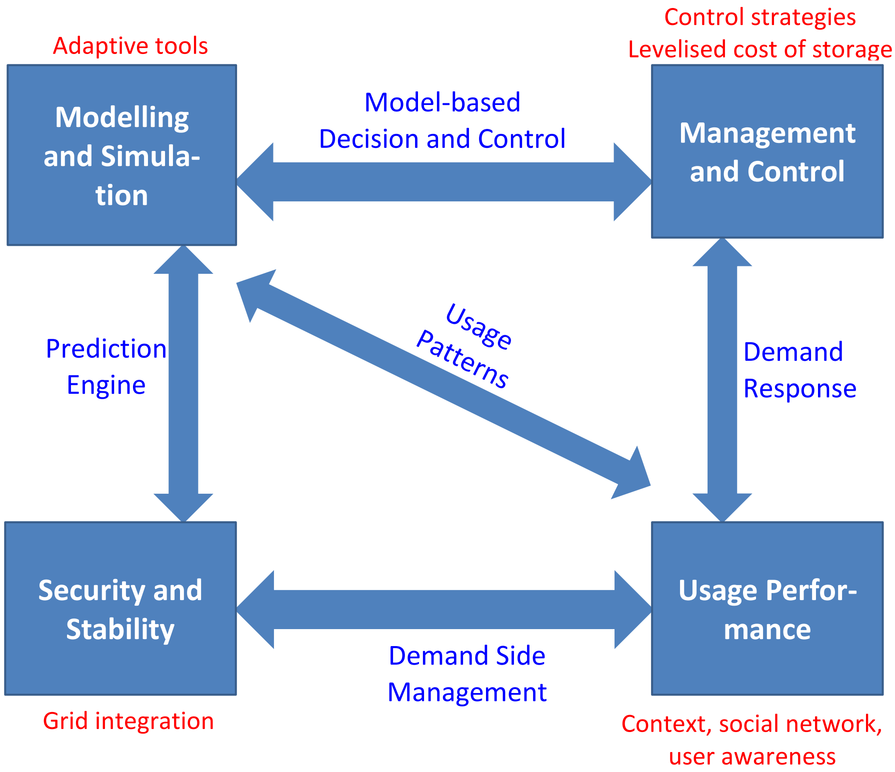


Figure 4.2 – Characteristics of the algorithm.

For example, if peak shaving is the chosen strategy, the system establishes a KPI that is a maximum usable instantaneous power value. This will enable to maintain a desirable quality of service (QoS).

For energy usage optimization, the system's management includes ways to limit and negotiate the user energy demand. It knows when to use the ESSs or the grid, to supply the user, and from which specific device within the set of storage units. In this part, the most important factors are price and time. The ESSs charge during the lowest-priced period of the day, in order to lower the cost of storage.

In order to supply the users with energy, the storage units discharge in appropriate periods, enabling energy usage whenever required.

Since the energy usage depends on, somewhat unpredictable, human behaviour, the algorithm has predictive capabilities. The impact of the instantaneous balance between supply and demand is not as important as its cumulated value, so, the system predicts, along a moving extended horizon, the demand response and usage consumptions. Ergo, this predictable engine requires reliable patterns of usage. This engine includes learning capabilities of the energy usage, provides the estimated values for user demand and foresees the status of the balance, between demand and supply, in an extended horizon.

This system requires physical devices, which connect to the power grid through the electrical installation of the building. Accordingly, it has to maintain security and stability measures. The security and stability factor relies on a set of operational restrictions applied to the system. This includes the protection of the ESS (BOP) and the power electronics required for grid integration. An example of a security measure is the input/output current and voltage limitations of each ESS.

For device comparison information, the algorithm produces a financial review of each ESS through the LCoS notion, cost of energy for the simulated time and the possible gains between using and not using ESSs. This knowledge provides insight on the final viability of the intelligent management of energy storage systems within buildings.

4.2.2.2 Justification

The specifications for the proposed algorithm in subchapter 4.2.2.1, detail its characteristics. However, it does not explain why these characteristics can optimize the energy consumption.

First, the system requires security and stability measures so that the grid-building connection is not impaired due to the addition of energy storage systems. Therefore, it includes power electronics to facilitate this connection and not incur in additional expenses related to equipment damage.

In addition, the system optimizes the energy consumption through the usage of its several components, depending on the implemented strategies.

For example, using a schedule of a daily cycle, from Figure 2.6 in subchapter 2.4.2.1, with three prices per day within the summer, the system manipulates the schedule to its own advantage. It can charge the ESSs within the cheapest periods, and discharge them when the price is the most expensive.

A possibility of prices, obtained from (ERSE, 2016), can include the lowest price as 0.0927 €/kWh, the average price as 0.1632 €/kWh and the highest price as 0.3179 €/kWh (with 10.35kVA contracted power). This way, if a specific ESS has a 75% global efficiency, it can store 7.5 kWh, using 10 kWh (75% of efficiency), with the cost of 0.927 € (within the lowest price period). If this energy is, later, discharged during the higher priced period, it saves around 2.384€ (7.5 kWh * 0.3179 €/kWh) of grid-supply cost. Therefore, through this transaction the user saved almost 1.5€ by using this algorithm, without including the cost of the storage systems that the LCoS notion represents.

The system can achieve this through the manipulation of charging and discharging the energy storage systems, predicting the user pattern of energy consumption and creating the KPIs based on the specific storage devices and the source that is available.

It, also, decides which storage device operates at each specific time, due to their performance characteristics, such as self-discharge. A device with a high self-discharge rate should be the last to charge and the first to discharge, so it does not stand idle for long, preventing energy losses.

Consequentially, this proposed algorithm can optimize the energy consumption by using energy when the price is the cheapest of the day and use it whenever required. Even if this functionality uses more energy than the required for usage consumption (due to storage devices efficiency), it enables the creation of multiple and diverse strategies, which can improve energy usage in different manners, such as the load management problem, expressed in subchapter 2.4.3, or the possibility of lowering the annual energy costs within a building.

None the less, the proposed approach ensures the maintenance of QoS by ensuring that if there is not enough stored energy, the grid outputs the remaining, even if it leads to a negative financial result. This is crucial, because the user should not notice if the energy comes from the storage system or the grid. The important factor is that usable energy is constantly available.

To test the viability of this proposed approach, the system implements a simulator, which is described below.

4.2.3 Simulator

As stated before, this system contains a simulation platform to check the results of the operations and the algorithms' behaviour. This platform produces the proof-of-concept of the proposed methodologies and consists on the following components: management system, knowledge repository, the plant simulator and a specific graphical user interface (GUI) for each component, except the knowledge repository (Figure 4.3).

The management system implements and executes the algorithm, transports information to and from the knowledge repository and sends actuator commands to the plant. The plant simulator includes the storage systems, energy sources and the user patterns and transmits the sensorial data back to the management system, containing the state of the plant.

The plant simulator is a physical plant of connections between ESSs and the energy source. However, for proof-of-concept testing and research, the author develops it as software. Through its GUI, the user can create usage patterns, ESSs and sources to emulate their real-life behaviour.

On the other hand, the GUI for the management system and knowledge repository are software blocks, created specifically for this system. This GUI displays the results obtained from the simulation and enables the choice between the possible strategies.

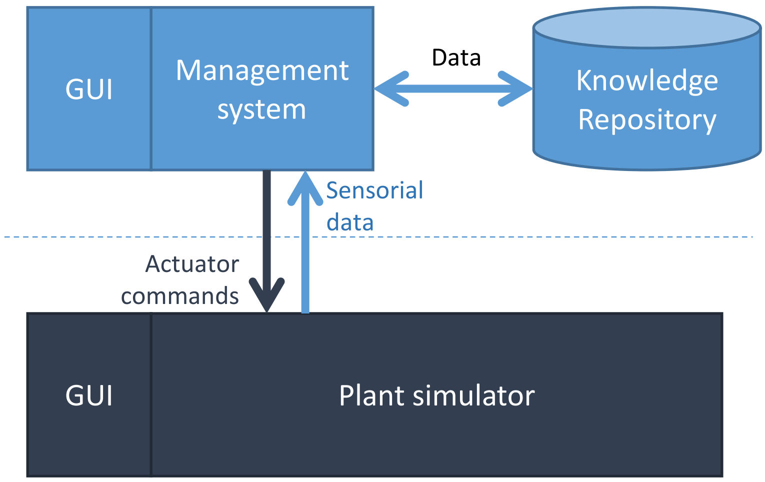


Figure 4.3 – Simulation platform operational method.

4.2.4 System's *modus operandi*

After the system's components explanation, this subchapter demonstrates the workflow of the designed architecture in Figure 4.4. This workflow represents the operational methodology of the algorithm to be developed, contained within the management system.

The user inserts, at least, one of every component through the plant simulator's GUI. Afterwards, to perform a simulation, the desired strategy and simulation duration is required. Next, when the simulation starts, for every iteration, the management system receives sensorial data from the plant simulator and checks if it is appropriate to charge or discharge the ESSs. The devices' specific characteristics influences the charging and discharging order, while the strategy chosen also affects the latter. At the end of each iteration, the charged and discharged energy update each unit's state of charge. The system updates the state of charge by subtracting the charging and discharging values. This cycle repeats itself until the simulation finishes as detailed in Figure 4.4. At the end of the simulation, the management system GUI displays the obtained results. If, in a specific iteration, it is not time to charge or discharge, both these values are zero, maintaining the same state of charge.

4.3 Relation between previous work and the proposed approach

The architecture proposed within chapter 4 differs from the previous work due to the combination of diverse energy storage systems to optimize energy consumption and lower the costs through multiple strategies. It includes the behavioural patterns in the form of energy consumption, without requiring utility specification and it applies to buildings with distinct necessities.

Therefore, this simulator can embrace the user's situation and test which storage devices are better suited for that specific application, providing a financial review regarding its viability.

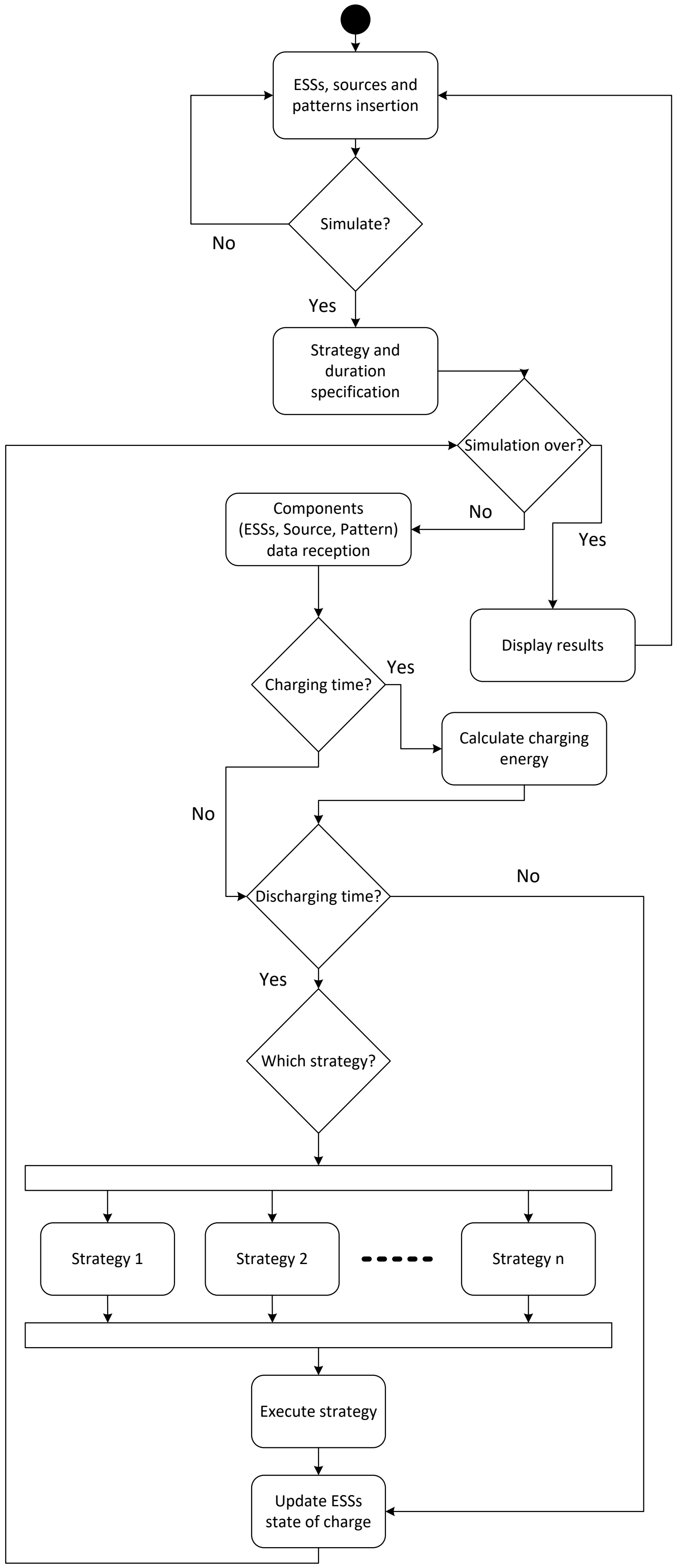


Figure 4.4 – Workflow diagram of the designed architecture.

5

Implementation

This chapter details the implementation of a specific system based on the architecture in chapter 4. It includes the specifications of the simulator and each subpart method of operation.

As mentioned in subchapter 4.2.3, the simulator needs to contain graphical user interfaces capable of data insertion and result display, a management system with a knowledge repository and the ability to simulate the ESSs, sources and user patterns. This chapter describes these functionalities below.

Consequently, the platform chosen for its implementation is Java, the programming language. The author picked this technology by virtue of its object-oriented programming and the ease to construct and design graphical user interfaces.

5.1 Simulator Components

This simulator divides itself between two diverse user interfaces: the plant simulator GUI and the decision system GUI (equivalent to the management system GUI in subchapter 4.2.3). The former enables the creation of ESSs, sources and user patterns while the latter displays the results obtained and permits the choice between different strategies. Besides each GUI, this subchapter also details each component's characteristics and their creation.

This simulator follows the diagram presented in Figure 4.4, therefore when starting the simulator, the plant simulator GUI appears, and the decision system's does not. The latter shows up only when simulating. When the former shows up, there are some component values already inserted, through an initialization file.

This method of implementation stipulated that the value of the power factor is one. Accordingly, each unit of apparent power (VA) is the same as a unit of active power (W).

According to the theme in hand, the system has a specific logo, presented in Figure 5.1.

Figure 5.1 – Logo created for the simulator.

5.1.1 Graphical User Interfaces

As mentioned above, there are two interfaces: the plant simulator and the decision system. Both have subdivisions to perform their roles.

5.1.1.1 Plant Simulator's GUI

For proper explanation, this subchapter follows the correct order to use the simulator with efficiency. It also displays the images of each subdivision, with their explanation, based on the usage order.

This block has five subdivisions: "Begin", "Configuration", "Add ESS", "Send to Decision System" and "Help". The first introduces the user to the simulator with some suggestions for proper usage as observed in Figure 5.2.

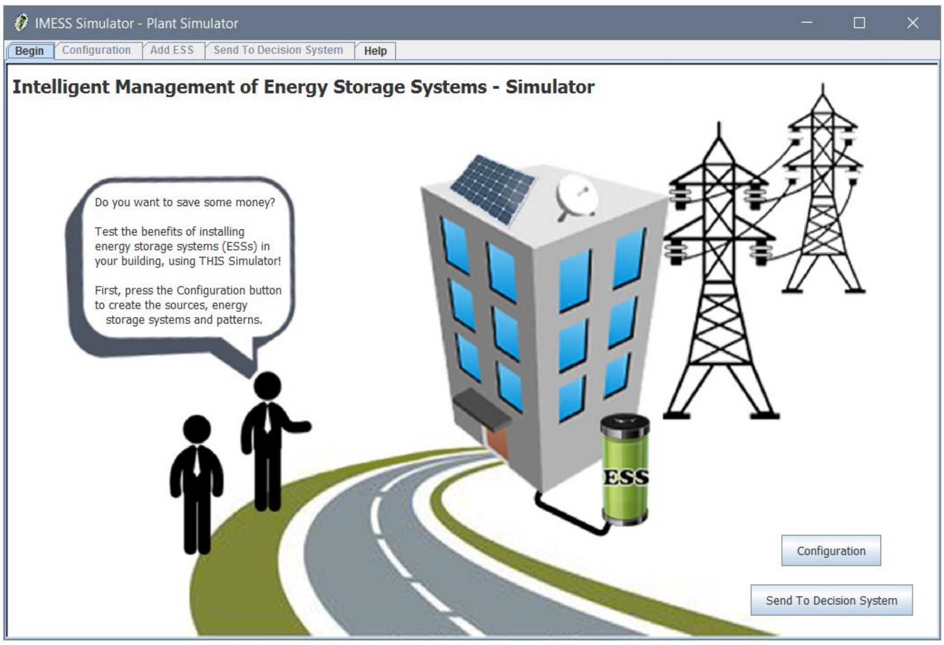


Figure 5.2 – "Begin" subdivision of the simulator. This window shows up when starting the simulator.

As the “Begin” tab (Figure 5.2) demonstrates, the first step is to insert ESSs, sources and user patterns in the simulator. Moreover, to do so, the user has to press the button, named “Configuration”, in the lower right corner. This leads to the subdivision “Configuration” displayed in Figure 5.3.

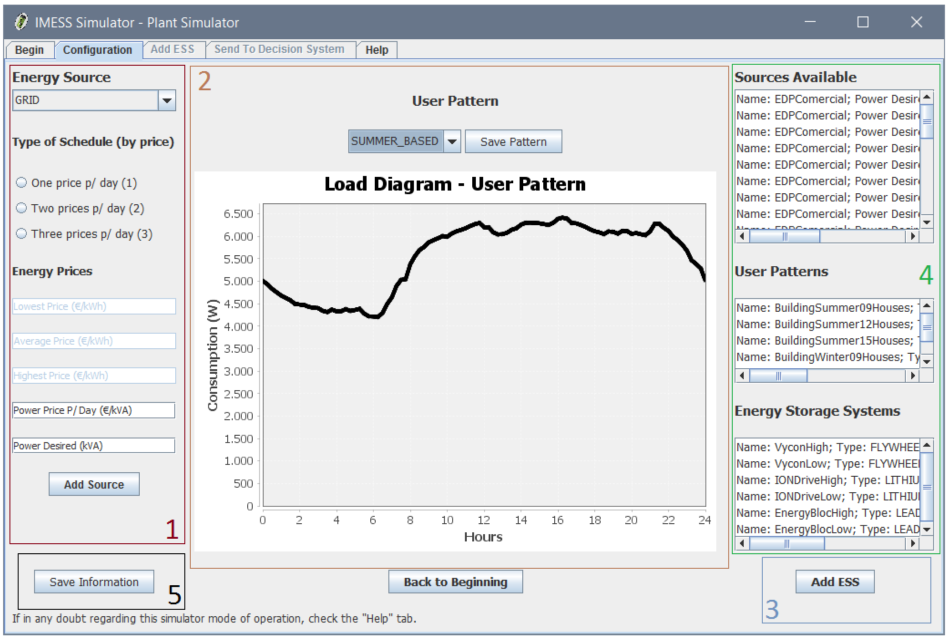


Figure 5.3 – An example of the configuration tab in the plant simulator, divided by areas.

Figure 5.3 shows a possibility of how the configuration tab looks like. In this subdivision of the plant simulator, the user can add sources, patterns and ESSs. This figure splits into five different areas with diverse purposes.

- Area 1 (red) → area to add the sources.
- Area 2 (orange) → location to add and visualise the user patterns.
- Area 3 (blue) → button that leads to the subdivision (“Add ESS” tab) to insert energy storage systems.
- Area 4 (green) → whereabouts of the lists that contain each component.
- Area 5 (black) → button that saves the information in each list (area 4) into an external file. This allows the initialization of the simulator with already stipulated objects.

Every object inside any of these lists is removable, through pressing the desired component with the computer mouse’s right button as displayed in Figure 5.4.

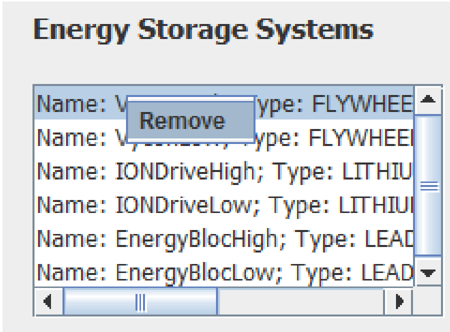


Figure 5.4 – Example of an object's removal.

The creation of two of the components, sources and user patterns, is in the "Configuration" tab, as displayed in Figure 5.3. However, for ESSs, it is through the "Add ESS" button. This action opens the corresponding "Add ESS" tab. In this subdivision, the user inserts the required ESS characteristics, with some being mandatory and others not, as represented in Figure 5.5.

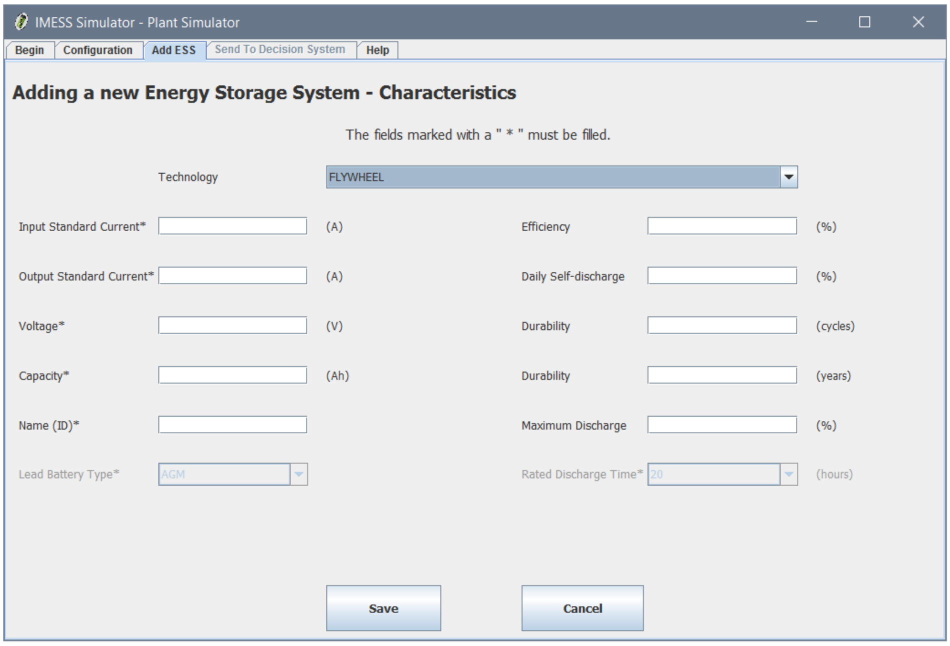


Figure 5.5 – Display of the "Add ESS" subdivision from the plant simulator.

First, the user chooses the technology because it influences which characteristics need input. Afterwards, inserts the mandatory fields, and, if desired, the ones not required. Then, to definitely create the specified ESS, the button denominated "Save" must be pressed. If the user does not fill the mandatory fields, the system does not allow the creation of the ESS. After the save, the system returns to the "Configuration" tab.

All characteristics that require input for ESS creation, in this simulator, are within the datasheets made available from the different device manufacturers.

After the creation of the necessary objects, the user presses the button entitled “Back to Beginning”, to continue further. Such action leads the user back to the “Begin” tab. However, it now displays different text, as shown in Figure 5.6.

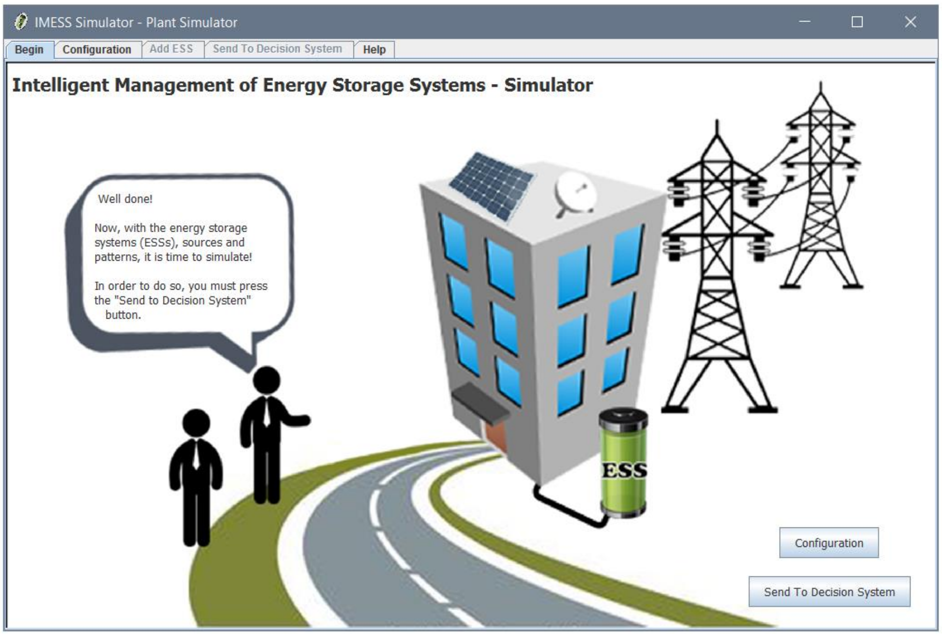


Figure 5.6 – “Begin” subdivision of the simulator. It shows different text because of the ESSs, sources and user patterns insertion.

As the new piece of text, in the “Begin” subdivision, states (Figure 5.6), the user needs to press the button denominated “Send To Decision System” in order to start the simulation. Subsequently, the tab named “Send To Decision System” opens for some decisions regarding the following simulation, as displayed in Figure 5.7. This Figure 5.7 is divided between different areas for easier explanation of their purpose.

- Area 1 (red) → list to choose the source to use in the simulation.
- Area 2 (orange) → slider to determine the simulation’s tempo.
- Area 3 (blue) → list to choose the ESSs (up to three).
- Area 4 (green) → box from which the user chooses the consumption pattern.
- Area 5 (black) → box to determine the strategy to implement.
- Area 6 (purple) → box to regulate the simulation’s duration.

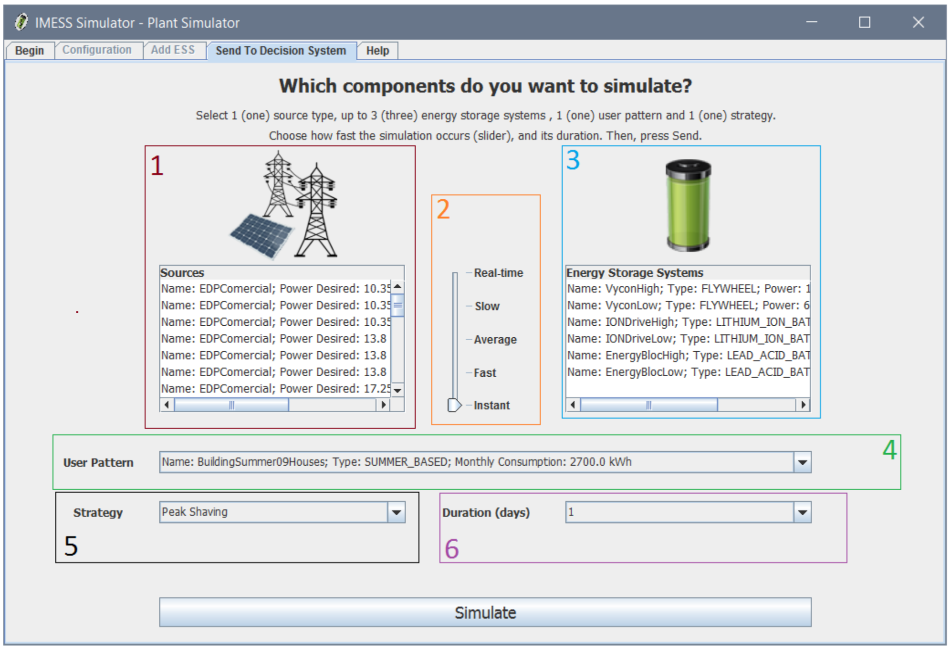


Figure 5.7 – Example of the plant simulator's "Send To Decision System" tab divided by areas.

As shown in Figure 5.7, the system requires one component from area 1 (source), up to three from area 3 (ESSs), and one each from areas 4, 5 and 6 (pattern, strategy and duration).

Eventually, after the stipulation of these variables, the user must press the button named "Simulate" to proceed for the simulation. When this action occurs, the GUI from the management system appears with its specifications to show the results of the specified simulation.

This concludes a cycle of correct and efficient usage of the plant simulator's GUI. However, there is still one more tab available: "Help". This subdivision is for user support purposes, hence, the presentation of a tutorial to fulfil a complete simulation (Figure 5.8). It details the sequence explained in this sub-chapter (5.1.1.1) for easier manipulation and understanding of the simulator's operational method.

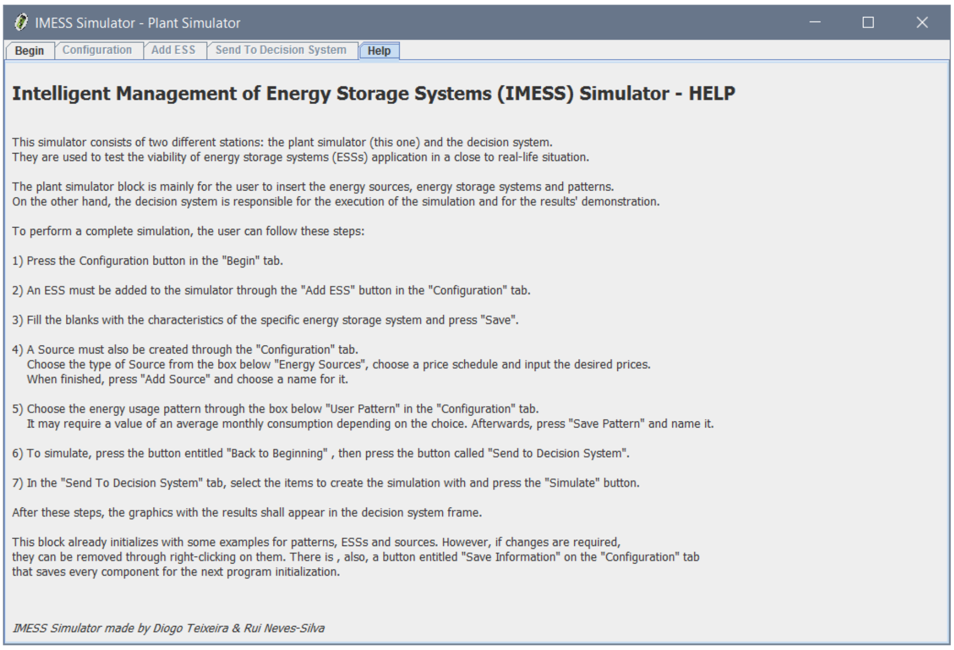


Figure 5.8 – “Help” tab of the plant simulator’s GUI.

5.1.1.2 Decision system’s GUI

As explained in 5.1.1.1, this GUI only appears when the user performs a simulation.

Therefore, this block has two subdivisions: “Strategy & Results” and “Help”. The former displays the results of the simulation in graphic and numeric form, while the latter, similarly to plant simulator’s GUI, introduces a tutorial for better understanding of this part of the simulator.

As mentioned above, the system presents the results through the “Strategy & Results” tab. Figure 5.9 represents the layout, divided by areas, of this decision system subdivision.

- Area 1 (red) → area of the graphic that displays the consumption of each energy storage system.
- Area 2 (orange) → location of the graphic that represents the state of charge of each energy storage system.
- Area 3 (blue) → position of the graphic that shows the real user consumption pattern (not the predicted one) and the grid consumption for comparison. This GUI does not display the predicted consumption because the chart would have too much information to be comprehensible.
- Area 4 (green) → whereabouts of the graphic that solely exhibits the consumption from the grid.
- Area 5 (black) → section that indicates the calculated values of LCoS.

- Area 6 (purple) → position of the financial review of the simulation. Displays the price if the user would consume only from the grid and from both the grid and the ESSs. In addition, it presents the possible gains from using storage systems in absolute values (€) and in prices per energy (€/kWh). The absolute values already include the price of power for the duration of the simulation, influencing the final price per energy. All the values presented have an uncertainty of 0.001 due to the round of values within the simulator.
- Area 7 (grey) → area that indicates the price values per energy (€/kWh) and their respective time intervals within a 24-hour cycle. There is up to three different prices.
- Area 8 (brown) → section that offers a brief explanation of the executed strategy and the option to change the threshold value (only applicable for the peak shaving strategy). The value input in the threshold box is the reduction, in percentage, that the user wants to inflict on the maximum value of the user consumption pattern.

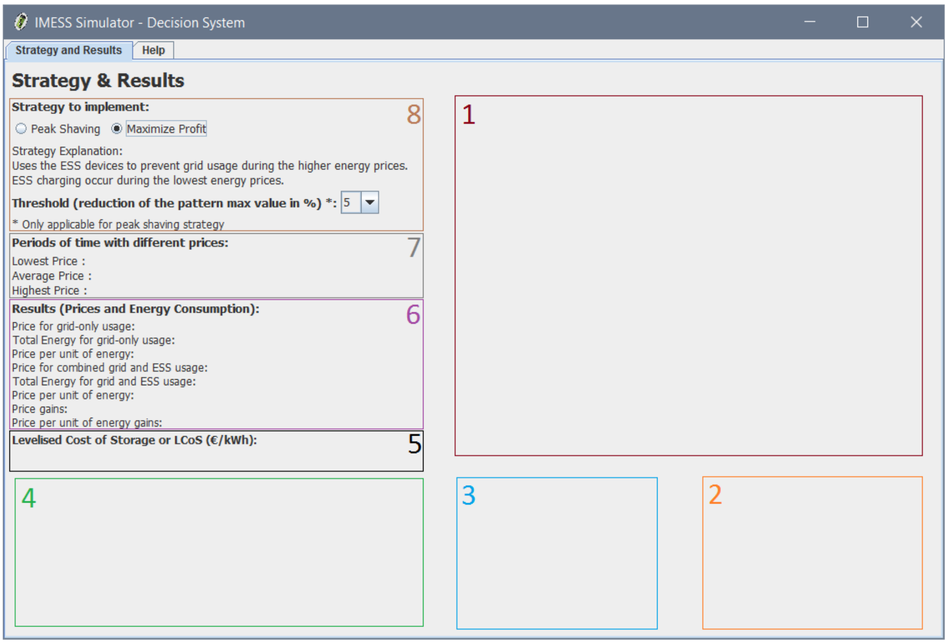


Figure 5.9 – Layout of the "Strategy & Results" tab in the decision system interface.

The system creates the results in graphical form due to the use of an external Java library entitled "JFree Chart" obtainable through their website (http://www.jfree.org/jfreechart/).

In the decision system module, the system also provides a subdivision that explains the content of "Strategy & Results". This subdivision, the "Help" tab, is accessible whenever the decision system is visible and Figure 5.10 demonstrates its design. The users can adopt this tutorial whenever required for better understanding of the results displayed in the interface.

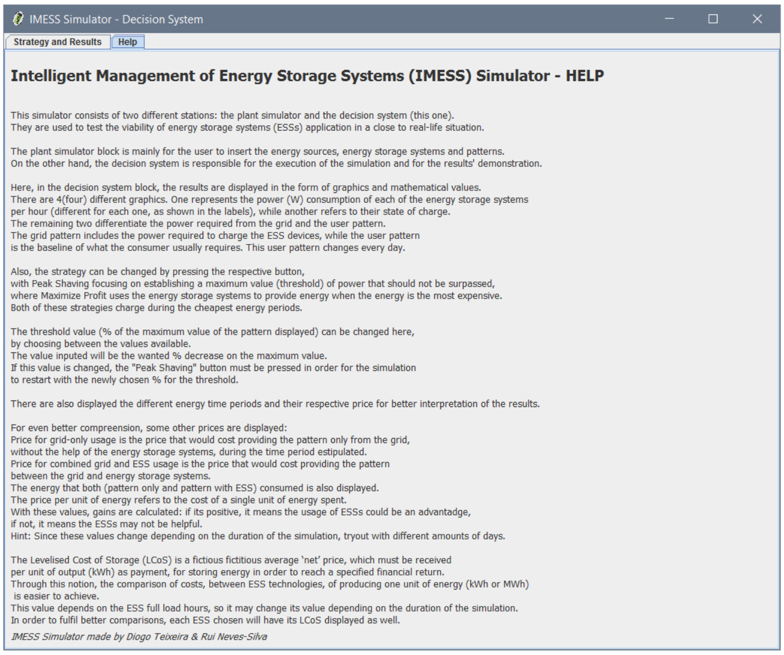


Figure 5.10 – Design of the "Help" tab in the decision system module.

5.1.2 Sources

These components represent the contract agreement between the consumer and the energy provider, as mentioned in subchapter 4.2.1. Each source contains the type of schedule and respective energy prices and the contracted power and its price per day, which this system expects at time of creation (Figure 5.11).

First, the user chooses the energy source. For this implementation, there is only one possibility: grid. Although renewable sources were a possibility, these are not available. This signifies that the user cannot test the building's personal energy generation through renewable production.

Afterwards, there is the type of schedule choice. It determines the price per energy variations throughout the day. This means that can exist one, two or three different prices during one 24-hour cycle. Figure 2.6 details the divisions created, by this item, within one day in subchapter 2.4.2.1, differing between weekly and daily cycles during diverse seasons. However, sources, in this simulator, only implement the daily cycle with season (winter and summer) variations. Therefore, the user can only choose one type, between one, two or three prices per day beneath the "Type of Schedule (by price)" label represented in Figure 5.11.

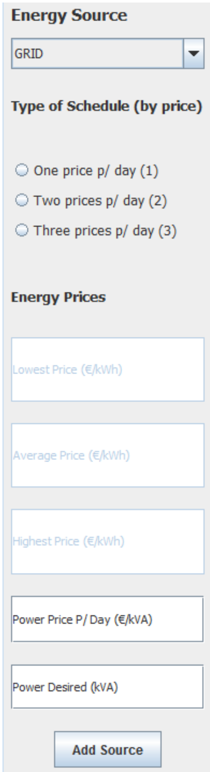


Figure 5.11 – Source insertion area of the "Configuration" tab of plant simulator's GUI.

Depending on the type of schedule choice, the respective text areas open up for value insertion.

1. One price per day → only uses the text area named "Average Price (€/kWh)", because the cost is constant during the 24-hour cycle.
2. Two prices per day → opens the "Highest Price (€/kWh)" and the "Lowest Price (€/kWh)", due to the existence of two different costs of energy throughout the day.
3. Three prices per day → frees all text areas as result of three diverse costs of energy over the course of the day.

The prices inserted must be in €/kWh for optimal simulation performance. On the other hand, the system organises the costs after insertion, which means that the text area's names are only suggestive.

Next, the system demands the insertion of the desired contracted power, in kVA, and its respective price per day in €/kVA. The former stipulates the maximum possible instantaneous power consumed by the user. Since the power factor has the value of one, the contracted power has the same value in kVA and kW.

To conclude, when pressing the button denominated "Add Source", the system requires a name for the created source.

As stated in subchapter 5.1, each component has some examples in the simulator when it initializes. Located in Appendix I, Table Appendix I 1 shows these sources based in the values mentioned in subchapter 2.4.2.1 and in (ERSE, 2016). The author created all these examples from data regarding Portugal.

5.1.3 User consumption patterns

As detailed in chapter 2, buildings represent a high share of electricity consumption. Therefore, the user patterns created relate to this section's usage.

Since building-only load diagrams are not available, the author manipulated the pattern values from the entire country (Figure 2.3 in subchapter 2.3.1). The data obtained from (Redes Energéticas Nacionais, 2016) relate to the entire country and have fifteen-minute intervals in-between values. Since this system requires patterns with every minute values and regarding only buildings, manipulation was in order.

After choosing one day per season for base patterns (21/02/2016 for winter and 07/06/2016 for summer), linear regressions calculated the necessary values between every fifteen-minute interval. This way, a countrywide pattern has predicted instantaneous power values for each minute.

However, the system needs to be able to draw patterns based on energy consumption. Since energy is the integration of power solved for a unit of time (equation 2), and the area beneath a curve is its integral, the system can calculate the total amount of energy spent within a load diagram. In this equation, $p(t)$ and $e(t)$ refer to power and energy functions, respectively.

$$p(t) = \frac{d}{dt} e(t) \leftrightarrow e(t) = \int p(t)\, dt \qquad (2)$$

Nonetheless, equation 2 refers to continuous functions, which these patterns are not. Consequently, for discrete functions, the area is calculated through the sum of each value throughout the course of the function. However, since power is energy per second, the time-scale has to adapt accordingly. Thus, to transform minutes to seconds, a division by sixty is included. Therefore, the system uses equation 3 to calculate the energy spent, where E is the total amount of energy, t is the simulation's amount of minutes and P is the instantaneous power value in a specified minute.

$$E = \sum_{1}^{t} \left(\frac{P}{60}\right) \Rightarrow E = \frac{1}{60} * \sum_{1}^{t} P \qquad (3)$$

With this ability and the average monthly consumption (300 kWh in Portugal, as detailed in subchapter 2.4), the simulator uses the consumption to create patterns, whether for summer or winter.

This means that the resulting pattern keeps the original layout, but recalculates its values so that the total energy is the inputted value.

Within the plant simulator's GUI, in the "Configuration" tab, there is an area to create user consumption patterns as shown in Figure 5.3. This specific area, visible in Figure 5.12, enables the creation of the user pattern and displays it. When the user chooses the type of pattern ("SUMMER_BASED" or "WINTER_BASED"), a pop-up appears to inquire for the monthly average consumption, as represented in the same figure.

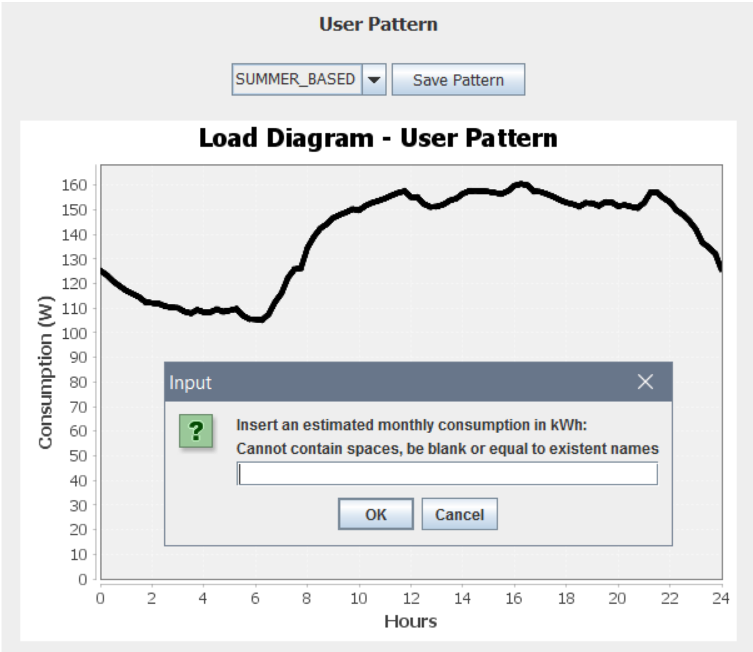


Figure 5.12 – Area that displays and enables the creation of a user consumption pattern. It includes the pop up that enquires for the monthly consumption.

After the insertion of the desired monthly consumption, through calculations mentioned above, this area displays a pattern regarding the season chosen for one day. To save it, the user can press the button entitled "Save Pattern" and attribute a name to it.

For graphical purposes, in the box where the user can choose between summer or winter pattern layouts, there is an option entitled "CLEAR". This alternative clears out the graphic displayed.

Focusing on residential buildings, due to the knowledge of average household consumption, the author created patterns that initialize with the simulator based on buildings with different numbers of houses. E.g. a building that contains ten households, following the average consumption in Portugal, consumes 3000 kWh per month.

Table Appendix I 2 in Appendix I enlists those patterns, which reflect the average consumption in Portugal.

5.1.4 Energy storage systems

Energy storage systems, or ESSs, being devices installed within a power system that can store and release energy, are key components for this implementation.

Thus, the author compared different ESSs in subchapter 3.3 in order to reach a conclusion on which technologies would be better suited for this project. The closure of this analogy between technologies resulted in the choice of lead acid batteries, lithium ion batteries and flywheels.

To understand the ESSs method of operation, type of technology, capacity, state of charge, discharge and charge times, efficiency, rated power, durability, self-discharge, maximum depth of discharge and specific investment costs are important factors. Although response time is an important characteristic, since its values are so low, the system establishes it as zero. Therefore, the system requires various inputs to simulate an energy storage system.

However, the user may not have access to every specific characteristic. Then, the author obtained datasheets from each technology to acknowledge which characteristics are omnipresent. Through analysis of (Calnetix Technologies, 2016; Exide Technologies, 2014, 2015; Saft Batteries, 2015), standard input and output current, voltage and capacity are the specifications that appear constantly. Consequently, these, the technology's name and type are mandatory, as observed in Figure 5.5. Nonetheless, the remaining characteristics also appear in some datasheets.

Lead acid batteries require more information, so this technology enables the "Lead Battery Type" and "Rated Discharge Time" inputs, which are also obligatory. The former represents which type of lead acid battery it is, while the former is the rated discharge time at which the manufacturer measures the battery's capacity. This information is within the technology's datasheet.

The rest of the specifications (efficiency, daily self-discharge, durability in cycles and years and maximum discharge) if not inputted, the system assumes the Table 3.2 values as default. State of charge always initialises with zero percentage.

Through this set of inputs and their manipulation, the system can successfully simulate an energy storage device.

Since the power factor has the value of one, the rated input and output power is the direct multiplication of the respective current value for the voltage. Capacity also changes its value, transforming it from ampere-hour (Ah) to watt-hour (Wh) by multiplying it for the voltage value.

For discharge and charge timers' calculation, the system uses different techniques because its calculation differs between technologies.

Regarding flywheels, charging and discharging methods are linear (Calnetix Technologies, 2016), which makes the timers' calculations similar, as seen in equations 4 and 5.

$$t_{charge}\ (hours) = \frac{Capacity(Ah)}{I_{input}(A) * Efficiency} \quad (4) \qquad t_{discharge}\ (hours) = \frac{Capacity(Ah)}{I_{output}(A)} \quad (5)$$

In the previous equations (4 and 5), t_{charge} and $t_{discharge}$ represent respectively, in hours, the time of charge and the time of discharge. Likewise, I_{input} and I_{output} are the standard input and output currents, respectively. The efficiency factor is included in the charging calculation, due to energy transformation losses. It is the global efficiency factor of the ESS. Since every physical device has losses, each ESS requires more than one unit of energy to store one unit of it.

The results of these equations are not perfectly accurate, due to the assumption of non-variable loads (same current throughout the cycle). However, they result in a reasonable approximation of a cycle's duration.

For the two battery technologies (lead acid and lithium ion), the charging processes are similar, but the discharging are not.

Therefore, the charging calculation is similar for both types (equation 6).

$$t_{charge}\ (hours) = \frac{Capacity(Ah)}{I_{input}(A) * Efficiency} * 1.4 \quad (6)$$

The variables within equation 6 are the same as used for flywheels. However, this incorporates a constant factor (1.4) that increases the charging time. This value represents the inability of either lead acid or lithium ion batteries to charge with constant current (Battery University, 2016a, 2016b; The Electropaedia, n.d.). During the charging, the current decreases drastically, due to the device's method of operation. Since it is not possible to charge at the standard charging rate, specified by the manufacturers, for the full duration of the charge, this equation gives a reasonable approximation of the time to charge an empty battery.

Respecting the discharge method, lead acid batteries use the Peukert's law to obtain its discharge time, as lithium ion uses Ragone plots (Battery University, 2016). Peukert's law is a formula that enables a good approximation on the calculation of lead acid batteries discharge timers. In addition, Ragone plot has the same purpose of Peukert's law, but for lithium ion batteries. However, since Ragone plots are difficult to implement within the simulator, the system uses equation 5 for lithium ion discharging purposes.

Nonetheless, the system implements Peukert's law for lead acid discharging time calculations, as expressed in equation 7 (All About Lead Acid Batteries, 2012).

$$t_{discharge}\,(hours) = H * \left(\frac{Capacity\ (Ah)}{I_{output}(A) * H}\right)^{k} \tag{7}$$

In this equation, $t_{discharge}$ represents the time to discharge the lead acid battery in hours. H refers to the rated discharge time, in hours, while I_{output} is the output current, in amperes, that the battery would be providing. Lastly, k is the Peukert's constant, which is different for each battery.

The Peukert's constant has different ranges of values for each lead acid technology. Therefore, Table 5.1 identifies the values used within the simulator, based on (All About Lead Acid Batteries, 2012; Battery University, 2016).

Table 5.1 – List of Peukert's constant values for the respective technology within the simulator.

Lead acid battery type	Peukert's constant (k)
AGM	1.1
Gel	1.2
Flooded	1.4

This formula has some limitations, because it does not incorporate the device's age and the temperature effect on the battery (All About Lead Acid Batteries, 2012). However, this law is a closer estimation to battery performance than simple extrapolations of the amp hour rating.

To conclude, the author tested the results of the equations within this subchapter, for each technology, comparing them to the charging and discharging values in the datasheets (Calnetix Technologies, 2016; Exide Technologies, 2014, 2015; Saft Batteries, 2015), with similar outcomes. This comparison reinforced that these equations (4, 5, 6 and 7) achieve reasonable approximations of real-life values.

The simulator initialises with six energy storage devices, two from each technology, based on the datasheets above-mentioned. Table Appendix I 3 in Appendix I details these devices.

5.2 Simulator’s Management System

After the explanation of the components, that the user has direct contact with, this subchapter details the simulator’s management system behaviour. This part of the simulator, as defined in subchapter 4.2.3, contains the algorithm and executes it, determining this system’s method of operation.

The management system establishes the connection between ESSs, sources and user patterns for simulation purposes and controls the energy storage devices charging and discharging processes, based on their characteristics and strategy chosen. Consequentially, it calculates the results of the simulation for presentation in its related GUI.

This system’s simulation, in order to produce results, has values for every minute. Therefore, every iteration corresponds to one minute in real-life. During each iteration, the system checks if the ESSs require charging or discharging and update their state of charge. In addition, it establishes that one day is the minimum simulation duration, which is upgradable up to thirty days.

If the duration is more than one day, the user patterns are slightly different between days, because the consumption usually changes day-by-day. Thus, this system calculates the average of the consumptions of the past days in order to predict the incoming consumption. However, failures may occur due to incorrect prediction and unpredictable human behaviour. To prevent these, whenever the system requires charging to have enough energy stored for the next day, instead of only charging the amount required, the system tries to charge each device to their maximum.

The characteristics of the base pattern, the number of days to simulate, which storage devices and source to use in the simulation are stored within the knowledge repository. Also during the simulation, the management system requires the sensorial data received from the plant simulator to check alterations in the ESSs state and the user consumption pattern. Additionally, it stores these values in the knowledge repository after every iteration, updating the previous data.

Therefore, since the charging and discharging methods, the energy optimization strategies and the result calculation are part of the management system’s tasks, the author describes them below.

5.2.1 Charging method

For charging purposes, the system needs to understand the charging operation of each technology with the charging timer being key to enable this process. Fortunately, the charge timer is available due its calculation when inserting a storage device (as explained in subchapter 5.1.4).

In addition, the simulator uses the daily cycle base for each type of schedule (Figure 2.6 in subchapter 2.4.2.1), which determines when each ESS can charge. This management system only enables charging when the energy price is the lowest, which means it has two different charging periods (between 00h00 and 08h00 and between 22h00 and 24h00). However, in the one-priced type of schedule, due to the lack of one lower energy price, the simulator establishes only the first period for charging, for simulation purposes.

Additionally, since the user pattern has values every minute, the charging values for each ESS requires the same time scale. Therefore, the system calculates the minute charge rates whenever charging is required.

For flywheels, the charging method is linear (Calnetix Technologies, 2016), therefore, the system uses the direct relation between the capacity and its charging time to calculate the minute charge rate.

However, charging batteries is not linear. As referred in subchapter 5.1.4, batteries cannot endure standard current for the whole charging duration, creating a non-linear function.

Based on (Battery University, 2016a, 2016b), lithium ion batteries charges up to 70% state of charge within only 25% of the charging timer, while lead acid charges up to 70% within 40% of the charging timer. This occurs due to the lower of the battery's charging current, which leads to a slower charge rate after the specified percentage. In addition, by lowering the current, these devices lower their input power.

Yet, the lithium ion batteries used for the simulation cannot perform according the charge model above-mentioned. Its datasheet (Saft Batteries, 2015), however, details its charging method: reaches 30% state of charge at 22% of total charging duration. For this battery technology, the system tries to implement the first, and base, model, but if these devices cannot sustain such performance, it changes to this charging method.

Consequently, depending for how long each technology is charging and their total capacity, the system calculates their charging rate for one minute. These charge rates are not constant for batteries, due to the different stages of charging. The system updates these and the technology's power consumption as they change.

Every iteration, after calculating the minute charge rates, the simulator detects in which day of simulation it is and which charging period, due to different consequences whether it is one or the other, as demonstrated in Figure 5.13. Since there are only two different periods, if not in the first, it is in the second. As the diagram represents, the system only relies on the second period of charge if the first was insufficient for the day's requirements. The first period consequences depend on which day of simulation it is. If on the first, it charges because ESSs initialize with no energy stored. However, if not, it detects if the storage units have enough energy for the predicted consumption. This enables the optimization of the energy usage.

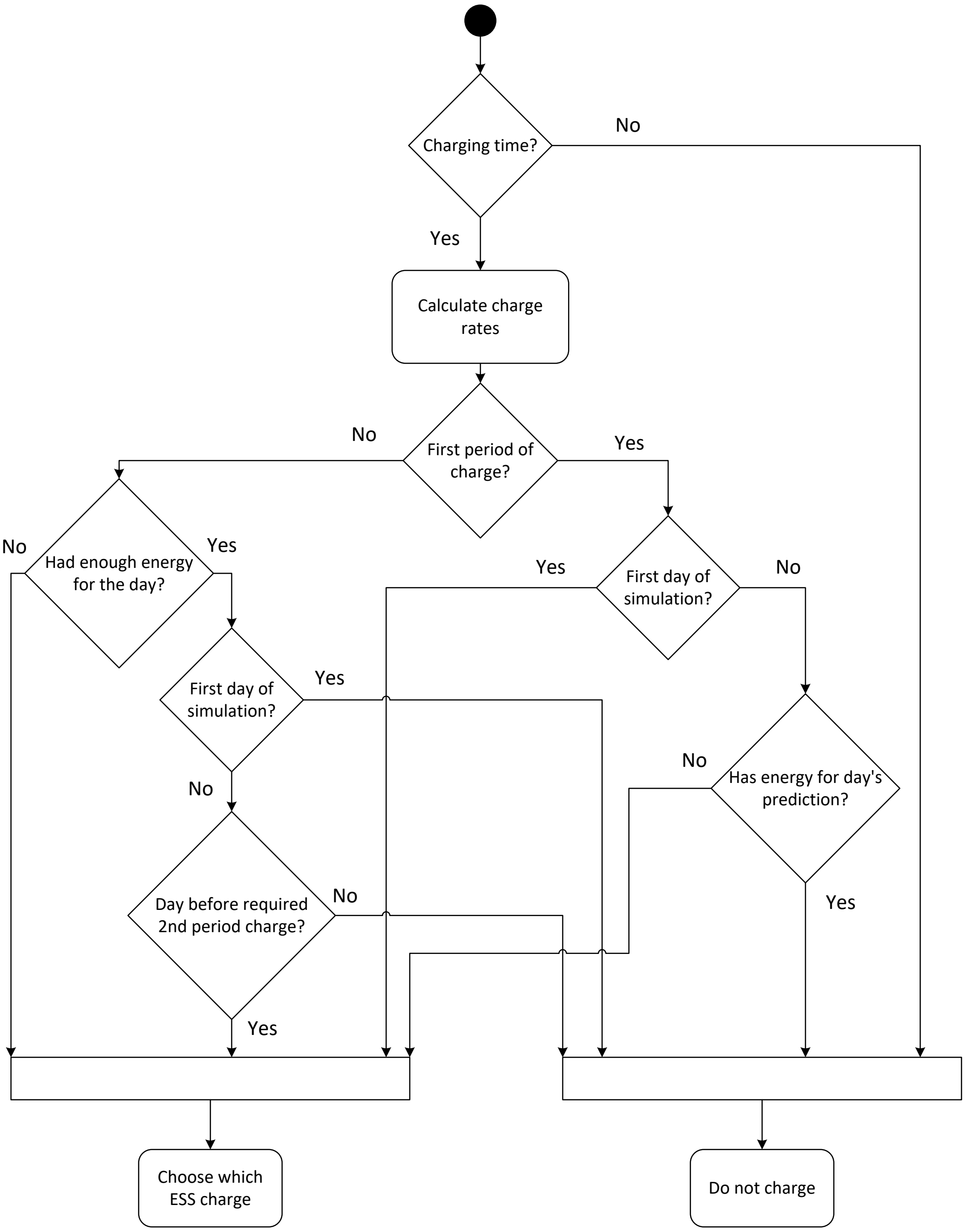


Figure 5.13 – Workflow that demonstrates when to charge.

If the system requires energy input, it chooses which storage unit charges and their specific order. There is a priority because there are limitations like the contracted power, the ESSs technology, their input power and their self-discharge.

Therefore, the system chooses between the ESSs as shown in Figure 5.14.

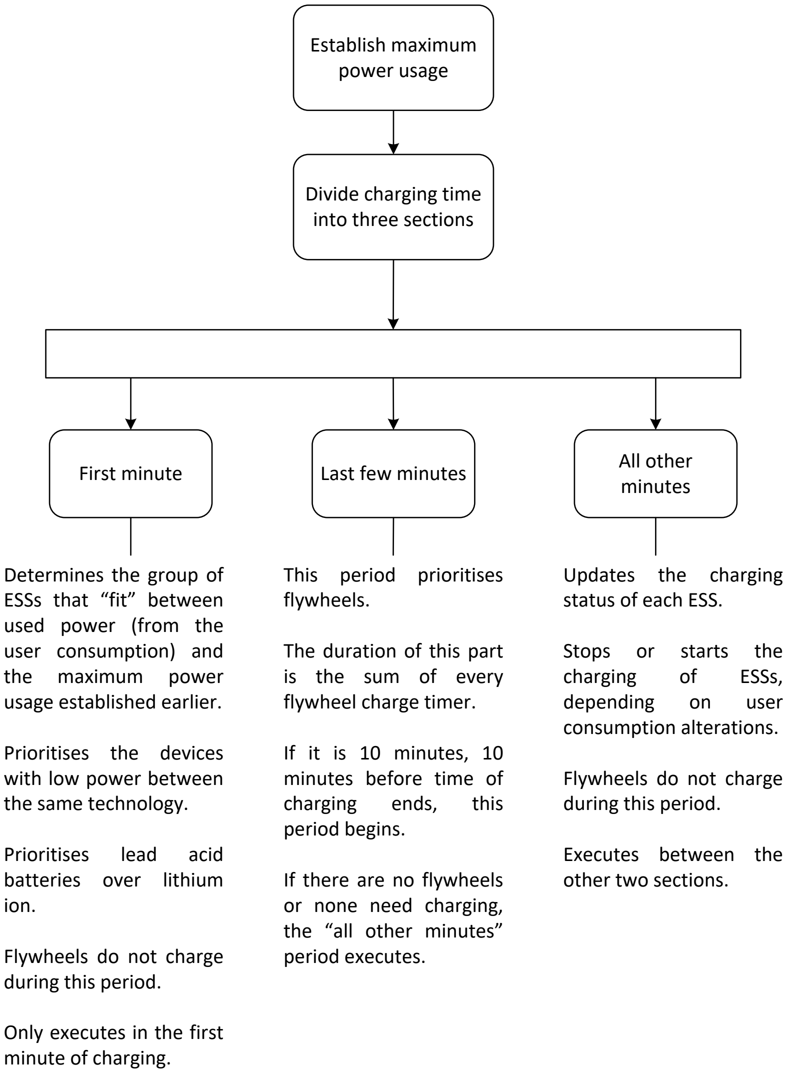


Figure 5.14 – Method of choice between ESSs for charging purposes. This applies to both charging periods.

First, the maximum power usage is established depending on the strategy implemented. Afterwards, the entire charging period divides itself into three sections. During the first minute, the system calculates the difference between the allowed power and the user consumption to see how much power is available to use. If there is power available to charge every ESS, all charge except flywheels. These technologies only charge in the last minutes because it has high self-discharge, which means the more time it stands idle, the more energy is lost. Consequentially, flywheels do not charge during the second period of charge, so that it does not stand idle for multiple hours.

The system establishes that both charge periods follow this method for ESS charging. The contracted power never is below the consumption because the simulator does not allow a simulation with such possibility.

For every technology, the simulator establishes a maximum percentage of state of charge due to possible over-charging damage. Therefore, battery technologies do not charge if above 98% and flywheel do not charge if above 96%.

After the specification of which device to charge, the charge rates are stored in the knowledge repository alongside its respective energy storage unit.

5.2.2 Discharging method

The energy discharge depends on the characteristics of the ESSs involved and on the strategy adopted. First, this process is limited due to the maximum depth of discharge of each storage device, disabling the usage of an ESS below a specific state of charge.

Additionally, regardless of the strategy adopted, there is a discharge priority regarding the storage devices. Due to high self-discharge, flywheels discharge prior to every other technology. If a simulation uses multiple flywheels, the one with higher power discharges first, because it loses more energy from self-discharge than the rest. Thus, flywheels charge last and discharge first to minimize the idle-state time.

After flywheels, lead acid batteries discharge first than lithium ion. The system stipulates this order, because usually lead acid have lower output power, which could lead to a performance constantly on its maximum output power and still not using the total of stored energy. This way, even if lead acid batteries cannot deliver the power required, other devices may help output the rest. Accordingly, between the same types of batteries, the one with lower power output discharges first.

The output power used from each technology differs regarding the system's necessity. Therefore, it analyses each device to acknowledge what they can provide.

First, the system verifies the amount of energy required for that iteration (minute). Afterwards, following the priority list mentioned above, it checks if the first device has enough energy stored and power output to provide all the required energy. In that case, the system stores the values of discharge rates and their respective output power in the knowledge repository. However, if not, the system analyses if the same device has enough energy to perform at its maximum power output. If so, it performs at its maximum, but if not, it deploys all its remaining energy with the respective power output (that enables the deployment of the remaining energy). In any case, the system saves these values within the knowledge repository for later usage. This sequence affects every ESS chosen to simulate, ordered based on the priority list, until the system requires no more energy in that iteration. Nonetheless, it is possible that the ESSs do not have enough energy to supply the need.

For the system to acknowledge when it should discharge energy from the storage devices, strategies are used. Therefore, this simulator implements two different strategies that are peak shaving and maximize profit, both explained below.

5.2.2.1 Peak shaving strategy

Peak shaving is similar to load levelling, but may be for reducing peak demand rather than for economy of operation. Therefore, it is a possible solution to the load management problem mentioned in subchapter 2.4.3.

As mentioned, electricity providers can use it for load management. However, consumers that the cost of supply is based both on the cost of energy (€/kWh) and on the maximum power demand (€/kW) also use this strategy. According to (Yeung, 2007), the savings can reach up to 30% by applying this method, because the price per power demand applies on the highest peak of consumption.

In this strategy implementation, the user chooses the threshold value to reduce the peak, being 5% its default value. The value inputted in the threshold box is the reduction, in percentage, that the user wants to inflict on the maximum value of the user consumption pattern (Figure 5.9). This also influences the charging process, because it establishes the threshold as the maximum allowed instantaneous power usage. Therefore, the energy estimated for consumption is the difference between the threshold and the usage consumption, when the latter is higher than the former.

In addition, this strategy, if the stored energy is not sufficient for the whole day it prioritises the discharges for the higher priced periods of the day, as seen in Figure 5.15.

As Figure 5.15 demonstrates, first, this strategy obtains the threshold value the user inputted on the decision system's GUI. Afterwards, it calculates the predicted energy required to fulfil the differences between the threshold and the user consumption.

When the simulation starts, during the course of one day, for every iteration, it verifies if the user consumption is above the specified threshold and only chooses which ESSs to discharge if they have enough stored energy for the higher priced periods. The system chooses between the storage devices based on the process explained above in subchapter 5.2.2.

The user can measure the results of this strategy through the graphics that appear in the decision system's GUI. If the simulated set of energy storage systems were able to shave the peaks of the user consumption, it is a good indication. However, the financial viability of such a system depends on the LCoS value and the savings that the strategy obtained.

Since this strategy limits the available power, the devices most suitable for this strategy should have low input power in order to enable their charge while maintaining the power usage below the threshold.

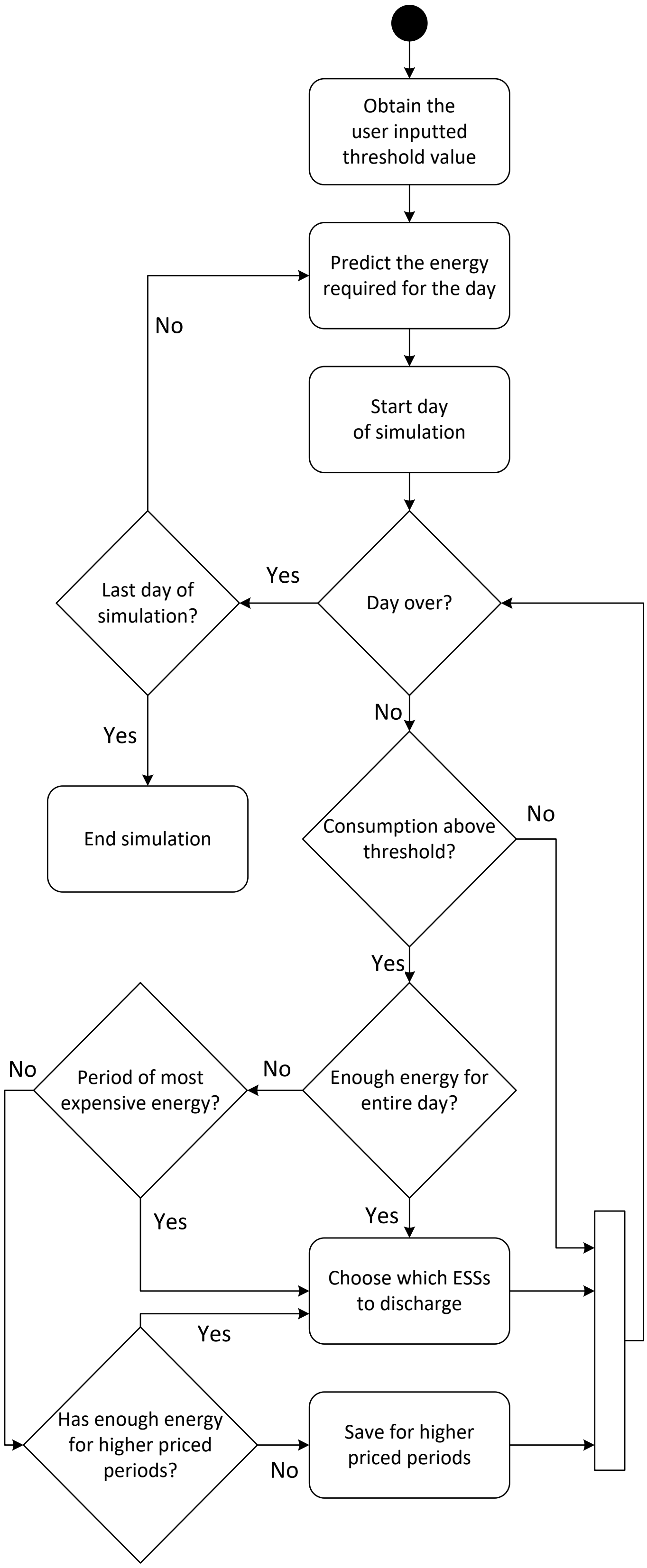


Figure 5.15 – Workflow of the peak shaving strategy implemented.

5.2.2.2 Maximize profit strategy

This strategy, differing from peak shaving, does not focus on the stabilisation of peak demand, but on financial return. Being focused on costs, consumers display further interest than service providers do.

Thus, the estimated energy for consumption is not the difference between the threshold and the user pattern, but the total usage consumption. Since there is no threshold, the maximum allowed power usage for charging is 95% of the total contracted power. The system does not use the total amount in order to enable user consumption fluctuations, without surpassing the contracted power.

Unlike peak shaving, which can discharge in any energy priced period, maximize profit does not discharge when the energy price is the lowest, as displayed in Figure 5.16. However, when the energy price is constant throughout the day, the simulator also enables the discharge of the storage units, to confirm the inability to obtain profit, when there are no energy price variations, during the 24-hour cycle.

It does not discharge in these periods because they are reserved for ESSs charging. If ESSs charge at the same-priced period than the discharging, the profit is negative because storage devices are not 100% efficient.

Consequentially, to maximize the profit, ESSs prioritises the discharge at the higher priced periods. They can discharge, however, at average priced periods (the average price within three-priced days) when the ESSs contain enough energy for the higher priced period. Regarding the discharge, the system chooses between the storage devices based on the process explained above in subchapter 5.2.2.

The user can measure the results of this strategy through the graphics that appear in the decision system's GUI. Nonetheless, since the main objective of this strategy is to obtain profit, a financial analysis is of key importance. Therefore, the system calculates and displays (in the decision system's GUI) the absolute gains, in €, of using storage devices and the gains per unit of energy (€/kWh), as demonstrated in Figure 5.9 in subchapter 5.1.1.2.

In addition, the simulator calculates the levelised cost of storage (LCoS) for each storage device used, which determines the price for storing one unit of energy (€/kWh) as explained in subchapter 3.2.

With these two notions, the user can detect if the components simulated can create a financially viable situation by subtracting the gains per unit of energy and the sum of each storage device's LCoS. If this result is above zero, the user can conclude that this situation may be viable as the opposite result demonstrates that the situation's viability is not achieved.

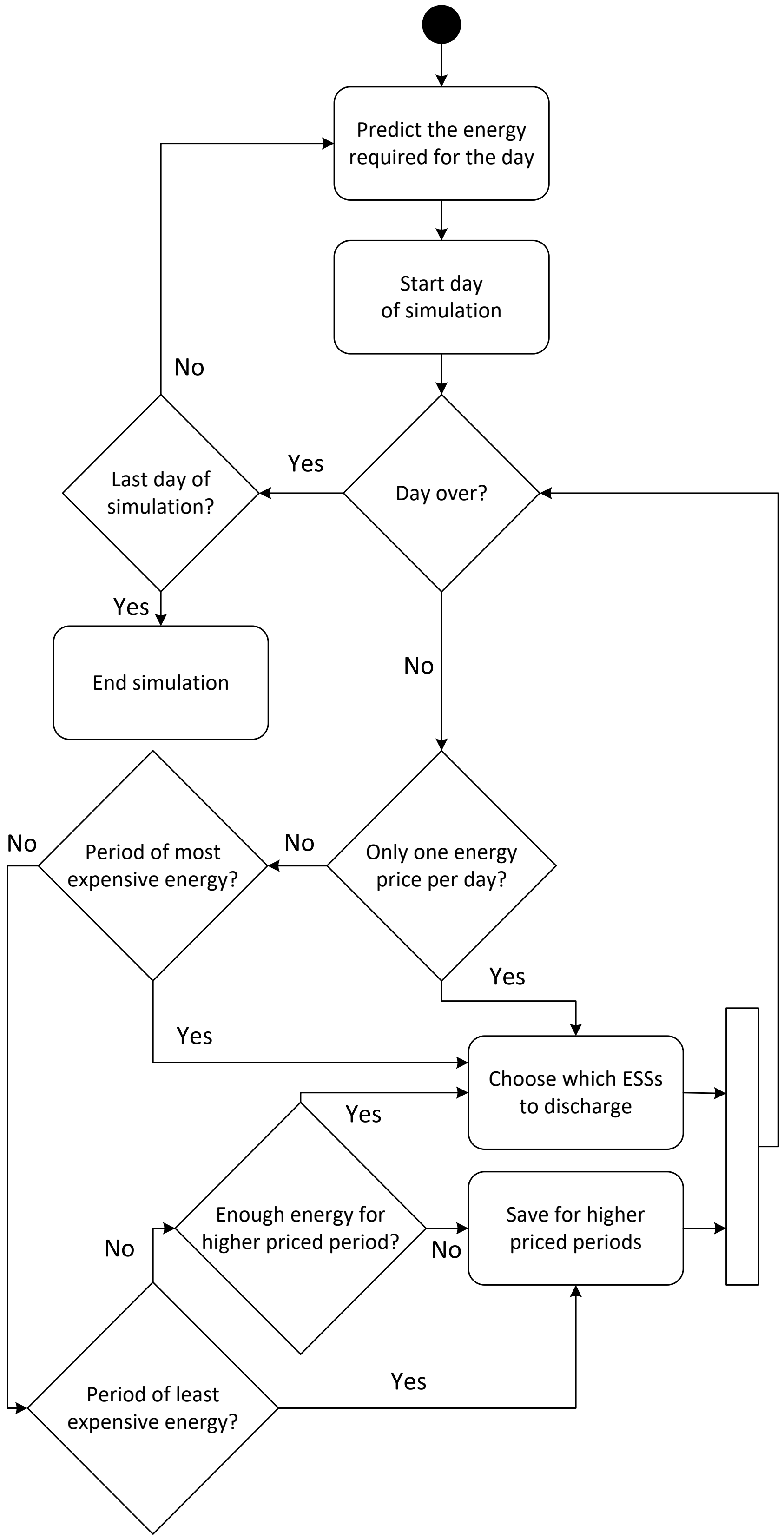


Figure 5.16 – Workflow of the maximize profit strategy implemented.

5.3 System’s *modus operandi*

After the demonstration and justification of the system’s components, methods and strategies, Figure 5.17 displays the system’s process for a complete simulation.

Comparing the implemented methodology (Figure 5.17) and the architecture’s design (Figure 4.4 in subchapter 4.2.4), besides some differences in the discharging part of the simulation, it can be concluded that both are similar.

The action blocks to determine if the storage units charge or discharge represent the charging and discharging methods detailed above (subchapters 5.2.1 and 5.2.2), while the execution of the strategy depends on the one chosen and its operational constraints specified in subchapters 5.2.2.1 and 5.2.2.2.

On the other hand, the system updates each device’s state of charge through equation 8.

$$State\ of\ charge = State\ of\ charge + (charging\ energy - discharging\ energy) \qquad (8)$$

The system can access these values regarding charging and discharging energy, because they are in the knowledge repository.

Using the graphical user interfaces, the user accomplishes the results’ display, the component insertion and the strategy and duration specification, while the management system controls the other functions, whether to make decisions or transfer data between itself and the other components.

The results obtained, from the simulator, depend on the simulation’s specific situation and require some interpretation. Accordingly, the author presents some results, for validation purposes, in the following chapter.

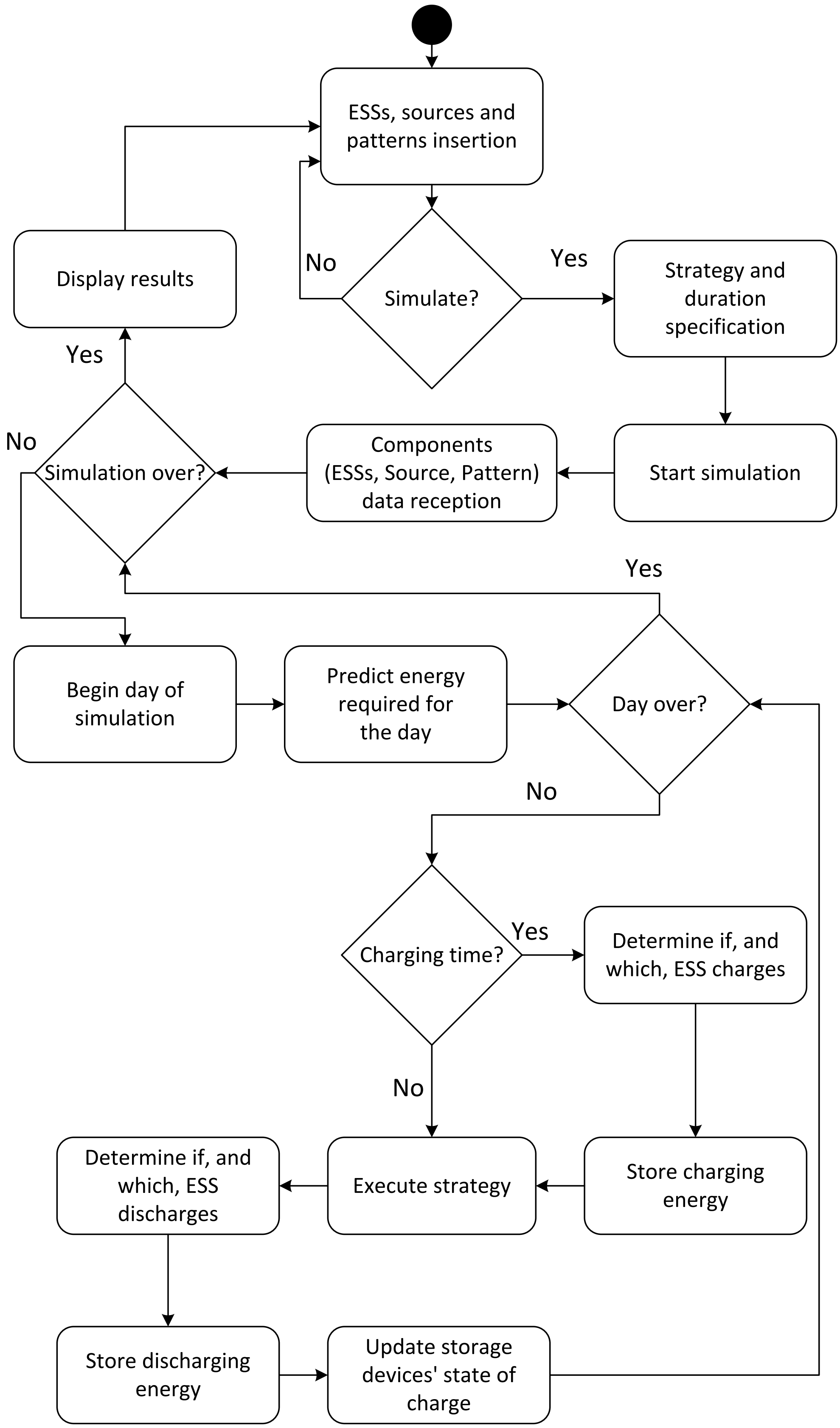


Figure 5.17 – Workflow of the system's process for a complete simulation.

6

Validation

This chapter displays the results of specific simulations and interprets them accordingly. The author obtains these results from the system implemented as described in chapter 5.

The simulations presented here, as results of the implementation of the system, validate the idea behind this dissertation, being proof-of-concept.

Since there are two distinct strategies, the author demonstrates the results of each in order. Therefore, this chapter divides itself between peak shaving and maximize profit simulations.

Within either strategy, the results divide between three different graphs: "Energy Storage Systems (ESSs) Consumption", "Individual ESS State of Charge" and "User Pattern and Grid Usage". These are the ones explained in Figure 5.9 in subchapter 5.1.1.2. The fourth graph, with the grid usage only, is not present within this chapter because the third graph (user pattern and grid usage) contains that information.

- "Energy Storage Systems (ESSs) Consumption" → graph that demonstrates the instantaneous output of each device in power per hour.
- "Individual ESS State of Charge" → chart that displays the amount of energy stored within each storage system in a percentage of total capacity (state of charge).
- "User Pattern and Grid Usage" → load diagram of user pattern and grid consumption. The user pattern is the real one and not the predicted consumption by the management system.

6.1 Maximize Profit Simulations

Within this subchapter, the author presents and analyses different simulations for maximize profit strategy (explained in subchapter 5.2.2.2). This strategy attempts to fulfil the load demands solely with the energy storage systems, by charging when the price is the lowest and discharging when it is the highest. For this simulation, the financial review is the most important factor for deciding its implementation.

6.1.1 First Simulation – one energy price per day and three ESSs for one day

The first simulation, Figure 6.1 and Figure 6.2, is the proof that this strategy is not viable for situations where the type of schedule only contains one price per energy.

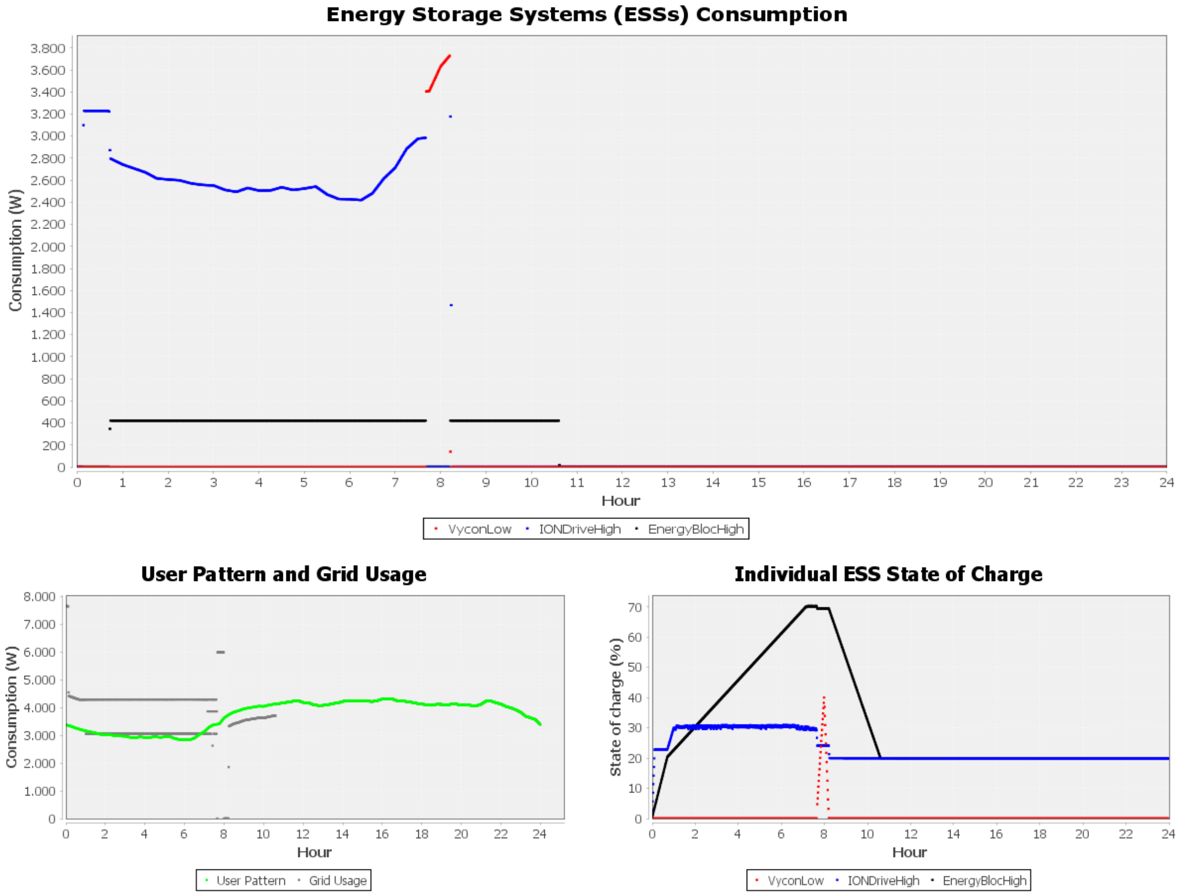


Figure 6.1 – Graphical results of a maximize profit simulation with only one price per day, three ESSs and a contracted power of 10.35kVA. This relates to a building with nine houses during the summer, simulated throughout one day.

This simulation uses VyconLow (flywheel and red line in chart), IONDriveHigh (lithium ion battery and blue line in chart) and EnergyBlocHigh (lead acid battery and black line in chart) as the storage systems. The source is EDPComercial with one-priced type of schedule and 10.35kVA of contracted power. The specified load is a building with nine houses (2700 kWh of monthly consumption) during the summer. The full characteristics of these components are within its specific tables in Appendix I.

In this situation, whenever ESSs have enough energy, they start discharging, however since the batteries have a 80% maximum depth of discharge, these only discharge when their state of charge is above 20% as shown in the "Individual ESS State of Charge" chart. However, since flywheels do not have restrains of maximum depth of discharge, whenever they have energy, it starts discharging as demonstrated by the red line in the charts. This chart also demonstrates that the charging time for this system is between 00h00 and 08h00 due to the increase in each unit's state of charge. In addition, as explained, flywheels only start to charge in the last minutes of the charging time to prevent energy loss through self-discharge. The flywheel does not reach full capacity, because while charging, it is also discharging.

The charging models of each technology and the energy discharge are affecting the rates at which the state of charge increases, which increases the time of a full charge. Within this charging time, the state of charge of the lithium ion battery (IONDriveHigh, blue line in the charts) is fluctuating around 30% between 01h00 and 07h00. This happens because when it surpasses the 30% state of charge, it enters the second phase of charging which lowers the input power and therefore the energy received. By lowering the charging energy, the discharging energy is higher than the former, lowering its state of charge below 30%. This continuously happens, because it keeps discharging and charging. However, when the time to charge the flywheel starts, other ESSs stop charging (due to power usage limitations), these fluctuations stops. From 08h00 to the end of the day, since it is not charging, it does not suffer from this occurrence. This fluctuation should not happen because it can damage the device causing lower durability.

Thus, in the "User Pattern and Grid Usage" chart, it appears to be two different grid usage series within the same time-span because when the battery alternates between its charging phases, it changes the input power. Since this occurs in consequential minutes, it appears that there are two lines, but it is just one with several fluctuations. Continuing in this chart, in the first few minutes, the grid is supplying almost 8kW, rapidly decreasing to around 4.5kW. This happens, because the ESSs start discharging, which means, that the grid is just charging the devices and providing the remaining energy that the ESSs cannot deliver. The minutes after 08h00, the grid does not deliver any energy, because the storage devices can endure the usage. However, when only the lead acid battery has energy, the grid has to supply the difference between the usage and the battery's output power. Afterwards, the grid usage and user pattern have the same values because the grid provides all the energy that the load demands.

As discharging goes, the "Energy Storage Systems (ESSs) Consumption" chart details its priority. When flywheel has energy, it is the first to discharge, as presented around 07h30, while when this system has no energy, the lead acid battery (EnergyBlocHigh, black line in the charts) discharges first and the lithium battery provides the rest. The user can observe that the maximum power output of the lead battery is around 400W as its characteristics detail.

Figure 6.1 demonstrates that while performing this strategy, the storage systems attempt to discharge all the energy that the load requires, and not just a small part of it.

After 08h00, since the energy systems are no longer charging, the system drains the ones with some energy left until their minimum as seen for the lead acid battery between 08h00 and 11h00.

In addition, Figure 6.2 displays the price results of this simulation.

Periods of time with different prices:
Average Price (0.1608 €/kWh) : All day long. From 00h00 to 24h00
Results (Prices and Energy Consumption):
Price for grid-only usage: 14.905 €;
Total Energy for grid-only usage: 90.0 kWh;
Price per unit of energy: 0.166 €/kWh;
Price for combined grid and ESS usage: 15.549 €;
Total Energy for grid and ESS usage: 94.002 kWh;
Price per unit of energy: 0.165 €/kWh;
Price gains: -0.644 €;
Price per unit of energy gains: 0.001 €/kWh;

Levelised Cost of Storage or LCoS (€/kWh):
It is the cost of storing 1 kWh of energy in a specific energy storage system.
LCoS[VyconLow]: 0.605 €/kWh;
LCoS[IONDriveHigh]: 0.075 €/kWh;
LCoS[EnergyBlocHigh]: 0.032 €/kWh;

Figure 6.2 – Price results of a maximize profit simulation with only one price per day, three ESSs and a contracted power of 10.35kVA. This relates to a building with nine houses during the summer, simulated throughout one day.

As observed from Figure 6.2, the price gains are below zero, which means that this situation would cause a loss of money. This happens, since storage devices are not 100% efficient, they require extra energy to charge. Therefore, since the price per energy is constant throughout the day, receiving energy from the grid would actually be cheaper than charging and discharging the ESSs. The values of price per unit of energy in Figure 6.2 are not the same of the price charged by the source, because the system includes the price of the contracted power in those calculations.

The price per unit of energy should be the same between only-grid and grid and ESS usage, but these values have an uncertainty of 0.001 (rounded numbers), which explain this result.

Therefore, as expected, this strategy is not well suited for one-priced type of schedules, because it is not financially viable and it can deteriorate the storage devices by discharging during their charging period.

6.1.2 Second Simulation – two energy prices per day and two ESSs for one day

The second simulation, Figure 6.3 and Figure 6.4, is proof-of-concept of this strategy's possible viability for situations where the type of schedule contains more than one price per energy.

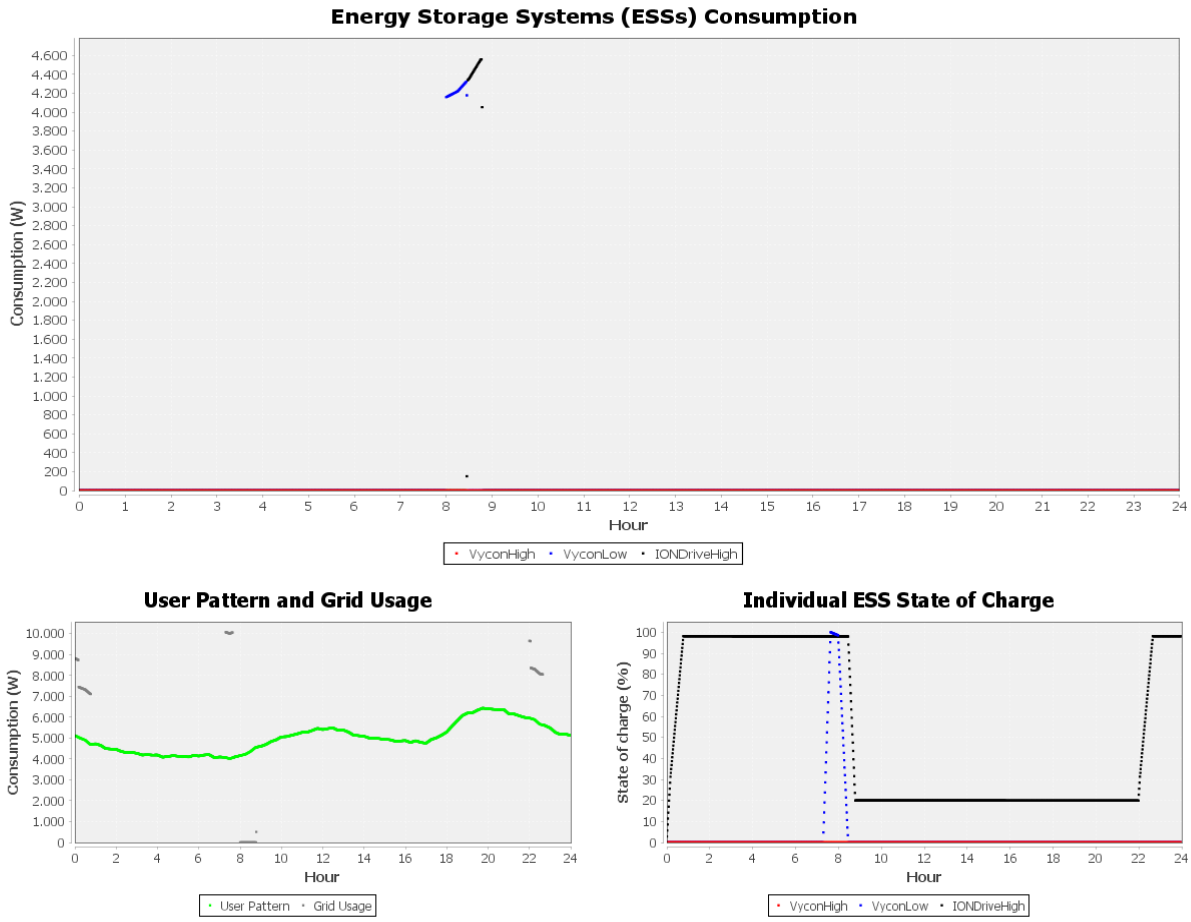


Figure 6.3 – Graphical results of a maximize profit simulation with two prices per day, three ESSs and a contracted power of 13.8kVA. This relates to a building with twelve houses during the winter, throughout one day.

This simulation uses VyconHigh (flywheel and red line in chart), VyconLow (flywheel and blue line in chart) and IONDriveHigh (lithium ion battery and black line in chart) as the storage systems. The source is EDPComercial with a two-priced type of schedule and 13.8kVA of contracted power. The specified load is a building with twelve houses (3600 kWh of monthly consumption) during the winter. Comparing it to the previous simulation is clear that the user pattern is different, due to the difference in seasons. The full characteristics of these components are within its specific tables in Appendix I.

In this situation, since there are two energy prices per day, the storage systems only charge during the cheapest period and discharge during the most expensive. Thus, in the “Energy Storage Systems (ESSs) Consumption” chart, in Figure 6.3, the storage devices only start discharging after 08h00, which is when the highest priced period starts. First, the flywheel discharges, to prevent self-discharge losses, and when it does not have any energy left, the other units start to discharge.

However, in this situation, even if it uses three ESSs, only two discharge (VyconLow and IONDriveHigh). This happens because the other storage unit, VyconHigh, does not charge nor discharge. It does not charge because it requires too much power, which the source cannot provide. This flywheel alone requires 12 kW of power to charge, which combined with the user consumption, far surpasses the maximum allowed power usage from the source.

The “Individual ESS State of Charge” graph demonstrates the inability to charge said flywheel, because when the flywheel-charging period starts, only VyconLow actually charges. Right before 08h00, this chart shows the decrease of energy available within the flywheel. This happens due to the self-discharge, which affects the unit when it is not charging or discharging. In addition, it appears the distinct two phases of charging lithium ion batteries, modifying the increase rate around 30% state of charge.

In this situation, there is another charging period, due to energy lower prices at the end of the day. As expected, flywheels do not charge to minimize their idle time. On the other hand, since the system did not have enough energy to fulfil the requirements of the day, the storage devices that can charge, do.

The “User Pattern and Grid Usage” chart in Figure 6.3, demonstrate what happens throughout the day. During charging periods, the grid usage surpasses the usage consumption, while when it is time to discharge, the grid usage is lower than the load demand. The highest value of grid usage is around 10kW due to the high input power (6kW) of VyconLow.

The major difference between the charge and discharge times is the cost of energy within each period. Therefore, Figure 6.4 presents the financial analysis for this simulation.

This situation obtains profit in absolute values, without considering the storage system costs. In addition, the price per energy gains are positive. Despite the higher usage of energy, the system can obtain profit while using ESSs. However, if this situation is viable, the price per energy gains must surpass the sum of the LCoS values, which does not happen in this situation as Figure 6.4 shows.

Therefore, as expected, this simulation demonstrates this strategy functioning correctly. However, the results show that the cost of storage is too high to reach financial viability.

Periods of time with different prices:

Lowest Price (0.0927 €/kWh) : 00h00 to 08h00 and 22h00 to 24h00;
Highest Price (0.1974 €/kWh) : 08h00 to 22h00;

Results (Prices and Energy Consumption):

Price for grid-only usage: 19.521 €;
Total Energy for grid-only usage: 120.0 kWh;
Price per unit of energy: 0.163 €/kWh;
Price for combined grid and ESS usage: 19.389 €;
Total Energy for grid and ESS usage: 122.475 kWh;
Price per unit of energy: 0.158 €/kWh;
Price gains: 0.132 €;
Price per unit of energy gains: 0.005 €/kWh;

Levelised Cost of Storage or LCoS (€/kWh):

It is the cost of storing 1 kWh of energy in a specific energy storage system.
LCoS[VyconHigh]: Not applicable;
LCoS[VyconLow]: 0.576 €/kWh;
LCoS[IONDriveHigh]: 0.397 €/kWh;

Figure 6.4 – Price results of a maximize profit simulation with only two prices per day, three ESSs and a contracted power of 13.8kVA. This relates to a building with twelve houses during the winter, throughout one day.

6.1.3 Third Simulation – three energy prices per day and three ESSs for three days

The third simulation, Figure 6.5 and Figure 6.6, represents this strategy's possible viability for situations where the type of schedule contains three price per energy. In addition, the duration of this simulation is three days.

This simulation uses IONDriveLow (lithium ion battery and red line in chart) and EnergyBlocLow (lead acid battery and blue line in chart) as the storage systems. The source is EDPComercial with a three-priced type of schedule and 17.25kVA of contracted power. The specified load is a building with fifteen houses (4500 kWh of monthly consumption) during the summer. The full characteristics of these components are within its specific tables in Appendix I.

In this situation, since there are three energy prices per day, the storage systems only charge during the cheapest period and discharge preferably during the most expensive. Thus, in the "Energy Storage Systems (ESSs) Consumption" chart, in Figure 6.5, the storage devices start discharging between 10h30 and 13h00 each day, which is when the highest priced period starts. At 19h30, since there is few available stored energy, there are discharges, but small ones, until no stored energy is left.

The "Individual ESS State of Charge" graph demonstrates that during the first day, IONDriveLow cannot fully charge within the first charging period. Thus, the system charges it at the second charging period (between 22h00 and 24h00), in order for it to reach maximum state of charge during the second day. It also shows that neither storage technology reach 100% state of charge, because the system establishes 98% as their maximum to avoid internal damage. Again, neither technology discharges below their maximum depth of discharge.

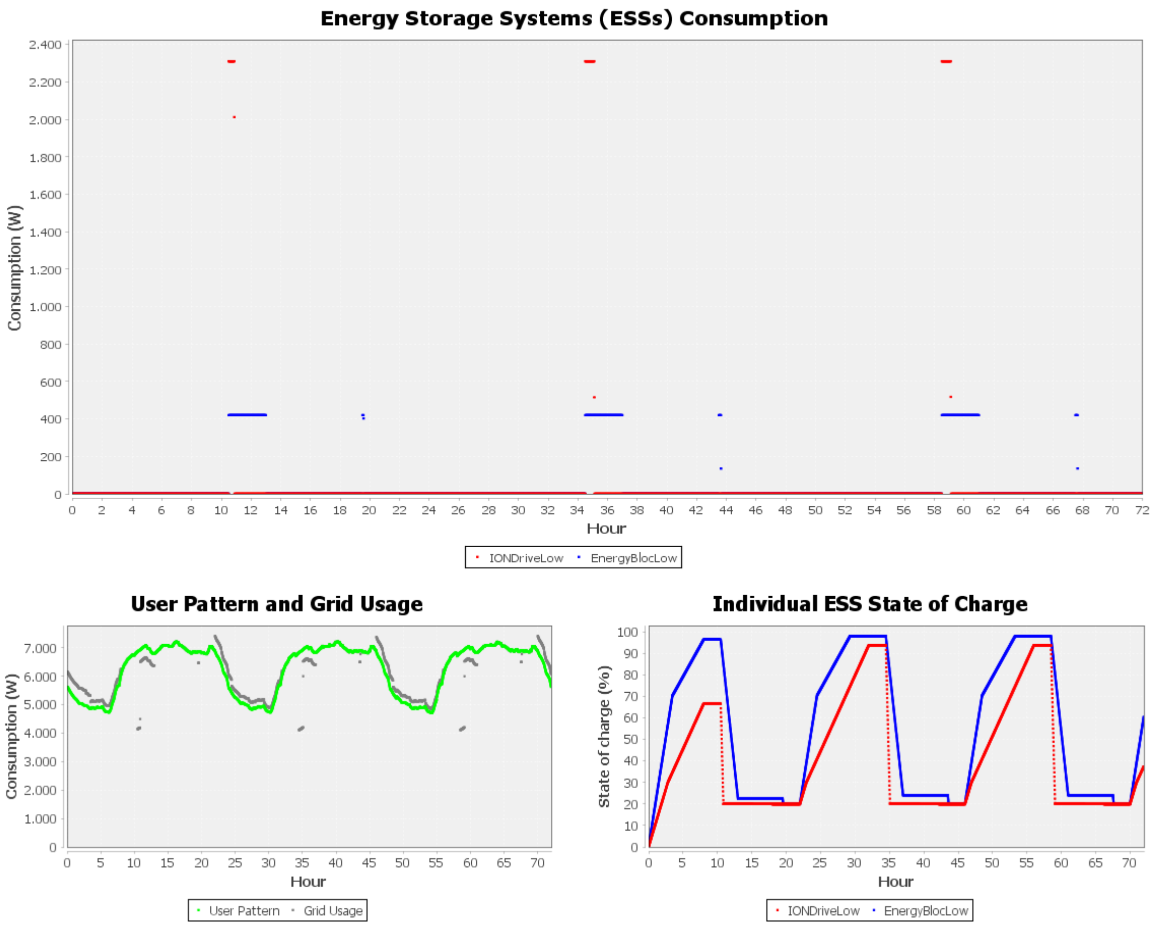


Figure 6.5 – Graphical results of a maximize profit simulation with three prices per day, two ESSs and a contracted power of 17.25kVA. This relates to a building with fifteen houses during the summer, throughout three days.

Regarding the ESSs consumption, both perform at their maximum power output, because the load demand is higher than the sum of their output. Since the EnergyBlocLow has higher capacity, it endures longer discharging at maximum power than IONDriveLow. Since the sum of the energy available throughout the storage devices is not enough to supply the load demand during the most expensive periods, the system does not let them discharge during other periods, for profit maximization.

In the "User Pattern and Grid Usage" chart in Figure 6.5, the grid consumption never varies greatly from the usage consumption due to the ESSs inability to supply the instant load demand and their input power being low compared to the user consumption. In addition, the user pattern slightly changes between days. As an example, the user consumption, right before the peak (around 15h00), is different throughout the days, which in day three has almost the same value as the peak. The system simulates this in order to become closer to a real-life situation.

Since the simulator predicts the consumption through the average of the last few days and the user pattern shown is the real consumption, when discharging, there are differences between the predicted energy and the real energy required. This creates possible failures on energy discharge calculations. However, since within this strategy the ESSs usually do not have enough energy for the entire day, the consequences of such predicament are not visible.

The major difference between the charge and discharge times is the cost of energy within each period. Therefore, Figure 6.6 presents the financial analysis for this simulation.

Periods of time with different prices:
Lowest Price (0.0925 €/kWh) : 00h00 to 08h00 and 22h00 to 24h00;
Average Price (0.1641 €/kWh) : 08h00 to 10h30, 13h00 to 19h30 and 21h00 to 22h00;
Highest Price (0.3183 €/kWh) : 10h30 to 13h00 and 19h30 to 21h00

Results (Prices and Energy Consumption):
Price for grid-only usage: 77.397 €;
Total Energy for grid-only usage: 450.379 kWh;
Price per unit of energy: 0.172 €/kWh;
Price for combined grid and ESS usage: 76.042 €;
Total Energy for grid and ESS usage: 452.751 kWh;
Price per unit of energy: 0.168 €/kWh;
Price gains: 1.355 €;
Price per unit of energy gains: 0.004 €/kWh;

Levelised Cost of Storage or LCoS (€/kWh):
It is the cost of storing 1 kWh of energy in a specific energy storage system.
LCoS[IONDriveLow]: 0.08 €/kWh;
LCoS[EnergyBlocLow]: 0.066 €/kWh;

Figure 6.6 – Price results of a maximize profit simulation with three prices per day, two ESSs and a contracted power of 17.25kVA. This relates to a building with fifteen houses during the summer, throughout three days.

This situation obtains profit in absolute values, without considering the storage system costs, and price per energy gains are positive. The profit, in €, is higher than previous simulations because it is for three days. Despite the higher usage of energy, the system can obtain profit while using ESSs. However, if this situation is viable, the price per energy gains must surpass the sum of the LCoS values, which does not happen in this situation as Figure 6.6 shows.

Therefore, as expected, this simulation demonstrates this strategy functioning correctly. However, with this set of storage units, this specific source and pattern of user consumption, the cost of storage is too high to reach financial viability.

6.1.4 Fourth Simulation – three energy prices per day and three ESSs for seven days

The fourth, and last, simulation for this strategy, Figure 6.7 and Figure 6.8, represents this strategy's possible viability for situations where there are three energy prices per day and the duration is seven days.

This simulation uses VyconHigh (flywheel and red line in chart), IONDriveLow (lithium ion battery and blue line in chart) and EnergyBlocLow (lead acid battery and black line in chart) as the storage systems. The source is EDPComercial with a three-priced type of schedule and 27.6kVA of contracted power. The specified load is a building with nine houses (2700 kWh of monthly consumption) during the winter. The full characteristics of these components are within its specific tables in Appendix I.

Figure 6.7 shows a simulation with a seven-day duration, which can be hard to analyse. It also demonstrates a working performance of VyconHigh, the flywheel with 12kW of input power.

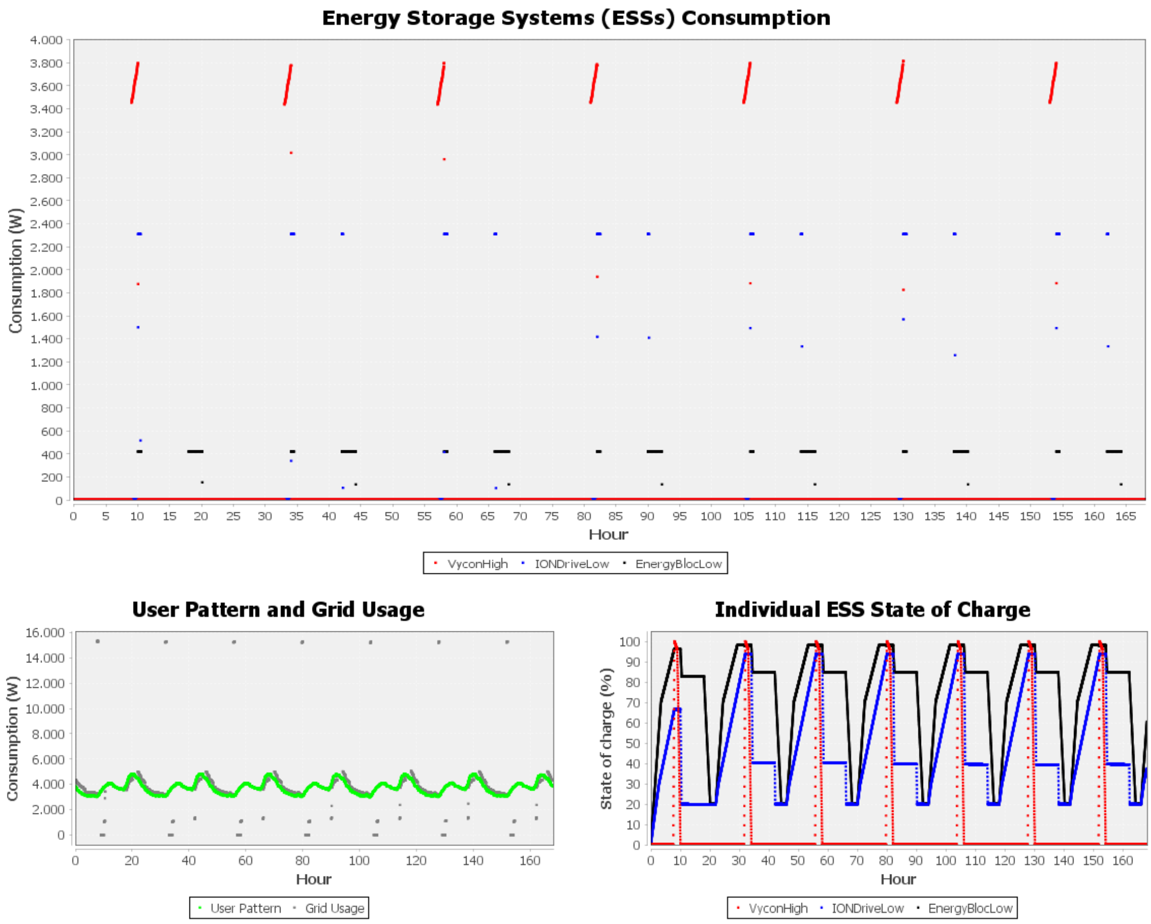


Figure 6.7 – Graphical results of a maximize profit simulation with three prices per day, three ESSs and a contracted power of 27.6kVA. This relates to a building with nine houses during the winter, throughout seven days.

The "Individual ESS State of Charge" chart demonstrates, as in previous simulations, that flywheels only charge in the last few minutes of the first charging time, while the remaining technologies charge during the first and second periods, if necessary. In this case, IONDriveLow requires a second-period charge to reach its maximum state of charge.

Regarding the grid and user pattern consumption, when the batteries are charging, their consumption is similar due to low input power. However, when VyconHigh charges, the grid consumption climbs up to near 16kW.

On the other hand, when the cheapest period of energy starts, the storage systems discharge and while the flywheel has energy, the grid does not supply any energy. When the flywheel is out of energy, the batteries perform at their maximum, but the grid has to supply the remaining energy that the load demands.

The major difference between the charge and discharge times is the cost of energy within each period. Therefore, Figure 6.8 presents the financial analysis for this simulation.

Periods of time with different prices:
Lowest Price (0.0805 €/kWh) : 00h00 to 08h00 and 22h00 to 24h00;
Average Price (0.1438 €/kWh) : 08h00 to 09h00, 10h30 to 18h00 and 20h30 to 22h00;
Highest Price (0.2878 €/kWh) : 09h00 to 10h30 and 18h00 to 20h30

Results (Prices and Energy Consumption):
Price for grid-only usage: 102.143 €;
Total Energy for grid-only usage: 631.186 kWh;
Price per unit of energy: 0.162 €/kWh;
Price for combined grid and ESS usage: 93.539 €;
Total Energy for grid and ESS usage: 637.114 kWh;
Price per unit of energy: 0.147 €/kWh;
Price gains: 8.604 €;
Price per unit of energy gains: 0.015 €/kWh;

Levelised Cost of Storage or LCoS (€/kWh):
It is the cost of storing 1 kWh of energy in a specific energy storage system.
LCoS[VyconHigh]: 0.576 €/kWh;
LCoS[IONDriveLow]: 0.058 €/kWh;
LCoS[EnergyBlocLow]: 0.032 €/kWh;

Figure 6.8 – Price results of a maximize profit simulation with three prices per day, three ESSs and a contracted power of 27.6kVA. This relates to a building with nine houses during the winter, throughout seven days.

This situation obtains profit in absolute values, without considering the storage system costs, and price per energy gains are positive. The profit, again, is higher than previous simulations because it regards seven days. This also applies to the price per unit of energy gains. However, for this situation to be viable, the price per energy gains must surpass the sum of the LCoS values, which does not happen in this situation as Figure 6.8 displays. It does not surpass even a single of the values obtained for each technology.

Therefore, as expected, the implementation of this system with these storage systems would turn into financial losses.

6.2 Peak Shaving Simulations

Within this subchapter, the author presents and analyses different simulations for the peak shaving strategy (explained in subchapter 5.2.2.1). This strategy creates a threshold that the consumption cannot surpass. In order to achieve that, it uses the storage systems to supply the remaining energy, by charging when the price per energy is cheapest and deploying whenever the consumption surpasses the threshold. For this simulation, the financial review is important, but not in the same way as maximize profit. The viability depends on how much the decrease of maximum power affects the final cost.

6.2.1 First Simulation – one energy price per day and one ESS for one day

The first simulation, Figure 6.9 and Figure 6.10 , is proof-of-concept of this strategy's possible viability for situations when there is only one energy price per day. The threshold-inputted percentage is 5%, as shown in Figure 6.10.

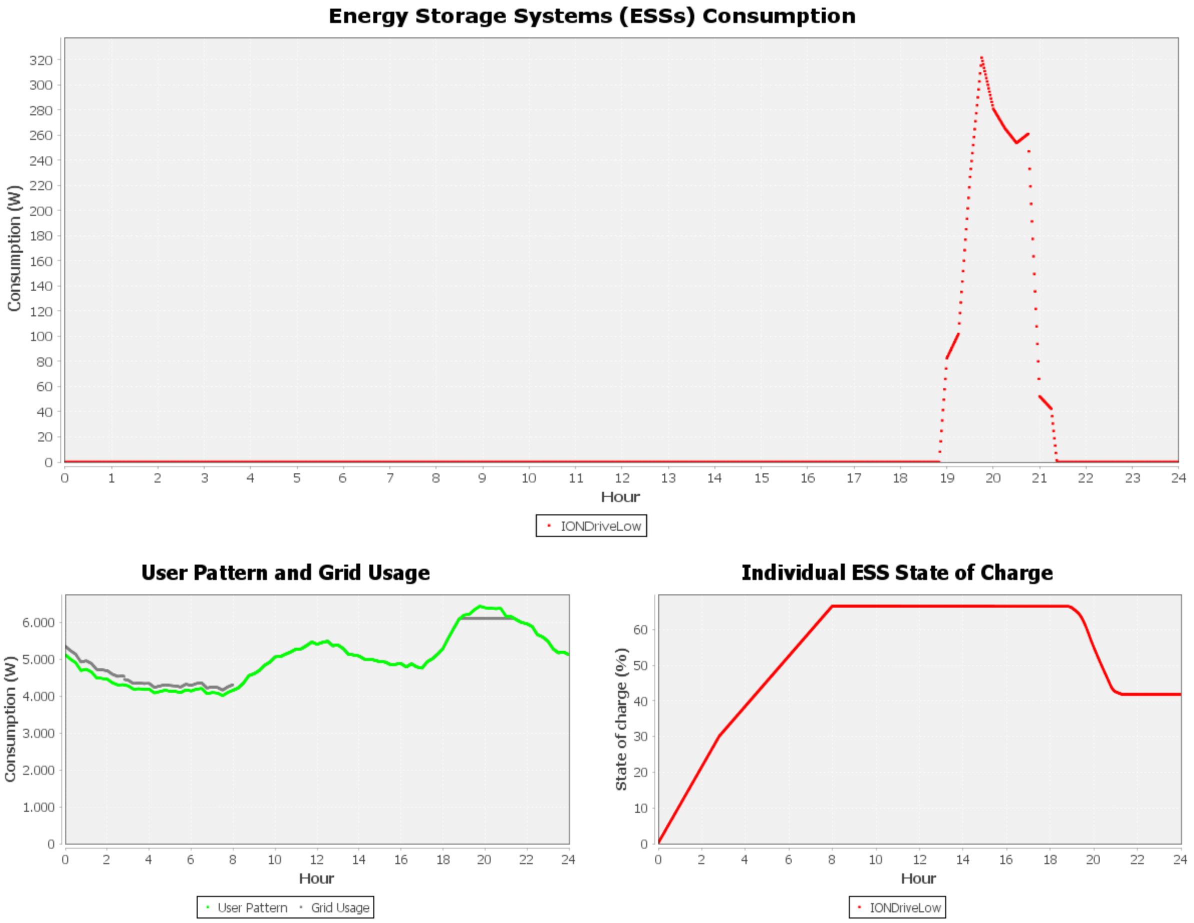


Figure 6.9 – Graphical results of a peak shaving simulation with only one price per day, one ESS and a contracted power of 13.8kVA. This relates to a building with twelve houses during the winter, simulated throughout one day.

This simulation uses IONDriveLow (lithium ion battery and red line in chart) as the storage system. The source is EDPComercial with a one-priced type of schedule and 13.8kVA of contracted power. The specified load is a building with twelve houses (3600 kWh of monthly consumption) during the winter. The full characteristics of these components are within its specific tables in Appendix I.

In this situation, the strategy fulfilled its objectives, as displayed in Figure 6.9.

The “User Pattern and Grid Usage” graph demonstrates, that when the user consumption surpasses the established threshold (5% of the maximum peak value of user consumption base-pattern), the storage system starts to discharge and the grid does not supply any more. On the other hand, during the charging time (00h00 until 08h00), the grid spends more than user consumption to charge the storage device.

The charging of the ESS goes through two different phases, as expected from a lithium-ion battery, by changing its charge rates and operational input power at 30% state of charge, as seen in the “Individual ESS State of Charge” chart.

Regarding the energy discharge, it occurs whenever the system requires. Since the user pattern consumption only surpasses the threshold between around 19h00 and 21h00, the storage devices only discharge during this time, with the amount of energy needed. The information on “Energy Storage Systems (ESSs) Consumption” graph confirms this.

Threshold (reduction of the pattern max value in %) *: 5

* Only applicable for peak shaving strategy

Periods of time with different prices:

Average Price (0.1608 €/kWh) : All day long. From 00h00 to 24h00

Results (Prices and Energy Consumption):

Price for grid-only usage: 19.868 €;
Total Energy for grid-only usage: 120.0 kWh;
Price per unit of energy: 0.166 €/kWh;
Price for combined grid and ESS usage: 20.024 €;
Total Energy for grid and ESS usage: 120.972 kWh;
Price per unit of energy: 0.166 €/kWh;

Levelised Cost of Storage or LCoS (€/kWh):

It is the cost of storing 1 kWh of energy in a specific energy storage system.
LCoS[IONDriveLow]: 0.092 €/kWh;

Figure 6.10 – Price results of a peak shaving simulation with only one price per day, one ESS and a contracted power of 13.8kVA. This relates to a building with twelve houses during the winter, simulated throughout one day.

Figure 6.10 represents the costs and energy used associated with this simulation. However, just these values do not establish if this situation is financially viable. Only with the access to the decrease of cost, due to the lowering of the peak demand value, a reliable conclusion could be created.

However, peak shaving improves the load management for this situation, with these specific characteristics, which is a good result.

6.2.2 Second Simulation – two energy prices per day and three ESSs for one day

The second simulation, Figure 6.11 and Figure 6.12, is a simulation of this strategy’s possible viability for situations when there are two energy prices per day. The threshold-inputted percentage is 10%, as shown in Figure 6.12.

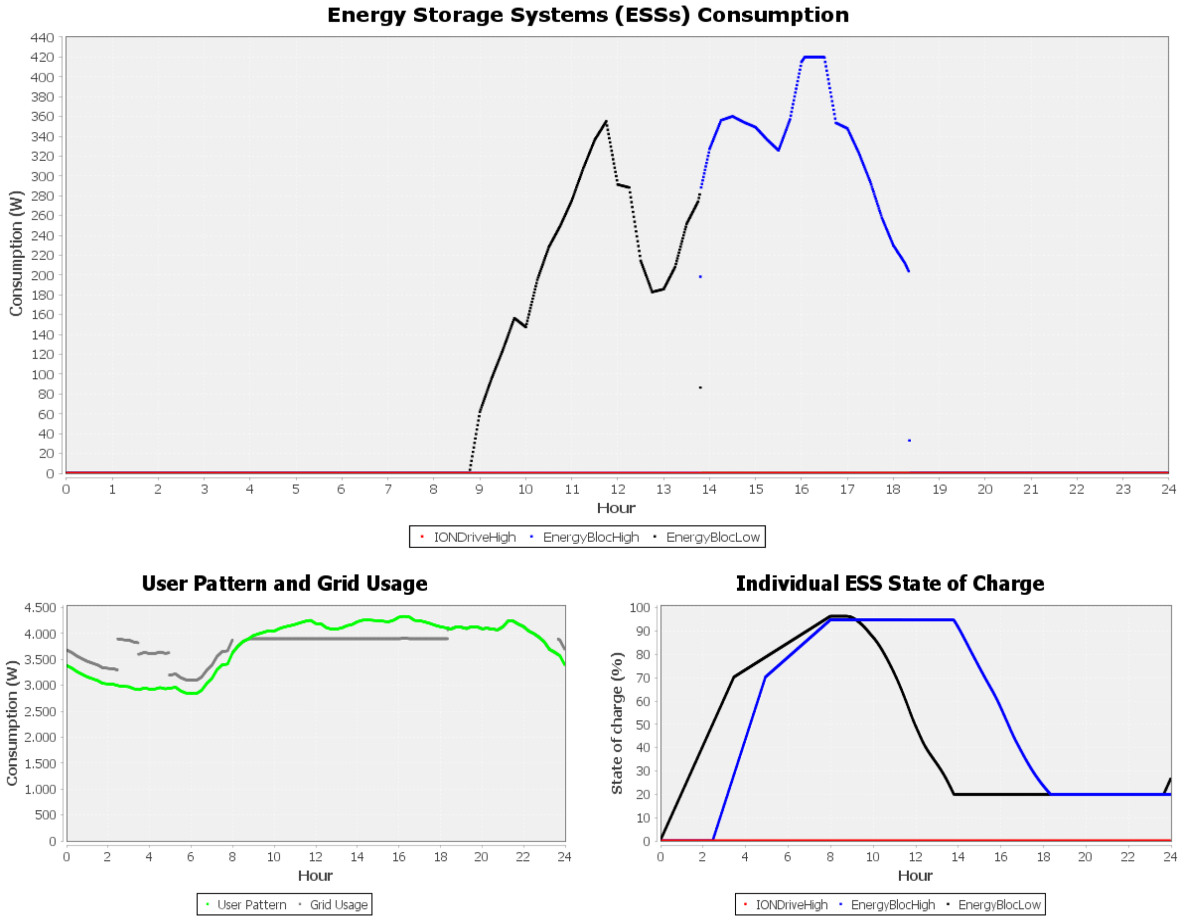


Figure 6.11 – Graphical results of a peak shaving simulation with two prices per day, three ESSs and a contracted power of 17.25kVA. This relates to a building with nine houses during the summer, simulated throughout one day.

This simulation uses IONDriveHigh (lithium ion battery and red line in chart), EnergyBlocHigh (lead acid battery and blue line in chart) and EnergyBlocLow (lead acid battery and black line in chart) as the storage systems. The source is EDPComercial with a two-priced type of schedule and 17.25kVA of contracted power. The specified load is a building with nine houses (2700 kWh of monthly consumption) during the summer. The full characteristics of these components are within its specific tables in Appendix I.

In this situation, the strategy did not fulfil its objectives, as displayed in Figure 6.11.

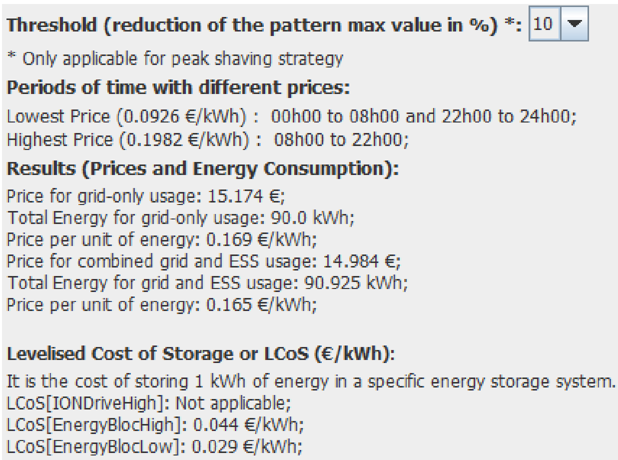
Despite having three storage systems, this simulation only uses two. This occurs due to power usage limitations. Since the threshold value is the maximum power usage, IONDriveHigh cannot charge, due to its high input power. Therefore, as expected, storage systems that require high input power are not suitable for this strategy. Consequentially, this lithium ion battery and flywheels are not useful for peak shaving purposes.

The “Energy Storage Systems (ESSs) Consumption” chart demonstrates the priority discharge of ESSs, being the lead battery first and the lithium next. In addition, around 16h00, the storage device reaches its maximum power output, which, in this case, leads to a failure in supply as seen in “User Pattern and Grid Usage”. Additionally, the storage devices stop having energy to supply around 19h00, which creates the need of grid supply. Therefore, this situation fails in this strategy’s objectives.

The threshold increase, in comparison to the previous simulation, affected this failure, because it lowered the maximum usage power and required more energy.

However, as there was not enough energy throughout the day, the ESSs charge during the second charging period (from 22h00 to 24h00), in order to perform better on the following day, as demonstrated in the “Individual ESS State of Charge” chart.

Regarding the price results of this simulation, in Figure 6.12, less energy is spent while using the storage systems, yet these components cannot fulfil this strategy’s needs. Accordingly, this simulation establishes that, with these characteristics, an implementation with these storage devices is not advisable.


Threshold (reduction of the pattern max value in %) *: 10

* Only applicable for peak shaving strategy

Periods of time with different prices:

Lowest Price (0.0926 €/kWh) : 00h00 to 08h00 and 22h00 to 24h00;
Highest Price (0.1982 €/kWh) : 08h00 to 22h00;

Results (Prices and Energy Consumption):

Price for grid-only usage: 15.174 €;
Total Energy for grid-only usage: 90.0 kWh;
Price per unit of energy: 0.169 €/kWh;
Price for combined grid and ESS usage: 14.984 €;
Total Energy for grid and ESS usage: 90.925 kWh;
Price per unit of energy: 0.165 €/kWh;

Levelised Cost of Storage or LCoS (€/kWh):

It is the cost of storing 1 kWh of energy in a specific energy storage system.
LCoS[IONDriveHigh]: Not applicable;
LCoS[EnergyBlocHigh]: 0.044 €/kWh;
LCoS[EnergyBlocLow]: 0.029 €/kWh;

Figure 6.12 – Price results of a peak shaving simulation with two price per day, three ESSs and a contracted power of 17.25kVA. This relates to a building with nine houses during the summer, simulated throughout one day.

6.2.3 Third Simulation – three energy prices per day and two ESSs for three days

The third simulation, Figure 6.13 and Figure 6.14, is a simulation of this strategy’s possible viability for situations when there are three energy prices per day and during three days. The threshold-inputted percentage is 15%, as shown in Figure 6.14.

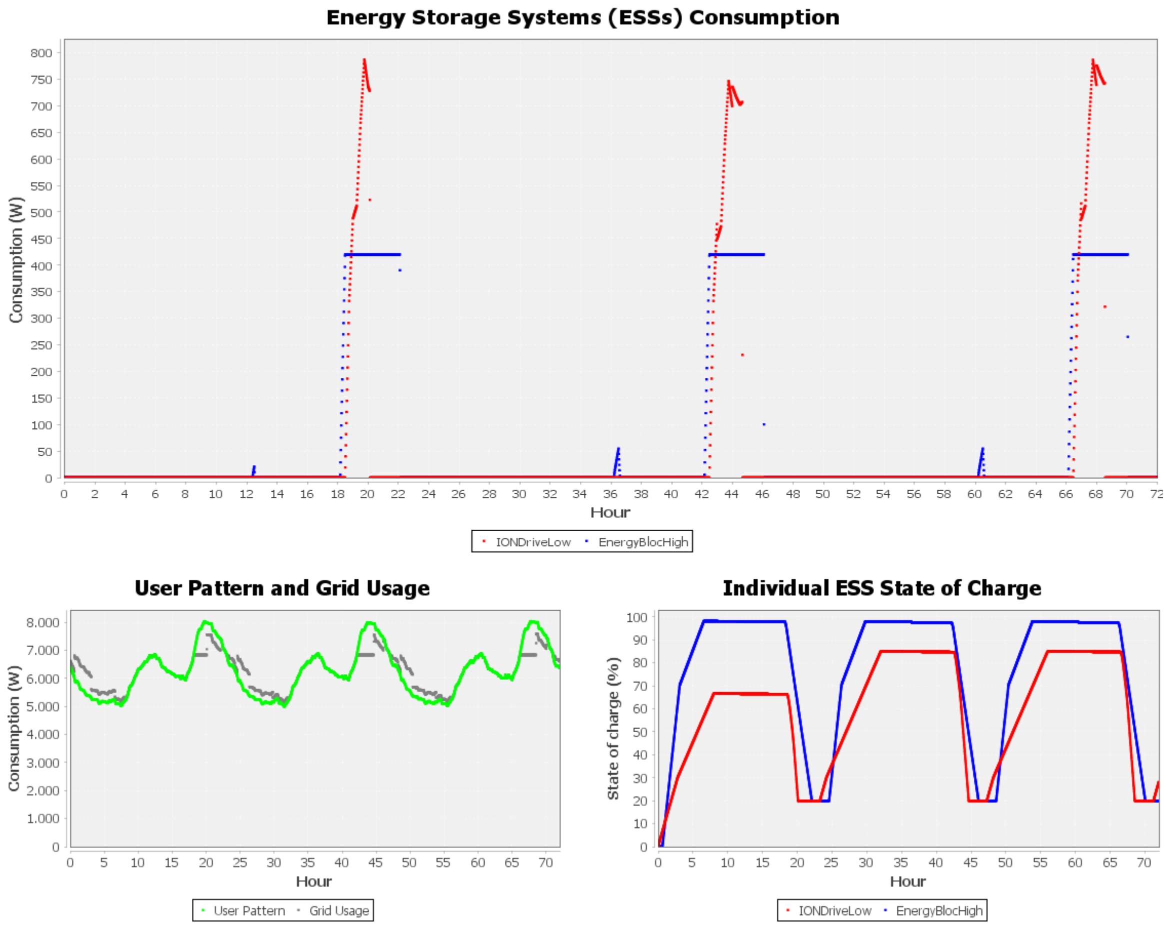


Figure 6.13 – Graphical results of a peak shaving simulation with three prices per day, two ESSs and a contracted power of 20.7kVA. This relates to a building with fifteen houses during the winter, simulated throughout three days.

This simulation uses IONDriveLow (lithium ion battery and red line in chart) and EnergyBlocHigh (lead acid battery and blue line in chart) as the storage systems. The source is EDPComercial with a three-priced type of schedule and 20.7kVA of contracted power. The specified load is a building with fifteen houses (4500 kWh of monthly consumption) during the winter, throughout three days. The full characteristics of these components are within its specific tables in Appendix I.

In this situation, the strategy did not fulfil its objectives, as displayed in Figure 6.13.

The "Energy Storage Systems (ESSs) Consumption" chart demonstrates the priority discharge of ESSs, being the lead battery first and the lithium next. In addition, it displays the change in the user consumption between days through the discharge changes, around 12h00, and the lower amount of discharge required at the peak on the second day.

In this simulation, the IONDriveLow lithium battery does not charge until its maximum state of charge, because at the time of the second charging period (22h00 to 24h00), there is no available power to charge it. Therefore, it only starts charging around 23h00, losing one hour of charging, as seen in the "Individual ESS State of Charge" chart.

Through the "User Pattern and Grid Usage" graph, it is clear that this situation did not accomplish its goals, due to grid usage above the threshold value. Between 18h00 and 22h00, the storage systems supply the necessary energy, but fall short after that period, which requires extra energy from the grid.

Therefore, this situation fails in this strategy's objectives. The threshold increase, in comparison to the previous simulation, affected this failure, because it lowered the maximum usage power and required more energy.

This simulation's results, shown in Figure 6.14, display less spending of energy while using the storage systems, yet these components cannot fulfil this strategy's needs. Accordingly, this simulation establishes that, with these characteristics, an implementation with these storage devices is not advisable.

Threshold (reduction of the pattern max value in %) *: 15

* Only applicable for peak shaving strategy

Periods of time with different prices:

Lowest Price (0.0935 €/kWh) : 00h00 to 08h00 and 22h00 to 24h00;
Average Price (0.1651 €/kWh) : 08h00 to 09h00, 10h30 to 18h00 and 20h30 to 22h00;
Highest Price (0.3192 €/kWh) : 09h00 to 10h30 and 18h00 to 20h30

Results (Prices and Energy Consumption):

Price for grid-only usage: 77.822 €;
Total Energy for grid-only usage: 450.107 kWh;
Price per unit of energy: 0.173 €/kWh;
Price for combined grid and ESS usage: 76.498 €;
Total Energy for grid and ESS usage: 451.814 kWh;
Price per unit of energy: 0.169 €/kWh;

Levelised Cost of Storage or LCoS (€/kWh):

It is the cost of storing 1 kWh of energy in a specific energy storage system.
LCoS[IONDriveLow]: 0.09 €/kWh;
LCoS[EnergyBlocHigh]: 0.118 €/kWh;

Figure 6.14 – Price results of a peak shaving simulation with three prices per day, two ESSs and a contracted power of 20.7kVA. This relates to a building with fifteen houses during the winter, simulated throughout three days.

6.2.4 Fourth Simulation – three energy prices per day and two ESSs for seven days

The fourth, and final, simulation for this strategy (Figure 6.15 and Figure 6.16) is a simulation of this strategy's possible viability for situations when there are three energy prices per day and during seven days. The threshold-inputted percentage is 5%, as shown in Figure 6.16.

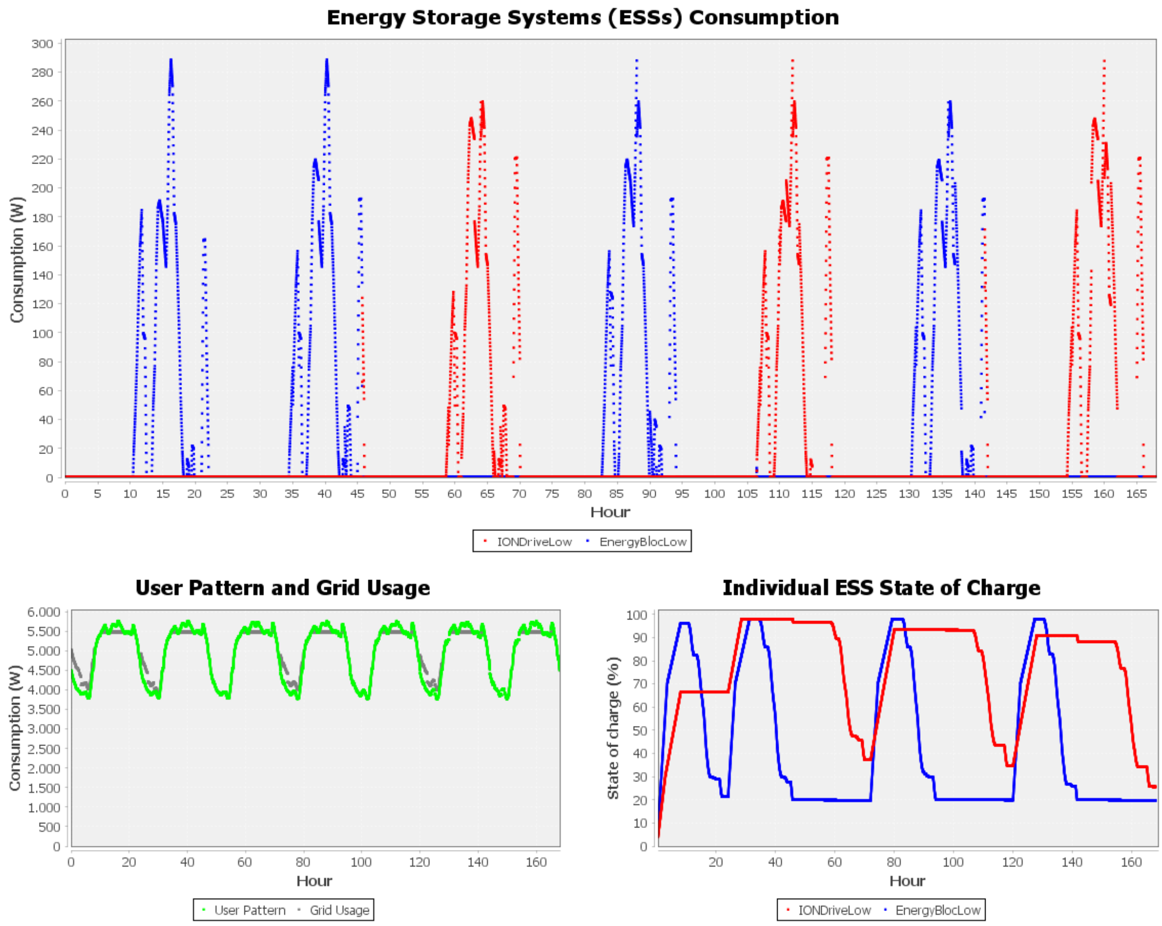


Figure 6.15 – Graphical results of a peak shaving simulation with three prices per day, two ESSs and a contracted power of 13.8kVA. This relates to a building with twelve houses during the summer, simulated throughout seven days.

This simulation uses IONDriveLow (lithium ion battery and red line in chart) and EnergyBlocLow (lead acid battery and black line in chart) as the storage systems. The source is EDPComercial with a three-priced type of schedule and 13.8kVA of contracted power. The specified load is a building with twelve houses (3600 kWh of monthly consumption) during the summer, throughout seven days. The full characteristics of these components are within its specific tables in Appendix I.

In this situation, the strategy fulfilled its objectives, as displayed in Figure 6.15.

The “Energy Storage Systems (ESSs) Consumption” chart demonstrates the priority discharge of ESSs, being the lead battery first and the lithium next. In addition, it displays the change in the user consumption between days through the discharge changes. It also shows differences between which storage device discharges, with the lead acid discharging in the first, second, fourth and sixth day. The lithium battery discharges a bit on the second day to help the first device and takes care of the third, fifth and seventh day. This happens, because the system acknowledges that the sum of the available energy within the storage devices is enough to fulfil the requirements.

Therefore, there is no need to charge the technologies every day, saving energy, as seen in the "Individual ESS State of Charge" chart. This is also an indication that the system accomplishes its goals, because it has enough energy to answer the day's requirements.

In addition, analysing the "User Pattern and Grid Usage", when the usage consumption surpasses the threshold, the gird delivers until that point and the storage systems supply the rest.

Figure 6.16 represents the costs and energy used associated with this simulation. However, just these values do not establish if this situation is financially viable. Only with the access to the decrease of cost, due to the lowering of the peak demand value, a reliable conclusion could be created.

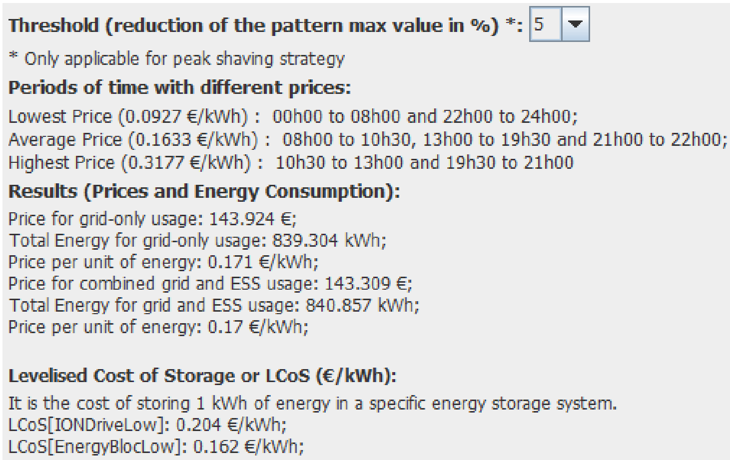


Figure 6.16 – Price results of a peak shaving simulation with three prices per day, two ESSs and a contracted power of 13.8kVA. This relates to a building with twelve houses during the summer, simulated throughout seven days.

However, peak shaving improves the load management for this situation and optimizes the energy consumption for these specific characteristics. Therefore, a system with these storage systems can lead to a favourable implementation for this situation.

6.3 Summary and conclusions

These simulations, in chapter 6, can help to reach a conclusion for this system and its strategies.

Maximize profit is not advisable for implementation, because the costs for storage are still too high for the gains per unit of energy to be sufficient for financial viability. This is the base-line conclusion of the simulations performed with this system.

For peak shaving, this system has situations where it accomplishes its goals. Specific sets of storage units, within specific environments, can manage the load and optimize energy consumption through this strategy. In addition, it can achieve financial viability, depending on the cost decrease of lowering the peak demand, which is not available in this simulator. Through the analysis of the results obtained from the simulations, this is the conclusion reached regarding this strategy.

For both strategies, the simulations for thirty days are not available for analysis due to the difficult interpretation of the charts if inserted here. However, the author simulated with those specifications, obtaining similar results for both strategies.

Nonetheless, either strategy accomplishes the preservation of security and stability with a good QoS.

7

Conclusions and future work

This chapter presents this project's conclusions while addressing future work.

7.1 Conclusions

Buildings are one of the biggest culprits for world energy consumption and its fluctuations. As a result, it is crucial to improve the load management and optimize the consumption of energy, according to its demand.

As energy management standards improve, so will increase their impact on human lives. Therefore, it seems inevitable that new designed technologies and strategies affect the management of energy and consequentially, optimize the energy consumption and improve the load stability.

Accordingly, the proposed approach within this dissertation lead to the creation of a simulator, which implements a system that has the main purpose of optimizing energy consumption through different strategies and technologies, taking into account the end-user energy consumption within buildings.

Regarding the technologies, the author compares energy storage systems, devices already implemented, but still penetrating the market and uses them to fulfil this system's objectives. Lithium ion batteries, lead acid batteries and flywheels are the storage units chosen to be part of this system's implementation, due to their performance characteristics.

The usage consumption within buildings, by depending on human behaviour, fluctuates between every situation. Therefore, this system establishes a base-pattern of consumption within buildings in Portugal depending on the season.

Using peak shaving and maximize profit strategies, this system can manage these technologies and the environment around them (power network and user pattern consumption) to optimize the energy consumption and improve load management.

After the creation of the simulator based on the above-mentioned attributes, simulations were performed, to analyse the results obtained, in order to acknowledge if implementation is viable.

However, the maximize profit strategy, due to the high cost of the technologies used makes its implementation unadvisable. On the other hand, according to the results obtained, peak shaving is implementable for load stabilization purposes and might be useful for cost optimization as well.

The results obtained in the simulator have an error margin associated, due to the system establishing the power factor as one and the charging or discharging methods of the battery technologies not being completely accurate.

Nonetheless, the general results obtained are positive, with the storage systems having costs that are still too high for implementation nowadays. However, this can change due to the assumption that these technologies will decrease in prices, in the future, enabling a financial return for their implementation.

If the reader requires access to the simulator or its source code, both are available in Appendix II.

7.2 Future work

The system implemented can improve through the creation of different strategies, usage of different energy storage technologies and different energy consumption patterns within the simulator.

In addition, the inclusion of Ragone plots for lithium batteries discharge, the change of the power factor value and the possibility to use renewable generation to unburden the power grid are options that would improve the work accomplished here.

In the future, the most important step is to couple this management system to a physical plant with energy storage systems and analyse its results on a real-life environment.

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Appendix I

Table Appendix I 1 – Sources that initialize with the simulator with values obtained from (ERSE, 2016).

Name	Type of Source	Type of Schedule	Lowest Price (€/kWh)	Average Price (€/kWh)	Highest Price (€/kWh)	Contracted Power (kVA)	Power Price (€/day)
EDPComercial	Grid	1	-------	0.1608	-------	10.35	0.4331
EDPComercial	Grid	2	0.0928	-------	0.197	10.35	0.4564
EDPComercial	Grid	3	0.0927	0.1632	0.3179	10.35	0.459
EDPComercial	Grid	1	-------	0.1608	-------	13.8	0.5718
EDPComercial	Grid	2	0.0927	-------	0.1974	13.8	0.5891
EDPComercial	Grid	3	0.0927	0.1633	0.3177	13.8	0.5922
EDPComercial	Grid	1	-------	0.1608	-------	17.25	0.7106
EDPComercial	Grid	2	0.0926	-------	0.1982	17.25	0.7217

EDPComercial	Grid	3	0.0925	0.1641	0.3183	17.25	0.7249
EDPComercial	Grid	1	-------	0.1608	-------	20.7	0.8495
EDPComercial	Grid	2	0.0926	-------	0.1983	20.7	0.8543
EDPComercial	Grid	3	0.0935	0.1651	0.3192	20.7	0.8643
EDPComercial	Grid	3	0.0805	0.1438	0.2878	27.6	1.3379
GALP	Grid	1	-------	0.166	-------	10.35	0.4315
GALP	Grid	2	0.1018	-------	0.2067	10.35	0.4315
GALP	Grid	1	-------	0.166	-------	13.8	0.57
GALP	Grid	2	0.1018	-------	0.2067	13.8	0.57

Table Appendix I 2 – Characteristics of the user consumption patterns. These patterns are the ones that initialize with the simulator.

Name	Type of pattern (which season)	Monthly Consumption (kWh)
BuildingSummer09Houses	Summer	2700
BuildingWinter09Houses	Winter	2700
BuildingSummer12Houses	Summer	3600
BuildingWinter12Houses	Winter	3600
BuildingSummer15Houses	Summer	4500
BuildingWinter15Houses	Winter	4500

Table Appendix I 3 – List of the characteristics of the ESSs that initialize with the simulator.

Characteristics	Values					
Name (ID)	VyconHigh	VyconLow	IONDriveHigh	IONDriveLow	EnergyBlocHigh	EnergyBlocLow
Technology	Flywheel	Flywheel	Lithium ion battery	Lithium ion battery	Lead acid battery	Lead acid battery
Capacity (Ah)	10	5	82	82	340	237
Capacity (Wh)	4000	2000	1894.2	1894.2	2040	1422
Input current (A)	30	15	160	10	100	50
Output current (A)	100	100	200	100	70	70
Voltage (V)	400	400	23.1	23.1	6	6
Efficiency (%)	99.4	99.4	90	90	77	77
Input power (kW)	12	6	3.696	0.231	0.6	0.3
Output power (kW)	40	40	4.62	2.31	0.42	0.42
Discharge time (minutes)	6	3	25	50	219	132
Recharge time (minutes)	21	21	48	766	371	518

Maximum discharge (%)	100	100	80	80	80	80
Daily self-discharge (%)	100	100	0.2	0.2	0.2	0.2
Durability (years)	20	20	6	6	15	15
Durability (cycles)	13000000	13000000	3000	3000	3000	3000
SIC (€/kW)	600	600	800	800	500	500
Type of lead acid	-------	-------	-------	-------	Flooded	Flooded

Appendix II

Below, the author displays links, which enable the access to the working simulator and its source code.

Simulator .jar file:

https://www.dropbox.com/s/00brbz2z8nq8yu2/Simulator%20for%20IMESS%20in%20Buildings.jar?dl=0

Simulator source code (in a .rar):

https://www.dropbox.com/s/1otw4t7vciq4pcd/IMESS.rar?dl=0