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Dimensionamento de Sistemas de Baterias para Armazenamento de Energia para Parques Eólicos

JOÃO AFONSO VAZ VARGAS PINHEIRO DA ROCHA
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Dimensioning of Battery Energy Storage Systems for Wind Energy Plants

João Afonso Vaz Vargas Pinheiro da Rocha

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2021

Instituto Superior de Engenharia do Porto

Department of Mechanical Engineering

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PALAVRAS-CHAVE

Acordo de Paris; Energias renováveis; European Green Deal; Potencial económico; Sistemas de baterias para armazenamento de energia; Tarifa flutuante.

RESUMO

O actual comportamento flutuante da tarifa diária nos mercados de energia introduz um conjunto de oportunidades para um melhor aproveitamento do potencial económico a isso subjacente. A energia resultante de fontes renováveis, como energia limpa que vê neste um momento um grande crescimento (associado a medidas como o European Green Deal e o Acordo de Paris), apresenta o maior potencial desperdiçado devido ao seu comportamento estocástico. É possível desenvolver estratégias no sentido de aliar o potencial económico das flutuações da tarifa diária à produção de energia limpa com origem em fontes renováveis. A estratégia abordada neste documento é o uso de sistemas de baterias para armazenamento de energia acoplados a um aproveitamento eólico para alocar a energia produzida por parques eólicos a horas em que tarifa diária se encontra mais baixa para horas nas quais a tarifa atinge os seus maiores valores diários. Para estudar o potencial económico desta estratégia foi desenvolvido um modelo em Python 3 que avalia o aumento das vendas para diferentes capacidades de armazenamento a partir de dados das tarifas e de uma série de produção de um parque eólico, seja esta produção real ou estimativas de produção a curto prazo. O modelo foi usado para investigar o impacto da capacidade de armazenamento das baterias, assim como para optimizar a estratégia da sua utilização. Foi também simulado o efeito da degradação da capacidade das baterias durante o período de vida do parque eólico. Para além disso, o programa poderá funcionar como software de operação de um sistema de baterias para armazenamento de energia num parque em funcionamento. Para criar o programa e avaliar o seu bom funcionamento foi utilizado um caso de estudo com dados reais de tarifa e produção.

KEYWORDS

Battery Energy Storage Systems; BESS; European Green Deal; Economic potential; Paris agreement; Tariff fluctuations; Renewable energy.

ABSTRACT

The current fluctuating behaviour of the daily tariff in the energy markets makes way for various opportunities for a better use of the underlying economic potential. Renewable energy, as clean energy, is currently growing at a high rate (due to international policies such as the European Green Deal and the Paris Agreement), it however has the greatest wasted potential due to its stochastic behaviour. It is possible to develop strategies to combine the economic potential of daily tariff fluctuations with the production of clean energy from renewable sources. The strategy addressed in this work is the use of Battery Energy Storage Systems (BESS) coupled with a wind farm to allocate the energy produced by the park from hours when the daily tariff value is lower to hours when the tariff reaches its highest daily values. To study the economic potential of this strategy, a script in Python 3 was developed to assess the increase in sales (or turnover) for different storage capacities based on tariff data and a production series of the park. This analysis uses data from the past and can be done even without the presence of a park on site. A simulation of the effects of degradation of the BESS throughout the park's operation period was included. In addition, the program may function as an operating software for a BESS in a functioning wind farm. To create the program and assess its proper functioning, a case study was used.

NOMENCLATURE

Abbreviations

BESS	Battery Energy Storage System
IEA	International Energy Agency
IREA	International Renewable Energy Agency
LA	Lead-Acid
DoD	Depth of Discharge
MCP	Market Clearing Price
MIBEL	Mercado Ibérico de Electricidade
NEMO	Nominated Electricity Market Operator
PBP	Pay Back Period
PCS	Power Conversion System
RE	Renewable Energy
RES	Renewable Energy Sources
SoC	State of Charge
TSO	Transmission System Operator
UPS	Uninterruptible Power Supply

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Introduction

1 Introduction

1.1 Driving Motivation

Electricity has become a core necessity for humanity's development. It is directly linked to the well-being of populations, as an enabler of various commodities, such as heating, lighting, powering of gadgets, access to the internet, among others. It is also an invaluable resource for technological and scientific advancements. Seldom, if any, are the fields which do not require electricity to develop new knowledge, be it for something as simple as a working computer and internet access. It is thus expected that the energy demand will rise, as quality of life should improve across the globe.

This foreseen increase in energy demand would implicate a rapid depletion of the Earth's reserves of fossil fuels, resulting in enormous carbon emissions, which contribute greatly to the acceleration of climate change. However, a solution to this imminent danger was found in obtaining energy from Renewable Energy Sources (RES), also known as Renewable Energy (RE). The main limitation of this type of energy is its stochastic and intermittent behaviour. Currently, there are many strategies being implemented to store high quantities of energy which would minimize this uncertainty. These strategies not only solve an old problem, but also pave the way to find new opportunities, such as the one that will be discussed in detail throughout this thesis.

Moreover, the fact that the Energy Market has become increasingly more sophisticated allows for a better management of energy during each day, which is another motivator to improve the reliability of the energy sold, as there are many economic advantages that can be seized upon. This improved management can include strategies such a more intelligent allocation of energy sold during the day to increase turnover. That is the goal of this thesis: to develop a model to assess the economic benefit of using energy storage systems to maximise profits in markets with fluctuating electricity tariffs. Subsidiary benefits regarding power delivery quality will be commented upon but not investigated in detail.

By the end of this thesis, I will have described a program that will help understand the feasibility of introducing a Battery Energy Storage System (BESS) to both an existing and a future RE farm. The criteria of feasibility will be the economic return of implementing a BESS for the sole purpose of allocating energy sold at low tariff hours to high tariff hours.

1.2 Renewable Energy

1.2.1 What is the state of Renewable Energy Growth

Renewable energy, as one of humanity's best alternatives to sate modern society's energy needs (without resorting to fossil fuels), has seen a great increase in penetration worldwide over the past years. If we were to analyse just the year 2020, there has been an increase of generation capacity of 260 GW (+10.3%) by the end of the year.

This increase can be separated in hydropower (20 GW, +2%), solar energy (127 GW, +22%), wind energy (111 GW, +18%), bioenergy (2 GW, +2%), and geothermal (164 MW). The protagonists of this expansion were wind and solar energy, jointly accounting for 91% of all net renewable additions in 2020. Figure 1.1 displays a bar graph that includes all the information previously mentioned and shows a clear tendency of worldwide growth of renewable energy capacity [1].

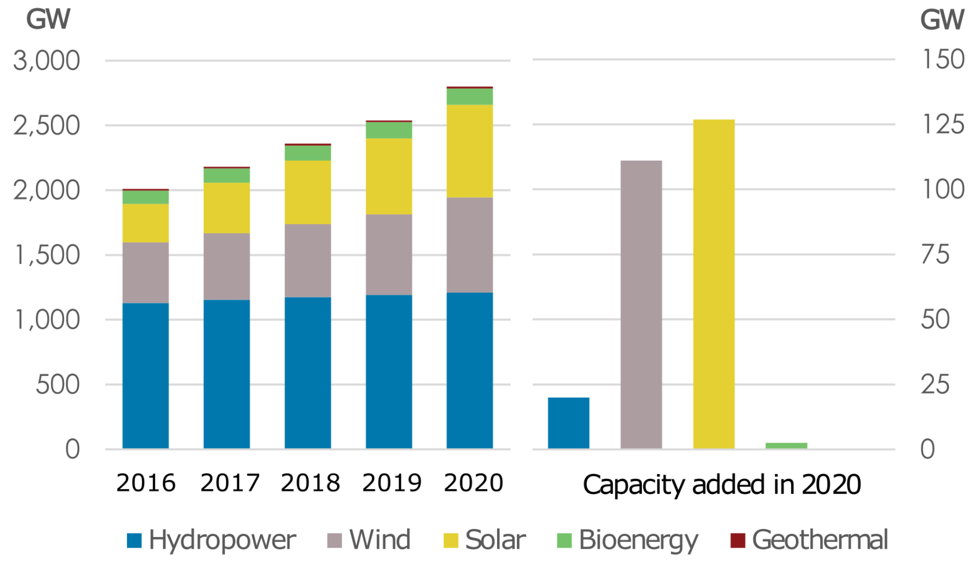


Figure 1.1 – Renewable Energy Capacity worldwide growth for the past five years and detailed growth by technology in 2020 [1].

All these advancements are crucial to move towards carbon neutrality by 2050, a goal set out by the European Green Deal, aligned with the EU's commitment to global climate action under the Paris Agreement.

Electric energy stemming from RES has become an extremely sought out resource by investors for a number of reasons: the development of technologies allows for a more efficient use of renewable resources, the rising international and state's investment on RE worldwide as a response to climate change and to achieve a more sustainable use of the resources available. [2]

1.2.2 The IEA forecast

The IEA Global Energy Review 2021 predicts that this year will become the fastest year-on-year growth of renewable energy generation since the 1970s. Having Solar PV and wind generation lead the charge by accounting for two-thirds of the expansion, an 8% global generation increase is foreseen, reaching a growth of about 8300 TWh. Figure 1.2 represents the current data of the IEA on RE generation increase, by technology, which was last updated on the 19th of Apr 2021 [3].

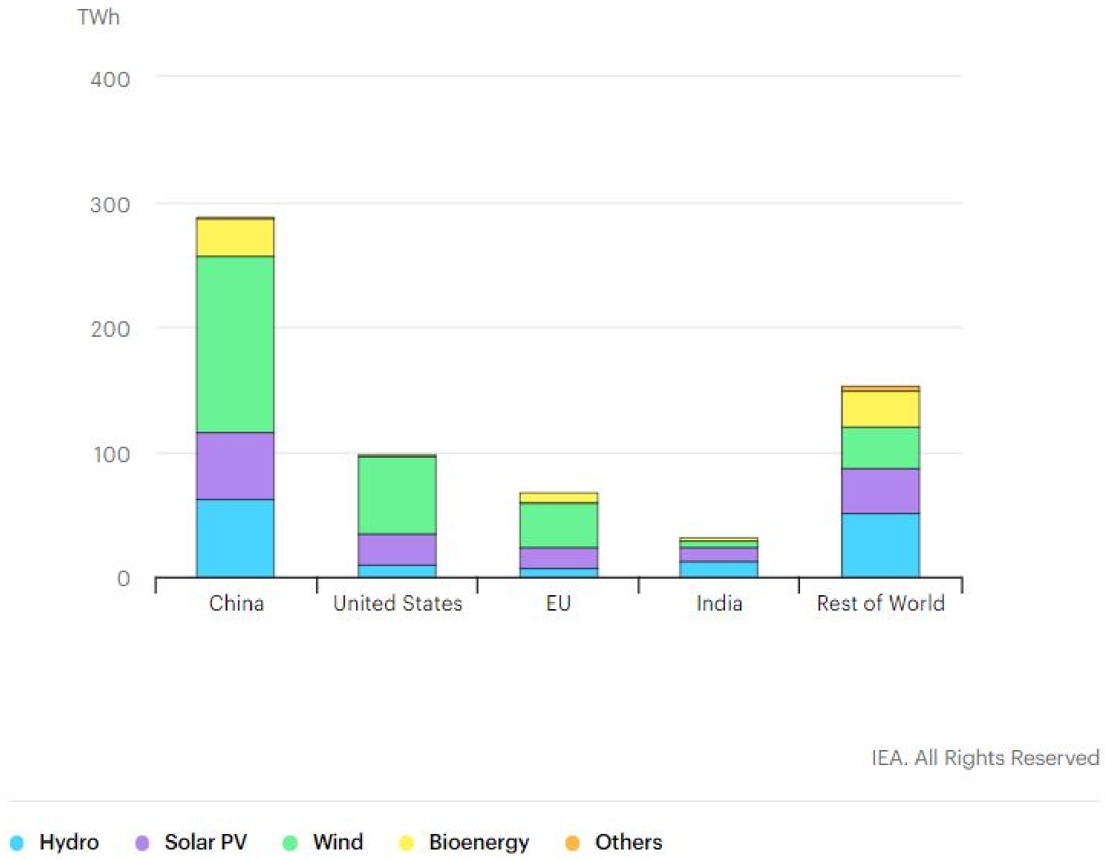


Figure 1.2 – Renewable electricity generation increase by technology, country and region, 2020-2021 [4].

A great number of incentives and policy support is being given worldwide towards the development of RE plants —mainly to wind and solar PV plants —, which justifies the continuous increase in RE generation for the past years and is a reason as to why we can expect a future growth as well. It is expected that, by the end of 2021, the RE share in the electricity generation mix will reach a record value of 30%. If we couple this value with nuclear energy generation, we can see that low-carbon sources have clearly surpassed the electricity output of the world's coal plants, as is shown in figure 1.3.

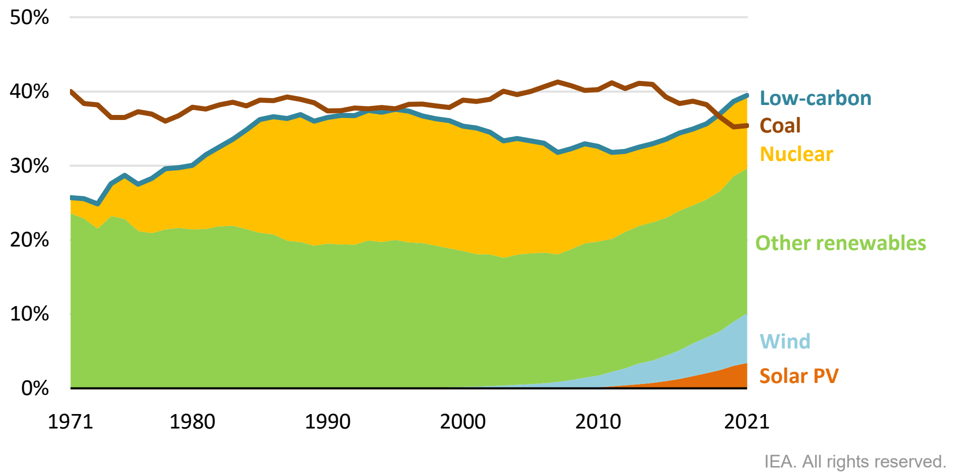


Figure 1.3 – Share of low-carbon sources and coal in world electricity generation, 1971-2021 [5].

1.2.3 *The European Green Deal: fit for 55 package*

The European Green deal, presented on the 11th of December 2019 by the European Commission, as a growth and development strategy, envisions to make Europe the first climate-neutral continent by 2050. On the 14th of July, 2021, the European Commission adopted the Fit for 55 package. This package serves to set a landmark on the road towards carbon neutrality, which is reducing greenhouse gas emissions by 55% (when compared to the values in 1990) as soon as the year 2030. Specific objectives were established for wind energy:

- Reach a total installed wind production capacity of 452 GW by 2030 (374 GW onshore and 79 GW offshore), which represents a growth of 220% to the current total installed capacity.
- Double yearly increase in power, from 15 GW to 30 GW.
- Increase the weight of RE on EU's total energy consumption, from the current 20% to 40%.

This set of policies will result in a continued growth of RE capacity, which brings short and long term relevance to the study carried out in this thesis [6][7].

1.2.4 *The hurdles to overcome*

The main drawback of using some RES is the inconsistency and unpredictability of their availability. Although there are increasingly more accurate forecasts, the inability to output electric energy at a moment's notice —in the specific case of solar and wind power plants, the two technologies that have seen the most significant increase in the past years, as mentioned before —is one of the reasons that sway investors away from supporting such technologies.

However, there have been devised many ways to store energy in large enough quantities as to justify the investment on RE power plants, such as the pumping of water up a dam for ”long duration” storage [8]. Not only is it easier to avoid penalties and fines that stem from the inability to meet contract demands, due to the unpredictability of the availability of the resources at all times, but it is also possible to allocate energy produced in low demand hours to high demand hours, which allows for a better economic gain from the energy produced. It is important to mention at this point that, up until now, BESS have been designed and used primarily for the first application. In this work, the focus is in analysing its benefits for the second application in markets of fluctuating electricity tariffs.

There are several different techniques used currently to store large quantities of energy generated from RES, which are commonly implemented to mitigate curtailment. The most common technologies for energy storage transform electric energy into mechanical energy, thermal energy, electrochemical energy, chemical energy, potential energy, among others. I will now name a few examples of Energy Storage Systems (ESS) presently in use [9][10]:

- Thermal energy: Excess electric energy can be used to power heat pumps that store it in a medium with high thermal capacity. Such media include large bodies of water - which is usually stored in artificial tanks or in deep aquifers -, large masses of land - like bedrock or native land - or other materials like eutectic solutions and phase-change materials. Energy stored can be accessed as late as months after it has been stored.

- Compressed air: Air is compressed into large containers, such as underground caverns. The compressed air is then channelled into an expansion turbine system that will produce electric energy when necessary.

- Pumped hydroelectric: Electricity is used to pump water up a reservoir, storing it as Potential energy. When water is released from the reservoir, it flows through a turbine to generate electricity.

- Flywheels: Electricity is used to accelerate a flywheel (a type of rotor), transforming it to kinetic rotational energy. When electric energy is needed, the spinning force of the flywheel is used to turn a generator. Some flywheels use magnetic bearings, operate in a vacuum to reduce drag, and can attain rotational speeds up to 60,000 revolutions per minute.

- Electrochemical: Batteries convert electric energy into chemical energy by means of an electrochemical oxidation-reduction reaction. The reverse reaction converts chemical energy into electric energy. These batteries can use lithium ion, lead acid, lithium iron and many other materials.

This thesis’ main focus will be on a specific type of energy storage: electrochemical energy in the form of a Battery Energy Storage System (BESS). The end goal is to produce a program that will evaluate what the optimal storage size is for a given production series and energy market tariffs, in order to make the most of tariff fluctuations during each day.

1.3 Energy Market

There are two main ways to acquire and sell energy from the European Energy Market, by using the Day-ahead market, also known as Single Day-ahead Coupling (SDAC), or by using the Intraday market, also known as Single Intraday Coupling (SIDC). A more detailed description of these markets is given below.

- Day-ahead: At 12:00 CET of every day of the year, a blind auction takes place to establish the prices and volume of electric energy that will be exchanged for every hour of the following day. In rough terms, the process begins with market participants sending two types of orders in the auction: one is their willingness to acquire or sell electric energy (in volume) from a set range of prices for every hour; the other are block orders that link many delivery periods together. Demand and supply curves are then created for each hour of the following day. At the intersection of both curves will be the value of market clearing price (MCP).

  The price coupling algorithm used is called PCR EUPHEMIA, which returns clearing prices, matched trades, scheduled exchanges, and the net position of bidding areas. The input data is provided by the Transmission System Operators (TSOs) - which provide the network capacities and constraints - and the Nominated Electricity Market Operators (NEMOs) —which provide the bids and offers of the blind auction —, it is extremely important to couple both agents because after deciding on the volume of energy that is required for each hour of a day, it is then of paramount importance to determine the technical viability of the trade. Ultimately, the purpose of the algorithm is to maximise social welfare. After the matching process, the results need to be delivered to the System Operator for further validation.

  This price setting mechanism is currently utilized in Spain, Portugal, Germany, Austria, Belgium, Bulgaria, Croatia, Slovakia, Slovenia, Estonia, France, Holland, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Finland, Sweden, Denmark, Norway, Poland, the United Kingdom, the Czech Republic, and Romania.[11][12][13]

- Intraday: This is a market that allows for electricity trade until 15 minutes before the delivery time. With the rise of renewable energy production, market participants have become more reliant on Intraday trade, because, as mentioned before, the stochastic behaviour of RES makes it much more difficult to keep the balance. The Intraday markets work as an important tool to adjust the day-ahead market's resulting schedule, answering to real-time needs. SIDC began as an initiative between NEMOs and TSOs to enable continuous cross-border trading across Europe. The Intraday markets are currently structured into six bidding sessions in the Iberian Electricity Market's (MIBEL) scope and a continuous cross-border European market, and they are carried out once the system operator has made the necessary adjustments after the day-ahead market so that the resulting schedule may be viable. There is a clear characteristic of immediacy of trade in this market, trades can happen as fast as 5 minutes before delivery, nevertheless, there is also possibility to make quarter-hourly, half-hourly and hourly contracts. This level of flexibility facilitates the maintenance of network balance and, as mentioned before, is a great response to real-time changes in demand and supply of electric energy[11][12][14]

.

In this thesis, only the day-ahead market trade is considered, since the script developed has to have well-defined hourly values of electricity tariff as an input.

1.4 State of the art

In this section a brief introduction to the current state of maturity of several secondary cells —or rechargeable batteries —will be given. These are the types of batteries used for energy storage applications, seeing that it is of interest to be able to run numerous cycles of charging and discharging.

1.4.1 Battery Technology

1.4.1.1 Battery Types

- Lead acid batteries (LA)

  Lead-acid batteries have existed since the end of the 19th century and, as such, the technology has reached a significantly high level of maturity, characterized by a well developed lead-recycling infrastructure, with a 99% recyclability rate and a low cost (200€/kWh) for high performance [15][16]. These batteries show a reasonably high efficiency of 80-90% and have a typical life cycle of 1500 cycles at an 80% DoD [17].

  LA batteries are commonly used to start up motorized vehicles, solar PV systems (75% of new solar PV systems in China use LA batteries), and, over the last decade, in smart-grid frequency regulation facilities and UPS systems [18].

  Some of its disadvantages are the low tolerability of deep discharge, the low energy density (30-50Wh/kg), slow and inefficient charging (inability to bulk charge the last 20% of battery capacity), Peukert's losses, and the emission of explosive gas and acid fumes. Valve regulated LA batteries mitigate most of these drawbacks, however, their lower life cycles make it so they are mostly used in back-up power supply and telecommunications applications [19][20].

- Redox Flow Batteries (RFB)

Redox Flow Batteries are still in the early stages of maturity, being a fairly recent technology, which is reflected in the overall cost of implementation. These batteries are especially interesting for stationary applications due to their long life cycles, low temperature ranges for operation, ability to undergo complete discharge cycles (100%DoD) without compromising the battery's performance, and the fact that we can manipulate storage capacity and rated power independently from each other. The price comes as a disadvantage, seeing that the most popular RFB uses Vanadium as an electrolyte, which is an expensive component to acquire. It is, however, a liquid electrolyte that has been successfully demonstrated to be almost 100% recyclable by the U.S. Vanadium LLC [16][21].

The current applications of Vanadium RFB (VRFB) include load levelling, remote-area power systems, renewable energy stabilization, UPS, back-up power, and power quality. They have a medium high efficiency of 75-80% and can have lifetimes of over 12000 cycles at 100% DoD with proper annual maintenance. Their energy density is less impressive, being in the order of 16-33 kWh/m^3, making them more suitable for small or medium stationary applications [16][19].

- Lithium-ion batteries (Li-ion)

Lithium ion batteries were first developed during the late 20th century, and have since seen a monumental growth in applications worldwide. From cellular phones to electric vehicles to even solar PV energy storage, Li-ion batteries are flexible enough to dominate the battery market. Such flexibility is due to high energy density (200 Wh/kg) and high load capabilities with power cells, long cycle and extended shelf-life (maintenance-free), high capacity, low internal resistance, good coulombic efficiency, simple charge algorithm and reasonably short charge times. The price trend for this battery technology is shown in figure 1.4, which strengthens the prevalent position it holds in autonomous technological development [15][19].

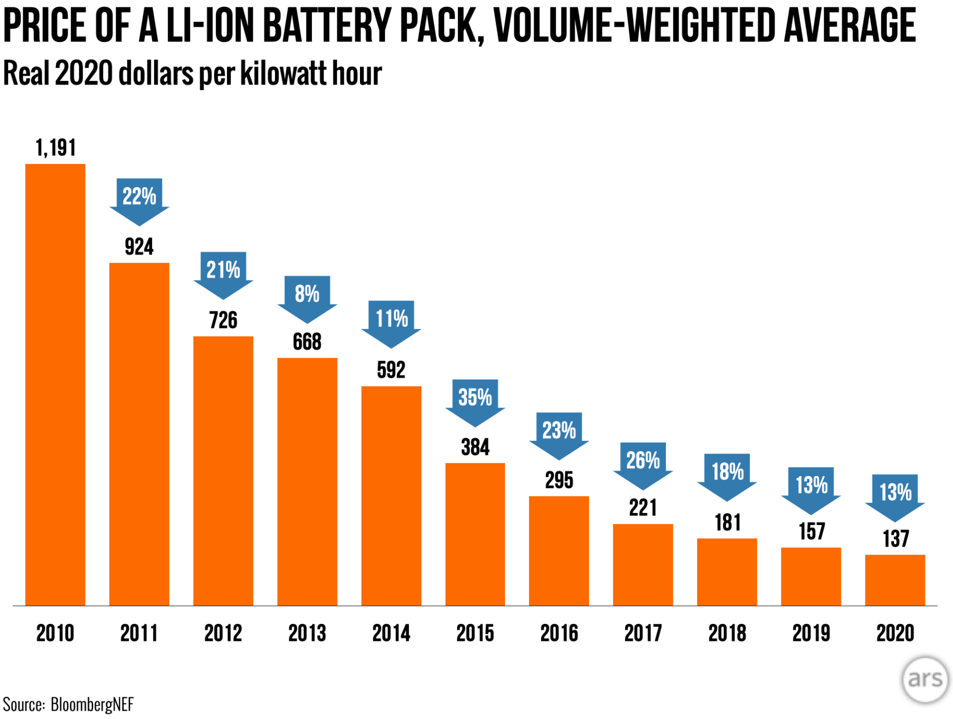


Figure 1.4 – Evolution of the cost of Li-ion Battery pack for the past 10 years in $/kWh [22].

The life cycle of a Li-ion battery depends greatly on the application. In the application discussed in this thesis - Battery Energy Storage Systems - the end of life happens while the battery still has a significant value of capacity, as it will be explained in detail in the next subsection. As such, the end of life of these batteries does not need to be exclusively the recycling of materials, instead, an entire market of second hand use arises in order to receive these still functional and efficient batteries, making the most of the second most important R in the three R's. The logistics of repurposing these products are even simpler than in other second hand markets, seeing that the new application can be dramatically different from the previous, which makes this market both dynamic and complex.

Recycling of lithium-ion batteries has been done for more than 15 years, with various efficiencies and recovery rates. China and South Korea are on the vanguard of the development of processes with high efficiencies that allow waste materials back into the battery value chain. These advances are promoted mainly by battery material producers and by the need of access to production scrap and consolidated volumes of waste batteries recyclers in these countries. Even though the rest of the world does not yet have the infrastructure to recycle high enough volumes, there is desire for change and growth in that direction [23]. When speaking of projects with a well-defined lifetime - in this case a Wind Farm typically functions for 20 years - it is important to assess the durability of every ancillary equipment, such as the BESS. Designing batteries is a problem that entails the balance between power and energy capacity, while guaranteeing an adequate lifetime with a certain degree of accuracy. This problem becomes especially complex when dealing with stochastic variables, such as requested powers for frequency regulation and the

battery capacity degradation.
The capacity fade happens for a number of reasons, mainly because of mechanical degradation of the electrodes, growth of solid electrolyte interface on the anode, formation of electrolyte oxidation at the cathode, lithium-plating on the surface of the anode caused by high charging rates [24]. Easier to understand factors include temperature variations (Arrhenius equation), state of charge (SoC) (Tafel equation), depth of discharge (Wöhler equation) and power ratings used [25][26]. One way of controlling fast degradation that is taken into account in the battery operation model discussed in this thesis is the SoC control strategy, which serves as a way to avoid the exponential behaviour of degradation when SoC is within the values of 0-20% and 80-100%. Maintaining temperatures between 18ºC and 25ºC is fairly easy with the aid of an AC system Several studies indicate that Li-ion batteries retain 80% of their original capacity after 2000 cycles [23], whereas other sources claim that at a 60% DoD Li-ion batteries retain 85% of their original capacity after about 4500 cycles [27]. There are also other sources that affirm that Li-ion batteries have a life cycle of 3000 cycles at 80% DoD [19][28].

1.4.2 Battery Energy Storage Systems (BESS)

The main focus of this thesis is to explore the economic gain we can achieve from controlling the sale period of the energy that is produced in a day. Nevertheless, the other advantages of implementing a BESS in a RE farm are numerous:

- Grid stability: It is crucial to be able to maintain balance between production and consumption in the electric grid, otherwise there could be black-outs. There are indicators of good balance, such as a frequency of 50 Hz (in the European network), which has a tolerance of 1%, meaning that it can fluctuate between 49.95 Hz and 50.05 Hz. When the production surpasses the demand, the frequency rises, when the opposite happens, frequency drops. If we are unable to guarantee the (50.0$\pm$0.5) Hz frequency, it could lead to equipment damage, which is usually avoided by forcing a black-out.

- Renewable smoothing: The stochastic nature of renewable resources introduces variability and unpredictability in the production of RE, therefore, the application of a BESS smoothens the curve, as shown in figure 1.5 Furthermore, the ability to manipulate the amount of energy that is sold to the energy grid is extremely valuable to meet energy contracts. If forecasts deviate from the promised output, BESS can work as dampeners which mitigate the consequences of such a normal occurrence when dealing with RES. Some consequences are contract breaches which lead to fining, and grid instability.

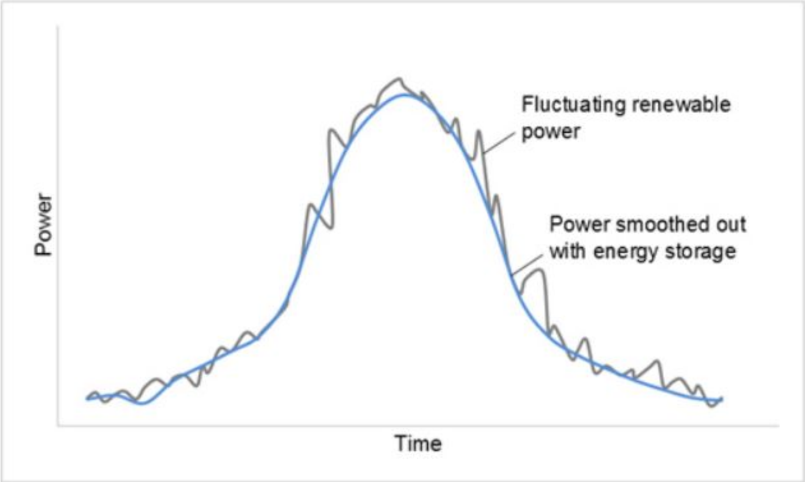


Figure 1.5 – Example of how a RE power curve can be smoothed into a well behaved curve [29].

- Handle Duck-curve: The Duck-curve problem arises from the fact that peak demand usually happens after sunset, which means that the need for generation stemming for dispatchable sources ramps up tremendously when solar PV generation stops. BESS work as a dispatchable source, thus reducing the necessity to resort to more polluting sources of electric production. A representation is present in figure 1.6.

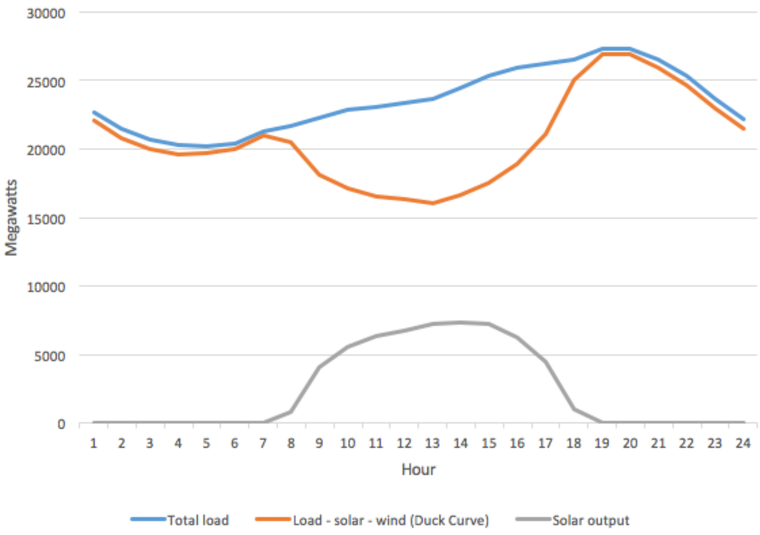


Figure 1.6 – Example of a standard Duck-curve [30].

- Reduced curtailment: If production of energy surpasses the amount the grid can accept or the value agreed upon (usually by contract), a reduction of output must happen to avoid causing an imbalance, which means a large amount of energy is ”wasted”. When a BESS is installed, such overproductions can be stored and sold at a later time, hence making full use of a RE farm’s generation capabilities.

- Energy Allocation: The daily average tariff curve showcases an accentuated change in tariff during the early morning and the evening. Such a change can be exploited by storing energy that would be otherwise sold at a low tariff to later be sold at a higher value. This allocation can of course be optimized to match the highest discrepancy of each day, thus maximizing turnover achieved by this strategy.

All these features contribute as a stimulus to invest in such technology, even though not every upgrade can be easily quantified in terms of monetary return. It can, however, greatly improve the quality and control of the energy that is being marketed, which carries enormous value in the sense that it not only allows for a better forecast of available resources (in this case RE in conditions to be sold) but also reduces the strain put on the energy grid.

In this case the BESS will be applied to a wind farm, giving special emphasis to the economic opportunities that result from energy allocation, as mentioned before.

Examples of BESS currently in use include the Luneng Haixi Multi-mixed Energy Demonstration Project, in China, which has a capacity of 100 MWh and the Jinjiang 100 MWh energy storage power station project, also in China.

1.5 Case study

The object of the tool developed can be any RE farm if there is access to the respective production series. If the wind farm does not yet exist only wind data can be converted to a production time series.

The data presented in this thesis comes from wind farms in Croatia, in the Balkans region of southeastern Europe. The data provided was from a wind farm with a 42 MW installed capacity and from a time interval from the 31st of January 2017 to the 31st of December 2019.

All weather data was taken from reanalysis available at MERRA 2 [31].

Methodology

2 Methodology

2.1 Introduction

A computational model was developed to evaluate the performance of a BESS as well as determine what its optimal size should be. The 2 inputs for the main script are the **hourly production series** of a RE farm and the corresponding **energy tariff** for said period. The outputs are the overall turnover (or loss) as well as the percentage gain (or loss) when compared to a situation where no BESS is used, and a number of graphs that can help study the behaviour of the BESS, thus assisting in making an informed decision on what size BESS would better fit the needs of the user. The development of the code was done using the data from the case study, which will be shown shortly, even so, the end goal is to be able to use this model to future wind farms using inputs from other sources.

The program was coded on Jupyter Notebooks using Python 3. The building process was done by creating a sturdy dataframe of the data to facilitate access to specific data by both the user and the programmer.

The data is organised using the software library Pandas, which is commonly used for data analysis and manipulation. It is a software that allows for the usage of time series and has various functions to call and view data easily. The `.loc`, `.iloc`, `.at`, `.iat` commands are frequently used during this code and can be used by the user of the interface to access graphical information from any time interval.

All graphs and tables shown originate from tests made to a BESS with a capacity of 100 MWh, while all other parameters refer to the case study.

2.2 Data cleaning and Organisation

The first step was to ensure that all data available referred to the same time interval and was organised in a way that allowed the script to properly read them. The actual code used for this section is displayed in appendix B.

This part of the code can be considered separately, it is a pre-processing needed to organise all the data available into a format that fits the model. Even though it was developed for real data from the case study, it can be easily altered to be able to understand data from production estimates or models of future fluctuations of the tariff.

The first data provided corresponded to the production series of several wind turbines of an existing wind farm, saved in a `.txt` file. This data was organised in intervals of 10 minutes, each turbine had two power generators and it was presented in terms of total energy accumulated in each 10-minute window. A representation of the format of the data is presented in table 2.1.

Blank	Generator 1 turbine 1	Generator 2 turbine 1	Generator 1 turbine 2	...
date (tab) minute 0	x	y	z	...
date (tab) minute 10	x	y	z	...
date (tab) minute 20	x	y	z	...
...	...	...	...	...

Table 2.1 – Model of first production data

This type of data organisation was sub-optimal for the data analysis desired, thus, some manipulation was necessary to transform it into a single column of hourly production data.

A number of steps (presented in appendix C) had to be followed in order to properly clean and organise the data:

1. **Filling missing data**
   Some values were missing from the columns, which would result in errors while running code that searched for integers in the file. This only happened when there were no variations of total energy accumulated, therefore, a simple `fillna` command was used to eliminate this issue, copying the previous existing value to the empty position. Tables 2.2 and 2.3 display real values of data from the case study and how they are cleaned.

   - Input: raw data of total energy accumulated every 10 minutes with missing values.

gen1 turb1	gen2 turb1gen1 turb2	gen1 turb2	gen2 turb2	...
50000000	3000000	49000000	3100000	...
50000000	3000000			...
50012000	3000030			...
50017000	3000030			...
50027000	3000030	49009000	3103000	...
50027000	3000030	49009000	3103000	...
...	...	...	...	...

Table 2.2 – Example input of file with missing data.

   - Output: data of total energy accumulated every 10 minutes with missing data replaced by previous data.

gen1 turb1	gen2 turb1gen1 turb2	gen1 turb2	gen2 turb2	...
50000000	3000000	49000000	3100000	...
50000000	3000000	49000000	3100000	...
50012000	3000030	49000000	3100000	...
50017000	3000030	49000000	3100000	...
50027000	3000030	49009000	3103000	...
50027000	3000030	49009000	3103000	...
...	...	...	...	...

Table 2.3 – Example output of a file with missing data properly filled.

2. **Production values**
   The goal is to have a production series, with that in mind, the total energy accumulated was transformed into instant production. Furthermore, the energy produced by each pair of generators for each turbine is added here to make up the total energy produced by the wind farm. Tables 2.4 and 2.5 display an example of what the transformation looks like.

   - Input: clean data of total energy accumulated every 10 minutes.

gen1 turb1	gen2 turb1gen1 turb2	gen1 turb2	gen2 turb2	...
50000000	3000000	49000000	3100000	...
50000000	3000000	49000000	3100000	...
50012000	3000030	49000000	3100000	...
50017000	3000030	49000000	3100000	...
50027000	3000030	49009000	3103000	...
50027000	3000030	49009000	3103000	...
...	...	...	...	...

Table 2.4 – Example input of a file with total energy accumulated every 10 minutes.

   - Output: clean data of total energy produced every 10 minutes. The resulting file will have 28 times fewer values.

Wind farm
0+x
0+y
12030+z
5000+a
22000+b
0+c
...

Table 2.5 – Example output of a file with energy produced every 10 minutes for the whole wind farm.

3. **Establishing the time interval**
   Because the values of the MCP are hourly, production series values should also be

hourly. As is done in the code present in appendix C, where the values are added to make up the production of every hour.

- Input: clean data of total energy produced every 10 minutes.

Wind farm
0+x
0+y
12030+z
5000+a
22000+b
0+c
...

Table 2.6 – Example input of a file with energy produced every 10 minutes.

- Output: clean data of total energy produced every hour. The file will have six times fewer values.

Wind farm
x++y+12030+z+5000+a+22000+b+c
...

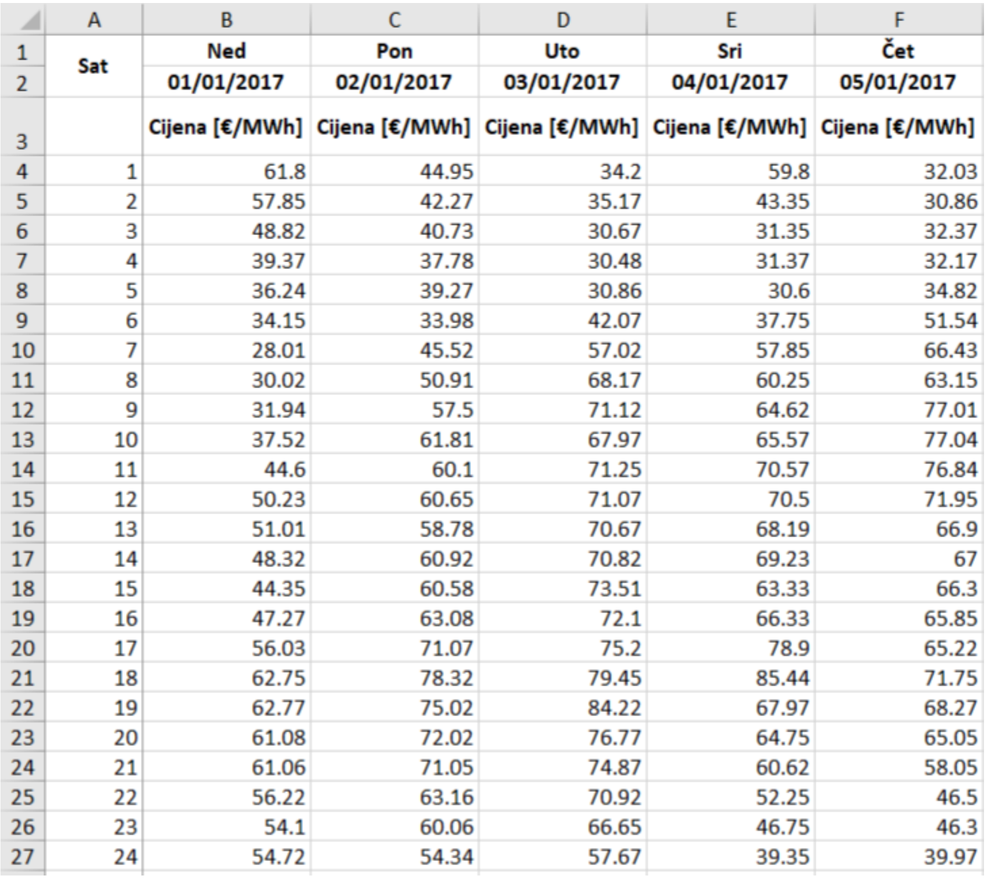
Table 2.7 – Example output of a file with energy produced every hour.

After these steps, the resulting file should be in the form represented in table 2.8, which is a simple file of hourly production of all the generators of the wind farm.

a
b
c
d
...

Table 2.8 – Model of optimal production series file

The MCP values used in the case study were provided by the Croatian NEMO, CROPEX, saved in an Excel file. The organization of the data is shown in figure 2.1, where all that needs to be replicated is the position of the useful data in the excel sheet: values for the MCP must be ordered by hour vertically and by day horizontally; the excel row for the first value of MCP of the first day must be the 4th (first hour); the excel column for the first value of MCP of the first day must be column B (first day). Information in the first three rows and A column of the excel file are irrelevant and can be filled with whatever information desired.



	A	B	C	D	E	F
1	Sat	Ned	Pon	Uto	Sri	Čet
2		01/01/2017	02/01/2017	03/01/2017	04/01/2017	05/01/2017
3		Cijena [€/MWh]	Cijena [€/MWh]	Cijena [€/MWh]	Cijena [€/MWh]	Cijena [€/MWh]
4	1	61.8	44.95	34.2	59.8	32.03
5	2	57.85	42.27	35.17	43.35	30.86
6	3	48.82	40.73	30.67	31.35	32.37
7	4	39.37	37.78	30.48	31.37	32.17
8	5	36.24	39.27	30.86	30.6	34.82
9	6	34.15	33.98	42.07	37.75	51.54
10	7	28.01	45.52	57.02	57.85	66.43
11	8	30.02	50.91	68.17	60.25	63.15
12	9	31.94	57.5	71.12	64.62	77.01
13	10	37.52	61.81	67.97	65.57	77.04
14	11	44.6	60.1	71.25	70.57	76.84
15	12	50.23	60.65	71.07	70.5	71.95
16	13	51.01	58.78	70.67	68.19	66.9
17	14	48.32	60.92	70.82	69.23	67
18	15	44.35	60.58	73.51	63.33	66.3
19	16	47.27	63.08	72.1	66.33	65.85
20	17	56.03	71.07	75.2	78.9	65.22
21	18	62.75	78.32	79.45	85.44	71.75
22	19	62.77	75.02	84.22	67.97	68.27
23	20	61.08	72.02	76.77	64.75	65.05
24	21	61.06	71.05	74.87	60.62	58.05
25	22	56.22	63.16	70.92	52.25	46.5
26	23	54.1	60.06	66.65	46.75	46.3
27	24	54.72	54.34	57.67	39.35	39.97

Figure 2.1 – Model of optimal MCP file.

The code creates a list of values that are ordered so that they can be added to the existing Dataframe easily.

This input data organisation was considered the standard and all MCP values that work as input for the script should be saved as shown. Alternatively, the pre-processing code can be easily altered for other input formats of the MCP values, seeing that it is being read in terms of row and column position.

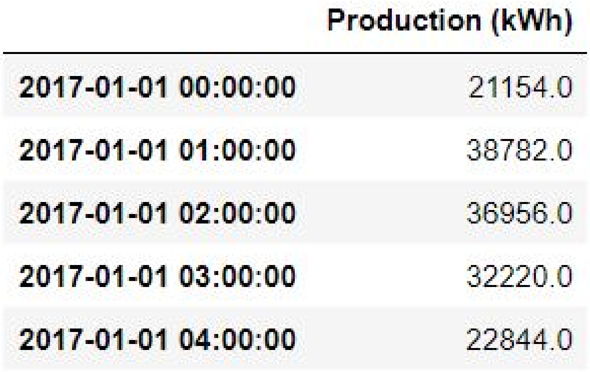
2.3 The Script

2.3.1 Building the Dataframe

Now that the user inputs are well-defined, the construction of the Data frame can begin:

Time frame: A big strength of this script is the ease with which one can access data from a specific window of time, be it hours, days, months or years. To achieve it, the index of the pandas Data frame needs to be defined as a time frame coordinated with the time frame of the inputs. To access data one has simply to use command `.loc["date1":"date2"]`, which slices the data frame into an interval of values that go from date 1 to date 2, although seeing a single date is also possible, by suppressing the other.

Production values: Production values can be added directly into the data frame - given that they are organised as explained previously - with a simple read command of a file that can be either a `.csv` file, a `.txt` file or an Excel (`.xlsx`) file. As an example, the data frame's first 5 lines will have the form presented in figure 2.2, by using the command `.head()`.

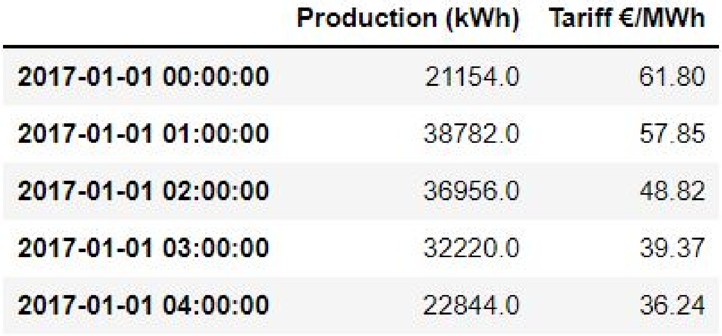


	Production (kWh)
2017-01-01 00:00:00	21154.0
2017-01-01 01:00:00	38782.0
2017-01-01 02:00:00	36956.0
2017-01-01 03:00:00	32220.0
2017-01-01 04:00:00	22844.0

Figure 2.2 – First 5 lines of the Data frame.

As one can see, the Time frame is well defined and works as the index of the values in the named columns.

MCP values: The `xlsx` file used as input has to undergo a transformation for it to be incorporated into the Data frame. This transformation is included while the script is reading the `xlsx` file. The new Data frame's first 5 lines will have the form presented in figure 2.3.



	Production (kWh)	Tariff €/MWh
2017-01-01 00:00:00	21154.0	61.80
2017-01-01 01:00:00	38782.0	57.85
2017-01-01 02:00:00	36956.0	48.82
2017-01-01 03:00:00	32220.0	39.37
2017-01-01 04:00:00	22844.0	36.24

Figure 2.3 – Data frame with all the input data.

At this point all the input data is organised properly in a data frame and it is now possible to call it easily and manipulate it in order to create new data. The pre-processing done in the previous subsection was crucial to achieve this level organisation without encountering setbacks.

2.3.2 Modelling Battery Operation

This is the most complex part of the script. Two separate strategies were initially attempted: one using the mean daily MCP curve and one using time-dependent 24-hour values for each day in turn. The battery has to be discharged in order to be recharged the next day, at this stage, the discharge is done by simply selling all available energy at the hour of highest tariff. Another condition imposed in the beginning is the establishing of the upper and lower capacity thresholds of the BESS, which will be 20% and 80% of the maximum SoC, respectively. This capacity interval works as a way to introduce some care towards the batteries' degradation. The ideal allocation of energy is represented in figure 2.4, where a hypothetical first day of charging is displayed, the charging does not necessarily happen in the first hours of a day. The BESS starts at 0% capacity and is filled up to 80%, when discharging the BESS, the energy sold will never surpass the maximum allowed (42 MWh in this case) and will only discharge until 20% capacity (20 MWh in this case, which means only 60 MWh are discharged in this case). By the end of this subsection, the script will be capable of recreating this exact process of energy allocation.

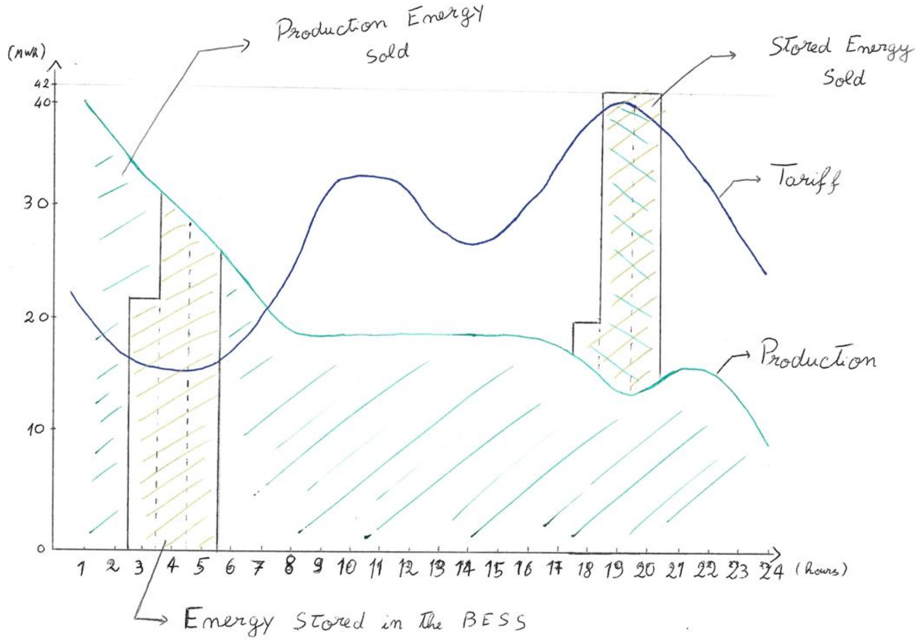


Figure 2.4 – Example of desired BESS operation.

2.3.2.1 Using the Mean MCP Curve

The building process started out fairly simple, with analysing the curve of mean daily behaviour of the tariff values during the 3 years provided. The curve has the shape of the line shown in figure 2.5, which is a predictable shape for a number of reasons: the low values between 23:00 and 8:00 are due to the fact that most industries do not operate at such hours (working schedule is in its majority organised in morning/afternoon shifts) and domestic use of electricity is also at its lowest (sleeping period, little to no devices being used), so energy demand is generally low; at 8 am begins the working day and with it start many industries and economical activities, such as the catering sector, although all economical activities require a fair amount of electricity to function; two peaks of tariff values appear during the day, one in the morning, at around 11:00 and, and the other in the evening, at around 20:00, these peaks can be attributed to the catering sector and domestic electricity use, since they coincide with lunch and dinner hours.

In this way, it is possible to estimate and define which are the optimal periods of time to store and sell energy. It is important to note that no special care was given for particularly different days, like the weekends. For these days a flattening of the line could be expected due to the fact that most industries cease functions during the ”rest days”.

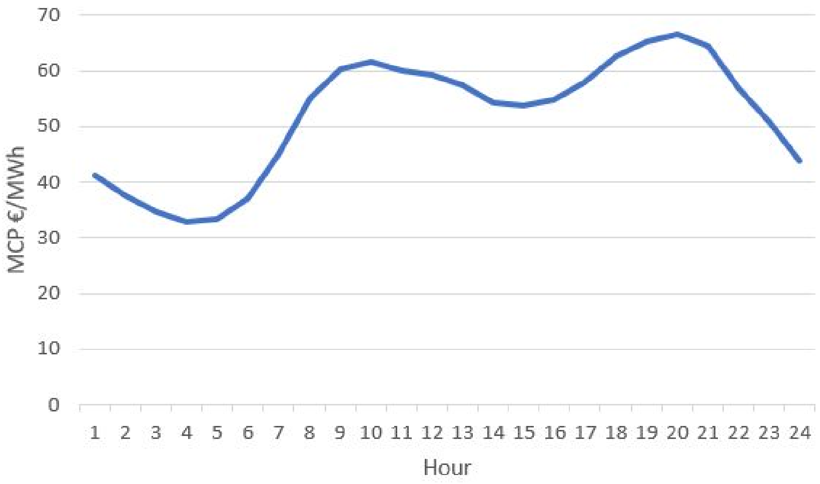


Figure 2.5 – Mean MCP values curve

By analysing this graph, a code emerged, where the time periods in which energy was to be stored and sold were set. The first constraint imposed was to only charge the BESS when the MCP values are lower than the average of the day, as such, hours from 0:00 to 7:00 and 22:00 to 23:00 were taken into account. Discharging happens at 20:00. This strategy would result in a charging graph like the one shown in figure 2.6.
From analysing the graph, it is possible to attest that, even though the hours when charging happened indeed had tariffs below the daily mean value for the tariff, the BESS was fully charged before having the opportunity to charge at an even lower tariff, which means that energy produced at the lowest tariff hours was sold at the lowest possible price of the day.

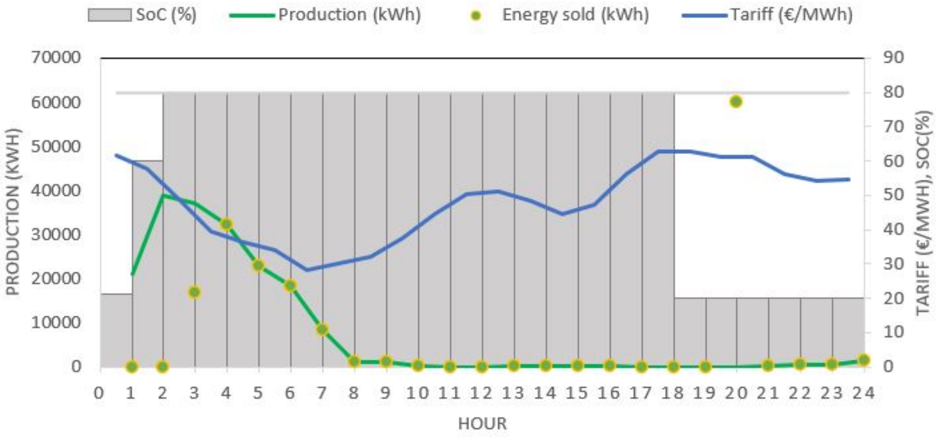


Figure 2.6 – Combined graph of production, tariff, SoC and volume of energy sold for the first strategy to charge the battery (01/01/2017).

Some variations were made to better understand what time interval would be best, nevertheless, it was quickly found that this was a sub-optimal way to decide energy storage, mainly due to the fact that tariff values can change drastically from one day to another, and the highest tariff can appear at an unusual hour. An example of an abnormal tariff curve appears in figure 2.7.

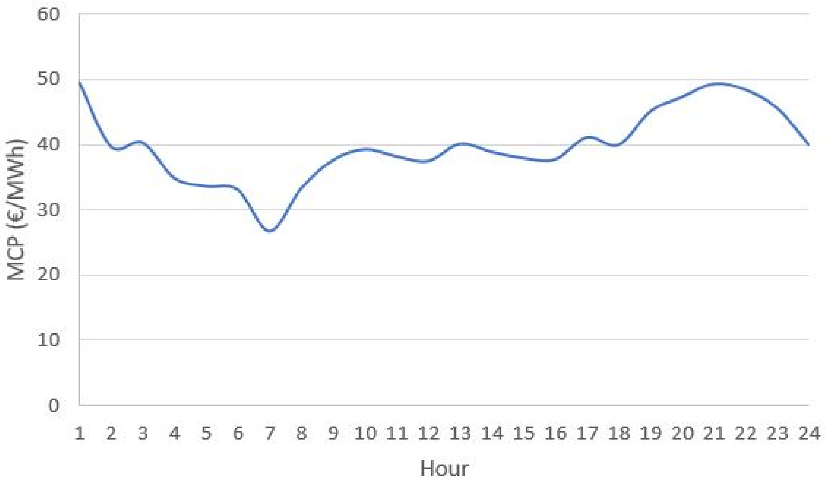


Figure 2.7 – Unexpected tariff behaviour.

The solution resided in evaluating each day's MCP values and only then deciding how to charge the battery.

2.3.2.2 Using specific MCP values for each day

To do such an evaluation, a snippet of every day was taken as a shorter Data frame. It is important to keep the data in Data frames so that the time frame is never lost, that is why lists are not used in this instance. The shorter Data frame is then ordered in ascending order of tariff values and the production values fill up the BESS capacity in order of time at which the lower tariff takes place. Basically, the process begins by ordering every hour of the day starting by the hour at which the MCP values are lowest. It is then easy to take the production corresponding to that hour and start adding it to a variable that cannot go higher than the maximum capacity of the BESS. When this threshold is reached, the other hours are no longer considered as potential charging hours. If the production exceeds the volume of energy that could be withstood by the BESS, it only charges exactly the amount necessary. This should result in a much more optimal charging of the BESS. As a result, the Data frame will have a different look (all tabled results for this section shown in appendix A), of which a graphical representation is shown in figure 2.8 which makes for an easier comparison to the previous strategy.

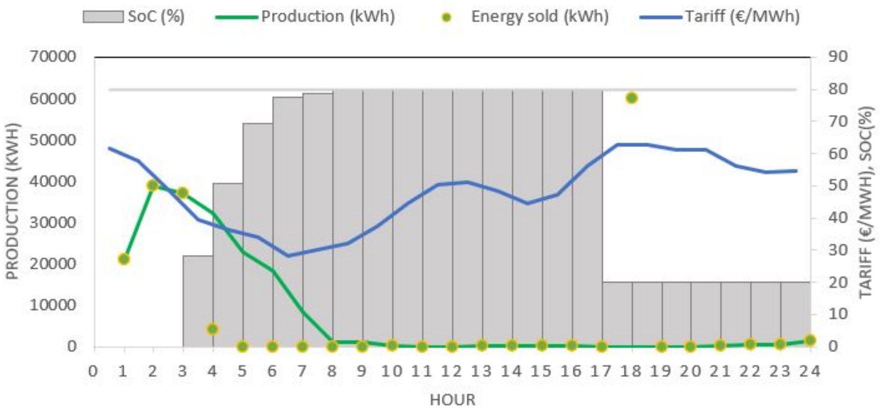


Figure 2.8 – Combined graph of production, tariff, SoC and volume of energy sold for the optimized strategy for charging the BESS (01/01/2017).

As one can see in detail in figure A.2 in the appendix A, the battery charges all that is produced at the lowest values of tariff. It is possible to see that the code is optimised by looking at the first hour of charging, where there are roughly 4000 kWh worth of energy that are not being charged into the battery. That is due to the fact that that is the most expensive hour to charge the battery among all hours needed to charge it to 80% capacity. A comparison between the 2 strategies can be easily achieved by calculating each turnover by the time the BESS is fully charged, in this case the turnover at 9:00. The difference in turnover is already 1661,42 euros in favour of the better charging strategy. This value was calculated using the code that will be described in the following chapters.

For the sake of evaluating if the code was performing adequately, a full discharging happened always at the hour of highest tariff. As a result, specific days like the one show in figure A.3 (in appendix A) showed that the code was working even in unusual wind conditions. Even though most of the change of SoC in figure 2.9 is harder to read than the data frame, a noticeable rise happens at the last hour of the day.

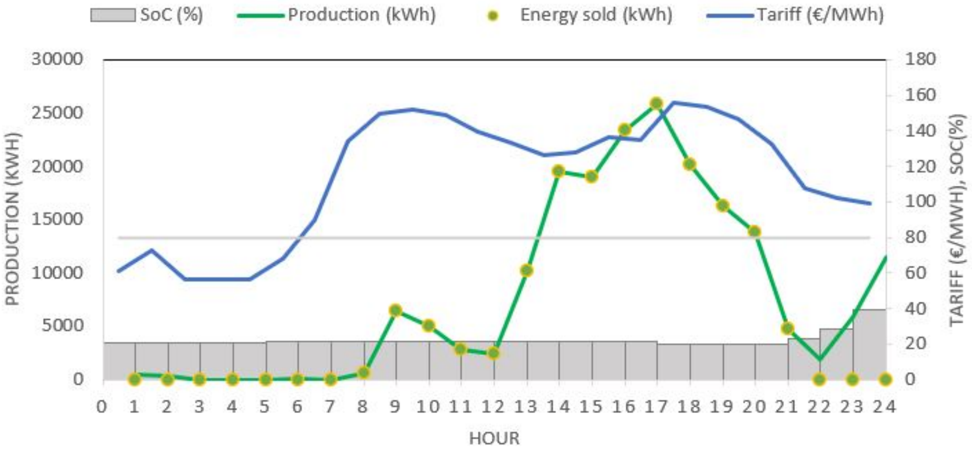


Figure 2.9 – Verifying optimized charging of the BESS (19/01/2017).

This figure shows that the code is doing what it is meant to do at this stage. The majority of the charging happens after the period in which energy has been sold. Moreover, the program properly fills every other hour while remembering to charge at the last hours of the day. In this case it happens because of a lack of production. However, it could have also happened if the values of tariff were lowest by the end of the day, which actually happens on the next day, as can be seen in figure 2.10.

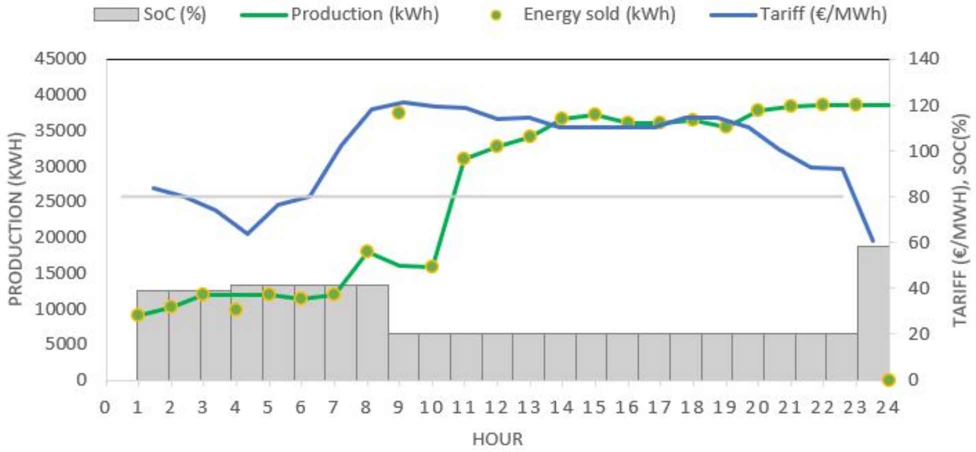


Figure 2.10 – Further verification of the optimized charging of the BESS (20/01/2017).

One could argue that this is not optimal, as many other low tariff hours could have been used to charge the BESS so that there was more energy to sell at the most expensive tariff. Even though that is a correct assumption, and there is possibility for such change in the code, the goal here is to evaluate the best way to charge the battery with the lowest tariff possible whilst reducing the occurrences of deep cycles.

It is crucial to bear in mind that this process is only possible when there is previous knowledge of both the MCP values and production values of the day, which is why only the Day-ahead market is taken into account. After implementing these changes (presented in appendix A), satisfactory values for and percentage turnover increase were achieved.
The analysis of the day's MCP values was also important in determining the most profitable hour to sell stored energy. The discharging needs special care as well, since it is not possible to sell all the energy available, contrary to what the previous version of the code was doing. Usually, energy contracts allow for as much as the nominal power of a RE farm to be sold every hour. In this case, since the nominal power is 42 MW, a total of 42 MWh can be sold every hour, which asks for a more precise discharging method than simply selling everything at the hour of highest tariff.

To do so, a similar strategy to the one responsible for charging the battery was implemented. The thought process was the same, using the sorted data frame to locate the hours at which tariff is at its highest value - until a lower threshold of the average value of the tariff of the day - and limit the amount of energy that can be sold. These constraints on volume of energy that can be sold are much more complex. Selling energy that is being produced at high tariff hours always takes priority over energy stored, therefore, first we need to ascertain that there is a window to sell stored energy, up to the nominal power of the farm at every hour considered. In simple terms, the sum of production and stored energy sold must be equal to the nominal power of the farm or less. The resulting Data frame is as is shown in figure A.5 (in appendix A). In figure 2.11 it is possible to visualize how the charging occurs. The good behaviour of the code for this situation becomes apparent when analysing figure A.5 (in appendix A) while visualizing the analogy from figure 2.4.

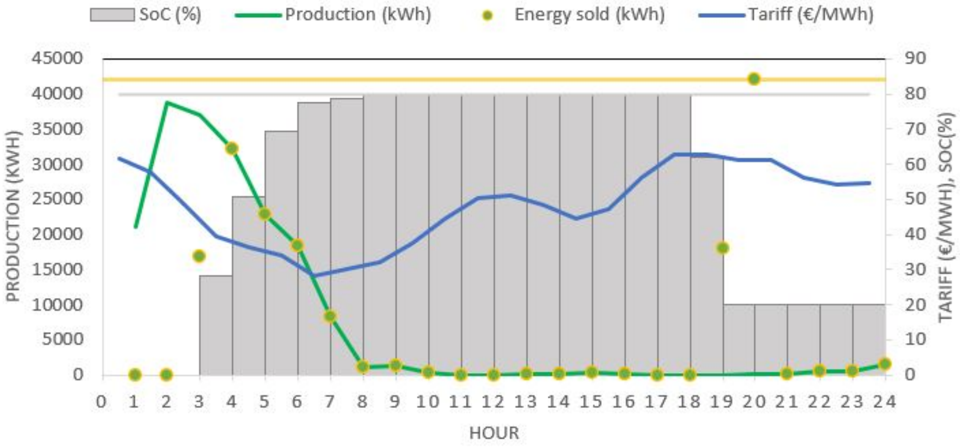


Figure 2.11 – Optimized discharging of the BESS, graphical representation (01/01/2017).

This is an example of a typical day but with a small twist. The BESS is fully charged by the time it reaches the highest selling hour, yet, some of the energy stored is sold in the previous hour. Only 18% of the stored is sold at the hour of second highest tariff, and that is because 42% (which is to say 42 MWh in this case, as the BESS capacity in this example is 100 MWh) is going to be sold at highest selling hour, which is why the value for energy sold coincides with the line that indicates the wind farm's maximum production. Another particularity of this day is that no energy is being produced by the wind farm at the selling hours. To show how the program deals with such situations, another day is shown in figure A.6 (in appendix A). Here, one can see that the code properly detects the threshold of energy that can be injected in the network and prioritizes keeping energy stored when the wind farm is producing energy. It becomes clearer when analysing figure 2.12, where it is possible to see that the high production values limit the amount of energy that can be extracted from the BESS so that no curtailment issues arise from having too much output electricity.

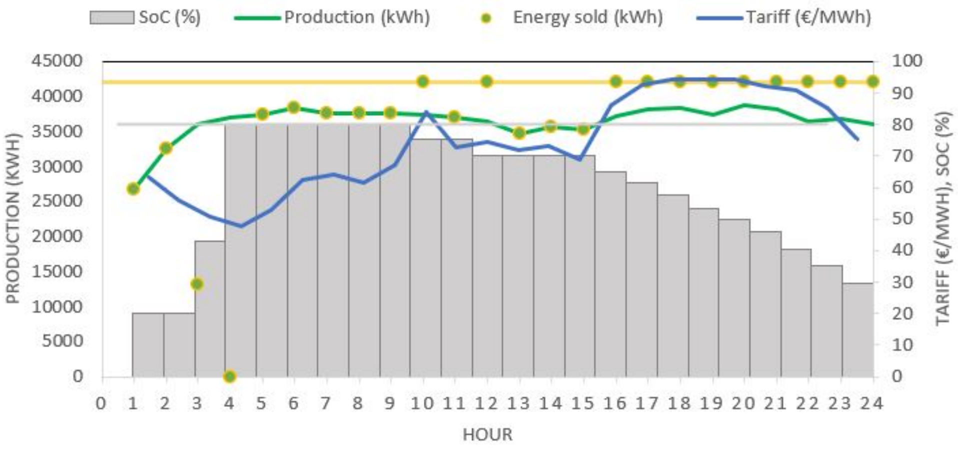


Figure 2.12 – Verifying optimized discharging of the BESS graphically (15/01/2017).

2.3.2.3 Cycle counting

An important information to extract from the SoC values is how many cycles a BESS goes through for a certain period of time. This value can be obtained by summing up every volume of energy charged to the BESS in decimal form. When 60% of the BESS fills up (20% to 80%) it counts as 0.6 of a cycle when it discharges the same amount. Only charging periods are considered because it is assumed that the BESS will eventually return to the lowest threshold. The code responsible for this is shown in figure C.8 (in appendix C).

2.3.2.4 Calculating Turnover

Everything is now in place to analyse the economic differences between a RE farm with and without a BESS for the sole purpose of allocating energy to maximise margins. A new column composed by a data series that simply multiplies the production by the tariff and then adds each day's value to the next is added for comparison. Adding the series that includes the turnover with the BESS takes extra steps:

- If the current SoC value is higher than the one before, evaluate the amount of energy that entered the BESS to decide whether or not all the production was used to charge the BESS. If it was not used in its entirety to charge, sell the difference between the amount produced and the amount charged;
- only sell from the BESS when the current value of SoC is lower than the previous (a discharge happened) and add it to the value of the production;
- if the current value of SoC matches the previous, sell all production.

The final Data frame has the form shown in figure 2.13 and graphical representations of every column are displayed in figures 2.14 and 2.15, which exclude in turn the tariff column and the production column, respectively. The last two columns represent the accumulated turnover of a wind farm with and without a BESS. An additional column was added to indicate the direction of the flow of energy in the BESS. The graphs show that the implemented allocation of energy from one hour to the next results in a higher accumulated turnover by the end of the day.

	Production (kWh)	Tariff €/MWh	SoC (%)	Direction	No BESS (€)	With BESS (€)
2017-01-01 00:00:00	21154.0	61.80	0.000	-	1307.31720	1307.31720
2017-01-01 01:00:00	38782.0	57.85	0.000	-	3550.85590	3550.85590
2017-01-01 02:00:00	36956.0	48.82	0.000	-	5355.04782	5355.04782
2017-01-01 03:00:00	32220.0	39.37	28.004	↑	6623.54922	5521.03174
2017-01-01 04:00:00	22844.0	36.24	50.848	↑	7451.41578	5521.03174
2017-01-01 05:00:00	18389.0	34.15	69.237	↑	8079.40013	5521.03174
2017-01-01 06:00:00	8241.0	28.01	77.478	↑	8310.23054	5521.03174
2017-01-01 07:00:00	1092.0	30.02	78.570	↑	8343.01238	5521.03174
2017-01-01 08:00:00	1196.0	31.94	79.766	↑	8381.21262	5521.03174
2017-01-01 09:00:00	234.0	37.52	80.000	↑	8389.99230	5521.03174
2017-01-01 10:00:00	0.0	44.60	80.000	-	8389.99230	5521.03174
2017-01-01 11:00:00	0.0	50.23	80.000	-	8389.99230	5521.03174
2017-01-01 12:00:00	50.0	51.01	80.000	-	8392.54280	5523.58224
2017-01-01 13:00:00	147.0	48.32	80.000	-	8399.64584	5530.68528
2017-01-01 14:00:00	244.0	44.35	80.000	-	8410.46724	5541.50668
2017-01-01 15:00:00	145.0	47.27	80.000	-	8417.32139	5548.36083
2017-01-01 16:00:00	5.0	56.03	80.000	-	8417.60154	5548.64098
2017-01-01 17:00:00	0.0	62.75	62.000	↓	8417.60154	6678.14098
2017-01-01 18:00:00	0.0	62.77	20.000	↓	8417.60154	9314.48098
2017-01-01 19:00:00	6.0	61.08	20.000	-	8417.96802	9314.84746
2017-01-01 20:00:00	122.0	61.06	20.000	-	8425.41734	9322.29678
2017-01-01 21:00:00	436.0	56.22	20.000	-	8449.92926	9346.80870
2017-01-01 22:00:00	551.0	54.10	20.000	-	8479.73836	9376.61780
2017-01-01 23:00:00	1437.0	54.72	20.000	-	8558.37100	9455.25044

Figure 2.13 – Final data frame, includes turnover with a BESS of 100 MWh capacity.

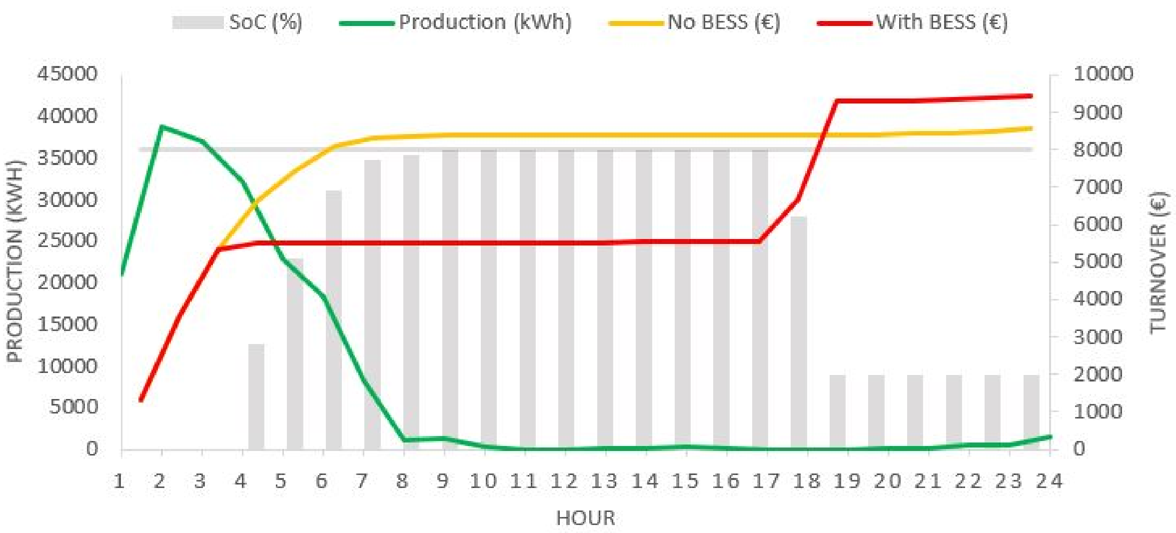


Figure 2.14 – Graphical representation of how the different turnovers behave in the data frame, excludes tariff values.

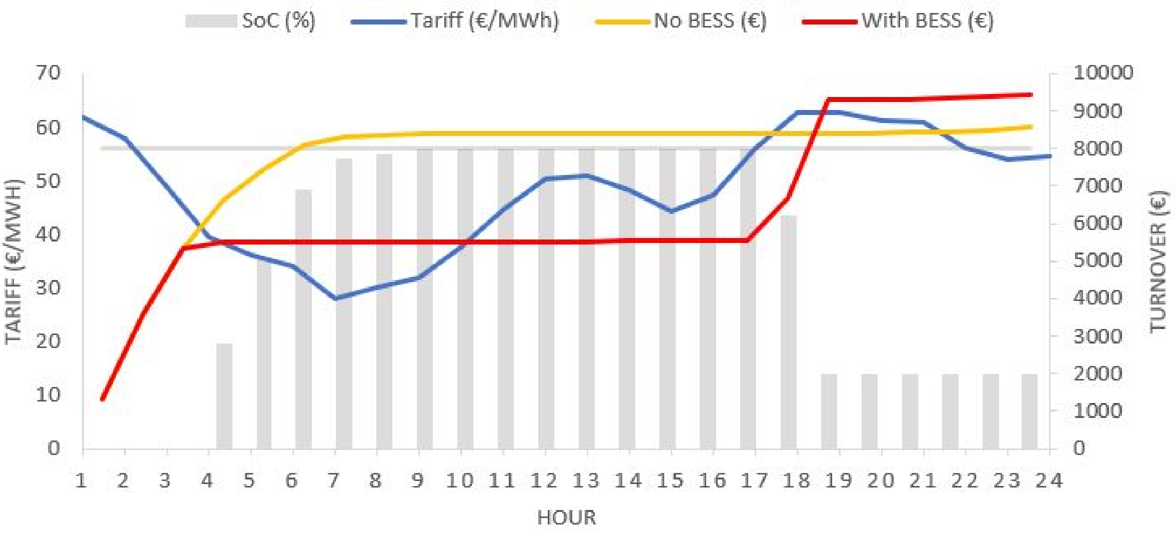


Figure 2.15 – Graphical representation of how the different turnovers behave in the data frame, excludes production values.

2.3.2.5 Comparing Capacities

After being able to completely analyse the turnover associated with using a BESS for a specific capacity, it is possible to loop the code to run for many BESS capacity values. Since most BESS used nowadays do not exceed a capacity of 100 MWh, the loop will include values from 5 MWh up to 100 MWh.

2.3.2.6 Additional Parameters used as Input to the Script

Capacity of the BESS:

The parameter `capaci` represents the capacity of the BESS; this value can be a function of time or number of charging cycles so that the manufacturer's information on battery degradation can be included in the code.

Nominal power:

The parameter `nompow` represents the nominal power of the RE farm being analysed.

Analysis window:

The parameter `interval` represents the number of windows we want to include in 24 hours or beyond it. If, for example, $\texttt{interval} = 4$, this means the charging and discharge method will be applied 4 times during each day, in windows of 6 hours. The value of the parameter must produce an integer number of windows but can be smaller than 1. In chapter 3 some results will be shown for windows other than the 24 hours ($\texttt{interval} = 1$), such as for 6 hours, 12 hours and 48 hours ($\texttt{interval} = 4$, $\texttt{interval} = 2$ and $\texttt{interval} = 0.5$).

2.3.3 Real life situation

In an operating wind farm, there is no known production series of the following day. Instead, most of the times there is a wind speed forecast. As such, a part of the code is designed to receive such data and transform it into a production series. The wind speed data must originate from a meteorological model capable to forecast wind speed in the wind farm with a good level of accuracy. In addition to the wind speed values, two additional parameters are needed: the height of the wind turbines' rotor and the specific power curve change with density, which is a file similar to the one shown in table 2.9. From these inputs a production series will be extrapolated by means of a simple interpolation program that will transform the weather data into energy produced by the wind farm. From there, the rest of the code is exactly the same.

	Air density (kg/m^3)					
Wind Speed (m/s)	0.97	1	1.03	1.06	1.09	...
4	53	56	59	61	64	...
5	253	148	153	159	165	...
6	271	281	290	300	310	...
...	...	...	...	...	...	...

Table 2.9 – Example of a power curve file, every value for air density corresponds to a specific power curve.

The shape of a manufacturer's power curve is represented in figure 2.16. It is necessary to perform a linear interpolation because the data provided for power curves is usually composed by discrete values of production for integers of wind speed.

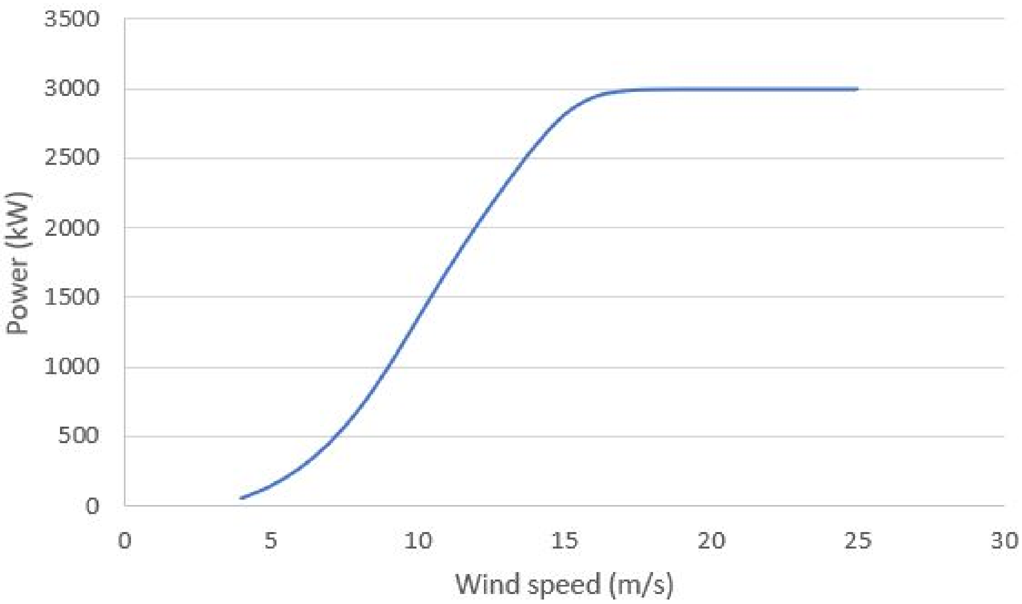


Figure 2.16 – Example of a manufacturer's power curve of a wind turbine.

It is also necessary to determine the air density a the rotor height and properly choose the power curve of the wind turbines. The air density is given by the equation of state for an ideal gas (equation 2.1):

$$\rho = \left(\frac{p}{RT}\right) . \tag{2.1}$$

where ρ is the value of the density of the air rotor high, p is the value of pressure at the height of rotor, R is the specific gas constant for air and T is the rotor level temperature. The values that are not yet known to calculate the air density are the values of p and T. Equation 2.2 gives the value for p:

$$p = p_0 \cdot \left(1 - \frac{Bz}{T_0}\right)^{\frac{g}{RB}} \quad , \tag{2.2}$$

where p and p_0 are the values of pressure at the height of rotor and at sea level respectively, B is the temperature change with altitude (lapse rate), z is the altitude of the turbine rotor above sea level, T_0 is the sea level temperature and g is the gravitational acceleration. The temperature at rotor height (T) can be found from equation 2.3:

$$T = T_0 - Bz \quad , \tag{2.3}$$

At this stage it is possible to calculate the value of the air density at rotor height and choose the correct power curve of the wind turbines.

It is important to understand that this method of transforming meteorological data into a production series of a wind farm is limited in terms of accuracy and was done with the purpose of including the possibility of receiving wind speed data in the code instead of production values. To elaborate, it was done as a proof of concept as to how the model would work using wind speed forecast data in a real operation scenario rather than past production data as used in the case study. As such, adding this feature adds to the operational value of the code.

To test out the accuracy of opting to use wind data as input, a test was made using reanalysis data from MERRA2. Comparing the output production series with the real data provided resulted in the graph displayed in figure 2.17, which shows that values of wind speed (and hence wind farm production) are grossly underestimated using MERRA2 directly. This is a result of the lack of precision of MERRA2 data, which is available at every 50 km at these latitudes. Since the wind farm is located on mountain ridges, wind speed values are much higher than the ones taken from MERRA2, because this effect is not taken into account. To include these particularities of the terrain, one would need to use mesoscale or even microscale models to improve the precision of wind speed predictions, which was not investigated here as it falls out of the scope of this thesis. The same can be said for the inclusion of other effects such as the effects of wind turbine wakes on each other. Still, it was decided to include this section in this thesis to show that the code is ready to receive and produce results if an accurate prediction of wind speed is used as input.

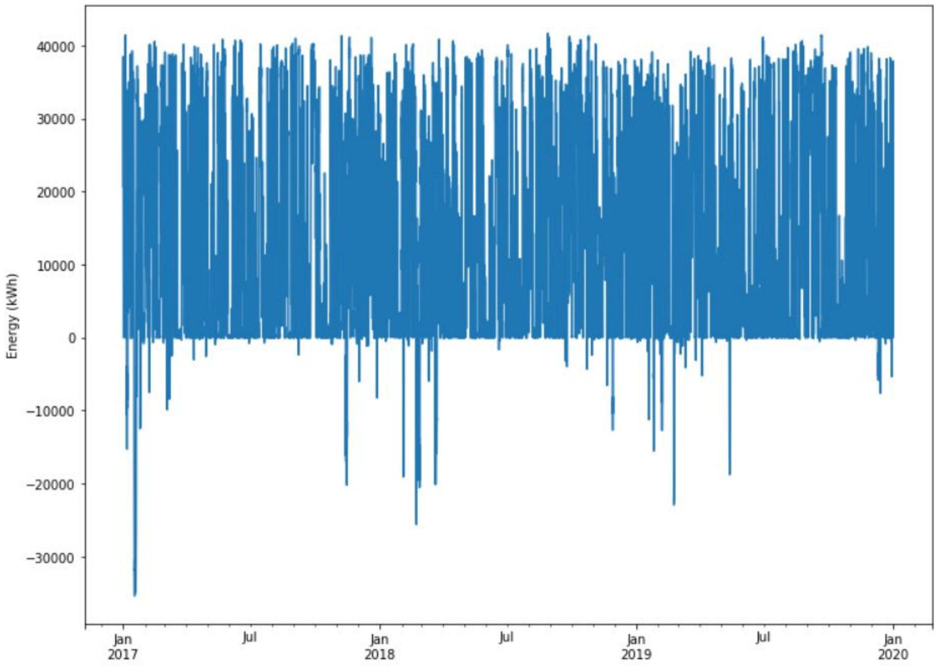


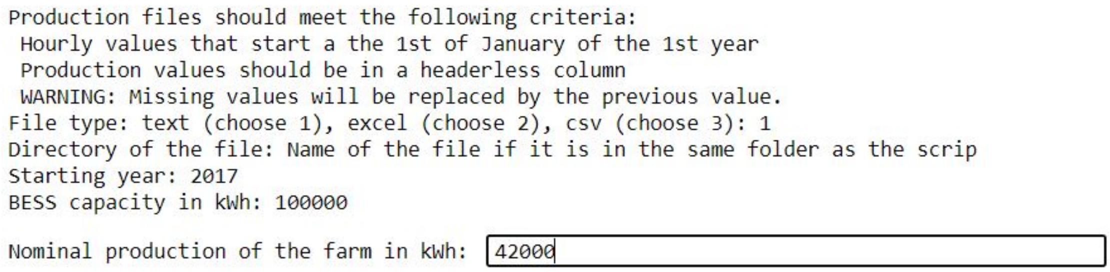
Figure 2.17 – The difference between the real production series and the extrapolated series.

2.4 Script Interface

In this section it will be explained how to properly navigate the program in order to gather as much information as possible.

2.4.1 Inputs

As long as the input data is properly organised, the script's interface is extremely easy to navigate. In figure 2.18 it is possible to see what needs to be fed early in the program to begin the Data frame. Even though some parameters are not yet necessary, they are defined early because at this stage battery capacity is also an input, therefore, when looping the program to evaluate the BESS behaviour for many capacity values it is important to define some parameters early.



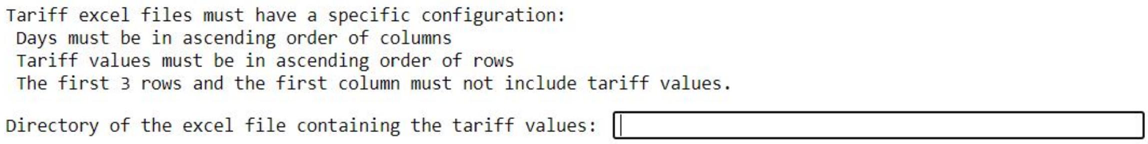
```
Production files should meet the following criteria:
 Hourly values that start a the 1st of January of the 1st year
 Production values should be in a headerless column
 WARNING: Missing values will be replaced by the previous value.
File type: text (choose 1), excel (choose 2), csv (choose 3): 1
Directory of the file: Name of the file if it is in the same folder as the scrip
Starting year: 2017
BESS capacity in kWh: 100000

Nominal production of the farm in kWh: 42000
```

Figure 2.18 – General aspect of the interface for the first inputs

A short message explains how the data should be organised and then 5 input boxes appear so that some particularities of the data and some parameters are defined. After filling the the boxes, a data frame like the one in figure 2.2 appears to allow for quick verification of the data organisation.

Running the second kernel causes another instruction to appear and requires the filling of another directory box, as it is shown in figure 2.19.



```
Tariff excel files must have a specific configuration:
 Days must be in ascending order of columns
 Tariff values must be in ascending order of rows
 The first 3 rows and the first column must not include tariff values.

Directory of the excel file containing the tariff values: 
```

Figure 2.19 – Interface for the tariff values' input.

A Data frame structured similarly to the one in figure 2.3 shows up to, again, verify the data until this point.

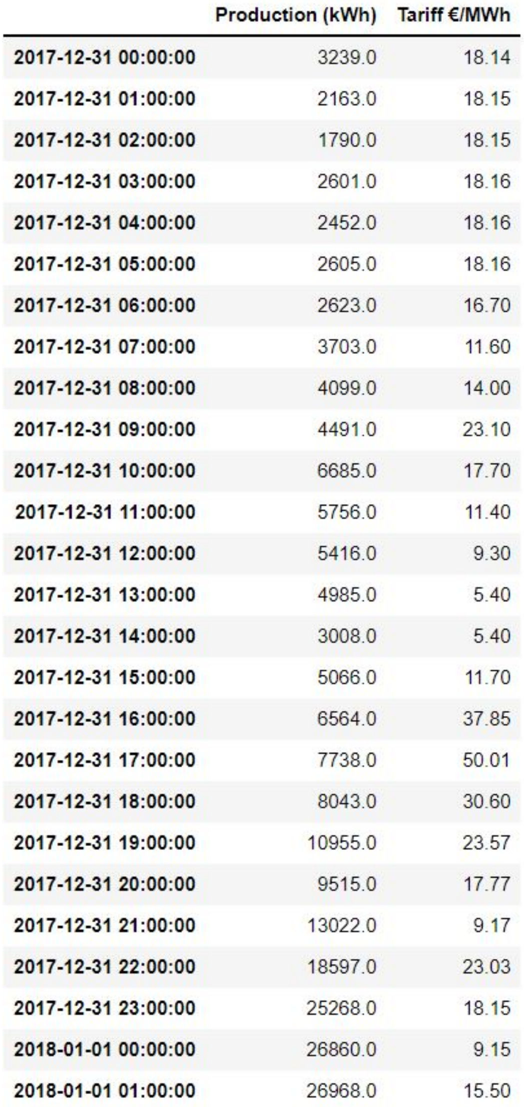
The command that returns the data frame's first five rows is the .head() command. The .tail() returns the last five rows. If more rows are desired, we need only put a number in the argument of the command. Another useful command to navigate the data frame is the .loc command. This command enables the slicing of the data by index, which is to say that we can access data from a specific date in time, down to the hour if needed. In figure 2.20 is an example on how to use this command in successively higher detail.

```
dfh.loc['2017']
dfh.loc['2017-01']
dfh.loc['2017-01-01']
dfh.loc['2017-01-01 00:00:00']

dfh.loc['2017':'2018']
dfh.loc['2017-01':'2018-01']
dfh.loc['2017-01-01':'2018-01-01']
dfh.loc['2017-01-01 00:00:00':'2018-01-01 00:00:00']
```

Figure 2.20 – Example of ways to use the .loc command. The second block showcases how to use the command to return more detailed time windows.

For data frame verification, this method has value for shorter time windows. An example of the flexibility of time intervals is shown in figure 2.21, where the time interval is defined with different degrees of detail and works nonetheless. The command given was dfh.loc['2017-12-31':'2018-01-1 01:00:00'].



	Production (kWh)	Tariff €/MWh
2017-12-31 00:00:00	3239.0	18.14
2017-12-31 01:00:00	2163.0	18.15
2017-12-31 02:00:00	1790.0	18.15
2017-12-31 03:00:00	2601.0	18.16
2017-12-31 04:00:00	2452.0	18.16
2017-12-31 05:00:00	2605.0	18.16
2017-12-31 06:00:00	2623.0	16.70
2017-12-31 07:00:00	3703.0	11.60
2017-12-31 08:00:00	4099.0	14.00
2017-12-31 09:00:00	4491.0	23.10
2017-12-31 10:00:00	6685.0	17.70
2017-12-31 11:00:00	5756.0	11.40
2017-12-31 12:00:00	5416.0	9.30
2017-12-31 13:00:00	4985.0	5.40
2017-12-31 14:00:00	3008.0	5.40
2017-12-31 15:00:00	5066.0	11.70
2017-12-31 16:00:00	6564.0	37.85
2017-12-31 17:00:00	7738.0	50.01
2017-12-31 18:00:00	8043.0	30.60
2017-12-31 19:00:00	10955.0	23.57
2017-12-31 20:00:00	9515.0	17.77
2017-12-31 21:00:00	13022.0	9.17
2017-12-31 22:00:00	18597.0	23.03
2017-12-31 23:00:00	25268.0	18.15
2018-01-01 00:00:00	26860.0	9.15
2018-01-01 01:00:00	26968.0	15.50

Figure 2.21 – Example of flexibility of the .loc command.

Everything that happens beyond this point does not need interference from the user. Further analysis can be made by means of graphical representations, which is the subject of the next section.

2.4.2 Graphical representations

Throughout the script there are several instances where data can be viewed in graphical format. This enables the user to see the format of their data in a more representative way.

Organising Data frame data into graphs is fairly easy, using the command .plot() a line graph is constructed. The .loc command can be used to define time intervals of interest. The user can access graphical representations of the production (like in figure 2.22), the tariff values (like in figure 2.23) and the state of charge of the battery (like in figure 2.24).

Intersecting two graphs can also help to understand how the system works and detect issues that need fixing. An obvious graph is the one shown in figure 2.25, where tariff values and SoC values are represented in the same graph, since tariff values do not exceed values of 100 €/MWh too often, the same axis could be used.

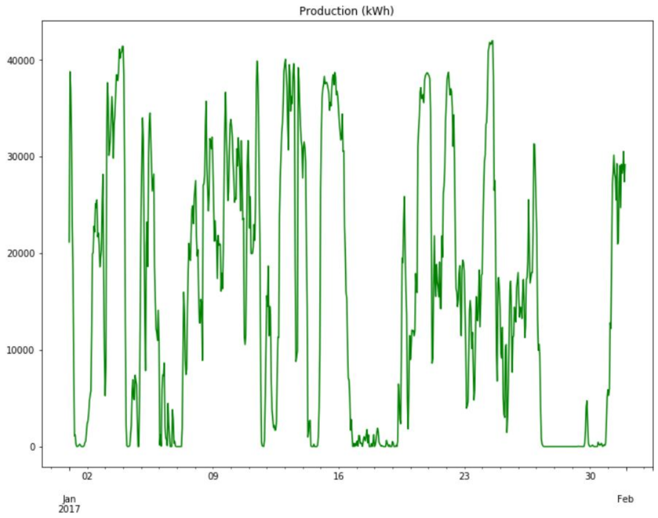


Figure 2.22 – Line graph of production values.

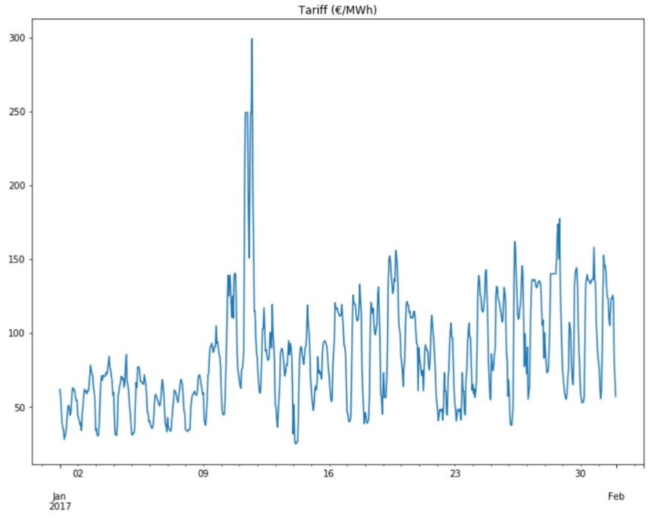


Figure 2.23 – Line graph of tariff values.

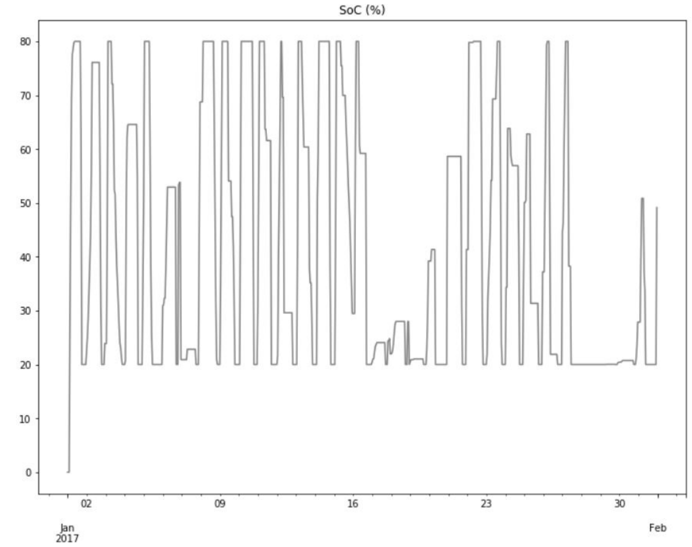


Figure 2.24 – Line graph of SoC values.

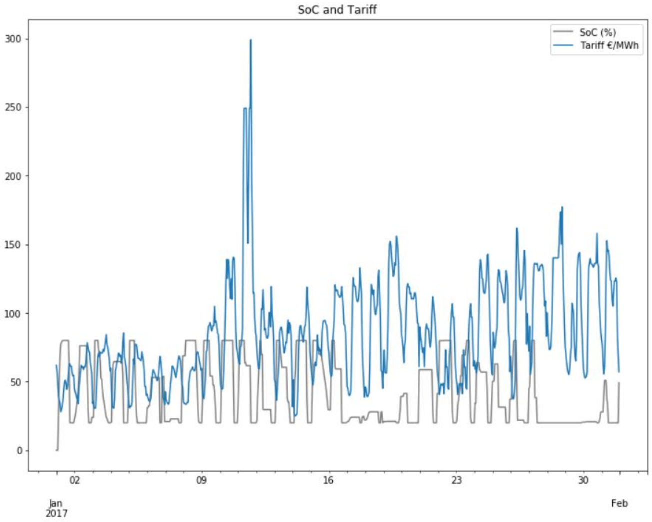


Figure 2.25 – Intersection of the SoC and tariff graphs.

If we wanted to include the 3 main objects (SoC, tariff and production), a new axis would have to appear and we would have a graph like the one shown in figure 2.26. The green line stands for production, the legend of the line does not appear because of an overlap problem but the colour scheme and existing legend make the distinction obvious.

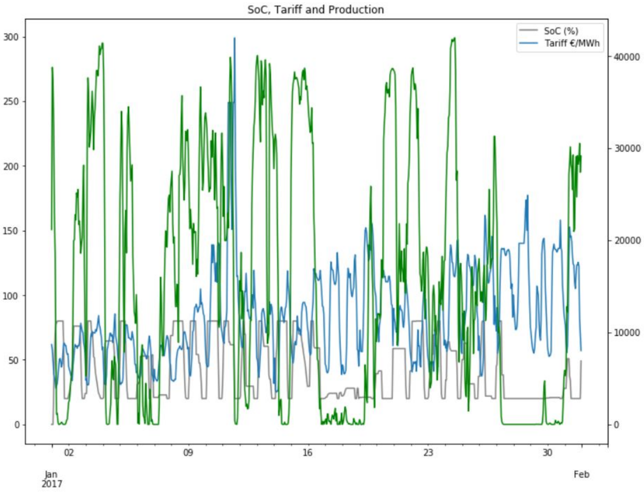


Figure 2.26 – Intersection of the SoC, tariff and production graphs.

A final graph appears when calculating the turnover over the time period being studied, as can be seen in figure 2.27. This graph can be useful to find patterns in higher slope regions, which can be linked to higher use of energy in certain periods of time of a year or to varying tariff conditions.

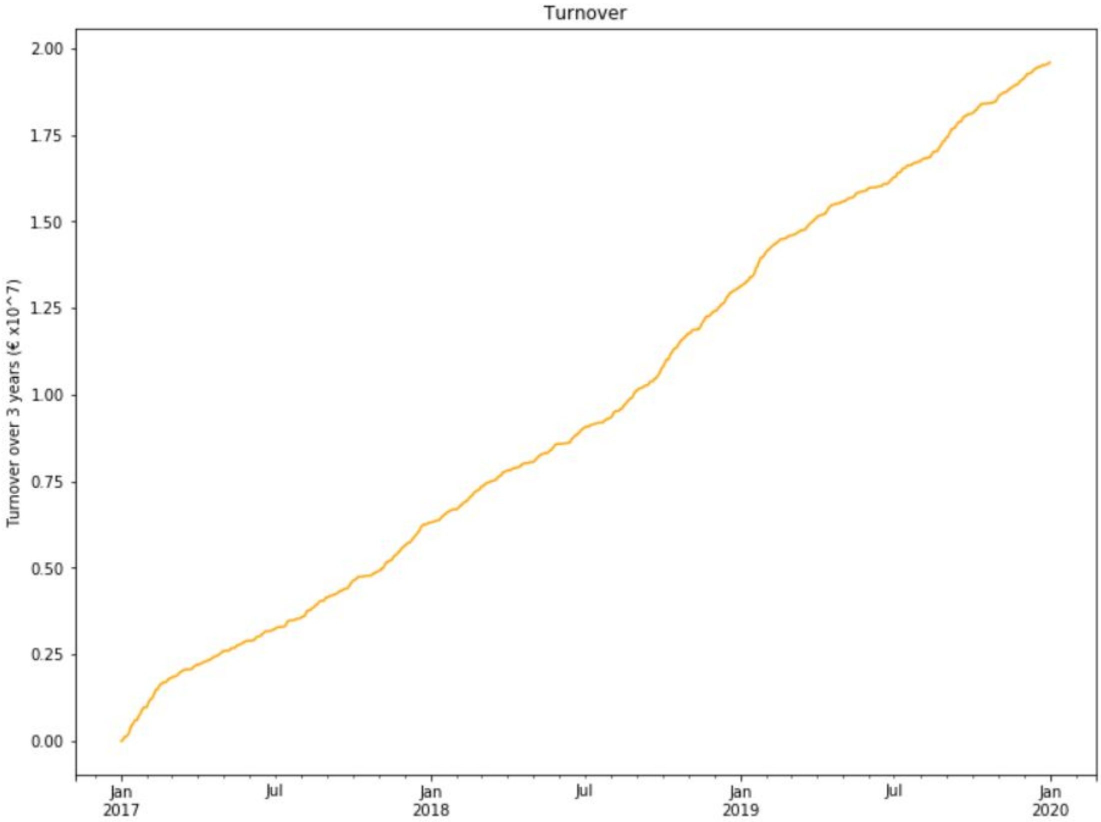


Figure 2.27 – Graphical representation of the turnover over the time period of the data frame.

All these graphs have some value in terms of raw information they present. Moreover, some additional information can still be extracted, in the form of other graphs like histograms or by changing the scope of analysis, like doing a seasonal behaviour study.

Take, for example, the construction of a histogram of the SoC, like the one in figure 2.28, where it is possible to see the frequency of each SoC, which is valuable information for modelling battery degradation. In this particular case, the most frequent values are the upper and lower thresholds, which is to be expected, but the fact that we can quantify these values (and the ones in between) is extremely valuable when using the SoC control strategy to mitigate fast degradation. The reason why the majority of the time the BESS is discharged is due to the fact that the park will very rarely be producing its nominal power, therefore, most of the times a full discharge is done.

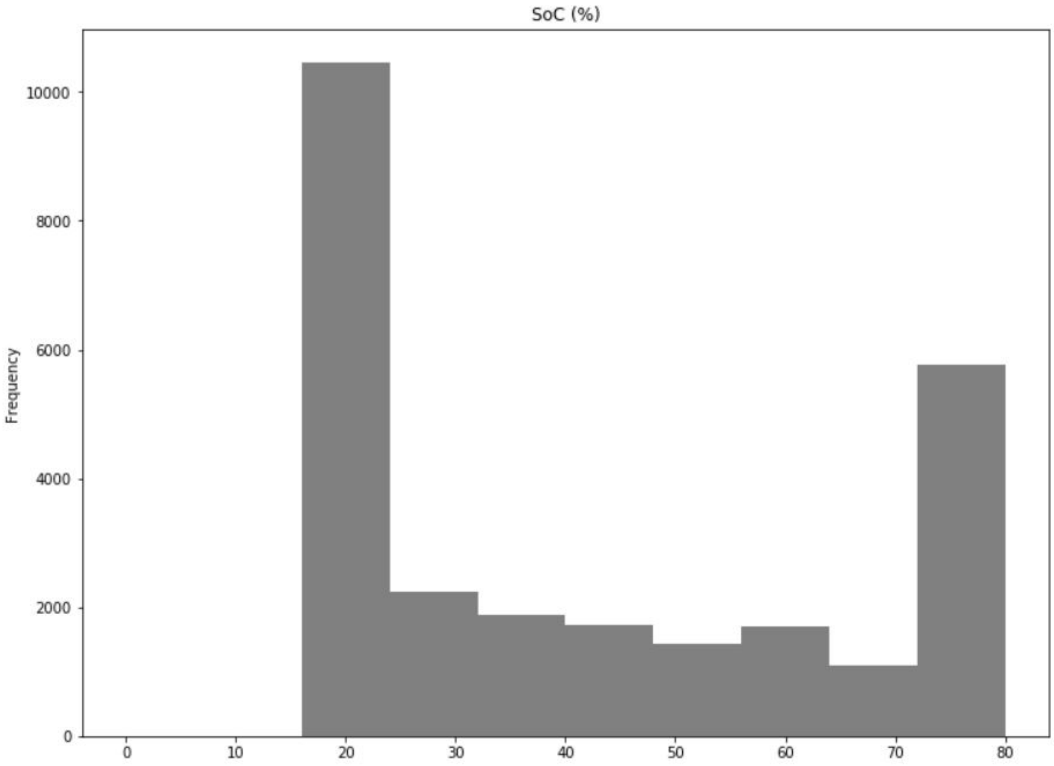


Figure 2.28 – Histogram of SoC values.

A seasonal study could be made for determining the season in which it would be most effective to utilize the BESS for energy allocation. Figures 2.29 and 2.30 perfectly show how important an analysis of this nature can be when making decisions that could greatly impact the outcome of an investment.

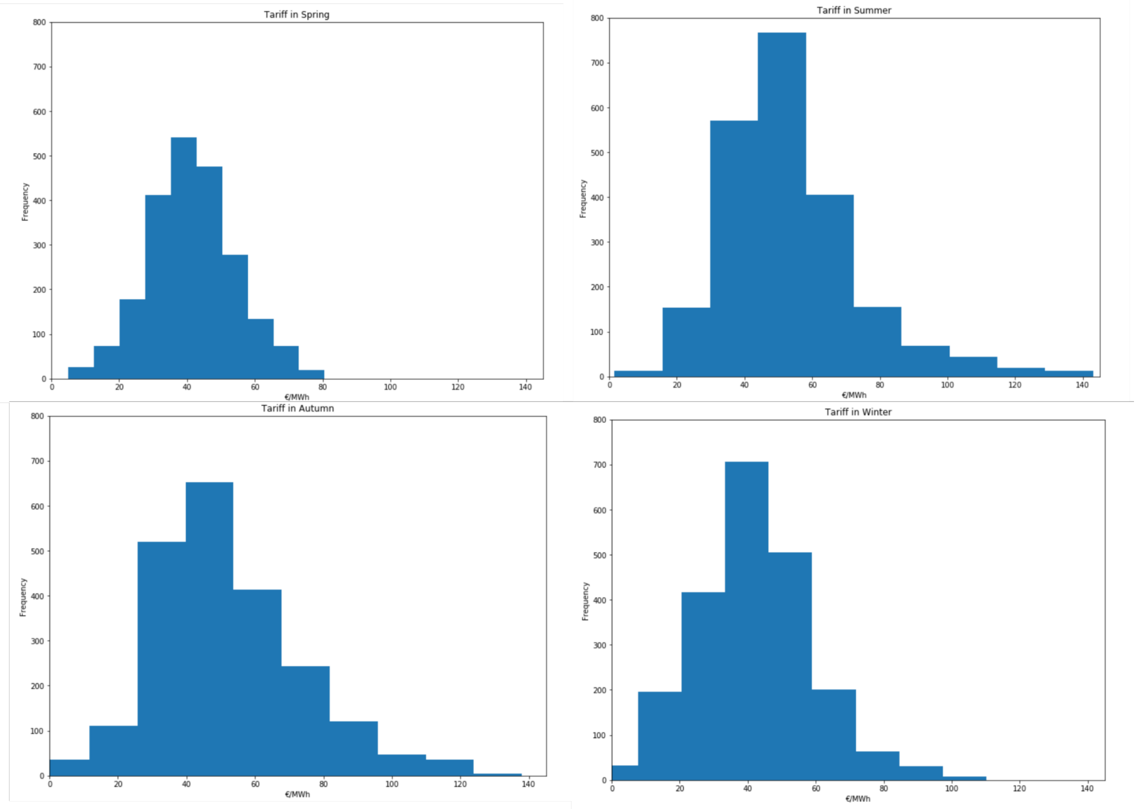


Figure 2.29 – Histograms of the case study’s tariff data for every season of 2017. The Winter histogram uses data from January and February of 2018.

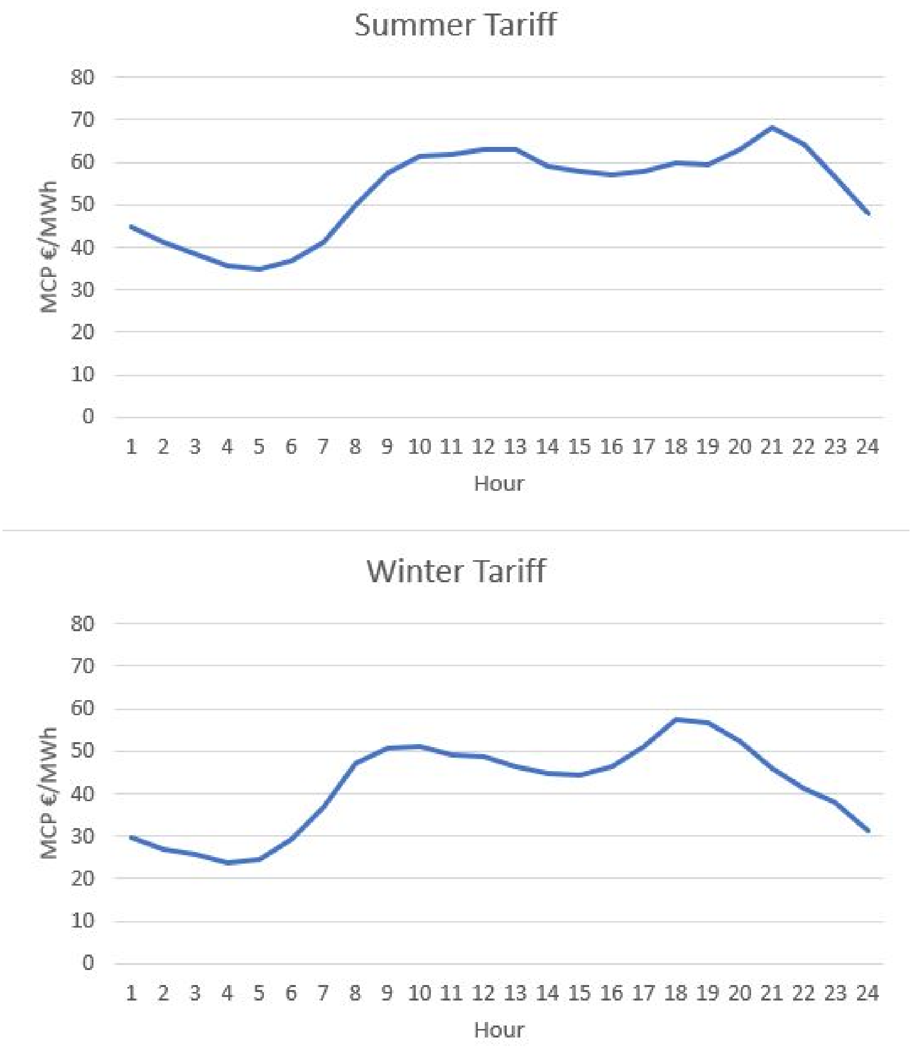


Figure 2.30 – Line graphs of mean tariff curves for Summer and Winter. Resulted from the same data used in figure 2.29.

From these simple histograms it is already possible to understand that Summer is the season that shows the highest values and the biggest amplitude of prices, which is indicative of more potential to employ the energy allocation strategy. Even though it may be common knowledge that more energy is consumed in this season —because of the need to combat the temperature changes by cooling the environment in question —, it is, however, necessary to study such graphs to understand what impact this fact has on the energy market. The same study could be done to identify seasonal particularities of the production.

Other interesting values are hourly mean values. In figures 2.31, 2.32 and 2.33 bar graphs are presented with relevant data on patterns that can be found for every hour of the day.

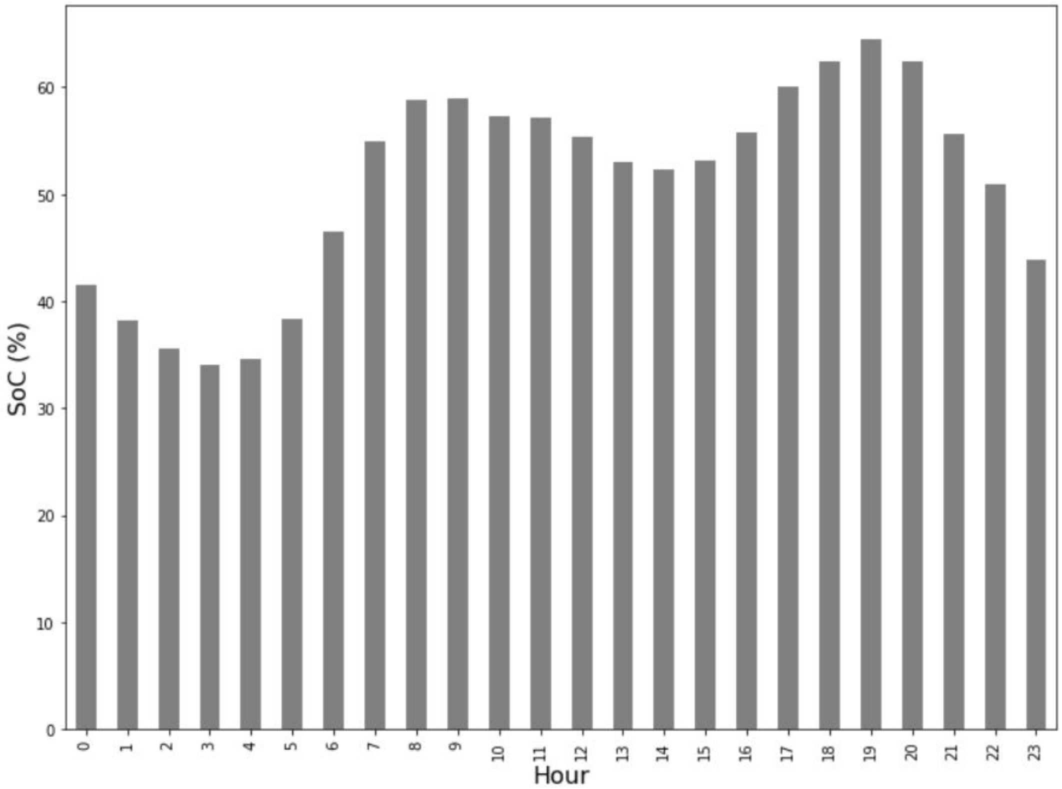


Figure 2.31 – Bar graph of mean values of SoC for every hour of the day.

As predicted, the values for SoC are highest at the hours that correspond in average to the lowest tariffs. Some selling periods appear around the hours of the first peak of figure 2.23 which accounts for some irregular behaviours of the tariff. The clear selling point appears at the hours corresponding to the second peak, around 19:00/20:00.

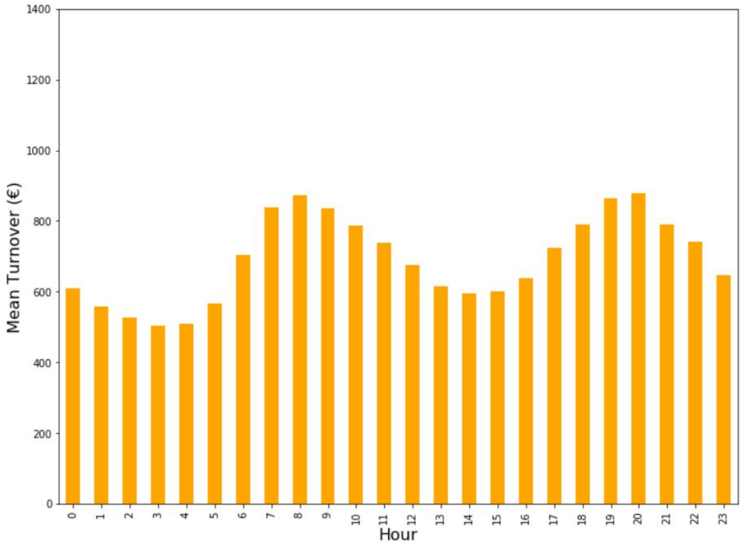


Figure 2.32 – Bar graph of mean values of turnover for every hour of the day without a BESS.

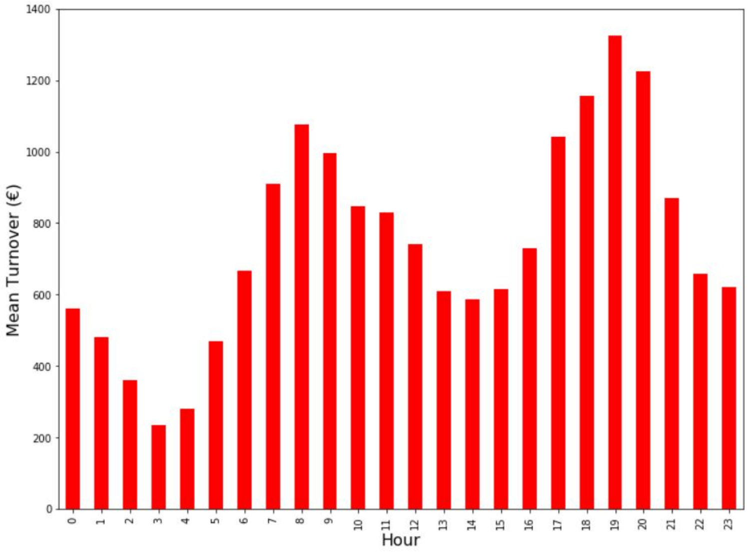


Figure 2.33 – Bar graph of mean values of turnover for every hour of the day with a BESS.

These 2 bar graphs present predictable values as well, there is a clear shift in value for the hours of lowest tariff towards the hours of highest tariff. The combined value for the day also experiences an increase.

The possibilities for data manipulation that can be done to achieve relevant results are many, but the main focus of the thesis is on doing a general evaluation of the economic return that could result from implementing a BESS to allocate energy in a wind farm for the duration of its operating period, which is why these variations were not explored in depth.

Results and Discussion

3.1 CASE STUDY RESULTS

3 Results and Discussion

3.1 Case study results

In this subsection the most relevant values that result from the application of the script to the case study will be presented. Four period windows will be used, the 6 hours window, the 24 hours window, the 48 hours window and the 12 hours window. A hypothetical degradation curve is created in order to simulate the behaviour of the BESS with a constant capacity drop.

The code described in detail in chapter 2 is looped for values of capacity that vary from 5 MWh to 100 MWh in increments of 5 MWh. This loop returns three important lists: a list of values of the difference between the turnover of a wind farm that uses a BESS for the purpose of allocating energy and a normal wind farm, for each BESS capacity; a list for the values of increased turnover per kWh of BESS capacity, which can be understood as a list of values of the maximum price of the BESS per kWh so that a Pay Back Period (PBP) of 20 years can be achieved, for each BESS capacity; a list of number of cycles that the BESS undergoes for each BESS capacity. Every list will be presented 4 times, one for each period window analysed, and a comparison between windows will be made in the end in graphical form. It is important to not forget that maintenance costs and battery degradation are **not** taken into account until point 6 of this subsection.

3.1.1 6 hour period

The code is run to charge and discharge the BESS 4 times a day, dealing with each 6 hours in isolated block without having any information about adjacent blocks. Although it could be expected a better turnover for a lower capacity BESS, by analysing the code carefully one realises that some decisions are suboptimal because of the lack of information regarding adjacent periods. Take, for example, a case where the BESS starts empty and tariff values drop linearly 12 hours in a row (2 six hour blocks): the first hours of the first block are not charged into the BESS because the tariff values are higher than the mean tariff for that interval, so only the latter hours will charged the BESS; when the second block comes we have a charged BESS that will discharge for the first hours of the block ,which correspond to the highest tariffs of the block but also to tariffs lower than the ones correspondent to charging hours of the previous block, which means energy was allocated from a higher selling hour to a lower selling hour. This situation in specific results in a negative turnover, which is an argument against shortening the period window of analysis. In table 3.1 the values for each list are displayed to help comprehend the implications of establishing a time window of the sorts.

The values for this table are not exactly satisfactory. In terms of turnover it needs to be compared to the other windows so that an informed opinion can be created; when looking at the increased turnover per kWh of BESS capacity it is also suboptimal when referring back to figure 1.4, since none of the BESS capacities would result in a PBP of 20 years with the current prices of Li-ion batteries, although that could change in the near future; in terms of cycles, it spans from high 5000 to close 10000 cycles, which puts a lot of strain in the batteries.

BESS capacity (kWh)	Increase in Turnover ($\times 10^6$€)	Increased Turnover per kWh of BESS capacity (€/kWh)	Cycles
5 000	0.569	113	9534.3
10 000	1.059	105	9009.1
15 000	1.545	102	8675.4
20 000	1.993	99	8398.2
25 000	2.424	96	8161.9
30 000	2.833	94	7905.1
35 000	3.212	91	7702.6
40 000	3.475	86	7457.1
45 000	3.806	84	7250.1
50 000	4.080	81	7051.1
55 000	4.362	79	6899.2
60 000	4.649	77	6742.5
65 000	4.919	75	6573.8
70 000	5.168	73	6434.1
75 000	5.470	72	6319.5
80 000	5.675	70	6175.8
85 000	5.900	69	6057.5
90 000	6.134	68	5944.0
95 000	6.317	66	5837.6
100 000	6.501	65	5718.0

Table 3.1 – Important values for the 6 hour period window.

3.1.2 24 hour period

This is the time period in mind during the construction of the script, as it is the most intuitive period window. Similarly to the previous period window, the problem lies at the borders of the window, where the lack of information could result in bad decisions being made. In this case such a problem is mitigated since great discrepancies between days are not as common as discrepancies between blocks of hours of the same day. We can always expect that a good decision for one day will not compromise the quality of the decision in the next, seeing that the aim is to end each day with an ”empty” BESS so that every day’s production is availed to its fullest. In table 3.2 it is already possible to see significant improvement when comparing the values of the previous table, as was expected from the conclusions reached by analysing table 3.1.

The turnover values are significantly higher, especially when considering higher capacities of the BESS. The increased turnover per kWh of BESS capacity values become reasonable for a lower capacity BESS, it would almost be feasible to implement a BESS with a capacity of 5 MWh for the sole purpose of energy allocation. In terms of cycles the spectrum is between 3000 and 3700 cycles, which is much less harmful for the BESS’s lifespan.

BESS capacity (kWh)	Increase in Turnover ($\times 10^6$€)	Increased Turnover per kWh of BESS capacity (€/kWh)	Cycles
5 000	0.678	135	3629.4
10 000	1.290	128	3544.3
15 000	1.870	124	3459.8
20 000	2.430	121	3398.8
25 000	2.973	118	3359.2
30 000	3.490	116	3318.0
35 000	3.994	114	3280.7
40 000	4.502	112	3260.3
45 000	4.970	110	3233.4
50 000	5.422	108	3205.8
55 000	5.867	106	3191.8
60 000	6.315	105	3174.0
65 000	6.750	103	3156.5
70 000	7.150	102	3134.8
75 000	7.535	100	3127.5
80 000	7.913	98	3102.1
85 000	8.277	97	3088.1
90 000	8.640	96	3066.4
95 000	8.992	94	3057.9
100 000	9.333	93	3037.3

Table 3.2 – Important values for the 24 hour period window.

3.1.3 48 hour period

Lastly comes the 48 hours window. Since the issue appeared to be lack of information, an analysis where more information was fed was due. Another problem arises, however, because the code is modelled so that the minimum amount of cycles happen during a period window, which means that there usually are two main moments: the charging and the discharge. Take, for example, a 2 day block where the first day has overall lower tariff values. The charging will take place on the first day at the lowest tariff hours and the discharge will happen on the second day at the highest tariff hours, which sounds optimal. The problem lies with all the other hours that are basically ignored by the program. It has already been shown that it is possible to have some sort of higher turnover almost every day, and this period window misses out on about half of the opportunities. Table 3.3 displays the results that will confirm these suspicions.

As predicted, the resulting turnover is unsatisfactory, especially for lower BESS capacities, although it rises steeply until a value similar to the one in table 3.1. The low turnover permeates to a disadvantageous increased turnover per kWh of BESS capacity, however, it shows the lowest variance, connected to the fairly linear rise in turnover. Lastly, it shows a spectrum of cycles between 1600 and 1700, which is the most amicable for the batteries lifespan. The combination of all these disadvantages shuts down any ideas of application of this period window solely for energy allocation.

BESS capacity (kWh)	Increase in Turnover ($\times 10^6$€)	Increased Turnover per kWh of BESS capacity (€/kWh)	Cycles
5 000	0.399	79	1660.8
10 000	0.780	78	1652.0
15 000	1.151	76	1630.8
20 000	1.515	75	1631.0
25 000	1.871	74	1630.6
30 000	2.218	73	1637.4
35 000	2.555	73	1640.6
40 000	2.898	72	1643.9
45 000	3.236	71	1646.9
50 000	3.546	70	1638.4
55 000	3.866	70	1630.3
60 000	4.205	70	1627.4
65 000	4.558	70	1639.7
70 000	4.840	69	1635.7
75 000	5.173	68	1638.9
80 000	5.456	68	1635.4
85 000	5.765	67	1634.7
90 000	6.054	67	1632.7
95 000	6.334	66	1626.9
100 000	6.599	65	1627.2

Table 3.3 – for the 48 hour period window.

3.1.4 12 hour period

This is a time period that is expected to show good values, since there are two peaks of tariff values, which happen about 10 hours apart, which means dividing the day in two will isolate both peaks from each other. There are still some discrepancies that are linked to the fact that the tariff curve of the first 12 hours of the day, although sometimes similar in shape to the tariff curve of the last 12 hours of the day, the values are most of the times higher on the latter half of the day. In table 3.4 it is possible to see how much better the values are when compared to frequencies other than the 24 hours.

The turnover values are particularly close to those in the 24 period window, especially when considering lower capacities of the BESS. When capacity values increase, the discrepancy between selling the cheapest energy at the second more expensive tariff of the day becomes clearer. The increased turnover per kWh of BESS capacity is not high enough for today's standard cost of Li-ion batteries, but it is not low enough to discredit the idea completely, under certain conditions of use it could show promising results. In terms of cycles the spectrum is between 4000 and 5300 cycles, which is a reasonable number of cycles for a lifespan of 20 years.

BESS capacity (kWh)	Increase in Turnover ($\times 10^6$€)	Increased Turnover per kWh of BESS capacity (€/kWh)	Cycles
5000	0.606	121	5281.8
10000	1.144	114	5034.0
15000	1.641	109	4886.7
20000	2.120	105	4782.5
25000	2.574	102	4699.4
30000	3.005	100	4625.2
35000	3.424	97	4557.3
40000	3.815	95	4486.6
45000	4.199	93	4424.9
50000	4.580	91	4381.5
55000	4.955	90	4340.7
60000	5.309	88	4300.2
65000	5.645	86	4257.1
70000	5.972	85	4225.6
75000	6.268	83	4176.9
80000	6.566	82	4138.3
85000	6.847	80	4104.5
90000	7.147	79	4068.6
95000	7.381	77	4037.0
100000	7.641	76	4003.6

Table 3.4 – Important values for the 12 hour period window.

3.1.5 Graphical comparison of the 4 periods

In this subsubsection there are three graphs, one for each value column where it is possible to compare each period window. Everything that was explained previously can now be seen graphically.

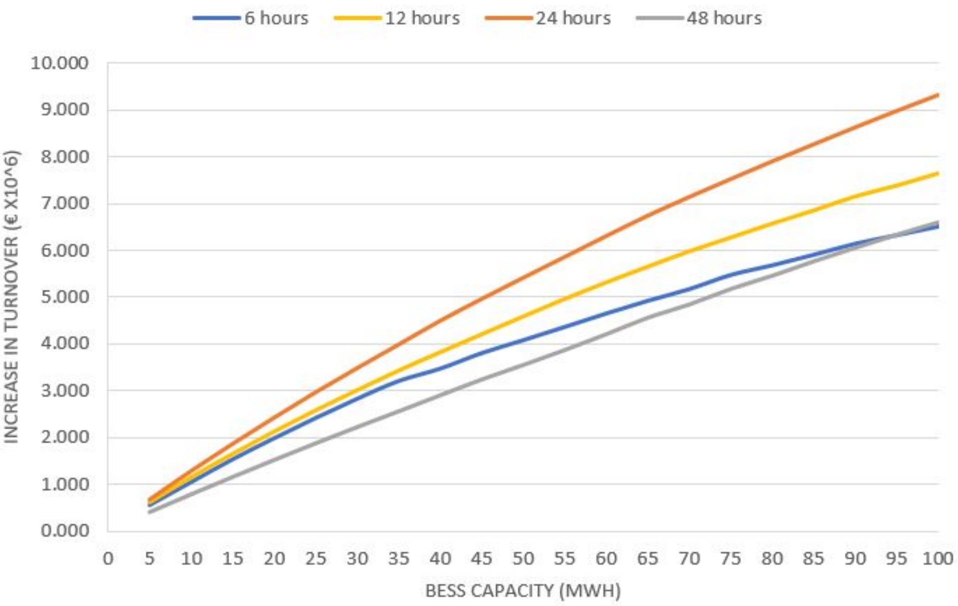


Figure 3.1 – Comparison between increased turnovers for the 4 period windows.

Figure 3.1 displays the increased turnover values, which are displayed as expected. The 24 hour curve is the most profitable, followed close but the 12 hour curve when dealing with lower BESS capacities, then a larger gap begins to form, which is to be expected as well since two charging periods during a day will become unnecessary when the storage capacity increases significantly. The 6 hour period curve is especially close to the optimum amount at lower capacities, for all the reason already described, it also experiences the biggest drop, since it will most certainly not be able to produce a fully charge BESS when capacities rise above a certain threshold. The 48 hour period shows a near linear growth, which can be explained by the fact that its value is highest when the storage capacity is such that it can always charge the highest amount of low price energy.

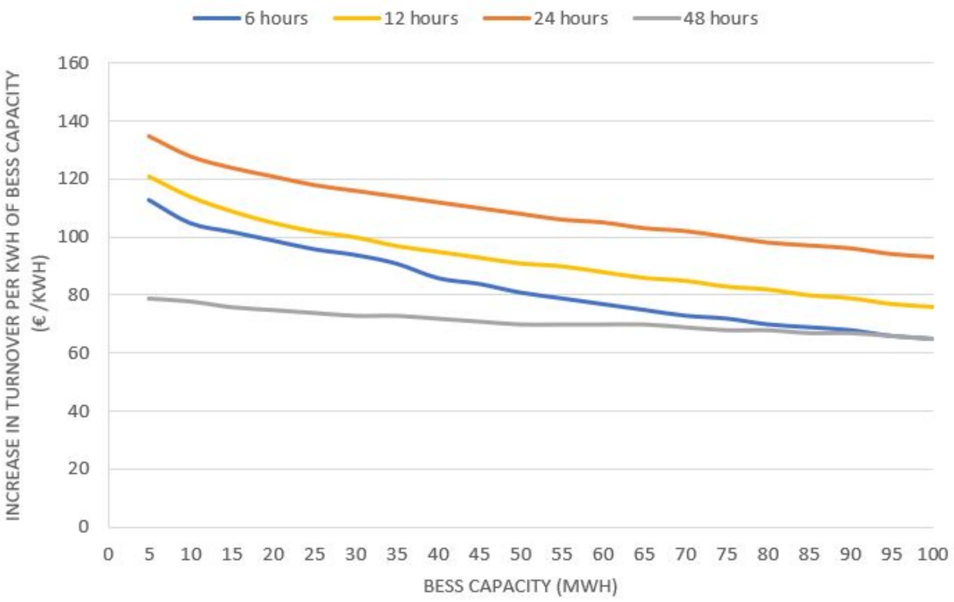


Figure 3.2 – Comparison between the increased turnover per kWh of BESS capacity for the 4 period windows.

The order in which the curves appear in figure 3.2 is unsurprising. The 24 hour period prevails as the best option, followed by the 12 hour period. The last 2 periods also show expected numbers: the 6 hour period is valuable when dealing with lower BESS capacities, where there is room to move energy in short bulks, losing relevancy for higher capacities; the 48 hour period shows an unwavering curve, justified by the fact that its value is more noticeable when dealing with high BESS capacities, seeing that large quantities of lowest cost energy of 2 days is sold at the highest tariff of the same 2 days.

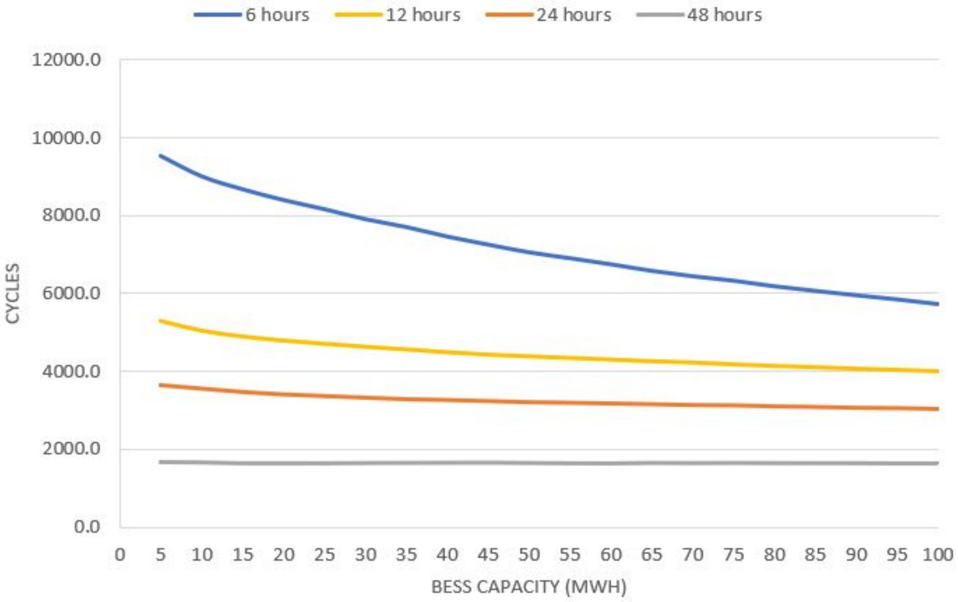


Figure 3.3 – Comparison between cycles for the 4 period windows.

Even though figure 3.3 also shows expected values, the conclusions one can take from it require some compromise. Bigger windows generate fewer cycles than small windows, which is apparent from a quick glance of the graph. Nevertheless, the rate at which each curve drops is relevant when making decisions. Starting by the 6 hour window, the BESS is most used at lower capacities, which will be the case for every window. However, as capacity increases, the number of cycles of the 6 hour window experiences the biggest drop; if the lowest capacity represents the most use of the BESS capacity, a big drop in cycles means that most of the BESS capacity is not utilized, rendering this window unproductive. The 12 hour window experiences a smaller drop, although still noticeable, also unproductive for very high values of storage capacity. The 48 hour window always uses the BESS to its full capacity, which is predictable since there are so many low tariff hours to fill up the BESS. For the 24 hour window, despite showing a slight drop, it is not as blatant as the ones for the shorter windows. Moreover, the degradation of the BESS is not included in any of these graphs and the amount of cycles heavily influences the speed at which a battery deteriorates. Thus, when analysing this particular graph it is important to take into account that more cycles mean more strain on the BESS.

3.1.6 *In case of a constant degradation*

Every result shown until now ignored any kind of change to the initial capacity of the BESS. In this section, the data of the 3 years was replicated in order to fabricate data for 20 years and a degradation constant was added to simulate the decaying capacity of the BESS after every single day. This constant was chosen so that the capacity of BESS became 60% of its initial capacity by the end of the 20 years, which is the minimum value advised by manufacturers, below which battery stability can no longer be guaranteed. The results are shown in table 3.5, which was built to ease comparison with table 3.2.

BESS capacity (kWh)	Increase in Turnover ($\times 10^6$€)	Increased Turnover per kWh of BESS capacity (€/kWh)	Cycles
5 000	0.540	107	3655.8
10 000	1.031	103	3573.5
15 000	1.495	99	3510.4
20 000	1.944	97	3454.0
25 000	2.381	95	3406.4
30 000	2.808	93	3367.5
35 000	3.221	92	3334.6
40 000	3.625	90	3305.2
45 000	4.018	89	3278.4
50 000	4.401	88	3256.1
55 000	4.777	86	3238.4
60 000	5.141	85	3220.6
65 000	5.499	84	3204.0
70 000	5.848	83	3188.8
75 000	6.188	82	3174.8
80 000	6.519	81	3161.0
85 000	6.842	80	3148.6
90 000	7.161	79	3132.4
95 000	7.469	78	3120.3
100 000	7.765	78	3107.8

Table 3.5 – for the 24 hour period window with a hypothetical degradation curve.

All other comparison graphs were replicated to emphasise the differences between an ideal BESS and a real BESS with a hypothetical degradation function. Figures 3.4, 3.5 and 3.6 all show how degradation negatively affects the results of the previous graphs.

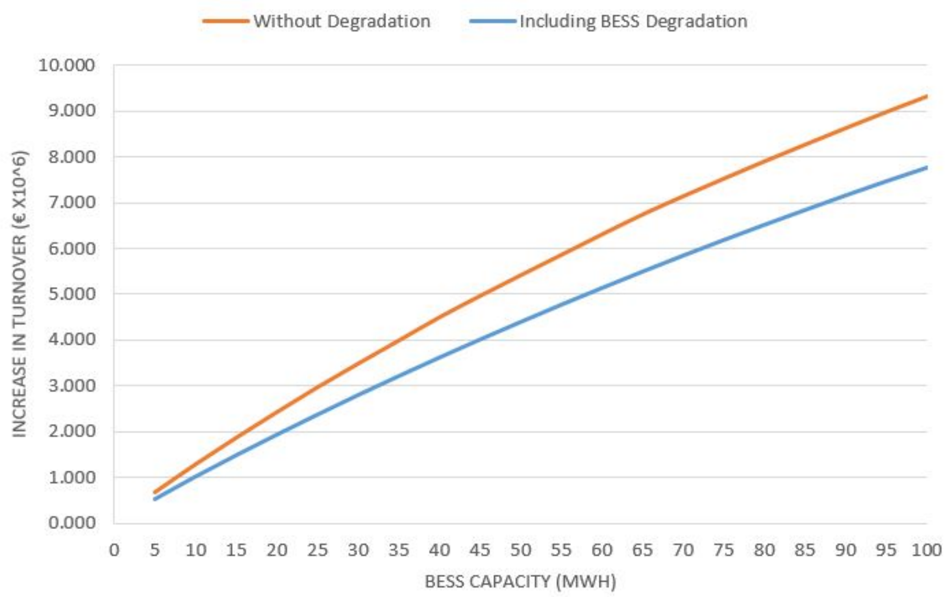


Figure 3.4 – Comparison between increased turnovers of an ideal BESS and a BESS with a hypothetical degradation curve.

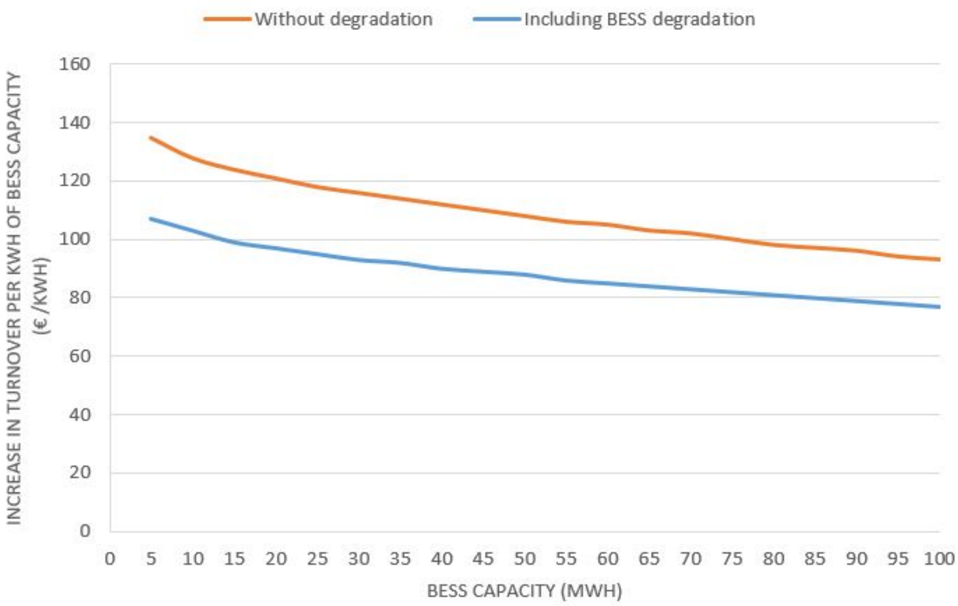


Figure 3.5 – Comparison between increased turnovers per kWh of BESS capacity of an ideal BESS and a BESS with a hypothetical degradation curve.

These two graphs display how this condition considerably worsens every result, as would be naturally expected. In terms of turnover, the highest the initial capacity, the biggest the drop in increased turnover, which makes sense considering that the amount of energy that can be stored diminishes by a set percentage (which makes it more noticeable at higher capacities) and the 24 hour window enabled a full charging of a high capacity BESS. In terms of increased turnovers per kWh of BESS capacity, it is also lower. It decreases at a lower rate because the increased turnover behaviour is more linear than the one from the curve without degradation.

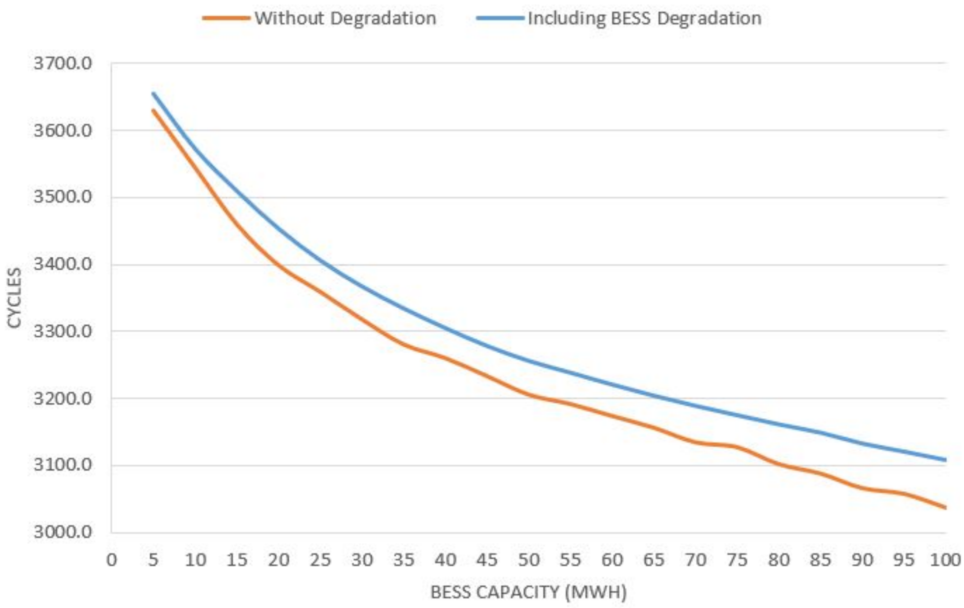


Figure 3.6 – Comparison between total cycles of an ideal BESS and a BESS with a hypothetical degradation curve.

This graph is particularly interesting because when analysing the different number of cycles of each window, a higher number of cycles was not a necessarily negative result. Here, however, a higher number of cycles means that the BESS is fully charged and fully discharged (until the respective thresholds) more often, which happens because the capacity of the BESS is gradually becoming lower and it becomes easier to reach the new thresholds. An increase in number of cycles is and indicative of lower capacity and increased strain put on the BESS.

As an ending remark for this chapter I would like to point out that most BESSs commonly used do not reach such high capacities due to the increased turnover per kWh of BESS capacity. The smaller the capacity of the BESS the better the returns on the investment, therefore, the best option most of the times is to acquire the smallest possible BESS capacity to achieve a certain purpose, so that every kWh invested on can return as much as possible.

Conclusions and Future Work

4 Conclusions and Future Work

4.1 Conclusions

This work serves as an additional tool to evaluate the reasonability of using BESS in RE farms. The program not only returns definite values of optimized size for greater increase in turnover, but also allows for an easier read on all the variables involved, from graphical information of the input data to BESS behaviour in various conditions. The possibilities for data manipulation are various and definitely valuable for analysing the characteristics of a BESS behaviour under different conditions.

Even though the reasons for implementing such a technology are numerous, the feature described in this thesis greatly favours its utilisation in today's energy market. A problem could arise if the tendency of the energy market steered in a path that would render this economic analysis irrelevant. Strategies like peak shaving, or an application like the one described in this thesis, work as a regulator of the energy tariff values, dimming down/dampening the daily fluctuations, which will in turn work against the feasibility of implementing a BESS focusing solely on energy allocation. Nevertheless, for the years in question in the case study the tendency does not show signs of future reduction in tariff fluctuations.

The take from this case study is that an investment on a BESS in these conditions - mainly no maintenance costs nor battery storage degradation - would have a PBP of close to 20 years at if a BESS of 5 MWh of capacity was implemented for the sole purpose of energy allocation. What is particularly important to realise is the fact that the Li-ion price has been seeing a decline during the past years and is expected to lower in the near future, thus allowing for more promising investment opportunities.

In conclusion, the lowering costs of Li-ion batteries and the consistency of the energy market both accentuate the benefits of implementing a BESS in a RE farm. If these two parameters maintain their tendencies, this script can prove to be a valuable tool to motivate such an investment.

4.2 Future Work

A software/program is an ever growing organism, therefore, the sturdy organization of the data enables the increase of complexity and the number of parameters that are taken into account. From the limitless possibilities, a few additions should have priority, such as the battery degradation and maintenance costs (specific to the manufacturer), a better definition of the SoC values to prolong battery life (which was roughly done by limiting the upper and lower values of SoC), seasonal and weekly particularities. Adding the efficiency of the batteries is also an important parameter that should be added as soon as the information is disclosed.

This program can work not only as an indicator for a future park but also as an operation software for modelling the battery SoC of the following day. For such applications only small changes need to be introduced, which adds to the value of improving it.

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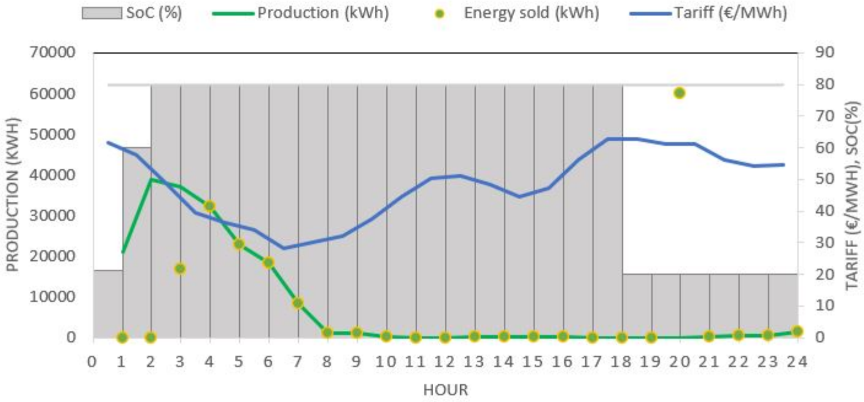
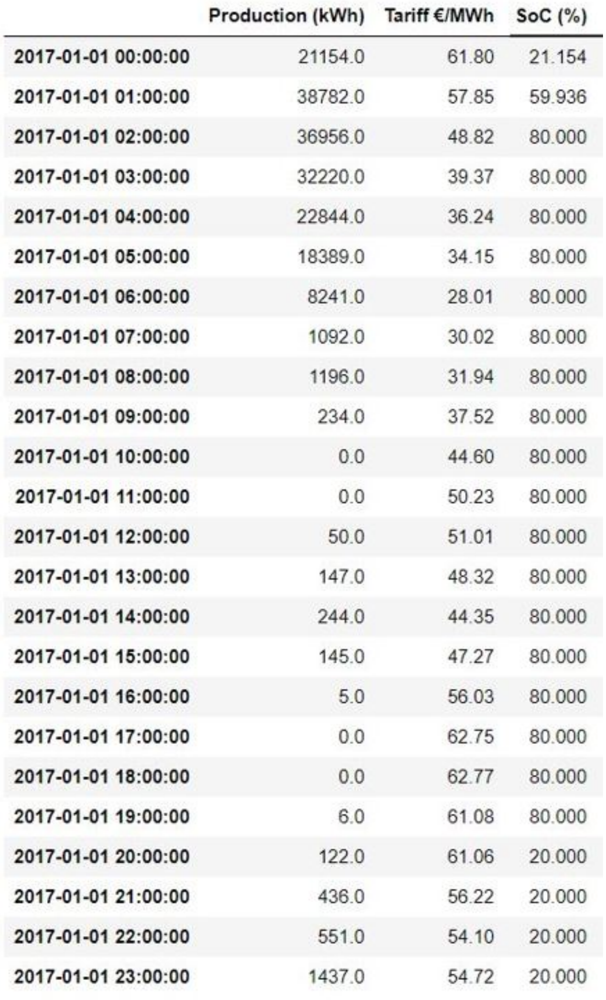
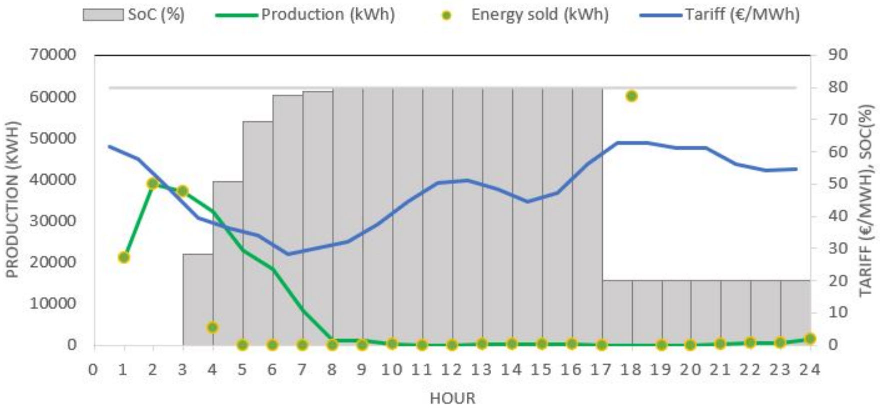
Battery modeling Figures

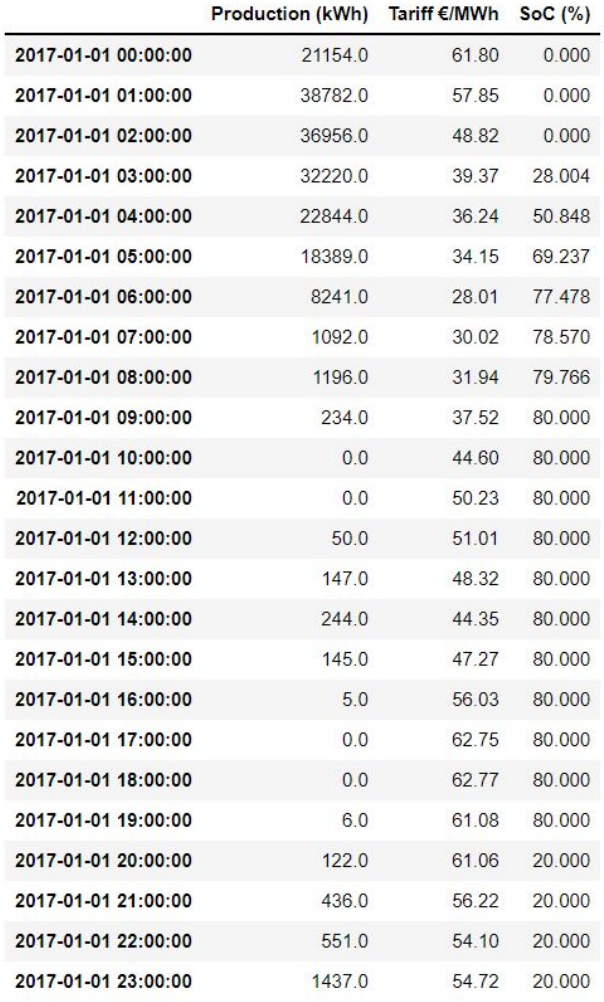




	Production (kWh)	Tariff €/MWh	SoC (%)
2017-01-01 00:00:00	21154.0	61.80	21.154
2017-01-01 01:00:00	38782.0	57.85	59.936
2017-01-01 02:00:00	36956.0	48.82	80.000
2017-01-01 03:00:00	32220.0	39.37	80.000
2017-01-01 04:00:00	22844.0	36.24	80.000
2017-01-01 05:00:00	18389.0	34.15	80.000
2017-01-01 06:00:00	8241.0	28.01	80.000
2017-01-01 07:00:00	1092.0	30.02	80.000
2017-01-01 08:00:00	1196.0	31.94	80.000
2017-01-01 09:00:00	234.0	37.52	80.000
2017-01-01 10:00:00	0.0	44.60	80.000
2017-01-01 11:00:00	0.0	50.23	80.000
2017-01-01 12:00:00	50.0	51.01	80.000
2017-01-01 13:00:00	147.0	48.32	80.000
2017-01-01 14:00:00	244.0	44.35	80.000
2017-01-01 15:00:00	145.0	47.27	80.000
2017-01-01 16:00:00	5.0	56.03	80.000
2017-01-01 17:00:00	0.0	62.75	80.000
2017-01-01 18:00:00	0.0	62.77	80.000
2017-01-01 19:00:00	6.0	61.08	80.000
2017-01-01 20:00:00	122.0	61.06	20.000
2017-01-01 21:00:00	436.0	56.22	20.000
2017-01-01 22:00:00	551.0	54.10	20.000
2017-01-01 23:00:00	1437.0	54.72	20.000

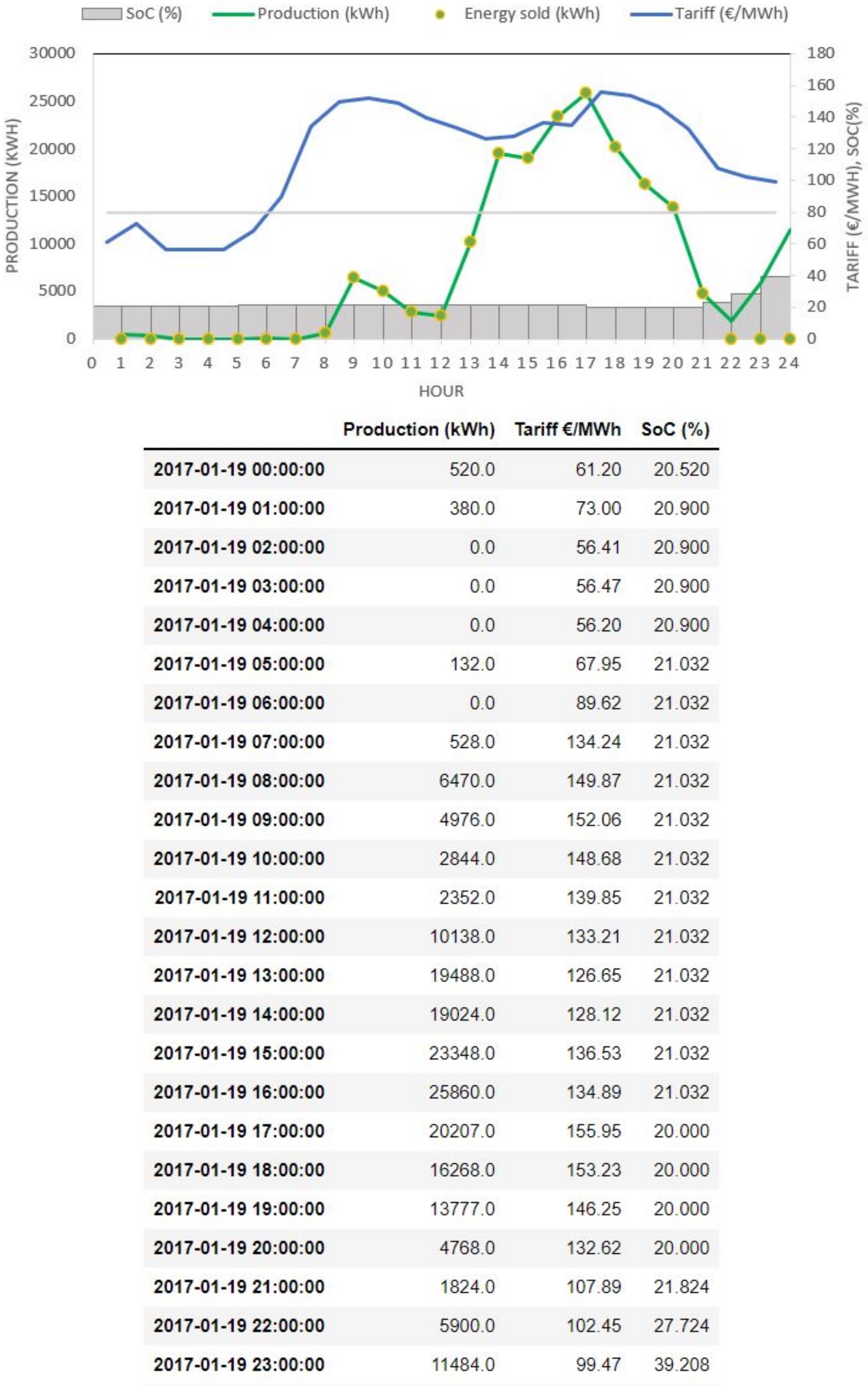
Figure A.1 – First try at charging the BESS.





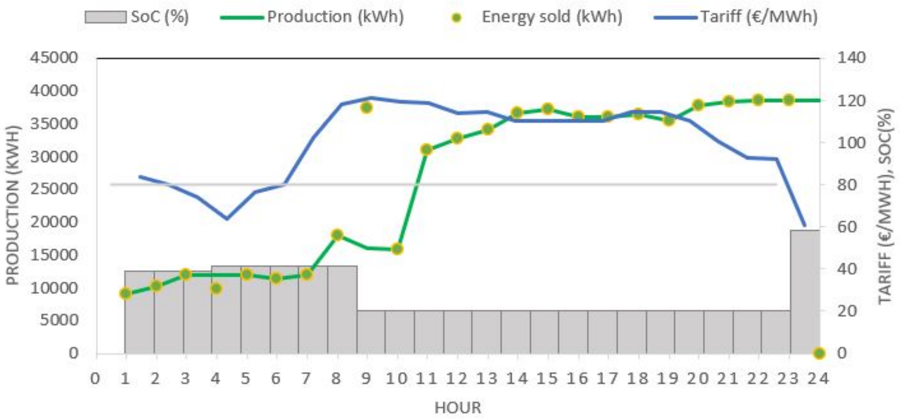
	Production (kWh)	Tariff €/MWh	SoC (%)
2017-01-01 00:00:00	21154.0	61.80	0.000
2017-01-01 01:00:00	38782.0	57.85	0.000
2017-01-01 02:00:00	36956.0	48.82	0.000
2017-01-01 03:00:00	32220.0	39.37	28.004
2017-01-01 04:00:00	22844.0	36.24	50.848
2017-01-01 05:00:00	18389.0	34.15	69.237
2017-01-01 06:00:00	8241.0	28.01	77.478
2017-01-01 07:00:00	1092.0	30.02	78.570
2017-01-01 08:00:00	1196.0	31.94	79.766
2017-01-01 09:00:00	234.0	37.52	80.000
2017-01-01 10:00:00	0.0	44.60	80.000
2017-01-01 11:00:00	0.0	50.23	80.000
2017-01-01 12:00:00	50.0	51.01	80.000
2017-01-01 13:00:00	147.0	48.32	80.000
2017-01-01 14:00:00	244.0	44.35	80.000
2017-01-01 15:00:00	145.0	47.27	80.000
2017-01-01 16:00:00	5.0	56.03	80.000
2017-01-01 17:00:00	0.0	62.75	80.000
2017-01-01 18:00:00	0.0	62.77	80.000
2017-01-01 19:00:00	6.0	61.08	80.000
2017-01-01 20:00:00	122.0	61.06	20.000
2017-01-01 21:00:00	436.0	56.22	20.000
2017-01-01 22:00:00	551.0	54.10	20.000
2017-01-01 23:00:00	1437.0	54.72	20.000

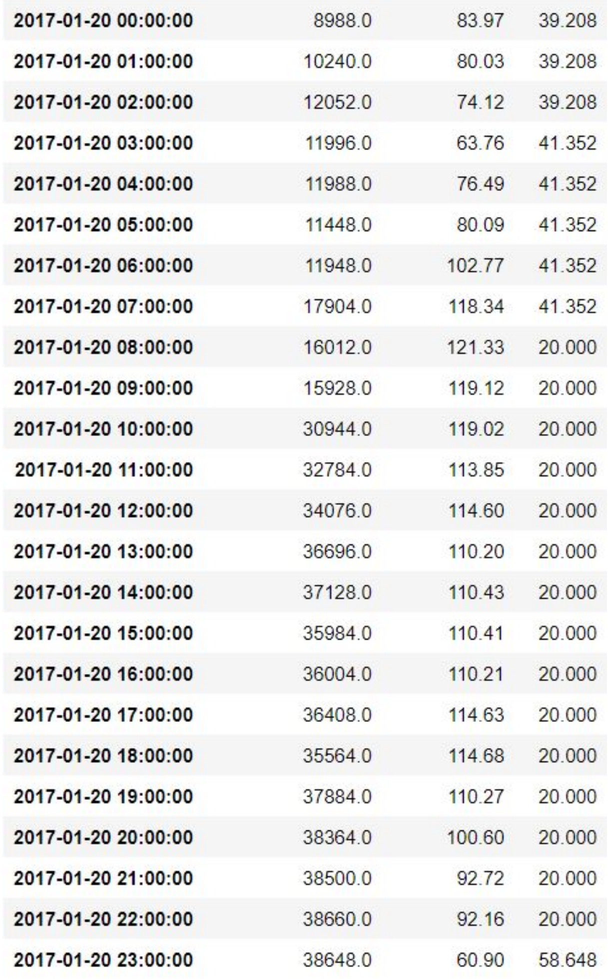
Figure A.2 – Optimized charging of the BESS.



	Production (kWh)	Tariff €/MWh	SoC (%)
2017-01-19 00:00:00	520.0	61.20	20.520
2017-01-19 01:00:00	380.0	73.00	20.900
2017-01-19 02:00:00	0.0	56.41	20.900
2017-01-19 03:00:00	0.0	56.47	20.900
2017-01-19 04:00:00	0.0	56.20	20.900
2017-01-19 05:00:00	132.0	67.95	21.032
2017-01-19 06:00:00	0.0	89.62	21.032
2017-01-19 07:00:00	528.0	134.24	21.032
2017-01-19 08:00:00	6470.0	149.87	21.032
2017-01-19 09:00:00	4976.0	152.06	21.032
2017-01-19 10:00:00	2844.0	148.68	21.032
2017-01-19 11:00:00	2352.0	139.85	21.032
2017-01-19 12:00:00	10138.0	133.21	21.032
2017-01-19 13:00:00	19488.0	126.65	21.032
2017-01-19 14:00:00	19024.0	128.12	21.032
2017-01-19 15:00:00	23348.0	136.53	21.032
2017-01-19 16:00:00	25860.0	134.89	21.032
2017-01-19 17:00:00	20207.0	155.95	20.000
2017-01-19 18:00:00	16268.0	153.23	20.000
2017-01-19 19:00:00	13777.0	146.25	20.000
2017-01-19 20:00:00	4768.0	132.62	20.000
2017-01-19 21:00:00	1824.0	107.89	21.824
2017-01-19 22:00:00	5900.0	102.45	27.724
2017-01-19 23:00:00	11484.0	99.47	39.208

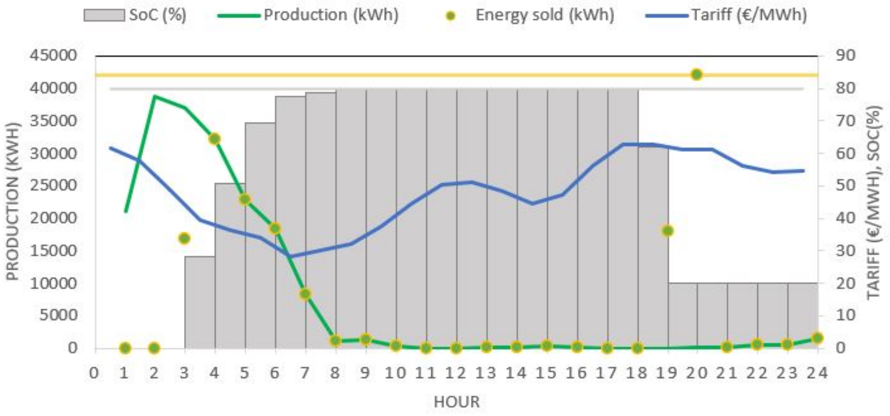
Figure A.3 – Verifying optimized charging of the BESS.

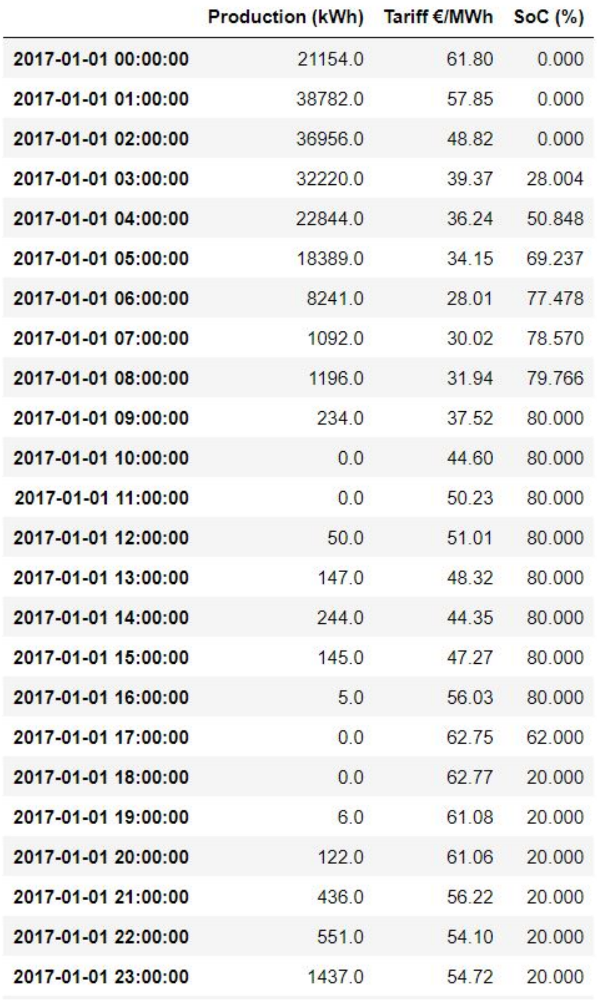




2017-01-20 00:00:00	8988.0	83.97	39.208
2017-01-20 01:00:00	10240.0	80.03	39.208
2017-01-20 02:00:00	12052.0	74.12	39.208
2017-01-20 03:00:00	11996.0	63.76	41.352
2017-01-20 04:00:00	11988.0	76.49	41.352
2017-01-20 05:00:00	11448.0	80.09	41.352
2017-01-20 06:00:00	11948.0	102.77	41.352
2017-01-20 07:00:00	17904.0	118.34	41.352
2017-01-20 08:00:00	16012.0	121.33	20.000
2017-01-20 09:00:00	15928.0	119.12	20.000
2017-01-20 10:00:00	30944.0	119.02	20.000
2017-01-20 11:00:00	32784.0	113.85	20.000
2017-01-20 12:00:00	34076.0	114.60	20.000
2017-01-20 13:00:00	36696.0	110.20	20.000
2017-01-20 14:00:00	37128.0	110.43	20.000
2017-01-20 15:00:00	35984.0	110.41	20.000
2017-01-20 16:00:00	36004.0	110.21	20.000
2017-01-20 17:00:00	36408.0	114.63	20.000
2017-01-20 18:00:00	35564.0	114.68	20.000
2017-01-20 19:00:00	37884.0	110.27	20.000
2017-01-20 20:00:00	38364.0	100.60	20.000
2017-01-20 21:00:00	38500.0	92.72	20.000
2017-01-20 22:00:00	38660.0	92.16	20.000
2017-01-20 23:00:00	38648.0	60.90	58.648

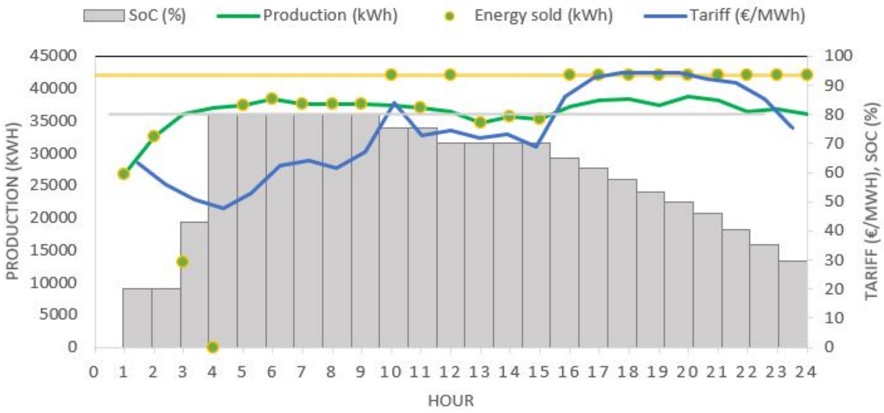
Figure A.4 – Further verification of the optimized charging of the BESS.

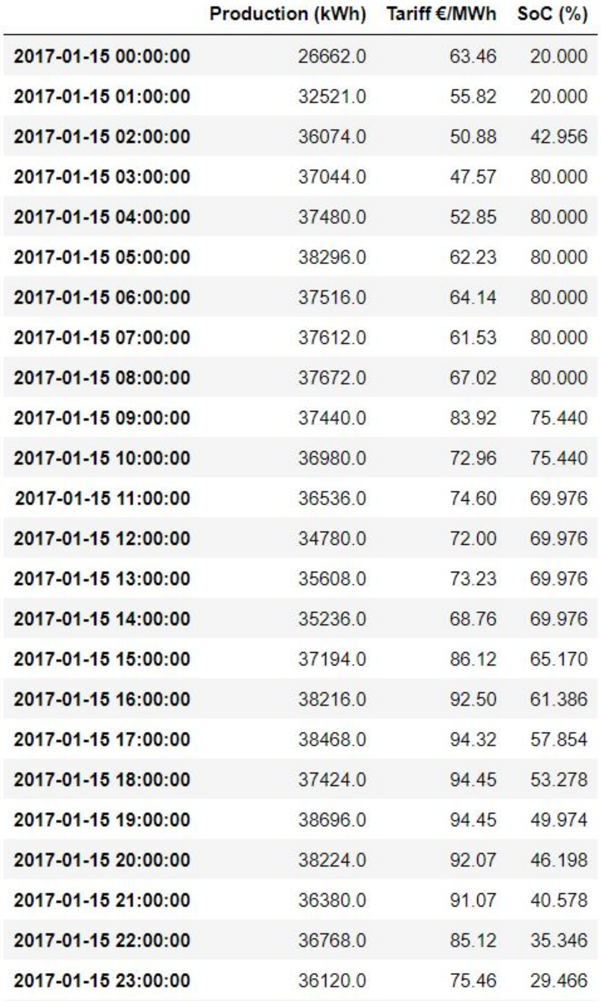




	Production (kWh)	Tariff €/MWh	SoC (%)
2017-01-01 00:00:00	21154.0	61.80	0.000
2017-01-01 01:00:00	38782.0	57.85	0.000
2017-01-01 02:00:00	36956.0	48.82	0.000
2017-01-01 03:00:00	32220.0	39.37	28.004
2017-01-01 04:00:00	22844.0	36.24	50.848
2017-01-01 05:00:00	18389.0	34.15	69.237
2017-01-01 06:00:00	8241.0	28.01	77.478
2017-01-01 07:00:00	1092.0	30.02	78.570
2017-01-01 08:00:00	1196.0	31.94	79.766
2017-01-01 09:00:00	234.0	37.52	80.000
2017-01-01 10:00:00	0.0	44.60	80.000
2017-01-01 11:00:00	0.0	50.23	80.000
2017-01-01 12:00:00	50.0	51.01	80.000
2017-01-01 13:00:00	147.0	48.32	80.000
2017-01-01 14:00:00	244.0	44.35	80.000
2017-01-01 15:00:00	145.0	47.27	80.000
2017-01-01 16:00:00	5.0	56.03	80.000
2017-01-01 17:00:00	0.0	62.75	62.000
2017-01-01 18:00:00	0.0	62.77	20.000
2017-01-01 19:00:00	6.0	61.08	20.000
2017-01-01 20:00:00	122.0	61.06	20.000
2017-01-01 21:00:00	436.0	56.22	20.000
2017-01-01 22:00:00	551.0	54.10	20.000
2017-01-01 23:00:00	1437.0	54.72	20.000

Figure A.5 – Values for optimized discharge of the BESS.

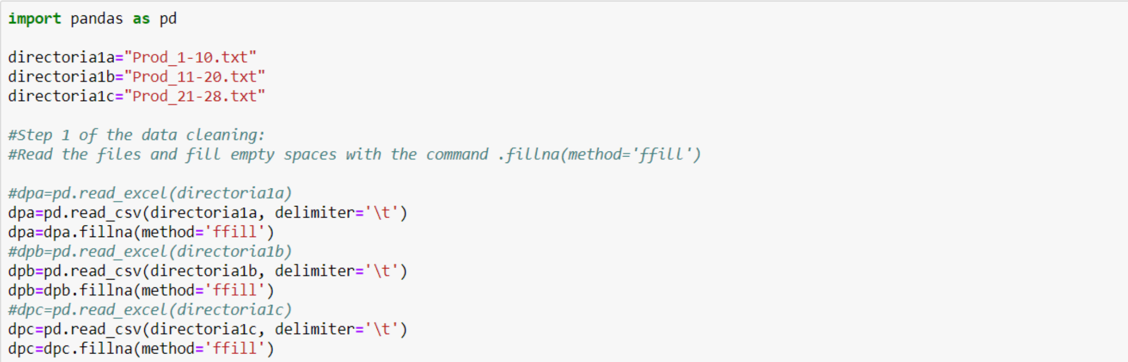




	Production (kWh)	Tariff €/MWh	SoC (%)
2017-01-15 00:00:00	26662.0	63.46	20.000
2017-01-15 01:00:00	32521.0	55.82	20.000
2017-01-15 02:00:00	36074.0	50.88	42.956
2017-01-15 03:00:00	37044.0	47.57	80.000
2017-01-15 04:00:00	37480.0	52.85	80.000
2017-01-15 05:00:00	38296.0	62.23	80.000
2017-01-15 06:00:00	37516.0	64.14	80.000
2017-01-15 07:00:00	37612.0	61.53	80.000
2017-01-15 08:00:00	37672.0	67.02	80.000
2017-01-15 09:00:00	37440.0	83.92	75.440
2017-01-15 10:00:00	36980.0	72.96	75.440
2017-01-15 11:00:00	36536.0	74.60	69.976
2017-01-15 12:00:00	34780.0	72.00	69.976
2017-01-15 13:00:00	35608.0	73.23	69.976
2017-01-15 14:00:00	35236.0	68.76	69.976
2017-01-15 15:00:00	37194.0	86.12	65.170
2017-01-15 16:00:00	38216.0	92.50	61.386
2017-01-15 17:00:00	38468.0	94.32	57.854
2017-01-15 18:00:00	37424.0	94.45	53.278
2017-01-15 19:00:00	38696.0	94.45	49.974
2017-01-15 20:00:00	38224.0	92.07	46.198
2017-01-15 21:00:00	36380.0	91.07	40.578
2017-01-15 22:00:00	36768.0	85.12	35.346
2017-01-15 23:00:00	36120.0	75.46	29.466

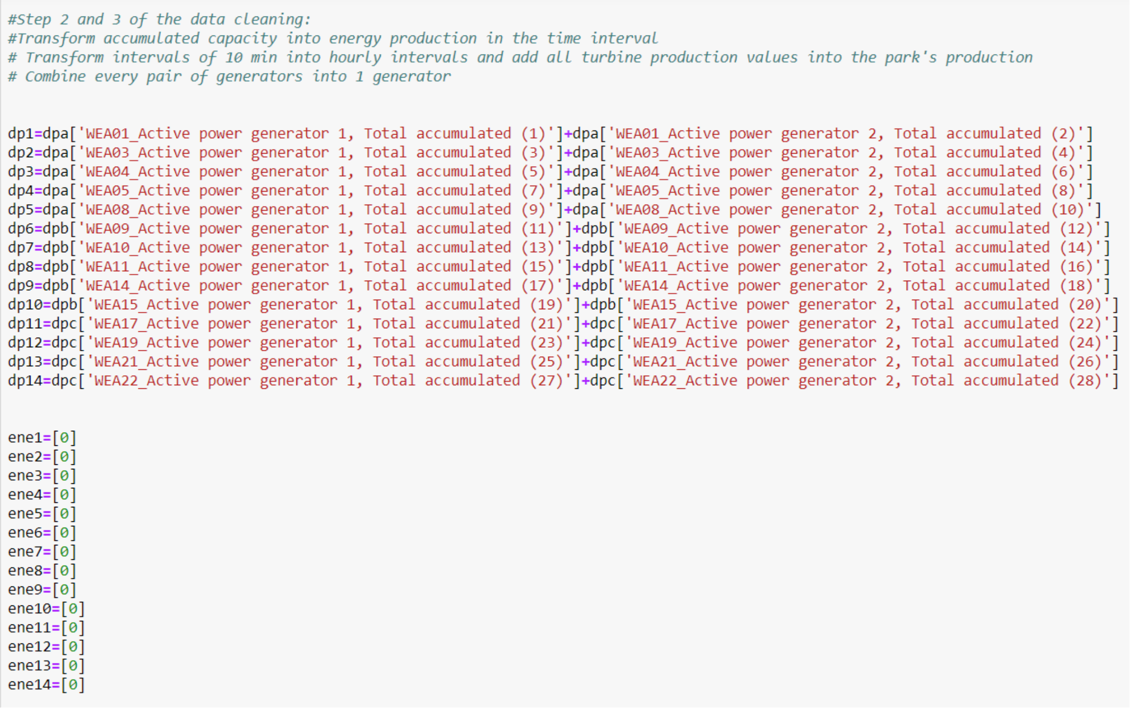
Figure A.6 – Verifying optimized discharge of the BESS.

Code for data cleaning



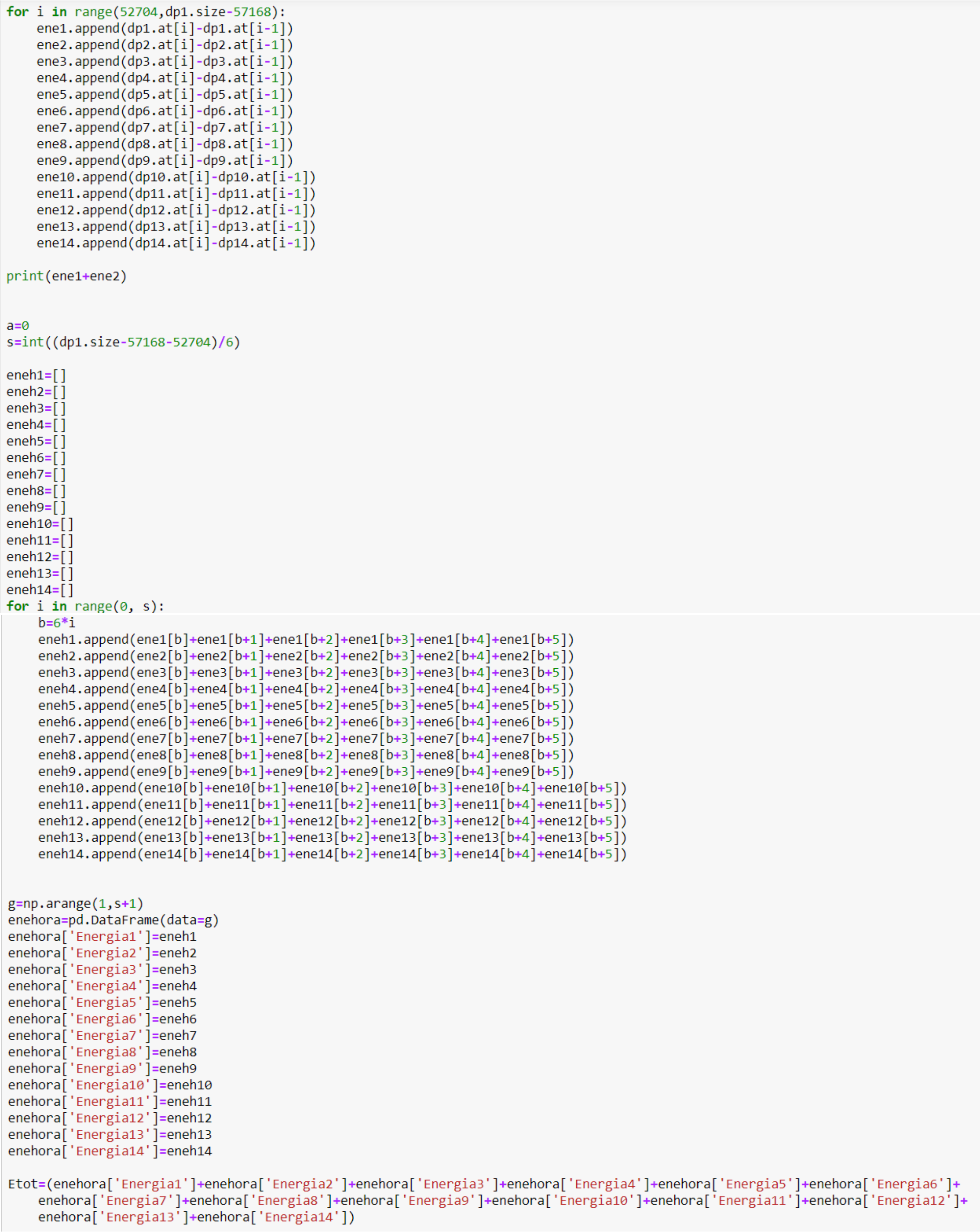
```
import pandas as pd

directoria1a="Prod_1-10.txt"
directoria1b="Prod_11-20.txt"
directoria1c="Prod_21-28.txt"

#Step 1 of the data cleaning:
#Read the files and fill empty spaces with the command .fillna(method='ffill')

#dpa=pd.read_excel(directoria1a)
dpa=pd.read_csv(directoria1a, delimiter='\t')
dpa=dpa.fillna(method='ffill')
#dpb=pd.read_excel(directoria1b)
dpb=pd.read_csv(directoria1b, delimiter='\t')
dpb=dpb.fillna(method='ffill')
#dpc=pd.read_excel(directoria1c)
dpc=pd.read_csv(directoria1c, delimiter='\t')
dpc=dpc.fillna(method='ffill')
```

Figure B.1 – Clean 1



```
#Step 2 and 3 of the data cleaning:
#Transform accumulated capacity into energy production in the time interval
# Transform intervals of 10 min into hourly intervals and add all turbine production values into the park's production
# Combine every pair of generators into 1 generator


dp1=dpa['WEA01_Active power generator 1, Total accumulated (1)']+dpa['WEA01_Active power generator 2, Total accumulated (2)']
dp2=dpa['WEA03_Active power generator 1, Total accumulated (3)']+dpa['WEA03_Active power generator 2, Total accumulated (4)']
dp3=dpa['WEA04_Active power generator 1, Total accumulated (5)']+dpa['WEA04_Active power generator 2, Total accumulated (6)']
dp4=dpa['WEA05_Active power generator 1, Total accumulated (7)']+dpa['WEA05_Active power generator 2, Total accumulated (8)']
dp5=dpa['WEA08_Active power generator 1, Total accumulated (9)']+dpa['WEA08_Active power generator 2, Total accumulated (10)']
dp6=dpb['WEA09_Active power generator 1, Total accumulated (11)']+dpb['WEA09_Active power generator 2, Total accumulated (12)']
dp7=dpb['WEA10_Active power generator 1, Total accumulated (13)']+dpb['WEA10_Active power generator 2, Total accumulated (14)']
dp8=dpb['WEA11_Active power generator 1, Total accumulated (15)']+dpb['WEA11_Active power generator 2, Total accumulated (16)']
dp9=dpb['WEA14_Active power generator 1, Total accumulated (17)']+dpb['WEA14_Active power generator 2, Total accumulated (18)']
dp10=dpb['WEA15_Active power generator 1, Total accumulated (19)']+dpb['WEA15_Active power generator 2, Total accumulated (20)']
dp11=dpc['WEA17_Active power generator 1, Total accumulated (21)']+dpc['WEA17_Active power generator 2, Total accumulated (22)']
dp12=dpc['WEA19_Active power generator 1, Total accumulated (23)']+dpc['WEA19_Active power generator 2, Total accumulated (24)']
dp13=dpc['WEA21_Active power generator 1, Total accumulated (25)']+dpc['WEA21_Active power generator 2, Total accumulated (26)']
dp14=dpc['WEA22_Active power generator 1, Total accumulated (27)']+dpc['WEA22_Active power generator 2, Total accumulated (28)']


ene1=[0]
ene2=[0]
ene3=[0]
ene4=[0]
ene5=[0]
ene6=[0]
ene7=[0]
ene8=[0]
ene9=[0]
ene10=[0]
ene11=[0]
ene12=[0]
ene13=[0]
ene14=[0]
```

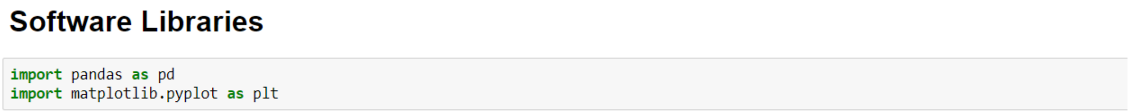
Figure B.2 – Clean 2.1



```
for i in range(52704,dp1.size-57168):
    ene1.append(dp1.at[i]-dp1.at[i-1])
    ene2.append(dp2.at[i]-dp2.at[i-1])
    ene3.append(dp3.at[i]-dp3.at[i-1])
    ene4.append(dp4.at[i]-dp4.at[i-1])
    ene5.append(dp5.at[i]-dp5.at[i-1])
    ene6.append(dp6.at[i]-dp6.at[i-1])
    ene7.append(dp7.at[i]-dp7.at[i-1])
    ene8.append(dp8.at[i]-dp8.at[i-1])
    ene9.append(dp9.at[i]-dp9.at[i-1])
    ene10.append(dp10.at[i]-dp10.at[i-1])
    ene11.append(dp11.at[i]-dp11.at[i-1])
    ene12.append(dp12.at[i]-dp12.at[i-1])
    ene13.append(dp13.at[i]-dp13.at[i-1])
    ene14.append(dp14.at[i]-dp14.at[i-1])

print(ene1+ene2)


a=0
s=int((dp1.size-57168-52704)/6)

eneh1=[]
eneh2=[]
eneh3=[]
eneh4=[]
eneh5=[]
eneh6=[]
eneh7=[]
eneh8=[]
eneh9=[]
eneh10=[]
eneh11=[]
eneh12=[]
eneh13=[]
eneh14=[]
for i in range(0, s):
    b=6*i
    eneh1.append(ene1[b]+ene1[b+1]+ene1[b+2]+ene1[b+3]+ene1[b+4]+ene1[b+5])
    eneh2.append(ene2[b]+ene2[b+1]+ene2[b+2]+ene2[b+3]+ene2[b+4]+ene2[b+5])
    eneh3.append(ene3[b]+ene3[b+1]+ene3[b+2]+ene3[b+3]+ene3[b+4]+ene3[b+5])
    eneh4.append(ene4[b]+ene4[b+1]+ene4[b+2]+ene4[b+3]+ene4[b+4]+ene4[b+5])
    eneh5.append(ene5[b]+ene5[b+1]+ene5[b+2]+ene5[b+3]+ene5[b+4]+ene5[b+5])
    eneh6.append(ene6[b]+ene6[b+1]+ene6[b+2]+ene6[b+3]+ene6[b+4]+ene6[b+5])
    eneh7.append(ene7[b]+ene7[b+1]+ene7[b+2]+ene7[b+3]+ene7[b+4]+ene7[b+5])
    eneh8.append(ene8[b]+ene8[b+1]+ene8[b+2]+ene8[b+3]+ene8[b+4]+ene8[b+5])
    eneh9.append(ene9[b]+ene9[b+1]+ene9[b+2]+ene9[b+3]+ene9[b+4]+ene9[b+5])
    eneh10.append(ene10[b]+ene10[b+1]+ene10[b+2]+ene10[b+3]+ene10[b+4]+ene10[b+5])
    eneh11.append(ene11[b]+ene11[b+1]+ene11[b+2]+ene11[b+3]+ene11[b+4]+ene11[b+5])
    eneh12.append(ene12[b]+ene12[b+1]+ene12[b+2]+ene12[b+3]+ene12[b+4]+ene12[b+5])
    eneh13.append(ene13[b]+ene13[b+1]+ene13[b+2]+ene13[b+3]+ene13[b+4]+ene13[b+5])
    eneh14.append(ene14[b]+ene14[b+1]+ene14[b+2]+ene14[b+3]+ene14[b+4]+ene14[b+5])


g=np.arange(1,s+1)
enehora=pd.DataFrame(data=g)
enehora['Energia1']=eneh1
enehora['Energia2']=eneh2
enehora['Energia3']=eneh3
enehora['Energia4']=eneh4
enehora['Energia5']=eneh5
enehora['Energia6']=eneh6
enehora['Energia7']=eneh7
enehora['Energia8']=eneh8
enehora['Energia9']=eneh9
enehora['Energia10']=eneh10
enehora['Energia11']=eneh11
enehora['Energia12']=eneh12
enehora['Energia13']=eneh13
enehora['Energia14']=eneh14

Etot=(enehora['Energia1']+enehora['Energia2']+enehora['Energia3']+enehora['Energia4']+enehora['Energia5']+enehora['Energia6']+
    enehora['Energia7']+enehora['Energia8']+enehora['Energia9']+enehora['Energia10']+enehora['Energia11']+enehora['Energia12']+
    enehora['Energia13']+enehora['Energia14'])
```

Figure B.3 – Clean 2.2

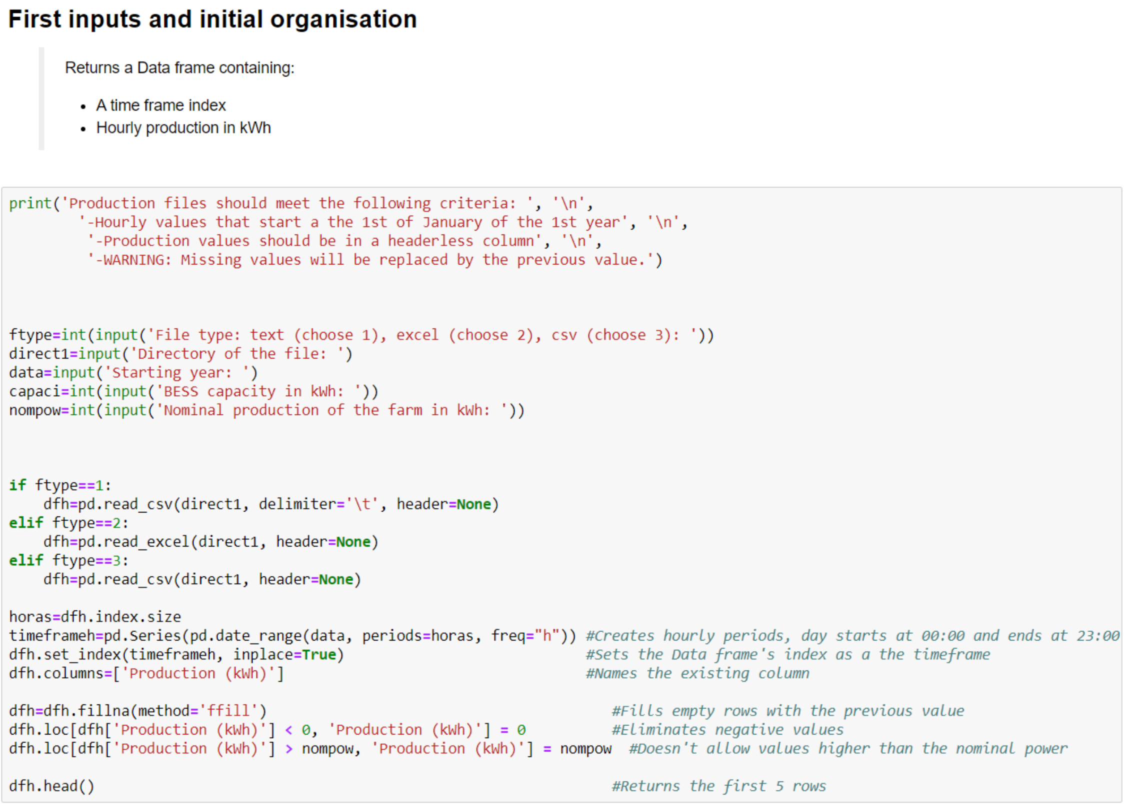
Code for the BESS



Software Libraries

```
import pandas as pd
import matplotlib.pyplot as plt
```

Figure C.1 – Block 1



First inputs and initial organisation

> Returns a Data frame containing:
>
> - A time frame index
> - Hourly production in kWh

```
print('Production files should meet the following criteria: ', '\n',
        '-Hourly values that start a the 1st of January of the 1st year', '\n',
         '-Production values should be in a headerless column', '\n',
         '-WARNING: Missing values will be replaced by the previous value.')



ftype=int(input('File type: text (choose 1), excel (choose 2), csv (choose 3): '))
direct1=input('Directory of the file: ')
data=input('Starting year: ')
capaci=int(input('BESS capacity in kWh: '))
nompow=int(input('Nominal production of the farm in kWh: '))



if ftype==1:
    dfh=pd.read_csv(direct1, delimiter='\t', header=None)
elif ftype==2:
    dfh=pd.read_excel(direct1, header=None)
elif ftype==3:
    dfh=pd.read_csv(direct1, header=None)

horas=dfh.index.size
timeframeh=pd.Series(pd.date_range(data, periods=horas, freq="h")) #Creates hourly periods, day starts at 00:00 and ends at 23:00
dfh.set_index(timeframeh, inplace=True)                            #Sets the Data frame's index as a the timeframe
dfh.columns=['Production (kWh)']                                   #Names the existing column

dfh=dfh.fillna(method='ffill')                                        #Fills empty rows with the previous value
dfh.loc[dfh['Production (kWh)'] < 0, 'Production (kWh)'] = 0          #Eliminates negative values
dfh.loc[dfh['Production (kWh)'] > nompow, 'Production (kWh)'] = nompow  #Doesn't allow values higher than the nominal power

dfh.head()                                                            #Returns the first 5 rows
```

Figure C.2 – Block 2

Tariff data

```
print ('Tariff excel files must have a specific configuration:','\n',
        'Days must be in ascending order of columns', '\n',
        'Tariff values must be in ascending order of rows', '\n',
        'The first 3 rows and the first column must not include tariff values. ')


direct2=input('Directory of the excel file containing the tariff values: ')


years=int(dfh.index.size/365/24)
year=[]
for i in range(years):
    year.append(int(data)+i)          #Creates list with titles of the excel pages


tariftot=[]
for i in year:
    tarifa=pd.read_excel(direct2, sheet_name=str(i))
    if i/4!=0:
        y=366
    else:                    #Leap year
        y=367
    for j in range (1,y):
        for k in range (2,26):
            tariftot.append(tarifa.iat[k,j])


dfh['Tariff €/MWh']=tariftot           #Creates tariff column with a specific title
dfh.head()
```

Figure C.3 – Block 3

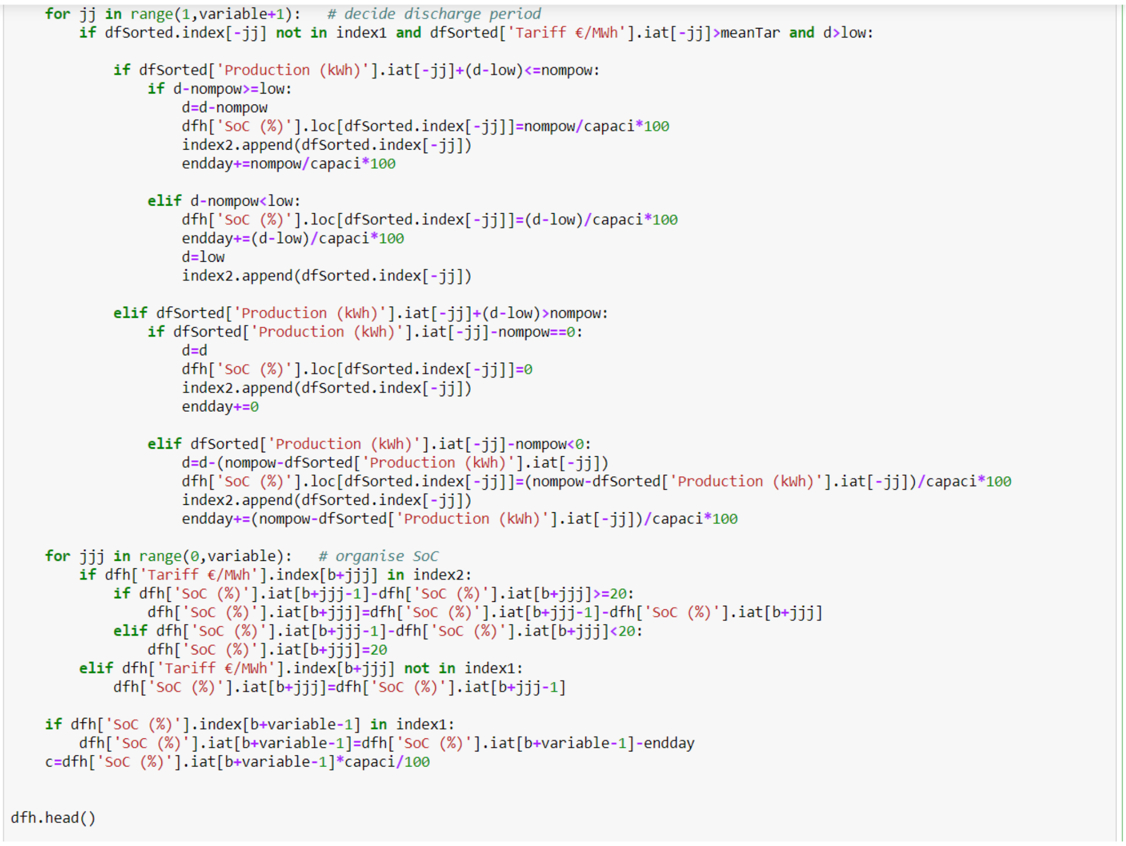
Charging the batteries

```
peri=(dfh.index.size)/24          #Number of days
days= int(peri)


soc=[]
for i in range (0, int(peri)*24):
    soc.append(0)
dfh['SoC (%)']=soc
extra=[]


low=0.2*capaci               #defining lower and upper threshold for battery charging, can be altered easily
up=0.8*capaci


c=0
d=0
b=0
x=0

interval=4
days=int(days*interval)
variable=int(24/interval)


for i in range(0,days):

    endday=0
    index1=[]
    index2=[]
    b=24*i

    dfc=dfh.iloc[b:b+24]
    dfSorted=dfc.sort_values(by=['Tariff €/MWh'])
    meanTar=dfSorted['Tariff €/MWh'].mean()

    for j in range(0,variable):     # decide charging period
```

Figure C.4 – Block 4.1

```
    for j in range(0,variable):     # decide charging period

        if dfSorted['Tariff €/MWh'].iat[j]<=meanTar and c<up:
            c+=dfSorted['Production (kWh)'].iat[j]
            index1.append(dfSorted.index[j])

            if c<up:
                dfh['SoC (%)'].loc[dfSorted.index[j]]=dfSorted['Production (kWh)'].iat[j]/capaci*100

            elif c>=up:
                dfh['SoC (%)'].loc[dfSorted.index[j]]=(dfSorted['Production (kWh)'].iat[j]-(c-up))/capaci*100
                c=up


    for jjj in range(0,variable):     # organise SoC

        if dfh['Tariff €/MWh'].index[b+jjj] in index1:
            dfh['SoC (%)'].iat[b+jjj]=dfh['SoC (%)'].iat[b+jjj-1]+dfh['SoC (%)'].iat[b+jjj]

        else:
            dfh['SoC (%)'].iat[b+jjj]=dfh['SoC (%)'].iat[b+jjj-1]

        if dfh['Tariff €/MWh'].iat[b+jjj]==dfSorted['Tariff €/MWh'].iat[-1]:
            d=dfh['SoC (%)'].iat[b+jjj]*capaci/100


    for jj in range(1,variable+1):    # decide discharge period
        if dfSorted.index[-jj] not in index1 and dfSorted['Tariff €/MWh'].iat[-jj]>meanTar and d>low:
```

Figure C.5 – Block 4.2



```
    for jj in range(1,variable+1):   # decide discharge period
        if dfSorted.index[-jj] not in index1 and dfSorted['Tariff €/MWh'].iat[-jj]>meanTar and d>low:

            if dfSorted['Production (kWh)'].iat[-jj]+(d-low)<=nompow:
                if d-nompow>=low:
                    d=d-nompow
                    dfh['SoC (%)'].loc[dfSorted.index[-jj]]=nompow/capaci*100
                    index2.append(dfSorted.index[-jj])
                    endday+=nompow/capaci*100

                elif d-nompow<low:
                    dfh['SoC (%)'].loc[dfSorted.index[-jj]]=(d-low)/capaci*100
                    endday+=(d-low)/capaci*100
                    d=low
                    index2.append(dfSorted.index[-jj])

            elif dfSorted['Production (kWh)'].iat[-jj]+(d-low)>nompow:
                if dfSorted['Production (kWh)'].iat[-jj]-nompow==0:
                    d=d
                    dfh['SoC (%)'].loc[dfSorted.index[-jj]]=0
                    index2.append(dfSorted.index[-jj])
                    endday+=0

                elif dfSorted['Production (kWh)'].iat[-jj]-nompow<0:
                    d=d-(nompow-dfSorted['Production (kWh)'].iat[-jj])
                    dfh['SoC (%)'].loc[dfSorted.index[-jj]]=(nompow-dfSorted['Production (kWh)'].iat[-jj])/capaci*100
                    index2.append(dfSorted.index[-jj])
                    endday+=(nompow-dfSorted['Production (kWh)'].iat[-jj])/capaci*100

    for jjj in range(0,variable):   # organise SoC
        if dfh['Tariff €/MWh'].index[b+jjj] in index2:
            if dfh['SoC (%)'].iat[b+jjj-1]-dfh['SoC (%)'].iat[b+jjj]>=20:
                dfh['SoC (%)'].iat[b+jjj]=dfh['SoC (%)'].iat[b+jjj-1]-dfh['SoC (%)'].iat[b+jjj]
            elif dfh['SoC (%)'].iat[b+jjj-1]-dfh['SoC (%)'].iat[b+jjj]<20:
                dfh['SoC (%)'].iat[b+jjj]=20
        elif dfh['Tariff €/MWh'].index[b+jjj] not in index1:
            dfh['SoC (%)'].iat[b+jjj]=dfh['SoC (%)'].iat[b+jjj-1]

    if dfh['SoC (%)'].index[b+variable-1] in index1:
        dfh['SoC (%)'].iat[b+variable-1]=dfh['SoC (%)'].iat[b+variable-1]-endday
    c=dfh['SoC (%)'].iat[b+variable-1]*capaci/100


dfh.head()
```

Figure C.6 – Block 4.3

Turnover

> No BESS

```
dfh['No BESS (€)']=dfh['Production (kWh)']*dfh['Tariff €/MWh']/1000

dfh['No BESS (€)']=dfh['No BESS (€)'].cumsum()
```

> With BESS

```
dfh['With BESS (€)']=dfh['Production (kWh)']
u=[]
b=0
for i in range(1,horas):

    if dfh['SoC (%)'].iat[i]<dfh['SoC (%)'].iat[i-1]:
        x=dfh['Production (kWh)'].iat[i]+(dfh['SoC (%)'].iat[i-1]-dfh['SoC (%)'].iat[i])*capaci/100
        dfh['With BESS (€)'].iat[i]=x

    if dfh['SoC (%)'].iat[i]>dfh['SoC (%)'].iat[i-1]:
        x=dfh['Production (kWh)'].iat[i]-(dfh['SoC (%)'].iat[i]-dfh['SoC (%)'].iat[i-1])*capaci/100
        dfh['With BESS (€)'].iat[i]=x

dfh['With BESS (€)']=dfh['With BESS (€)']*dfh['Tariff €/MWh']/1000
dfh['With BESS (€)']=dfh['With BESS (€)'].cumsum()
```

Figure C.7 – Block 5

Important values

```
percent=(dfh['With BESS (€)'].iat[-1]/dfh['No BESS (€)'].iat[-1])*100-100
difference=dfh['With BESS (€)'].iat[-1]-dfh['No BESS (€)'].iat[-1]

print('Percentual increase','--->',int(percent), '%')
print('Battery price for a PBP of 20 years','--->', int(dif/capaci), '€/kWh')
print('Turnover over no BESS farm','--->',dif)
```

```
# Cycle counting
dfh['Cycles']=dfh['SoC (%)']
for i in range(0,horas-1):
    dfh['Cycles'].iat[i+1]=dfh['SoC (%)'].iat[i+1]-dfh['SoC (%)'].iat[i]

    if dfh['Cycles'].iat[i]<0:
        dfh['Cycles'].iat[i]=0

dfh['Cycles']=dfh['Cycles']/100
dfh['Cycles']=dfh['Cycles'].cumsum()

print('Number of cycles is','--->', dfh['Cycles'].iat[-1])
```

Figure C.8 – Block 6

Graphs

```
Seasons

['2017-03-01':'2017-05-31']       #Spring
['2017-06-01':'2017-08-31']       #Summer
['2017-09-01':'2017-11-30']       #Autumn
['2017-12-01':'2018-02']          #Winter
```

- **Production**

```
ax=dfh['Production (kWh)'].loc['2017-01':'2017-02'].plot(kind='line', figsize=(12, 9), title='Production (kWh)')
```

- **Tariff**

```
ax=dfh['Tariff €/MWh'].loc['2017-01':'2017-02'].plot(kind='line',figsize=(12, 9), title='Tariff (€/MWh)')
```

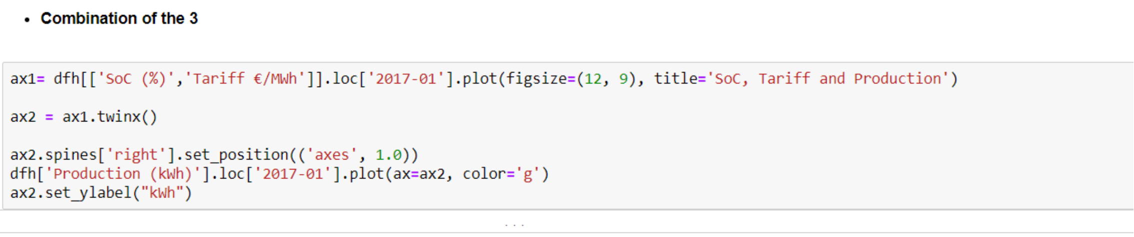
- **State of Charge**

```
ax=dfh['SoC (%)'].loc['2017-01':'2017-02'].plot(kind='line',figsize=(12, 9), title='SoC (%)')
```

- **SoC and Tariff**

```
ax=dfh[['SoC (%)','Tariff €/MWh']].loc['2017-01'].plot(kind='line', figsize=(12, 9), title='SoC and Tariff')
```

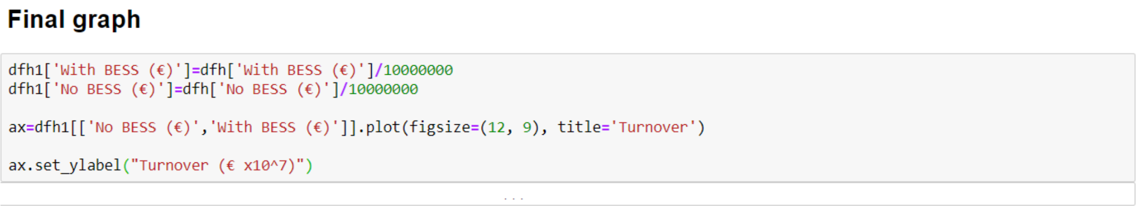
Figure C.9 – Block 7.1



- **Combination of the 3**

```
ax1= dfh[['SoC (%)','Tariff €/MWh']].loc['2017-01'].plot(figsize=(12, 9), title='SoC, Tariff and Production')

ax2 = ax1.twinx()

ax2.spines['right'].set_position(('axes', 1.0))
dfh['Production (kWh)'].loc['2017-01'].plot(ax=ax2, color='g')
ax2.set_ylabel("kWh")
```

Figure C.10 – Block 7.2



Final graph

```
dfh1['With BESS (€)']=dfh['With BESS (€)']/10000000
dfh1['No BESS (€)']=dfh['No BESS (€)']/10000000

ax=dfh1[['No BESS (€)','With BESS (€)']].plot(figsize=(12, 9), title='Turnover')

ax.set_ylabel("Turnover (€ x10^7)")
```

Figure C.11 – Block 8