Multiple Market Participation of Battery Storage System

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I would like to dedicate this thesis to my loving parents …

Summary

In recent years, the share of renewable energy sources in the electricity networks worldwide has been in a constant increase. Wind power generation is predominated among all renewable energy sources-based generation. However, when compared with non-renewable generation its share in the electricity market is still limited. Mainly due to its lack of multiple services provision. Battery energy storage systems, on the other hand, have proven the ability to provide a wide range of services in the electricity market.

The main emphasis of this project is put on the investigation if the battery energy storage systems ability in multiple service provision could help increase the wind power share in the generation mix. For that, a hybrid system is hypothetically formulated taking into consideration battery and wind turbines technologies. Furthermore, an operational scheduling strategy which could be used by the battery energy storage system operator is used to evaluate project profitability. Considering electricity price forecast, grid arrangement and optimum unit commitment strategy and size. Moreover, to create a good business case with at least as possible uncertainties, battery energy storage system lifetime model is developed. With the model, battery degradation behavior is account for in the different services provision schemes estimated.

Analysis of the practical operation scheduling scheme developed shows a good ability in capturing the possible revenue streams from the different market while taking into consideration stochastic variables such as price. From the different market bidding strategies formulated is observed revenue values close to 18 Million dollars when a battery is providing all services in the electricity market. However, the degradation effect is also high to accommodate the rapid energy change in the battery.

Finally, it is concluded that with the integration of battery energy storage, multiple services provision are added to the wind power generation. Furthermore, the degradation should be bound by the unit commitment problem. This technology is representing an attractive solution, as high revenue streams can be derived from its multiple services provision capabilities. With the increasing research on the topic in combination with new electricity market rules to accommodate system rapid response, an increase in battery deployment is expected in the future. Not only as a utility-scale storage solution but in other applications as well.

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Nomenclature

Parameters and Constants

η_c BESS Charge Efficiency.

η_d BESS Discharge Efficiency.

γ_{dn} Actual Energy Deployed in the REGDN Market.

γ_{nsp} Actual Energy Deployed in the NSPIN Market.

γ_{ru} Actual Energy Deployed in the REGUP Market.

γ_{sp} Actual Energy Deployed in the RRS Market.

$\mu_{(t)}$ Binary Variable.

$\pi_{(t)}^{NSP}$ NSPIN Market Price at Time t.

$\pi_{(t)}^{RD}$ REGDN Market Price at Time t.

$\pi_{(t)}^{RT}$ RTM Price at Time t.

$\pi_{(t)}^{RU}$ REGUP Market Price at Time t.

$\pi_{(t)}^{SP}$ RRS Market Price at Time t.

C_c Operational Cost Due to Charge.

C_d Operational Cost Due to Discharge.

C_E BESS Purchase Cost Related to its Energy Capacity.

$C_{fade\_calendar}$ BESS Capacity Fade Due to Idling.

$C_{fade\_cycling}$ BESS Capacity Fade Due to Cycling.

C_P BESS Purchase Cost Related to its Power Capacity.

$C_{total\%}$ Total BESS Capacity Fade in Percentage.

C_w Operational Cost of the Wind Park.

cd Cycle Depth During One Cycle.

E^b_{cap} BESS Nominal Energy Capacity.

k Letter Used to Defined the Number of Years in Project Implementation.

m Storage Time in Months.

nc The Number of Cycles.

NPV_{ratio} Net Present Value Ratio.

$NPV_{t=20}$ Net Present Value after 20 years.

P^b_{cap} BESS Nominal Power Capacity.

$P^c_{(t)}$ BESS Charge Power at Time t[MW].

$P^d_{(t)}$ BESS Discharge Power at Time t[MW].

$P^{NSP}_{(t)}$ Energy Bid in the NSPIN Market at Time t.

$P^{RD}_{(t)}$ Energy Bid in the REGDN Market at Time t.

$P^{RU}_{(t)}$ Energy Bid in the REGUP Market at Time t.

$P^{SP}_{(t)}$ Energy Bid in the RRS Market at Time t.

$P^w_{(t)}$ Wind Farm Power Output at Time t[MW].

P^b_{cap} BESS Purchase Cost Related to its Power Capacity.

P^{max}_{disch} Maximum Power Allowed in Line 1 at Time t.

r The Annual Required Rate of Return.

$SoC_{(t)}$ BESS State-of-Charge at Time t.

SOC_{AV} Average SOC During One Cycle in Percentage.

SOC_{LV} SOC Storage Level in Percentage.

$\pi_{(t)}^{DAM}$ Energy price in the DAM.

Acronyms / Abbreviations

ACF Autocorrelation.

AGC Automatic Generation Control .

AIC Akaike's InformationCriterion.

ANN Artifical Neural Network .

ARIMA Autoregressive Integrated Moving Average.

AS Ancillary Service.

ASM Ancillary Service Market.

BESS Battery Energy Storage System.

CapEx Capital Expenditures.

DAM Day-ahead market.

DCS Disturbance Control Standard.

DOD Depth-of-Discharge.

DRUC Day-Ahead Reliability Unit Commitment.

E&C Engineering and Construction.

EMS Energy Management System.

ERCOT Electric Reliability Council of Texas.

FERC Federal Energy Regulatory Commission.

HRUC Hourly Reliability Unit Commitment.

IEA International Energy Agency.

ISO Independent System Operator.

Li-ion Lithium-ion .

LMP Locational Marginal Price.

LP Linear Programming.

MAPE Mean absolute percentage error

MILP Mixed Integer Linear Programming.

NERC North American Electric Reliability Corporation.

NPV Net Present Value.

NSPIN Non-spinning Reserves.

O&M Operation and Maintenance.

OpEx Operating Expenses.

PACF Partial Autocorrelation.

PSO Particle Swarm Algorithm.

QSEs Qualified Scheduling Entities.

REGDN Regulation-down.

REGUP Regulation-up.

RES Renewable Energy Sources.

RHC Receding Horizon Control.

RRS Responsive Reserves.

RTM Real-time energy market.

RTO Regional Transmission Organization.

SOC State-of-Charge.

TBATS Trigonometric Box-Cox ARMA Trend Seasonal.

TMS Thermal Management System.

USA United States of America.

WF Wind Farm.

WRUC Weekly Reliability Unit Commitment.

Chapter 1

Introduction

This chapter describes the background behind the thesis definition and introduces an overview of modern trends in storage systems. A literature review is given based on recent studies done in the topic. Furthermore, the definition of the problem which this thesis is aimed at solving is discussed along side the methodology applied to solve such problem. Finally, the limitations of the project are describe and an outline of the thesis is shown.

1.1 Background

Wind power generation have increased its share in the power generation mix, as a result of its cost-effectiveness, in recent years. According to [4], wind power additions continued at a rapid pace in 2016, with 8,203 MW of new capacity added in the United States and 13.0 billion invested. In a global scale, the report adds that 54,600 GW was commissioned in 2016. The United States of America (USA) is the second-leading market in terms of cumulative capacity and 2016 annual wind energy production, behind China. Other countries have achieved high levels of penetration as well; end-of-2016 wind power capacity was estimated to supply the equivalent of more than 40% of Denmark's electricity demand, and between 20% and 35% of demand in Portugal, Ireland, and Spain [4]. So it's clearly observed a increasing trend in use of wind power, especially in the USA, where states like Texas had the highest installed capacity in 2016 with 2,611 MW.

Despite the increase in wind power, its share in the electricity market is still small. Figure 1.1 from the International Energy Agency (IEA) shows that globally coal is the highest form of electricity generation reaching 9,551,747 GWh in 2015, while wind generation reached

838,546 GWh during the same year, showing the potential growth for wind energies in the electricity market.

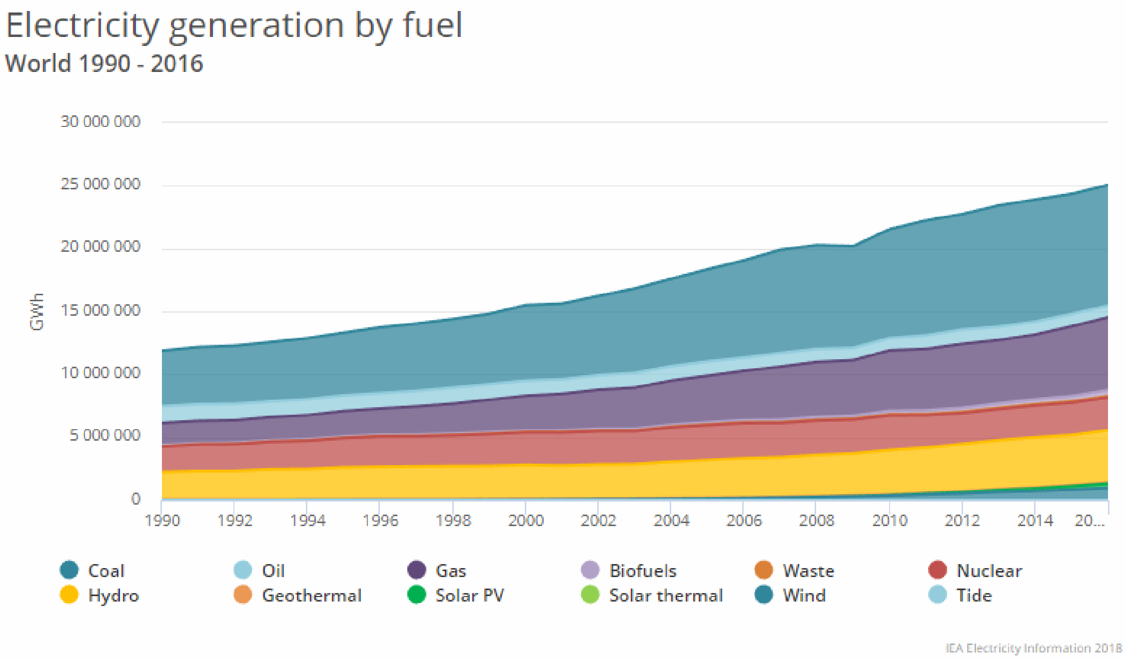

Figure 1.1 World Wide Electricity Generation by Fuel from 1990 - 2016 [5].

In the electricity market, wind generation is capable of participating in the Day-Ahead Market (DAM) operations, buying or selling energy capacity, as a stand-alone system [6]. Nonetheless, Wind Farm (WF) operators often resort to higher reserves in the power system to smooth out the unpredictable power fluctuations. After all, inconsistencies between energy offered and energy delivered can lead to high penalties [1]. Developing a grid-tied energy storage system is generally a practical solution to facilitate the massive integration of wind power [7]. These grid-tied energy storage systems help the WF fulfill its energy commitment in the DAM. Not only that but also increase the number of services a WF can provide in the electricity market, often leading to high revenue streams.Therefore, energy storage system can help increase the wind power penetration in the electricity market, by extending the number of services provided in the electricity market.

1.2 Energy Storage System

According to a recent study made for the G20 [8], energy storage systems will be at the heart of the energy renewable sources transition, providing a wide range of services that can also support the integration of variable renewable energy e.g. electric energy time shifting. Figure 1.2 illustrate the wide range of services in which a storage unit could be used in the power system. The focus of this thesis is specific on the services highlighted in red.

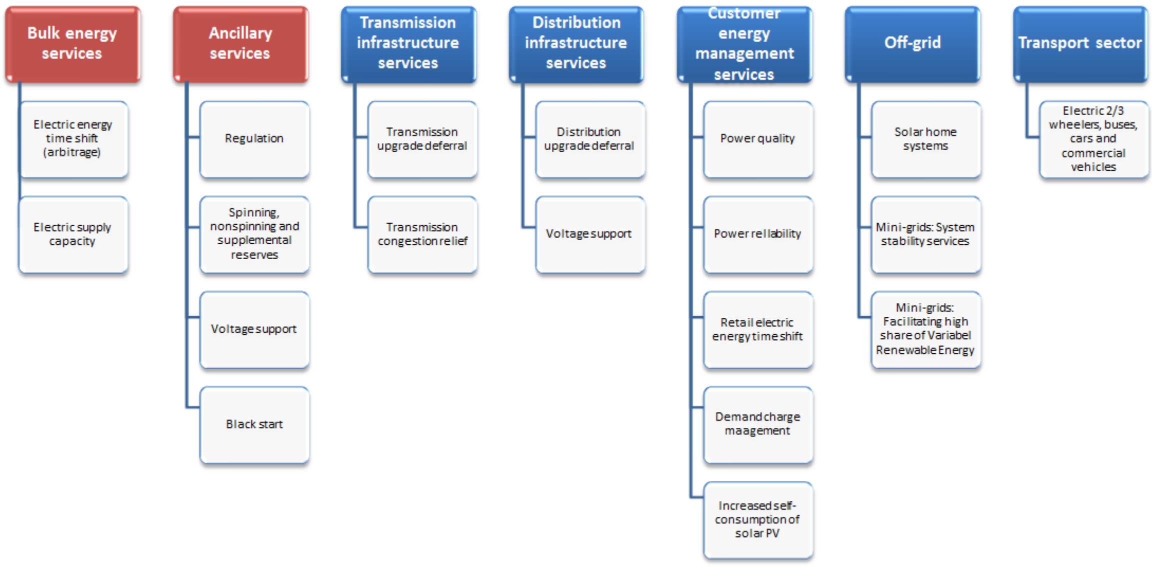

Figure 1.2 Range of Services that can be Provided by Electricity Storage [8].

According to [8], pumped hydro storage have a large share in the market when it comes to energy arbitrage. Thermal storage, on the other hand, is often used in energy arbitrage and as a supplemental reserve. However, the high turbine-heat system cost seems to be a downfall for system implementation [8]. Such systems are implemented in the electricity market due to their proven technologies and solid components reliability. However, the economics of providing grid services are more challenging especially due to fast time response required from a storage system performing ancillary services. For that reason, when it comes to frequency regulation the most used form of storage is Battery Energy Storage System (BESS), these types of storage can participate in both services highlighted in red (Figure 1.2). Even though they have been used as solutions; their profitability has been questionable, mainly to wrong assessment of possible streams revenues [9].

Nevertheless, in recent years the deployment of BESS as one storage solution for wind power applications has significantly grown, especially due to the fallen cost of implementation [10].

1.2.1 Battery Energy Storage System

Integrating BESS offers enormous benefits to increase the wind power share in the electricity market. According to [11], battery as a storage unit can improve power quality, deferring investment in transmission and distribution network, and provide ancillary services to the system. Moreover, a BESS can lessen the need for emergency reserves of energy.

In the electricity market, a BESS can provide different types of services, which allows it to participate in different markets bidding strategies [12]. The BESS's ability to participate in multiple market services has been proven in [13, 14], where different projects around the globe are presented. In Berlin an 8.5 MW / 8.5 MWh battery is used to provide spinning reserve and frequency control, whereas in the USA an 8 MW / 2MWh battery is used for frequency regulation and wind turbine integration.

The ability to derive multiple revenue streams by providing a range of services with one storage system enables the "stacking" of revenue and improvement in project implementation. For instance, Table 1.1 present the profit increase of a 100 MW hypothetical generation plant when the ancillary service market is considered as form of revenue [3]. The 81% increase shows a clear potential in considering multiple market services provision, from a generation unit perspective.

Table 1.1 Selling ancillary services in addition to energy increases profits in Texas for 2005 simulation of a 100 MW hypothetical engine driven generating plant [3].

Annual profits in $ millions	Texas
Energy Only	$6.3
Energy when selling AS	$4.1
Regulation	$2.1
Spin	$1.3
Non-Spin	$3.9
Total With Energy & AS	$11.3
Additional Profit	**$5.1**
Increase	**81%**

Ultimately, by combining the BESS and the wind generation in a hybrid system, the operator could exploit the potential profitability of multiple markets. Through BESS proven ability to provide multiple services and the cheap energy generation from wind turbines [12].

Nevertheless, BESS are complex systems with a wide range of possible structures and peculiarities. Therefore, when analyzing profit with such systems the best approach is often to define one technology in the studies. This reduces the search space, leading to more precise results.

1.2.2 Lithium-ion Batteries

There are different types of battery technologies, which can be divided based on their chemical reactions. Lead–acid batteries have high time response, but low charge/discharge cycling number, up to 2000, describing the battery lifetime. Sodium–sulfur batteries, on the other hand, have higher cycling times, up to 4500. However, these batteries have high operational cost (80 $/kW/year) [14].

Leading technology in grid-based battery energy storage is Lithium-ion (Li-ion) batteries, which have become an established technology in portable electronics and electric vehicle applications due to their high energy density. The market for grid-based Li-ion batteries is expected to grow significantly over the coming years. Analysts predict that approximately 28,000 MW of Li-ion storage will be installed globally between 2014 and 2024, comprising the greatest share (35%) of total new grid energy storage capacity [15].

This expected growth is mainly based on the Li-ion batteries proficiencies: fast time response, high power capability, long cycle lifetime at partial charge/discharge cycles, low self-discharge rate and long calendar lifetime. Despite the increasing deployment of such technologies in recent years, one of the massive drawbacks in the installation of Li-ion BESS units for stationary storage applications is its economic viability [16]. To evaluate the economical viability of Li-ion BESS, it is first necessary to understand the parameters which largely impact the implementation of this technology.

The first parameter is the size of the BESS. This parameter has great effect on purchase cost of BESS. A BESS can be sized based on its power and energy capacity. The power capacity of a BESS is strong related to its converter size. The power converter must be able to accommodate the maximum amount of power that can be drawn from the battery at any given time. Similarly, the energy capacity of the BESS, is related to the maximum amount of energy a BESS can store at any given time. In many cases, the usable energy capacity is less than the advertised nominal one. This difference is accommodated by limiting the battery State-of-Charge (SOC) within an upper and lower limit during operations [16].

The SOC is given, in terms of percentage, as the amount of energy stored in the battery at a given time t divided by its capacity, as shown in Equation 1.1. Limiting the SOC range can also help in battery damage mitigation, once rechargeable batteries are not meant to be fully discharged [16].

$$SoC = \frac{E_{(t)}}{E_{cap}} * 100 \tag{1.1}$$

The second important parameter to be considered when dealing with Li-ion battery is its lifetime model. This parameter has a great effect in battery operation, when not considered the observed revenue from the storage is unrealistic, once its capacity during operation is not the same throughout the simulated interval.

The charging-discharging cycling and calendar life, are the key factors influencing a BESS lifetime. The first one represents the number of cycles a battery can perform for different cycle depths until its capacity degrades to 80% of its original capacity. At this stage, the battery presents a non-linear behavior and is assumed "dead". The last factor represents the degradation behavior of a battery at a specific SOC level at which the battery is idle [17].

Therefore an optimum operation scheme must be used when evaluating the profitability of Li-ion BESS in multiple market services provision. This BESS operation must consider the two parameters presented in this section, size and degradation. In order to present a conclusive implementation assessment.

Hereafter, a brief literature review is presented, describing how different studies have considered these parameters when evaluating the profitability of BESS in multiple market schemes.

1.3 Literature Review

Many papers have undertaken the problem of finding the revenue streams of different markets from an integrated storage system. However, when it comes to a battery energy storage system the research is actually scarce, to the best of the author's knowledge. The papers only discuss a few types of market bidding strategies, missing different possibilities of market revenue streams [18, 19].

Most of the present literature use the Linear Programming (LP) or the Mixed Integer Linear Programming (MILP) approach to solve the BESS power commitment problem i.e. when to charge and discharge energy. This is often done in order to define the revenue prospects from energy arbitrage only, neglecting other markets revenue [18–21]. However, a drawback of such analyses is the lack of degradation effect for the BESS.

As recognized in [17] a battery has power and energy capacity often refer as nominal capacity. This capacity, however, diminishes over battery use. A linear degradation model is often used to quantify this effect. This results in a wrong assessment of actual profitability as shown in [22], where a linear and a cycle counting model were used to quantify degradation. The results show that the battery degradation is a non-linear function depending on charging-discharging cycles and calendar lifetime [17].

Some papers [17, 22–24] have derive formulations on the relation between battery cycle life and Depth-of-Discharge (DOD) using different fitting techniques. Generally, an equation is derived to represent the battery lifetime, based on information found on the manufacturer datasheet. Such equation gives a relationship between DOD[1] and lifetime.

Regardless of the specified cycle life model, a rainflow[2] counting algorithm is commonly used to calculate a battery's lifetime. As referenced in [17, 25, 26]. The issue with such an approach is the computational burden; rainflow algorithms are black-box equations of fatigue analyses with exponential equations presenting a non-linear behavior leading to complexity. This complexity can be enough to turn a feasible problem into an infeasible one. Nonetheless, most of these studies only assess the storage in one market, or similar to [18, 27], two markets.

The battery profitability is co-dependent of its degradation, disregarding degradation in the optimum bidding strategy would make the battery use all its capacity blindly. Authors in [27] used a combine economic-degradation model, where they calculated revenue and degradation associated with 11 operational policies aimed at constraining SOC range used. The best policy found was to keep the SOC within a smaller swing range (e.g. 0-25%), only two markets were used in this study. However, this range can change depending on battery purpose, in [24] the SOC range used for a microgrid application was 35% - 65%. Therefore, there is a relationship between using less available energy capacity and battery's project profit.

In terms of operational strategy for the BESS, authors in [26, 28, 29] used combined forecast-operation strategy to evaluate actual revenue from storage systems. This is often done to evaluate the real revenue from systems with stochastic variables, such as energy price. The receding horizon operation is often used as a good real operation strategy, where the stochastic variables are forecast for a receding horizon e.g. one day or one week. Then, the battery scheduling operation is defined based on the forecasted variables [26, 29].

[1] The DOD is the inverse of the SOC; 1 - SOC.

[2] A common methodology used in material fatigue analysis.

When it comes to accessing BESS size, it is also observed that most papers fix the battery capacity in order to evaluate project implementation [18–21], which does not provide an optimum size for each market bid schemes. Considering optimum size in a MILP would create a non-convex problem since the battery capacity is defined by its maximum power charge/discharge [3].

With the information presented in this section is possible to describe a few key points below. These key points are necessary to better comprehend the problem investigated in this thesis.

1. The BESS requires a optimum unit commitment strategy, often done using MILP in the literature.

2. The BESS degradation needs to be assessed. However, the algorithm used to quantify it leads to non-linearity in the MILP formulation.

3. A receding horizon strategy is often used to defined the profitability of a BESS. Which requires a forecasting method.

4. When considering different revenue streams, the BESS size is often fixed and different markets schemes are neglected in the profitability analysis.

Therefore, a real operation strategy that takes into consideration these key points must be used in order to assess which market scheme provides the highest profitability. The information presented in previous sections is used to define the investigated problem in the following section.

1.4 Problem Definition

Considering the information presented in the background section that wind power generation has a low share in the electricity market mix. This Master's thesis focuses on investigating the possible revenue streams accrue from a BESS-WF hybrid system participating in multiple market services provision. Different forms of revenue streams are studied in order to evaluate monetary compensation and profitability in implementing a Li-ion BESS alongside a WF.

The BESS profitability in multiple market services provision is evaluated through a real scheduling operation. Such an operation takes into consideration different market bid strategies, optimum unit dispatch, and price forecast. The scheduled operation is conducted

[3] Is possible to make such problem convex by only looking at revenue and battery cost.

for yearly data to account for seasonal patterns. The year 2017 is chosen due to its wide range of available data.

A cost-benefit analysis is issued to evaluate the best market bid scheme and project profitability. Taking into consideration, BESS degradation, BESS size, BESS revenue and BESS operating expenditure.

Different electricity markets have different rules and regulations. Therefore, the Texan market in the USA is used in the carried out analysis due to its large free available data. However, the methodology demonstrated can be used for different markets noting their respective rules. To accomplish such analysis important objectives are defined in the next section.

1.5 Project Objectives

A bottom-up approach is used to defined the thesis objectives. Firstly, in order to evaluate the profitability in multiple market provision, the market used must be defined. Therefore, the Texan electricity market is to be investigated and its rules and regulations interpreted. Subsequently, the hypothetical hybrid system inserted in this market must be describe, serving as foundation for the practical operation strategy.

The practical operation strategy is developed for the battery owner considering price forecast and optimum BESS unit commitment. Therefore, a price forecast method, which can be used for different markets, must be establish. Furthermore, the BESS unit commitment ought to be formulated taking into consideration the different market schemes and hybrid system parameters.

With the market and hybrid system information; the price forecast method and BESS unit commitment formulated, the practical operation scheme is to be develop. Ultimately, a cost-benefit analysis considering degradation and economical terms is done to evaluate the BESS profitability

In summary, this thesis will focus on the following specific objectives:

1. Assess the Texan electricity market rules and regulations.

2. Develop an hypothetical hybrid system to be used in the analysis.

3. Define a price forecast method to be used in the practical operation scheme.

4. Investigating different optimization methods for correct sizing and market operation of BESS.

5. Determining different market bidding scenarios in order to make a comprehensive profitability analysis.

6. Identifying a practical operation scheme to be used for the BESS owner in real world operations.

7. Implement an economic assessment do identify the optimum market bid scheme. Considering BESS degradation.

8. Implement a sensitivity analysis to identify the cost-benefits in restricting BESS energy capacity.

With the objectives defined, the methodology used to archive them is describe in the following section.

1.6 Project Methodology

The hypothetical BESS-WF hybrid system used in the multiple market participation of battery storage system analysis is formulated taking into consideration important wind turbine and battery parameters.

An electricity price forecast is identified comparing three different forecast methods present in price forecasting literature [2]. The best forecast method identification is done using the software R® and MATLAB®.

The BESS profitability will be assessed through a combination of two heuristic algorithms. The first algorithm is created using the optimization formulation program YALMIP® [30], to deal with the BESS optimum unit commitment problem. The problem is built as a MILP, for each market bid scheme analyzed. The software package Gurobi® [31] is used to solve each MILP defined. The second algorithm is develop based on evolutionary optimization theory and solved using MATLAB® to identify the optimum BESS size considering degradation and economic terms.

The practical operation of the system is developed taking into consideration the forecast and mathematical formulations previously explained. Different cases of market bidding are assessed to defined the best bidding scheme and the actual profitability of implementing the BESS along with a sensitivity analysis. The flowchart in Figure 1.3 helps clarify the project methodology.

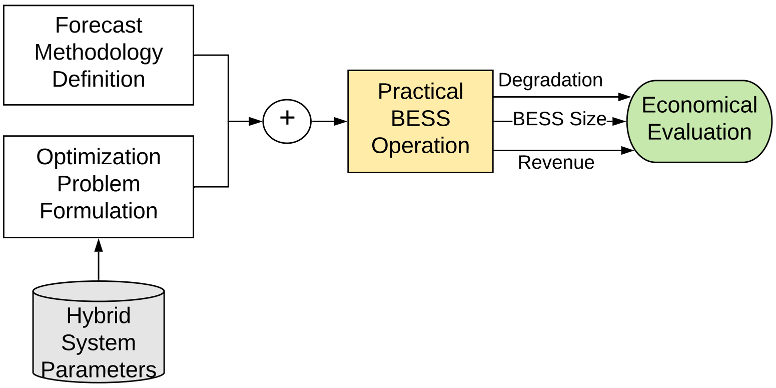

Figure 1.3 Simplify Thesis Methodology Flowchart.

1.7 Limitations

The limitations of this project are considered to be the following:

- No maintenance downtime is assumed.
- No cost related to generation use is considered.
- The BESS degradation is not defined as part of the unit commitment problem.
- No convex rainflow transformation is assessed.
- The analyses are limited by the available data in the ERCOT market.
- No reactive power constraints are considered since the system is not formulated for such intention.

1.8 Outline of the Thesis

This thesis consists of seven chapters, summarised below.

- Chapter 1 - Introduction:
  In this chapter, the background of the study is presented. First, an overview of the recent trend in renewable is presented. Subsequently, the problem aimed to be analyzed is explained with the methodology and its limitation.

- Chapter 2 - Electricity Market:
  With the focus on possible revenue streams in energy bidding. An overview of the American electricity market is given, to better grasp the rules and regulations present in the market used for the analyses, necessary to formulate the optimization problem.

- Chapter 3 - Hybrid System Components:
  This chapter describes the hybrid system used in the analyses carried out. In parallel, presenting key elements, in each component, necessary for profitability evaluation.

- Chapter 4 - Price Forecast:
  In this chapter, the forecast methods are presented. Different forecast methods are evaluated. Eventually, the forecast method with the smallest errors is used to forecast price in different markets.

- Chapter 5 - Optimization Problem Formulation:
  Relevant cases to evaluate are presented in this chapter. These consider different market bid schemes, constraints and revenue streams. Each case is validated to prove its mathematical formulation. The optimization procedure is explained in stages, one dealing with optimum dispatch and another stage dealing with the economical implementation. Subsequently, a benchmark case is used to evaluate the mathematical formulation of the optimization procedure.

- Chapter 6 - Operating Schedule Strategy:
  In this chapter, a scheduling strategy is assessed. The cases defined in Chapter 5 are used to obtain the battery's size that best suits each bid scheme defined. An examination is carried out on the results for the practical operation. The project implementation are assess alongside a sensitivity analysis.

- Chapter 7 - Conclusion:
  The summary and conclusion of the thesis are presented in this chapter. In addition, the possible further work based on this project is discussed.

Chapter 2

Electricity Markets

A brief overview of the USA power market is given in this chapter, with a focus in the ERCOT market schemes. This chapter captures the rules and regulations present in the energy arbitrage and ancillary service markets, explaining the different services and operations found in both markets.

2.1 Introduction

The electricity market is a mechanism used for trading electrical energy between producers and consumers. The institute of electricity markets has evolved significantly over the period of its existence. Its working principle has a high complexity [32]. Most of its complexity accrues from the fact that electricity may not be stored on a large scale. Thus, it has to be consumed at the moment it is generated. Any unbalance between production and consumption causes instability in the power system and decreases system reliability [32].

There are seven distinct power markets in the USA (Figure 2.1). In addition, there are three similar markets located within Canada. These markets are each operated by an Independent System Operator (ISO) or Regional Transmission Organization (RTO), hereafter jointly referred to as in ISO/RTO. Each ISO/RTO manages the transmission infrastructure in its service territory, administers markets for energy and ancillary services, and is responsible for ensuring system reliability requirements established by the North American Electric Reliability Corporation (NERC) are met.

With the exception of the Electric Reliability Council of Texas (ERCOT), each ISO/RTO is subject to the jurisdiction of the Federal Energy Regulatory Commission (FERC). As the

ERCOT system is wholly contained within a single state, it does not participate in interstate commerce and is therefore not subject to FERC jurisdiction [33].

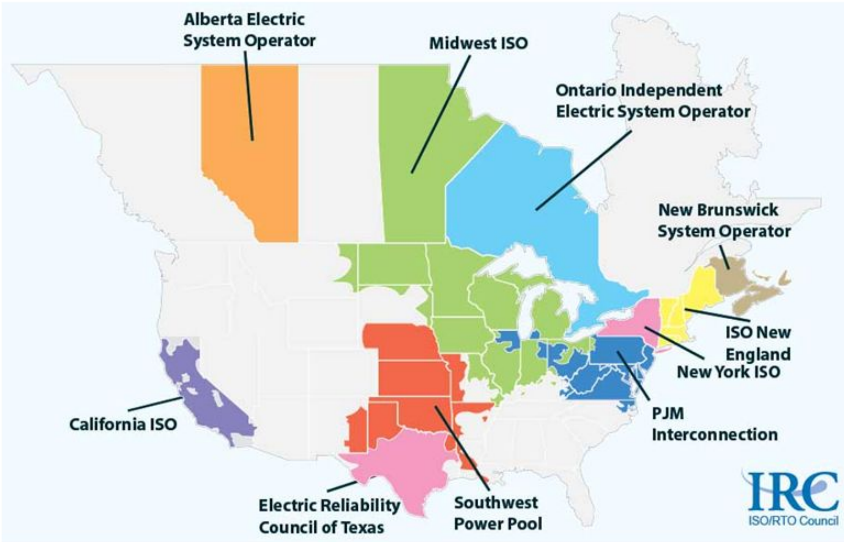

Figure 2.1 Map of the Transmission Operators that Serve the USA.

A subset of these ancillary services are commonly procured through market-based mechanisms; namely: regulation, spinning, and non-spinning Reserves [33].

In order to respond to supply/demand imbalances over one to several seconds resources that provide regulation reserves are needed. These resources adjust their generation or load levels in response to Automatic Generation Control (AGC) signals provided by the system operator [33]. Operating reserves are maintain to provide additional generation capacity in the event of load increase or other supply-side resources reduce their output or are taken offline. These reserves are typically separated into two categories: spinning, and non-spinning reserves.

Each of the seven power markets in the USA offers its own set of ancillary services, and precise definitions, requirements, and market mechanisms differ between markets. Accordingly the ERCOT market display high price volatility, not only in energy arbitrage prices but also in the ancillary services market. This volatility can lead to high revenue. The market also has solid ancillary services rules and regulations, imperative information to define a BESS operation. Furthermore, the area regulated by ERCOT has high wind power penetration, making it a good candidate to test the profitability of a battery associated with a wind park.

Therefore the ERCOT market is chosen for the analysis carried out in this thesis, its description is given in the following section.

2.2 ERCOT

2.2.1 Overview

ERCOT was organized in its present form in 1970 as one of the ten Regional Reliability Councils within NERC. Figure 2.2 represents the zones operated by ERCOT in Texas, the state is divided into four interconnected zones. In the Zonal market scheme, a price is established across a large geographic area to represent the value of energy in that area. ERCOT covers most—but not all—of the state of Texas (75%), which entails to 85% of the electric load in Texas comprise of 23 million Texas customers. It has an overall generating capacity of approximately 80,000 MW with 68,305 MW recorded on August 3, 2011.

Figure 2.2 ERCOT Coverage and Zones

ERCOT must match generation output and system demand to ensure day-to-day reliability of the transmission grid. Therefore, continual dispatch of generation is required to meet the system demand fluctuations. ERCOT perform this dispatch at the least cost executing competitive markets to purchase energy and capacity services needed to reliably serve the system demand. ERCOT must also be able to respond quickly to ever-changing system conditions, including rapidly increasing or decreasing demand or sudden loss of generation. Thus, ERCOT procures and reserves additional capacity from certain generators that can respond quickly enough to meet changing system conditions, called ancillary services [6].

2.2.2 Market Operation

Market prices and schedules are decided in one round, after receiving bids from generators and demand day-ahead. ERCOT calculates the energy output of each electrical busbar based on the offer made by the generation plant connected in the busbar. By doing so ERCOT clears the market and establishes an electricity price, which is equal to the marginal cost of providing an additional unit of generation at a particular time and place on the grid. ERCOT uses a Nodal Market strategy, in summary, that means that a Locational Marginal Price (LMP) is calculated in every power plant point of connection in the system to later be arranged in a settlement point price [1].

Two processes that are completed in the day-ahead operation are DAM and Day-Ahead Reliability Unit Commitment (DRUC). The DAM allows Qualified Scheduling Entities (QSEs) to bid and/or offer energy and to offer ancillary services. The DRUC ensures that there is sufficient generation capacity committed in the proper locations to reliably serve the forecasted load and forecasted transmission congestion by committing offline resources if required [6]. Figure 2.3 illustrate the day-ahead operation and the operating day activities, where an Hourly RUC (HRUC) is fed with updated demand and wind forecast performed every hour and within the operating hour and economical dispatch is realized every 5 minutes.

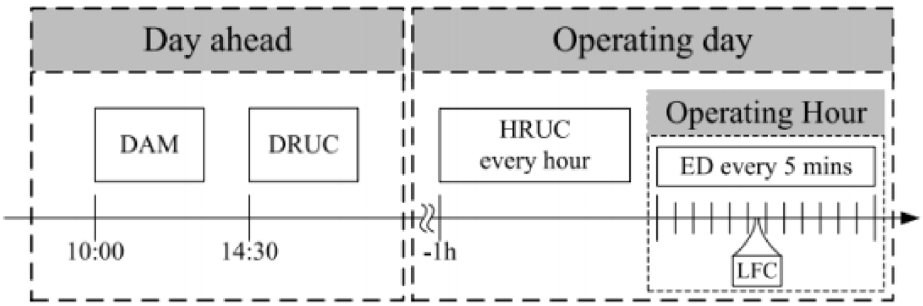

Figure 2.3 ERCOT Practical Operation (simplified).

ERCOT also operates a DAM for four ancillary services, Responsive Reserves (RRS), Regulation-up (REGUP), Regulation-down (REGDN), and Non-spinning Reserves (NSPIN). These services are co-optimized along with energy provisions in the DAM [6].

- Ancillary Service (AS) awards are physically binding. It is not permitted to change the quantity of AS awarded through the ERCOT procurement process.
- DAM Energy Only, awards are financially binding, but not physically.

- DRUC is used to ensure reliability for the ERCOT transmission grid.

Qualified QSEs to provide ancillary services provides a bid for one to all four of the services in the AS Market (ASM). The bid consists of an amount of capacity offered (in MW) and the resource operator’s willingness to sell that capacity (in $/MW per hour). These bids are "stack" in merit order and ERCOT establishes a market clearing price at the bid price of the last bidder needed to purchase the required amount of each ancillary service [1]. QSEs can submit offers in which the same capacity is offered into more than one of these markets [1].

2.2.3 Ancillary Services

As explained the specific services offered and exact definitions of each service differ from market to market. Winning bids for energy and ancillary services are mutually exclusive, but a generator can be compensated for both generation and ancillary service provision in the same period as long as the capacities allocated to each do not overlap. According to [1], "Ancillary Services are those services necessary to support the transmission of energy from resources to loads while maintaining reliable operation of transmission provider’s transmission systems in accordance with Good Utility Practice." AS products receive a "capacity payment", stand by with excess capacity to provide electricity to the grid generates profits in this case.

Regulation Reserve

Regulation service is used to constantly and automatically balance small fluctuations in supply and demand in real time. Generation units that are providing regulation service must be able to respond to AGC signals from the system operator and change their output accordingly on very short time scales, typically on the order of one to several seconds [34]. ERCOT offers separate products for REGUP and REGDN. REGUP means the capacity available to increase output i.e. a generator can increase its power output. REGDN means the capacity available to decrease output, for instance a BESS present this ability when charging energy.

Responsive Reserve (RRS)

Response reserve, sometimes also referred to as spinning reserves or synchronized reserves, are intended to help the system respond quickly to forced outages or other contingency events. Spinning reserves are provided by generation units that are online but are not generating at full capacity and can, therefore, increase their output quickly to provide additional capacity to the system [34]. Typically, generation units must be able to fully ramp up their generation within 10 to 15 minutes of receiving instructions to do so, depending on the details of the market [34]. ERCOT responsive reserves are calculated in four-hour blocks on the basis of forecasted load and wind patterns.

Non-Spinning Reserve (NSPIN)

Non-spinning reserves, sometimes referred to as supplemental reserves, are also intended to help the system recover from unplanned contingencies. However, non-spinning reserves can also be provided by generation units that are offline, as long as they are able to start up and increase their output to the target level within a predefined period of time, 30 minutes for ERCOT's market [34]. Online units with available capacity can also provide non-spinning reserves. Therefore, the amount of non-spinning reserve capacity in a system is often calculated inclusive of any surplus spinning reserve capacity [1, 34].

The ERCOT market is extensive and complex, with different types of operations and parameters calculations. However, most of this information is neglected and only the important points are presented in this chapter. A summary of the key points to be remembered is given in the following section.

2.3 Summary

In this chapter the USA electricity market structure is described to set the foundation of the ERCOT market. Furthermore, the ERCOT market used in the analyses is defined. Its market operations are discussed, taking into consideration key elements such as day-ahead operations and energy bids transactions. ERCOT possess two different markets, the energy arbitrage, and the ancillary services market. The ancillary service market is subdivided into four distinctively markets: REGUP, REGDN, RRS, and NSPIN. Each of these services is explained taking into consideration the most relevant facts to demonstrate how a BESS can provide them. In order to analyze BESS rentability in multiple market provision from a WF operator point of view, a theoretical hybrid system is used. The following chapter will describe such a system and its components.

Chapter 3

Hybrid System Components

This chapter describes the wind farm and battery balance of plant. The output power of the wind farm is addressed. Lastly, the key parameters of each component are described individually.

3.1 Balance of Plant

The hybrid system is composed of wind turbines and a battery system, these elements are presumed to be inside the WF structure studied. The simplistic wind turbines and BESS arrangement used for the studies is given in Figure 3.1. It is assumed that the WF and the BESS are connected at the Busbar by two different lines. The BESS consists of a Thermal and Energy Management unit, TMS and EMS respectively, and a battery pack with modules made of battery's cells.

Line 1 connects the system with the external grid, the lines have a capacity limit of 200 MW, this restriction is important because it constrains the amount of power that can flow within the system. It is important to point out that this is merely a theoretical assumption. In reality, this scheme would be more diverse, accounting for reactive power, system losses, power transformation, etc.

The converter presented in the BESS is assumed to have bi-directional capabilities.

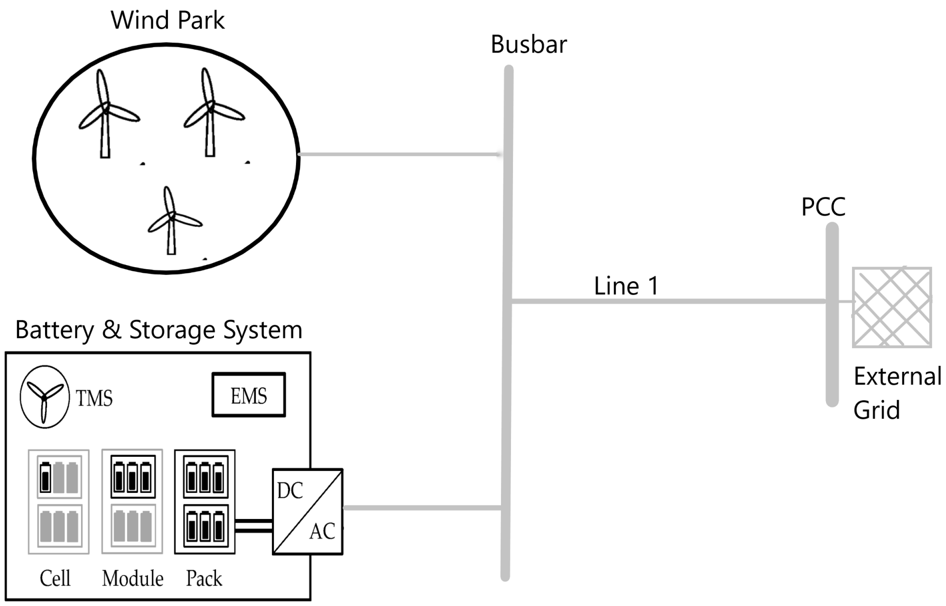

Figure 3.1 Wind Farm/Park and BESS Arrangement.

The external grid represents the ERCOT market. Therefore, is assumed that energy beyond the PCC point is sold without any power losses due to power transmission. The WF is assumed to have a solid wind power forecast i.e. the wind power output is know ahead of the running hour with 100% confidence. The WF parameters are given in the following section.

3.2 Wind Farm Parameters

The theoretical WF used is located in the West Zone ERCOT market, consisting of fifty 4 MW wind turbines. Vestas V136-4.2 MW [35] wind turbine specifications are used for output power calculations. The power generated from the turbine depends on the availability of the wind. Therefore the output power can be calculated with respect to wind speed which is shown as a piecewise function below:

$$P_w = \begin{cases} 0 & v < v_c \; or \; v > v_f \\ P_r \times \frac{v - v_c}{v_r - v_c} & v_c \leq v \leq v_r \\ P_r & v_r \leq v \leq v_f \end{cases} \tag{3.1}$$

where P_r is the rated turbine power, v_c is the cut-in wind velocity, v_r is the rated wind velocity and v_f is the cut-off wind velocity [36]. The wind speed data used is collected from the measuring station present in the Midland[1] airport [37].

The wind turbines power output are calculated hourly based on hourly wind speed values. The maximum power output in one hour by the WF is 200 MW at any time interval, therefore the WF can produce 200 MWh of energy.

3.3 Battery Energy Storage System Parameters

The BESS TMS and EMS is disregarded in the analysis. Therefore is assumed that the BESS operator has control over both management systems and can guarantee optimum battery operation.

A battery system has charge and discharge efficiencies, most of the time these values are only a reflection of battery parameters. However, the converter efficiency losses can also be aggregated in the battery's round-trip efficiency, which is the fraction of energy charged in the battery that can be retrieved. A 15% losses take into account the losses due to converter and battery systems. Therefore a round-trip of 85% is used in the problem formulations, to accommodate converter losses.

The BESS degradation or capacity fade is one important parameter that needs to be consider. Such parameter depends on the battery operation.

Authors in [17] developed a model to capture capacity fade due to cycling and idling based on the results of the accelerated aging test. The expression for capacity fade due to cycling is as follows:

$$C_{fade\_cycling} = 0.021 \cdot e^{-0.01943 \cdot SOC_{AV}} \cdot cd^{0.7162} \cdot nc^{0.5} \tag{3.2}$$

where SOC_{AV} is average SOC during one cycle in percentage, cd is cycle depth during one cycle in percentage and nc is the number of cycles. Capacity fade due to idling is given as:

$$C_{fade\_calendar} = 0.1723 \cdot e^{0.007388 \cdot SOC_{LV}} \cdot m^{0.8} \tag{3.3}$$

where SOC_{LV} is SOC storage level in percentage and m is storage time in months.

To extract all the necessary input parameters in equation 3.2, a rainflow cycle counting algorithm is used. This method is used by different authors [25, 38], to decompose battery's

[1] City located in the west part of Texas.

SOC profile into cycles of different cycle depths performed at different SOC levels. The steps used to accomplish the capacity faded is given in greater detail in [39]. Figure 3.2 illustrates the procedure done to find the degradation cost related to battery capacity fade.

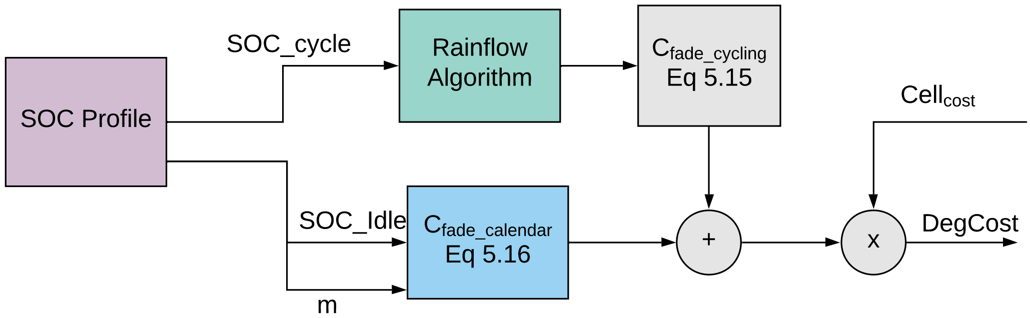

Figure 3.2 Procedure done to identify the degradation cost used in NPV.

3.4 Summary

In this chapter, the hybrid system used throughout the thesis is presented. The WF and battery grid arrangement are considered to have a power limit capacity of 200 MW. Batteries important parameters are defined. The battery efficiency is used to accommodate for converter losses. The battery degradation model is derived and presented to be used in the cost-degradation analysis. The next is to define a price forecast methodology, consider in the next chapter.

Chapter 4

Price Forecast

In this chapter, the price forecasting methodology is assessed. Firstly, a preliminary assessment of both DAM and RTM prices is introduced. Furthermore, three different forecast methodologies are defined and evaluated. Lastly, the best forecast methodology is defined based on an accuracy test.

4.1 Electricity Market Data

4.1.1 Day-Ahead Market

Both the DAM and the RTM are difficult markets to predict due to their volatility. However, some patterns can be observed in price markets which help in the prediction, Figure 4.1 shows the average price curve for the DAM in 2017 [6], it can be observed that prices peak between 14 - 15 PM. It can also be observed that at these hours the market price can reach values close to 250 $/MWh.

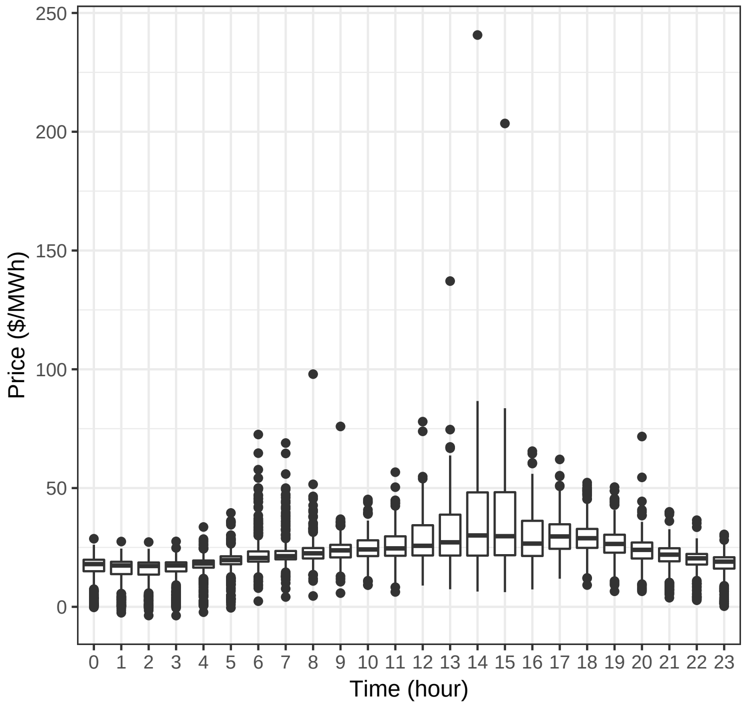

Figure 4.1 Aggregated Hourly DAM Prices, Year 2017 [1].

The Box-Plot also show the outliers; in the morning (6-8) the price spikes can be quite significant compared to the median at these hours, the same is observed in the evening (19-20). Figure 4.2 shows the price variation in the day-ahead market throughout 2017, with price spikes reaching values close to 250 $/MWh. High prices are not recurrent in the DAM, the average price in this market is actually close to 23.73 $/MWh for 2017.

Analyzing both figures (4.1 and 4.2) it's also observed that at some hours prices are negative. Negative DAM prices are usually explained by exceeding generation. A large variation in prices occurs in the summer months. Texas is known for its high temperature in summer resulting in high air-conditioner use, an explanation for these high prices.

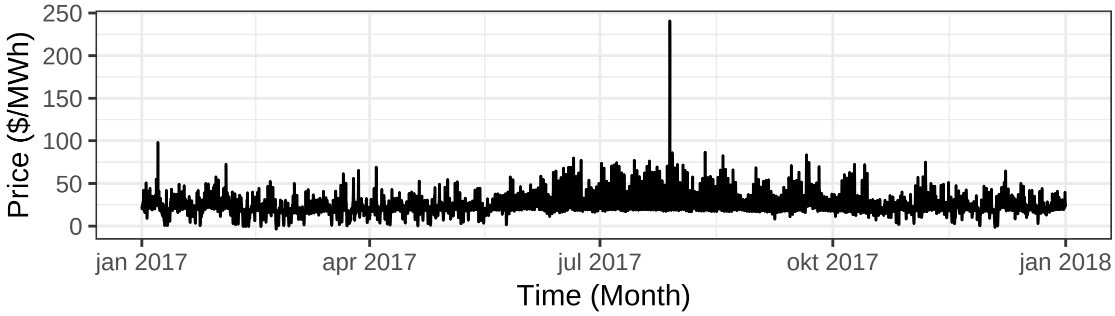

Figure 4.2 Day-ahead Market Prices, Year 2017

Ancillary Services Day-Ahead Market

As mentioned before, the Ancillary Services DAM are procured in four different markets within the day-ahead operations, they are REGDN, REGUP, RRS, and NSPIN. From Figure 4.3 it can be noticed the differences in each of the four markets. REGDN has a lower maximum price when compared with the others. REGUP been the one with a higher maximum price. From a purely graphical analysis, it seems as if RRS and NSPIN have a strong correlation with the DAM prices. It is clear how all four markets have their own behavior, consequently own forecast complications.

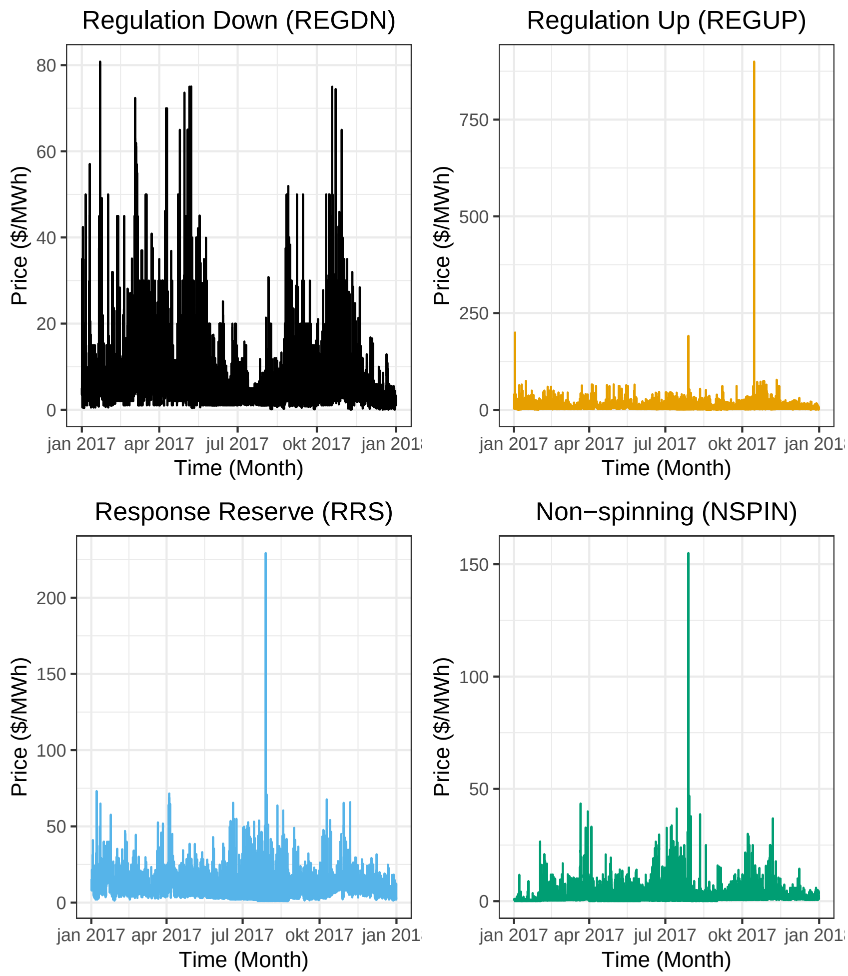

Figure 4.3 DAM Prices for all four Ancillary Services, Year 2017.

Comparing all the markets in the day-ahead operations, it is observed that the highest price comes from the REGUP service: 900 $/MWh. Almost four times the DAM maximum price of 250 $/MWh, showing the potential revenue of the ASM. The average value of all 4 ASMs is, however, lower than the DAM, being RRS market the one with the highest average of 10 $/MWh. Therefore, a good price forecast is necessary in order to capture high market prices.

4.1.2 Real-Time Market

Visually examining the RTM prices in Figure 4.4, it is observed a high price fluctuation, making this market more volatile. In Figure 4.5 (A) the hourly prices in the RTM is exhibit, notice the large number of outliers when compared with DAM (Figure 4.1). Clearly indicating the high volatility of this market when compared with the DAM.

However, if the outliers are removed one can notice the same hourly-price fluctuation as in the DAM, Figure 4.5 (B). The highest price in 2017 is close do 900 \$/MWh, three times the DAM price. The RTM takes into account various factors to settle price, such as congestion, blackout, wind uncertainties, loss generation, etc. That's why the values are often quite high, therefore when defining a forecasting method the markets must be analyzed separately for seasonality and trend effects.

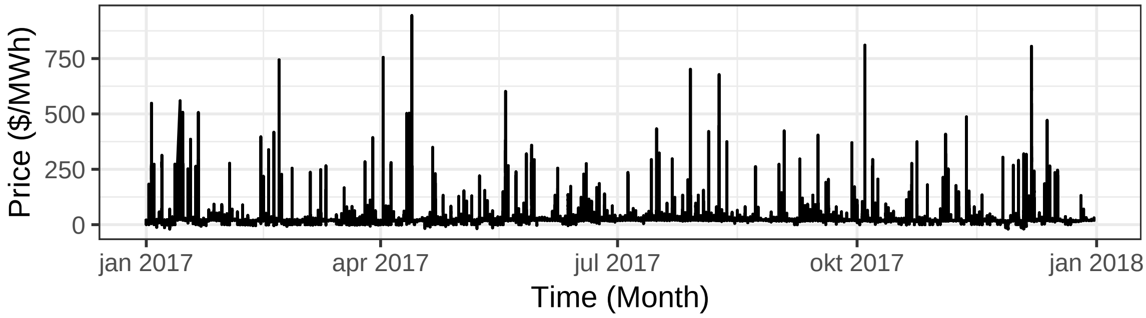

Figure 4.4 RTM Prices, Year 2017

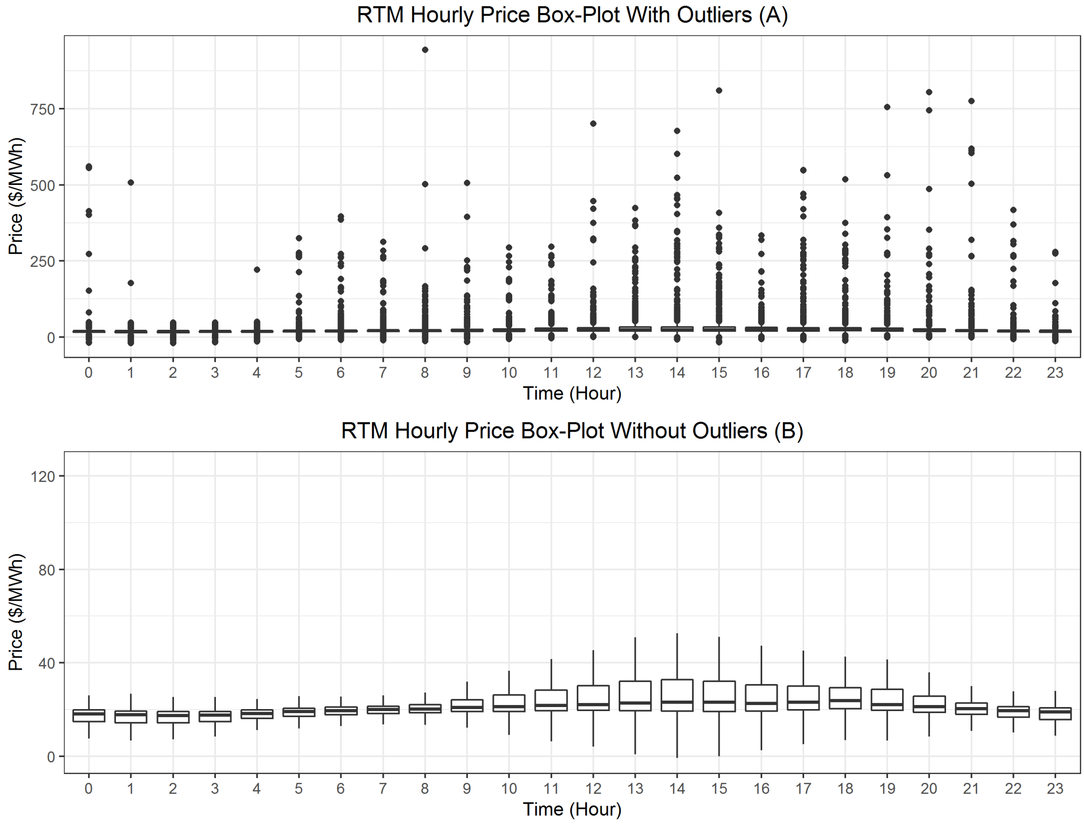

Figure 4.5 Aggregated Hourly RTM Price, Year 2017.

With this preliminary assessment of the markets, the forecasting analysis is carried out in the next section.

4.2 Forecasting Methods

This section will discuss three different methodologies present in the literature in terms of electricity price forecasting. In the interest of information clarity, only the DAM price forecast will be shown in this analysis. Therefore, the best method found is then applied for all other markets used in the practical operation scheme later in the thesis (REGDN, REGUP, RRS, NSPIN, and DAM).

The DAM prices data is collected from the ERCOT website [1]. Ranging from 2012 to 2017. The 2017 data is used to assess the accuracy in the forecast methods. Therefore, the data from 2012 to 2016 is used to train the different methods to predict.

Time Series Analyses

A sequence of observations collected at a specific time interval is called time series. In the case study, hourly prices. The frequency of a time series is the number of cycles per observations. For hourly data, there could be a daily, weekly or annual cycle, i.e. the series could present a similar behavior every day of the year. The simplest time series forecasting methods use only the past variable values as information for prediction. That can introduce complexity into predicting future values, particularly if said variable has strong external factors e.g. gas prices, population density, etc. [40].

The preliminary analyses showed a daily cycle in the DAM price, however, it was difficult to confirm any sort of trend or seasonality with accuracy, when only a daily interval was used. A trend means that, on average, the measurements tend to increase (or decrease) over time. A seasonality signifies that the times series is influenced by seasonal factors (e.g., a quarter of the year, the month, or day of the week)[40].

An analysis of different plots is made to assess different patterns in the data, the most relevant ones are presented in Figure 4.6. Plot (A) shows the DAM prices between 2012 and 2017, observe the lower fluctuation in prices between 2016 and 2017, when compared with previous years. Such difference can have various reasons.

The report from [41] express a high correlation between DAM prices and gas prices in the ERCOT market. Gas prices have been decreasing since 2015 and so have DAM prices. Plots (B) and (C) display the aggregated monthly and weekly DAM price respectively, it can be deduced that in August prices tend to rise (the horizontal blue lines indicate mean value). However, no strong pattern is seen during the weekdays. Plot (C) shows the autocorrelation between different lags, representing daily, weekly and annually seasonality. There is a small correlation in daily prices, but not in weekly or annually prices. Therefore, is possible that the increase in price seen in August may not be seasonal i.e. other years may have a different monthly pattern.

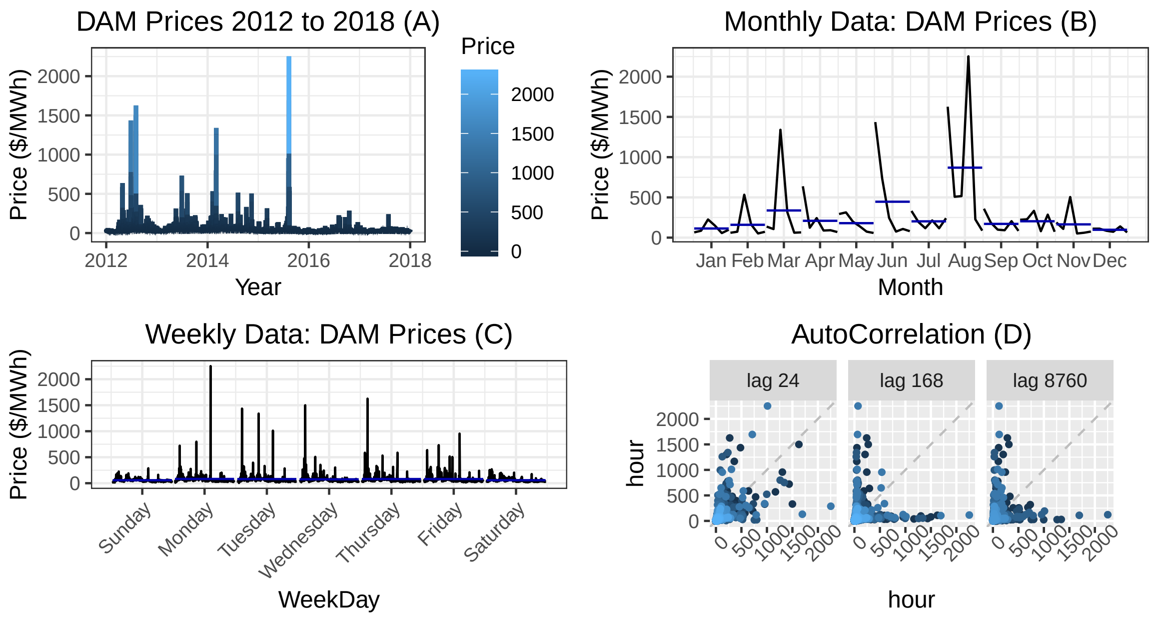

Figure 4.6 Seasonality Analyses in DAM Price.

4.2.1 ARIMA Model

The first model to be evaluated for forecast will be an ARIMA(p,d,q) model, ARIMA stands for Autoregressive Integrated Moving Average. ARIMA models are the most widely used approach to time series forecasting. ARIMA models aim to describe the autocorrelations in the data combining differencing, autoregression and a moving average. Therefore, the three parameters p,d, and q must be defined [2].

The time series; however, presents different variations at different levels of the series. According to [40], a data transformation might be a convenient way to stabilize the data. Therefore, a log-transform is done to stabilize the variation. Logarithms transformation, in particular, are useful because they are more interpretable: changes in a log value are relative (percentage) changes on the original scale.

To estimate (p,q,d) two functions are widely used Autocorrelation (ACF)[1] and Partial Autocorrelation (PACF)[2] functions. The series is differentiated to removed the trend component. Figure 4.7 shows both ACF and PACF for the differentiated data, a strong seasonality is seen in lag 24 confirming the daily seasonality.

[1]Give the relationship between present value and previous values.
[2]The amount of correlation with each lag that is not accounted for by more recent lags.

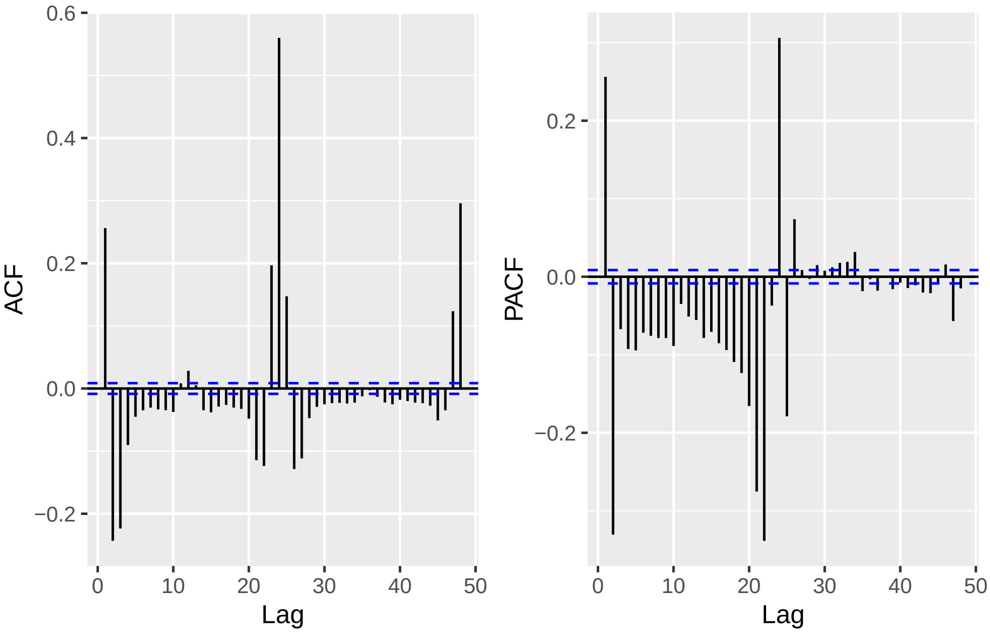

Figure 4.7 ACF and PACF for DAM Prices Time Series.

Even after differentiating the series it is observed some large peak at lag 24, which shows a seasonal effect in the data. The ARIMA model is adjusted to accommodate the seasonality as describe in Table 4.1. A recurring algorithm is used to define the parameters present in Table 4.1. The approach is defined in the flowchart at Figure 4.8. Akaike's Information Criterion (AIC) is used to compare various ARIMA models and define the best, the procedure is done using the software environment R®.

Table 4.1 Sesonal Arima Model

ARIMA	(p,d,q)	$(P,D,Q)_m$
	Non-seasonal part of the model	Seasonal part of the model

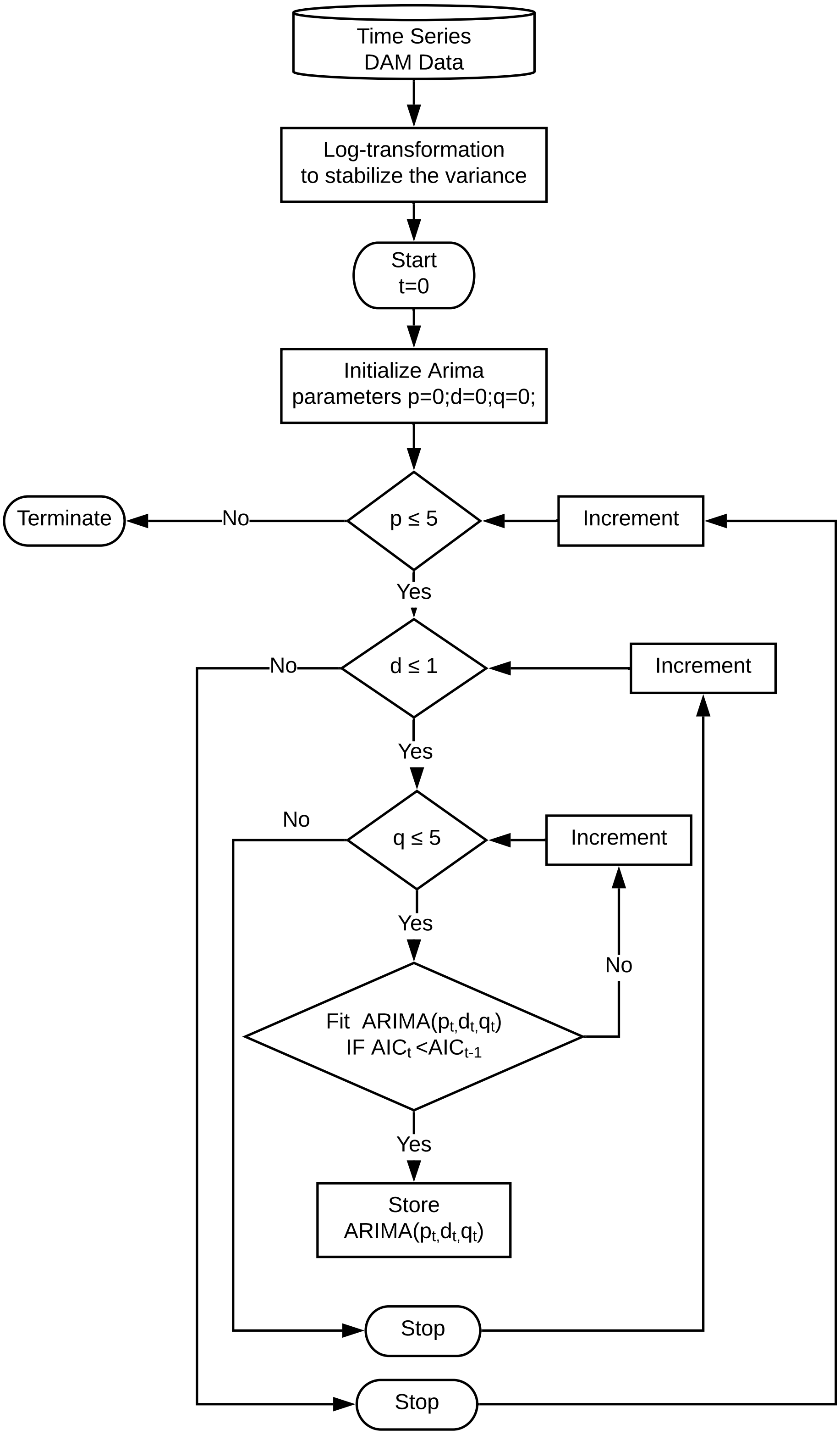

Figure 4.8 Process Used to Defined Best ARIMA Model.

ARIMA Model Evaluation

The final ARIMA model used for the forecast is $ARIMA(5,1,0)(2,1,0)_{24}$. Figure 4.9 shows in green the prices from 2016. The forecasted prices for the first week of 2017 from the ARIMA model are given by the blue line, along with its confidence interval. The longer the prediction horizon the larger will be this interval. In red is plotted the real prices for the first week of 2017.

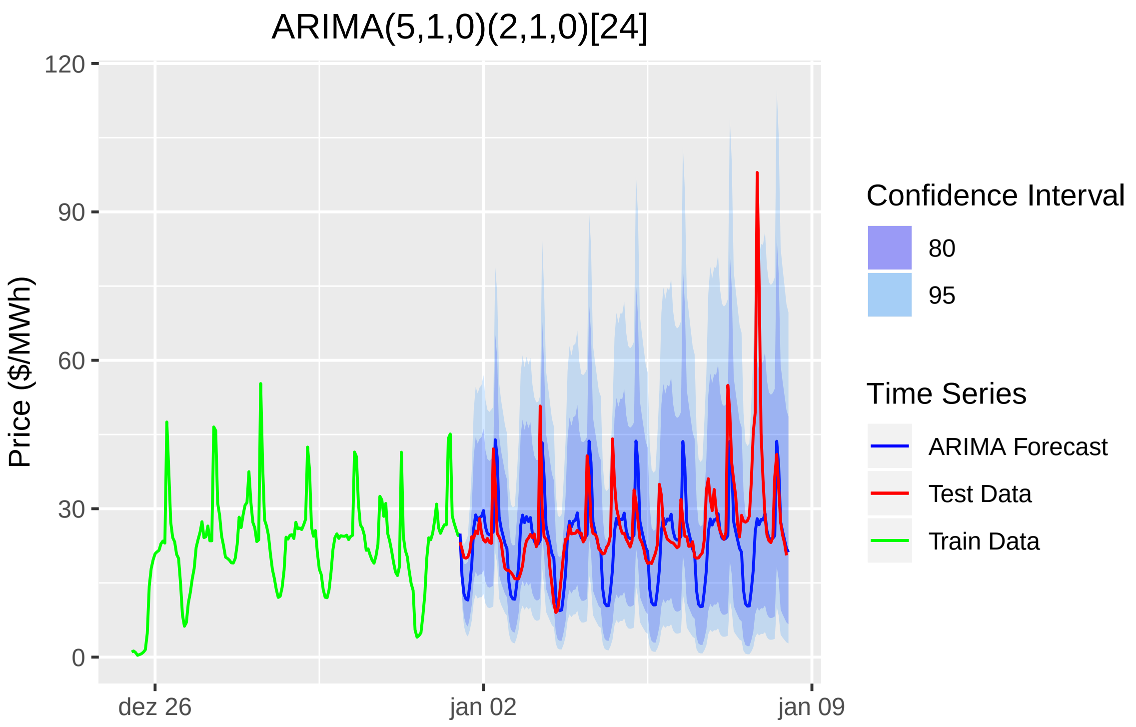

Figure 4.9 DAM Price Forecast with Seasonal-ARIMA Model.

Graphically the ARIMA model seems to capture the seasonal pattern, and the real prices are within the confidence intervals for the first week in 2017. However, due to high volatility, the model is not able to capture variation in prices very well. A peak price in Jan-07 falls outside the confidence intervals while the forecast predicted a lower value. A better representation of the forecast is achieved by looking at the residuals i.e. the difference between forecasted and real values.

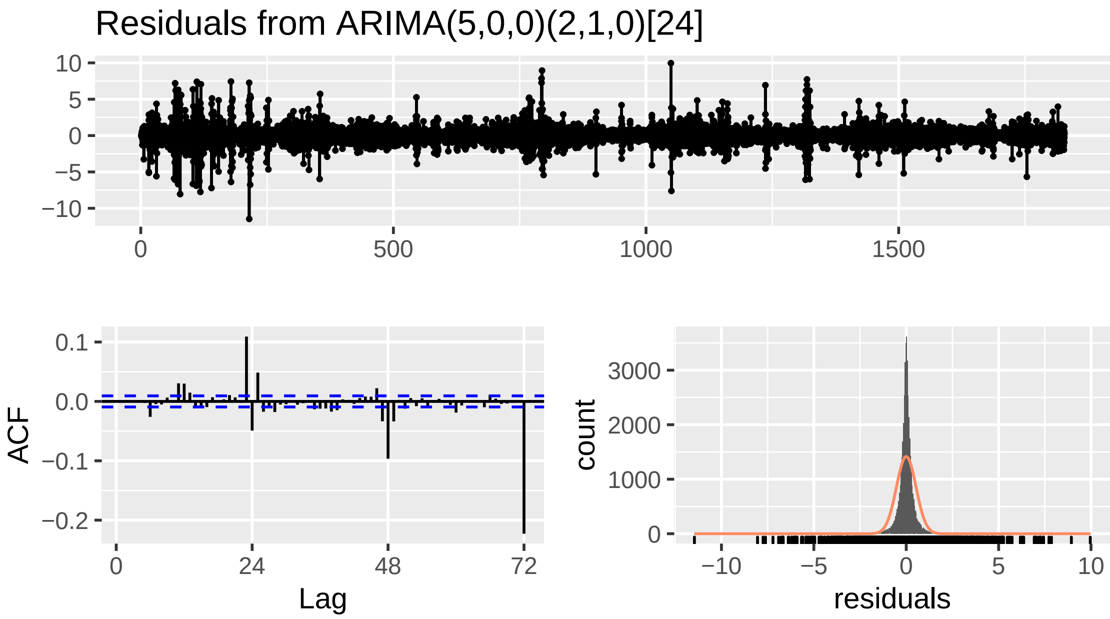

Figure 4.10 Residuals from the ARIMA Model.

Figure 4.9 shows high correlation in high lags e.g. 48 and 72. In addition, the residuals are not normally distributed. The residual analysis shows that the forecast can be improved.

Only the daily pattern was assessed in this model. However, the findings of the residuals indicate a multiple seasonality effect in the data. Therefore, the next model investigated will be one able to account for multiple seasonality effects.

4.2.2 TBATS Model

TBATS stands for Trigonometric Box-Cox ARMA Trend Seasonal, this approach developed by De Livera, Hyndman, & Snyder [42] uses a combination of Fourier terms with an exponential smoothing state space model and a Box-Cox transformation. Taking into consideration different seasonality patterns in time series analysis, more information can be found in [42].

A TBATS model differs from the ARIMA previously used because seasonality is allowed to change slowly over time i.e. different patterns can alter the forecast depending on the time period. A better understanding can be obtained from Figure 4.11, where the time series is decomposed in into five elements:

- A trend, showing that prices have been decreasing over the years.
- A daily seasonality (Seasonal24).

- A weekly seasonality (Seasonal168).
- A yearly seasonality (Seasonal8766)
- Remainder, what is not explained by the previously mentioned components.

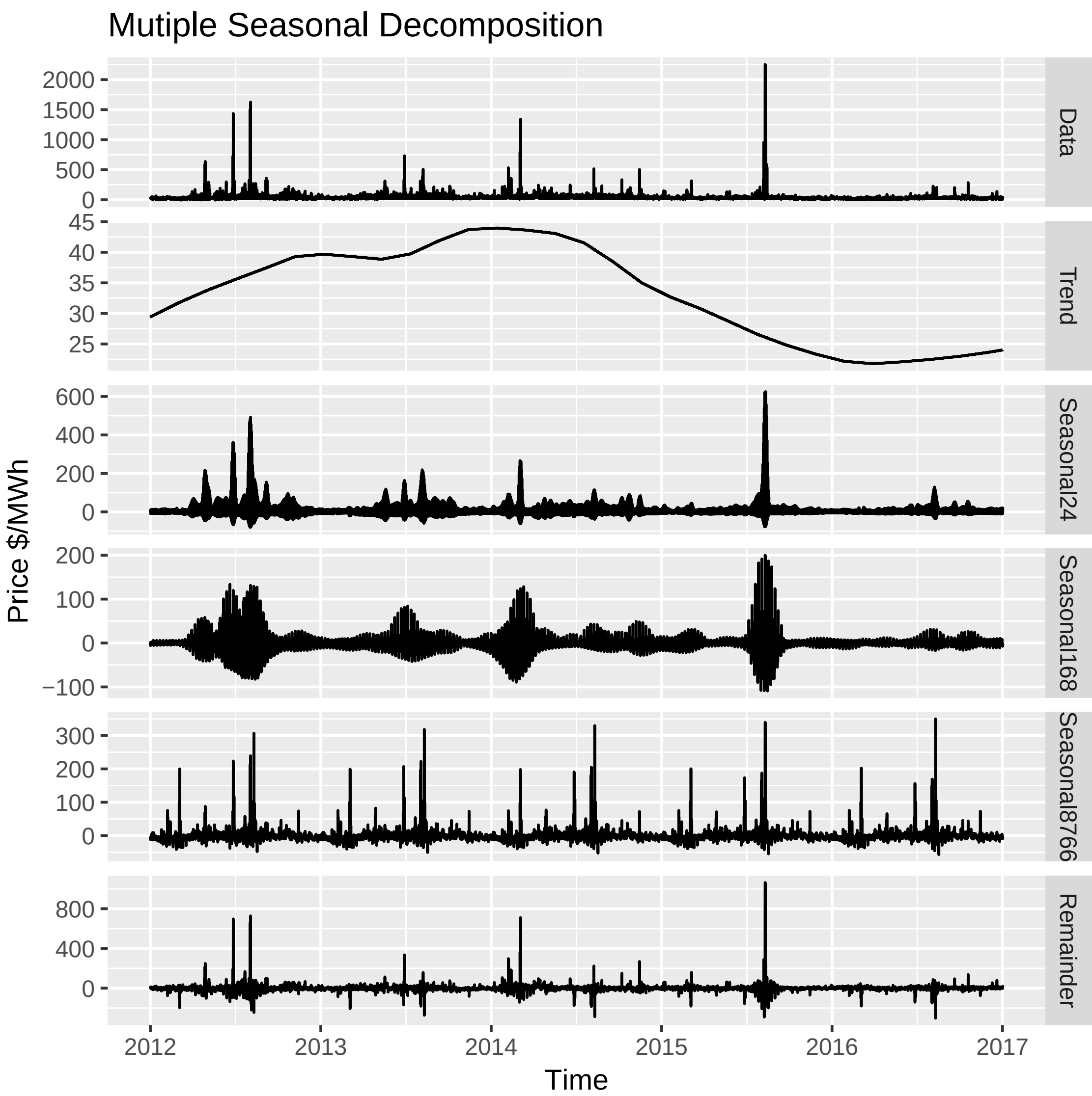

Figure 4.11 Time Series Data Decomposition

Figure 4.11 display some important characteristics: the annually seasonal pattern is relatively stable i.e. the prices in the begin and middle of the year are likely to be high. The prices in the vertical axis illustrate that the trend component is rather small in magnitude when compared to the seasonal components. The weekly and daily seasonal patterns seem to be good indicators of the actual DAM price. The weekly seasonality has high price drops. Different scenarios could explain such behavior, one being a holiday and high renewable production at the same time. Nevertheless, a good portion of the prices cannot be explained by the seasonal components. The "Remainder" still presents high prices fluctuations that could be proven difficult to forecast.

The parameters for the TBATS model are automated generated in R® using the function **tbats**. Hereafter, the model found for TBATS is presented.

TBATS Model Evaluation

The TBATS model forecast can be seen in Figure 4.12. The price spike by the end of the week is still not forecasted with precision. The improvement here is that this price is within the confidence interval bounds. Even if the forecasted value is not the same as the real one. The model offers a price interval which envelopes the real price.

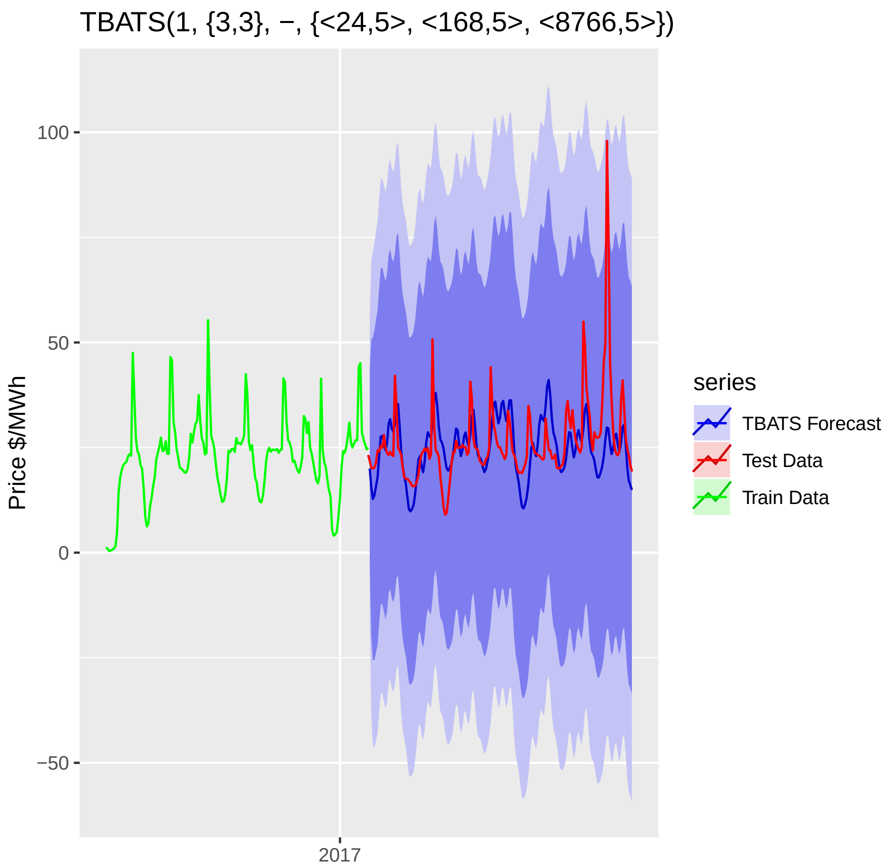

Figure 4.12 DAM Price Forecast with TBATS Model.

So far the forecasted models have been used for a univariate time series, these model simplify the forecast methodology by only looking at the time series in order to predict future values. However, in such data as electricity market price other external factors can affect the data and improve the prediction. These more complex models allow for control of other factors in predicting the time series e.g. holiday, temperature, day of the week, wind speed, etc. The Artifical Neural Network (ANN) models take into consideration external factors which can help predict a time series.

It is also good to inform that more intricate ARIMA [3] models can be used to account for the problems found in the forecast. However, the definition of the parameters of such models fall outside the scope of this thesis.

4.2.3 Artificial Neural Network Model

ANN are forecasting methods based on simple mathematical modeling of the human brain. They allow complex nonlinear relationships between the response variable and its predictors [2]. A neural network consists of "neurons" which are organized in layers. The predictors (or inputs) form the bottom layer, and the forecasts (or outputs) form the top layer. There may also be intermediate layers containing "hidden neurons". Figure 4.13 shows a simple example of a non-linear model with one hidden layer, four predictors (inputs) with one output (forecast). In such structure, each layer of nodes receives inputs from the previous layers using linear combinations [2].

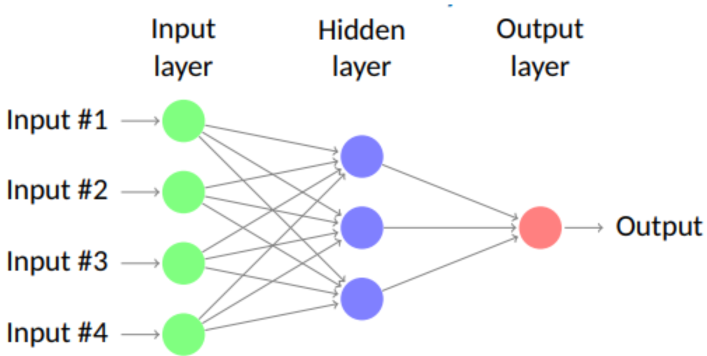

Figure 4.13 Simplified Version of a Neural Network [2].

Each weight (representing by arrows in Figure 4.13) takes random values to begin with, which are then updated using the observed data. There is an element of randomness in the

[3]ARIMAX model allows the inclusion of other predictors. ARIMA+GARCH models could be used to deal with the high volatility in the data.

predictions. So the network is usually trained several times using different random starting points, and the results are averaged. The weights are them "learned" by the neural network using a "learning algorithm" that minimizes a "cost function" such as the error between forecast and real value [2]. Some parameters must be taken into account before initializing the neural network: the number of inputs and the number of hidden layers.

It has been stated that, as long as enough neurons are chosen, one hidden layer is enough to estimate any continuous function for applications [43, 44]. Therefore a forward heuristic simulation is developed to decide the proper number of hidden neurons. The training process starts with a small number of hidden neurons and increases the number by one until no significant improvement is achieved to avoid overfitting issues.

The selection of inputs variables is problem dependent; for electricity price some terms are known to be better predictors: temperature, holidays, power demand, and especially for ERCOT, gas price. Recurrent patterns are easy to predict, such as holidays, but future demand or gas price required their own forecasting structures. Therefore, they will not be assessed [4].

The input selection is then based on explanatory analysis, simple correlations are used to rank the importance of different inputs. The variables feeding the input layer are presented in Table 4.2, temperature, dew point, and wind speed are forecast values, this values can be forecasted with a 95% accuracy for a one week horizon [2]. These values can be found in the same forecast station used for wind power output analysis presented at Chapter 3 [37]. In Table 4.2, $DAMPrice_{t-k}$ represents lagged values of the time series, corresponding to the indices k =24, 25, 26, 48, 49, 50, 72, 73, 74, 96, 97, 98, 120, 121, 122, 144, 145 and 146.

[4] If such forecast is accessible it is recommended to use it.

Table 4.2 Input selection used in the ANN.

	Variable	Correlation With DAM Price
Input #1	Temperature [°C]	0,083
Input #2	Dew Point [°C]	-0,0014
Input #3	Wind Speed [m/s]	0,016
Input #4	Day of the week	0,42
Input #5	Hour	0,66
Input #6	Whether is a holiday	0,30
Input #7 to #25	$DAMPrice_{t-k}$	[0,095; 0,544; 0,256; 0,079; 0,296; 0,150; 0,061; 0,184; 0,108; 0,051 ;0,123; 0,083 ; 0,046; 0,112;0,079; 0,047]

The train and test data are the same as the previous methods, the hyperbolic tangent activation function is employed with the networks, and the Levenberg–Marquardt method is used to train the model, the neural network is trained using the Neural Net Fitting tool in Matlab®.

ANN Model Evaluation

Ultimately the ANN has 25 neurons in the input layer, 20 neurons in the hidden layer, and the only output if the forecast price. Figure 4.14 display the forecast price for the first week of 2017 alongside the real price. The forecast is not perfect, but the ANN seems able to identify the peaks and valleys of the actual market. Different from the other methods presented, the ANN forecast does not possess a confidence interval once its forecast strategy is based on input-output and not on probabilistic terms i.e. the accuracy in forecasting one hour ahead is the same as forecasting one week ahead as long as the inputs for the network are known [2].

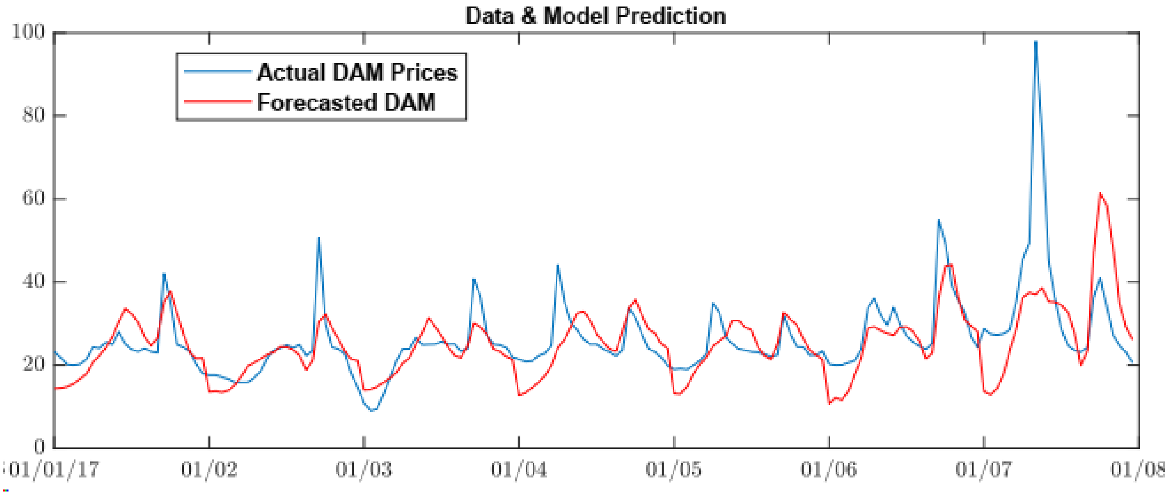

Figure 4.14 ANN Model Forecast.

With the three different forecast method defined and the first week of 2017 evaluated, the next section will compared the methods and defined the best.

4.3 Forecast Methods Evaluation

In order to evaluate which of the three different forecast method present in this chapter is the best, a rolling window methodology forecast is used. Prices will be forecast for a week ahead, then prices for the forecasted week will be updated with real prices and the next week will be forecast. This is done for the DAM price in 2017. To measure the accuracy between the forecast methods, the yearly forecasted will be compared with the real DAM prices.

Figure 4.15 shows the three forecast methods evaluated with a zoom-in for the month of July. The ARIMA forecast is good in predicting the daily seasonality, but it uses the same pattern for the whole year. Therefore, a month with high prices, like July and August, are not well predicted. The TBATS is better in including the different patterns in the data but seems to work poorly in forecasting high and low price fluctuations. From a graphical analysis, the ANN model seems to perform the best out of the three methods. The network is able to forecast with high precision the fluctuations. In terms of price spikes, it looks able to forecast the high prices moments, but not the actual price.

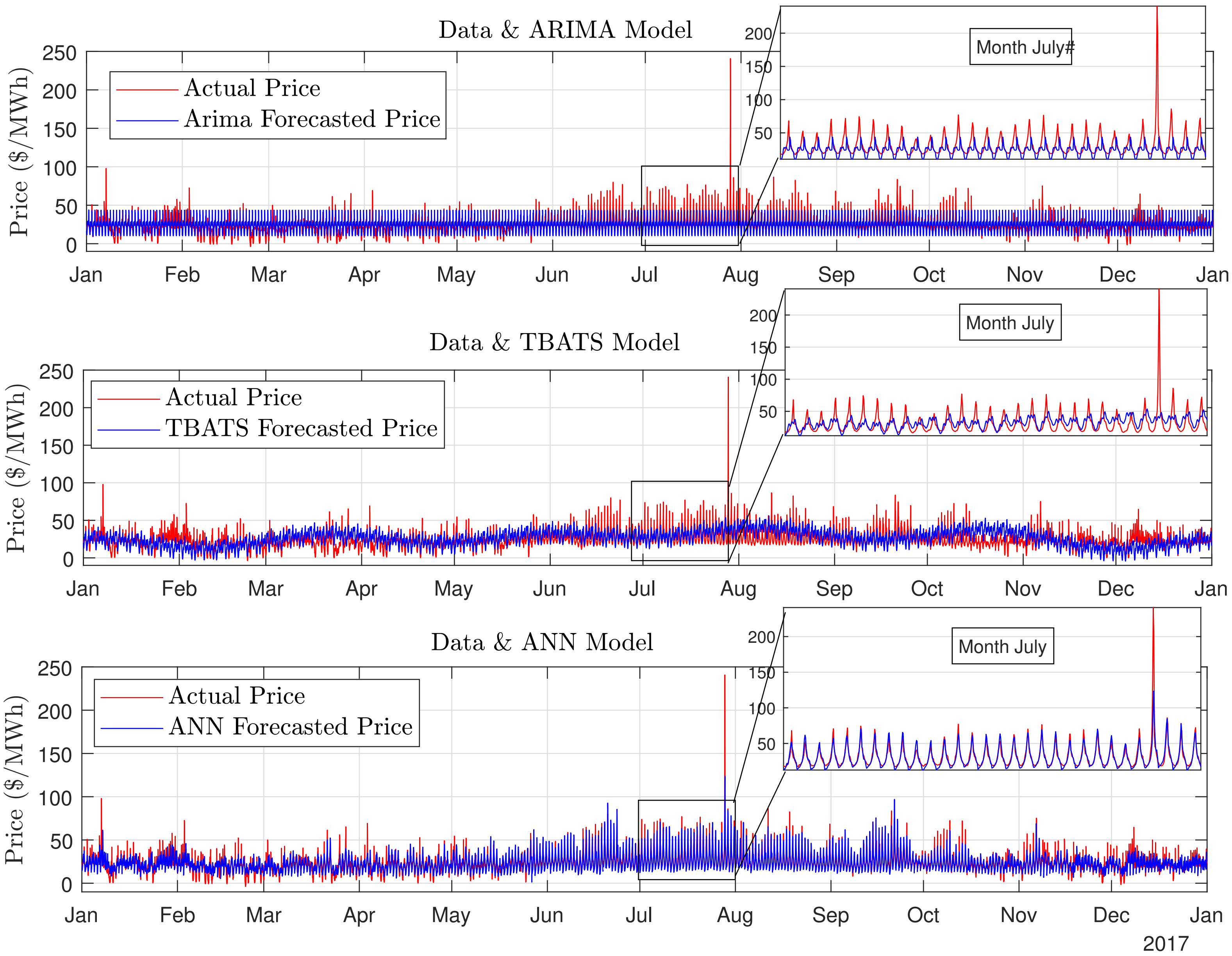

Figure 4.15 Forecast from ARIMA, TBATS and ANN for 2017.

According to [2], a better measurement for forecast accuracy is the mean absolute percentage error (MAPE), defined in Equation 4.1, where $\hat{y}_{T+h|T}$ denotes the forecast of y_{T+h}, and H is the forecasted horizon, one year in this case. A high MAPE indicates high forecast error, difference between actual and forecast prices. A low MAPE indicates the opposite i.e. the difference between actual and forecasted values is low.

$$MAPE = \frac{100}{H} \sum_{H}^{h=1} \left| y_{T+h} - \hat{y}_{T+h|T} \right| / |y_t| \tag{4.1}$$

Table 4.3 Accuracy Test for the Forecast Models.

	ARIMA	TBATS	ANN
MAPE:	49.5738	53.5450	38.8263

Table 4.3 presents the MAPE for each method. The ANN method posses the lowest MAPE, making it the best among the three methods used. Therefore, the ANN method will be used to forecast the DAM REGUP, REGDN, SPIN, and NONSPIN market prices.

A summary of the procedure done and the key outcome form this chapter is given in the following section.

4.4 Summary

In this chapter, the price forecast methodology later used in the practical operation scheme is defined. Firstly a market data assessment is made in order to identify patterns that could explain prices fluctuations observed in the ERCOT electricity market. Subsequently, three different forecast methods are defined and used to forecast the DAM prices for 2017 data. An accuracy test is used to define which of the three methods performs best in forecasting the DAM prices. The ANN was found to have the lowest MAPE. Therefore, it's used to forecast the DAM REGUP, REGDN, RRS, and NSPIN market prices later in Chapter6. The following chapter 5 will present the other key element necessary for the operational schedule strategy, the optimization problem formulation.

Chapter 5

Optimization Problem Formulation

This chapter discusses the optimization problem formulation as a procedure. The procedure is firstly described by explaining the different cases formulated for the analysis. Furthermore, the full optimization procedure is divided and explained as a two stages optimization problem. Each stage and its objectives are discussed. Later on, the two stages are combined to represent the full optimization procedure used to evaluated profitability. Lastly, a benchmark case is used to verify the full optimization procedure.

5.1 Mathematical Formulation

With the information specified in previous chapters, the optimization problem can be developed. Firstly, different cases will be defined. Each case will take into consideration a possible bidding strategy presented to the BESS in the ERCOT electricity market. These case will then be used to formulate different BESS unit commitment optimization problems. After all, each bidding strategy will have a different set of constraints needed to be addressed in the BESS unit commitment.

The assessment of the optimal bidding strategy is divided along with services in the ancillary market. REGUP and REGDN are consider regulation services. RRS and NSPIN are regarded as reserve services. Four different bidding strategies (cases) are formulated taking into consideration the energy arbitrage and the ancillary services. Table 5.1 present each case number and bidding strategy used.

Table 5.1 Cases Definition for the Optimal Bidding Strategy Assessment.

Bidding Strategy	Case 1	Case 2	Case 3	Case 4
Energy Arbitrage	✓	✓	✓	✓
Regulation Services		✓		✓
Reserve Services			✓	✓

At this point is important to recapitulate some important information defined in section 1.3. The BESS unit commitment will be different for each case defined in Table 5.1. Therefore, a different MILP must also be formulated for each case. The formulated MILPs do not take into consideration factors such as BESS size and degradation because, as previously explained, such information introduces non-linearities that could lead to infeasibility. For that reason, the optimization procedure is dived into two stages.

The first stage deals with the BESS optimum unit commitment issue. In this stage, the different MILPs will be mathematically formulated for each case considering their idiosyncrasies.

The second stage deals with the optimum BESS size. At this stage, two genetic algorithms will be presented to deal with the non-linearities previously mentioned and a future sensitivity analysis in Chapter 6. At this stage, a degradation-profit approach is used to define the BESS optimum size for each of the defined cases, considering economic terms. Figure 5.1 helps illustrate the actions taken to formulate the full optimization procedure.

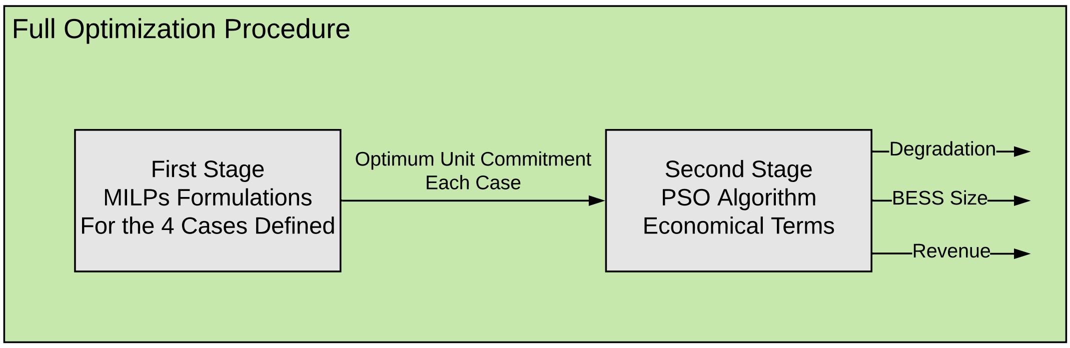

Figure 5.1 Full Optimization Procedure and its Stages.

In the first stage, the first week of operation in 2017 is used to verify the battery charge and discharge scheme and validate the mathematical models. The battery capacity is chosen arbitrarily as 20 MW / 40 MWh with 10-90% SCO range for these validation tests.

5.1.1 First Stage Optimization Problem

In the first stage of the optimization procedure, the MILP for each of the four cases will be formulated taking into consideration grid and battery constraints. For a unit commitment problem such as this a MILP is the best approach if dealing with linear relationship. A MILP can be defined by the form presented in Equation 5.1

$$\begin{aligned} \min \quad & c^T x \\ \text{s.t.} \quad & Ax = b, \\ & x \geq 0, \\ & x_i \in \mathbb{Z} \forall i \in I \end{aligned} \tag{5.1}$$

where an objective function is defined to be minimized using a set of decision variables e.g. x in Equation 5.1, subjected to a set of linear equality and/or inequality constraints. The problem is said to be "Mixed" because some of the decision variables need to be an integer, in the battery case a binary variable that can only take values of 0 and 1 is used to constrain its charge and discharge operation [45].

The objective function maximizes revenue. For each case, this function will be different to accommodate the different forms of revenue streams. The battery is subject to constraints related to its energy capacity as well as grid capacity. To avoid redundancy, Case 1 will be used to explain the MILP formulation steps, while in later cases the MILP will be given with information about the new add variables.

Case 1 - Energy Arbitrage Only

For energy arbitrage only two decision variables are necessary, $P^c_{(t)}$ and $P^d_{(t)}$, charge and discharge power, respectively. The hourly revenue is dependent on the amount of energy sold or bought to/from the grid. The objective function, in this case, maximizes revenue, given by Equation 5.2.

- Objective Function: Case 1

$$Max \sum_{t=1}^{T} [(1-C_w)P_{(t)}^{W} + (1-C_d)P_{(t)}^{D} - (1-C_c)P_{(t)}^{C}] \cdot \pi_{(t)}^{DAM} \cdot \Delta t \tag{5.2}$$

where C_w, C_d and C_c are the cost related to wind park operation , cost of discharging and cost of charging at time t in (\$/MWh), respectively. $P_{(t)}^{W}$, $P_{(t)}^{D}$ and $P_{(t)}^{C}$ are the power produced by the wind park, the power discharge and charge by the battery at time t in (MW), respectively. The $\pi_{(t)}^{DAM}$ symbolize the price of electricity in the DAM at time t in (\$/MWh) and Δt is the optimization interval, one hour in this case.

A battery cannot charge and discharge at the same finite time, thus the binary variable [1] $\mu_{(t)}$ is used to constrain the battery operations. The set of constraints are present as follow:

- Constraints
  - **Energy constrains**
    The SOC estimation is given by Equation 5.3. The SOC at time t is calculated using the previous state: $SoC_{(t-1)}$, plus the charged energy minus the energy discharge. Variables η_c and η_d stand for charge and discharge efficiency, respectively. A round-trip efficiency of 85% is used to accommodated converter losses. E_{cap}^{b} is battery nominal energy capacity used to calculate the SOC due to charge or discharge.

$$SoC_{(t)} = SoC_{(t-1)} + \frac{\eta_c P_{(t)}^{C} \Delta t}{E_{cap}^{b}} - \frac{P_{(t)}^{D} \Delta t}{E_{cap}^{b} \eta_d} \tag{5.3}$$

    In order to maintain BESS operation and reduce its degradation, SOC is constrained between safe operational limits:

$$SoC_{min} \leq SoC_{(t)} \leq SoC_{max} \tag{5.4}$$

  - **Capacity constrains**
    The battery operation is also bound by capacity constraints, at any point in time the battery discharge or charge power should not exceed its power rating P_{cap}^{b}. The binary variable $\mu_{(t)}$, ensures only one operation at time t.

$$0 \leq P_{(t)}^{D} \leq P_{cap}^{b} \cdot \mu_{(t)} \tag{5.5}$$

[1] Is advise to use fewer integer variables as possible in a MILP, as they can increase the problem difficulty, this case, for example, can be simplified to have only one decision variable and no binary variables.

$$0 \leq P^{C}_{(t)} \leq P^{b}_{cap} \cdot (1-\mu_{(t)}) \tag{5.6}$$

The aggregated power output of the system cannot surpass "Line 1" power capacity (defined in Chapter 3). Therefore P^{max}_{disch} symbolize the maximum power that can be discharged by the system. The battery can be charged by the Wind Park or the external grid. Therefore, the maximum charge power $P^{max}_{charg(t)}$ is the sum of the Wind Park output and the line power capacity at time t.

$$P^{D}_{(t)} \leq P^{max}_{disch(t)} \tag{5.7}$$

$$P^{C}_{(t)} \leq P^{max}_{charg(t)} \tag{5.8}$$

The problem formulation is given by the set of equality and inequality constraints as well as the Objective Function by Equations 5.9 - 5.9g, all decision variables are non-negative quantities.

$$\max_{P^{D}_{(t)}, P^{C}_{(t)}, \mu_t} \quad \sum_{t=1}^{T} \Big[(1-C_w)P^{W}_{(t)} + (1-C_d)P^{D}_{(t)} - (1-C_c)P^{C}_{(t)}\Big] \cdot \pi^{DAM}_{(t)} \cdot \Delta t \tag{5.9a}$$

$$\text{s.t.} \quad P^{D}_{(t)} \leq P^{max}_{disch(t)} \quad \forall t \in T, \tag{5.9b}$$

$$P^{C}_{(t)} \leq P^{max}_{charg(t)} \quad \forall t \in T, \tag{5.9c}$$

$$0 \leq P^{D}_{(t)} \leq P^{b}_{cap} \cdot \mu_{(t)} \quad \forall t \in T, \tag{5.9d}$$

$$0 \leq P^{C}_{(t)} \leq P^{b}_{cap} \cdot (1-\mu_{(t)}) \quad \forall t \in T, \tag{5.9e}$$

$$SoC_{(t)} = SoC_{(t-1)} + \frac{\eta_c P^{C}_{(t)} \Delta t}{E^{b}_{cap}} - \frac{P^{D}_{(t)} \Delta t}{E^{b}_{cap} \eta_d} \quad \forall t \in T, \tag{5.9f}$$

$$SoC_{min} \leq SoC_{(t)} \leq SoC_{max} \quad \forall t \in T. \tag{5.9g}$$

Mathematical Validation

Figure 5.2 shows the BESS charge and discharge scheme (negative power values means battery charge). The SOC profile is also shown to validate the mathematical formulation.

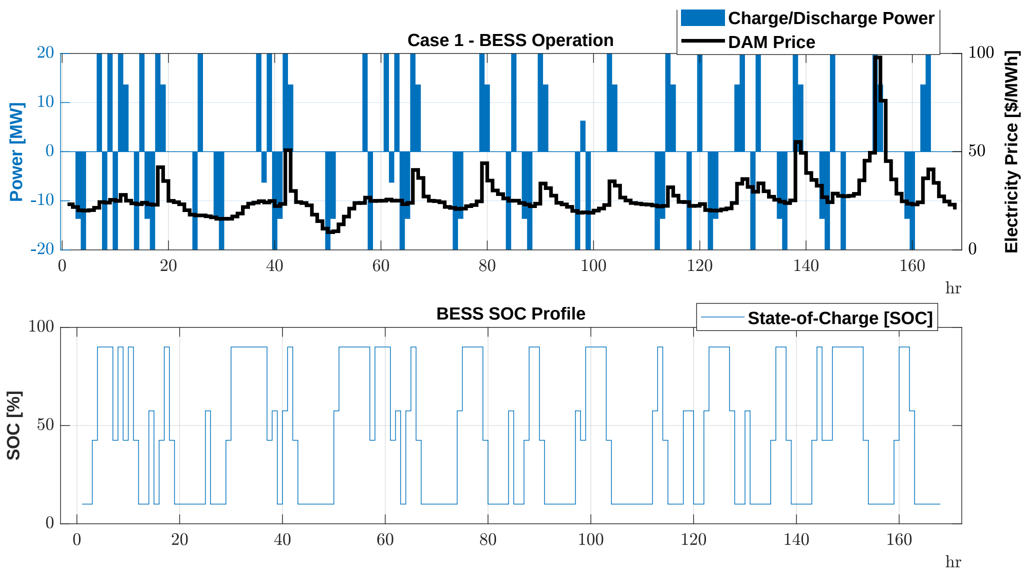

Figure 5.2 BESS Operation for Case 1.

From the plots it can be observed the battery charging when prices are low and discharging at high prices, no charge and discharge schedule happens at the same time. The SOC plot shows the battery operation within the specified SOC limits (10 -90%). However, the SOC profile does not look good for battery degradation. The battery seems to charge and fully discharge quite often leading to a high average SOC, highly damage to a battery lifetime [17].

Case 2 - Energy Arbitrage + Regulation Services

In Case 2, REGUP and REGDN markets are considered, which opens for an additional arbitrage opportunity between the day-ahead price and the real-time price. This structure can be different depending on the ISO, in ERCOT there are two separated markets for each service, as seem in Chapter 4. The REGDN market present very low prices when compared to the DAM, which could present an opportunity for the BESS to procure energy in this market rather than the DAM.

Equations 5.10a to 5.10h accounts for the optimization in Case 2. Two new decision variables are added, $P^{RU}_{(t)}$ and $P^{RD}_{(t)}$ describing the energy offered into the REGUP and REGDN market at time t, respectively. The price for both regulation services is secured in the day-ahead market, based on the REGUP and REGDN market prices, $\pi^{RU}_{(t)}$ and $\pi^{RD}_{(t)}$, respectively. The net energy, however, is settled at the real-time price ($\pi^{RT}_{(t)}$).

There is no guarantee that the capacity reserved will actually be deployed. In order to quantify the change in SOC from participation in the regulation market, it is useful to defined the REGUP efficiency γ_{ru} as the fraction of the REGUP reserve capacity that is actually deployed in real-time (on average). The same for REGDN with γ_{dn}. In actual operation of a storage system, these efficiencies will vary over each time interval. To formulate the problem as an MILP, a known value must be employed. Therefore, the average value should be used. Typically, the optimization solution is not sensitive to the choice of γ_{ru} and γ_{dn}, so the uncertainty in these parameters does not significantly impact the accuracy of the results.

A sensitivity analysis is presented in [46] showing that the average value gives a realistic assessment between what happens in real operation and the optimum revenue. The same energy and grid constraints used in Case 1 are used here, with the addition of both market.

$$\max_{P^{D}_{(t)},P^{RU}_{(t)},P^{C}_{(t)},P^{RD}_{(t)},\mu_t} \sum_{t=1}^{T} \Big\{ (\pi^{DAM}_{(t)} - C_w)P^{W}_{(t)} + (\pi^{DAM}_{(t)} - C_d)P^{D}_{(t)} - (\pi^{DAM}_{(t)} + C_c)P^{C}_{(t)} +$$

$$\big[\pi^{RU}_{(t)} + \gamma_{ru}(\pi^{RT}_{(t)} - C_d)\big]P^{RU}_{(t)} + \big[\pi^{RD}_{(t)} - \gamma_{rd}(\pi^{RT}_{(t)} + C_c)\big]P^{RD}_{(t)} \Big\} \Delta t \tag{5.10a}$$

s.t.

$$0 \le P^{D}_{(t)} + P^{RU}_{(t)} \le P^{max}_{disch(t)} \cdot \mu_t \qquad \forall t \in T, \tag{5.10b}$$

$$0 \le P^{C}_{(t)} + P^{RD}_{(t)} \le P^{max}_{charg(t)} \cdot (1 - \mu_t) \qquad \forall t \in T, \tag{5.10c}$$

$$0 \le P^{D}_{(t)}, P^{RU}_{(t)}, P^{C}_{(t)}, P^{RD}_{(t)} \le P^{b}_{cap} \qquad \forall t \in T, \tag{5.10d}$$

$$0 \le P^{D}_{(t)} + P^{RU}_{(t)} \le P^{b}_{cap(t)} \qquad \forall t \in T, \tag{5.10e}$$

$$0 \le P^{C}_{(t)} + P^{RD}_{(t)} \le P^{b}_{cap(t)} \qquad \forall t \in T, \tag{5.10f}$$

$$SoC_{(t)} = SoC_{(t-1)} + \frac{\eta_c P^{C}_{(t)} \Delta t}{E^{b}_{cap}} + \frac{\gamma_{rd}\eta_c P^{RD}_{(t)} \Delta t}{E^{b}_{cap}} - \frac{P^{D}_{(t)} \Delta t}{E^{b}_{cap}\eta_d} - \frac{\gamma_{ru} P^{RU}_{(t)} \Delta t}{E^{b}_{cap}\eta_d} \qquad \forall t \in T, \tag{5.10g}$$

$$SoC_{min} \le SoC_{(t)} \le SoC_{max} \qquad \forall t \in T. \tag{5.10h}$$

Mathematical Validation

Figure 5.3 represents the BESS operation for Case 2. The battery has three options of markets now, from the first plot it can be seen that for the first 100 hours the battery choose to bid in the REGUP market. The reason for that can be seen in the second plot, where the markets prices are plotted. The RTM (blue line) has high prices at the first operating hours of the week, considering the revenue stream from the RTM higher than from the DAM the battery decides to discharge.

Despite the fact that REGDN has lower prices than the DAM, it is still more advantageous to "charge" in the DAM prices, once the penalty cost applied for decreasing production takes the RTM price into consideration. However, once the profitability arises, the battery decides to "charge" in the REGDN market, e.g. after 100 hours, especially if RTM prices are lower than DAM prices. Also worth mentioning that the battery breaks down the amount of power it should discharge between the two possible markets (DAM and REGUP) as it can be seen in the first plot around 140 hours.

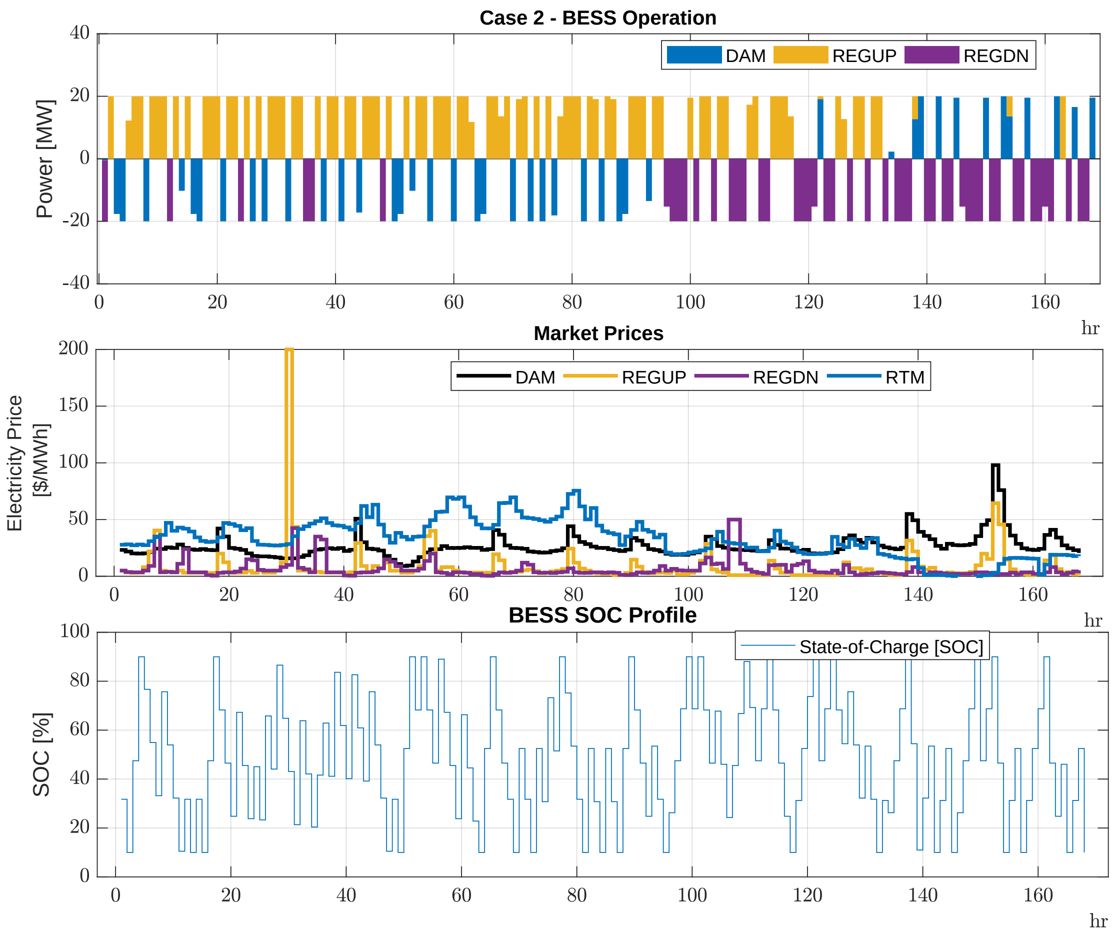

Figure 5.3 BESS Operation for Case 2.

Figure 5.3 also delineate the SOC profile, the battery present rapid changes in its SOC levels to accommodates the markets price fluctuations.

Case 3 - Energy Arbitrage + Response Services

In Case 3 the response market is considered with two new options, spinning, and non-spinning. This limit the charge stream to only DAM or Wind Park. This, however, opens the opportunity for arbitrage in the RRS, NSPIN, and RTM. The decision variables used for energy offered in RSS and NSPIN are $P^{SP}_{(t)}$ and $P^{NSP}_{(t)}$, respectively. The optimization problem is defined by Equations 5.11a - 5.11g. The RSS market price is defined by $\pi^{SP}_{(t)}$ and NSPIN market price as $\pi^{NSP}_{(t)}$. As for Case 2, the amount of energy offered in the RSS and NSPIN markets is not guaranteed to be fully used in the operating hour, thus two efficiency terms are defined for each market, γ_{sp} and γ_{nsp}, respectively. The same grid and battery constraints used in Case 1, is used to formulate the optimization problem for Case 3, with the addition of the two new markets.

$$\max_{P^D_{(t)}, P^{SP}_{(t)}, P^{NSP}_{(t)}, P^C_{(t)}, \mu_t} \sum_{t=1}^{T} \Big\{ (\pi^{DAM}_{(t)} - C_w)P^W_{(t)} + (\pi^{DAM}_{(t)} - C_d)P^D_{(t)} - (\pi^{DAM}_{(t)} + C_c)P^C_{(t)} +$$

$$\left[\pi^{SP}_{(t)} + \gamma_{sp}(\pi^{RT}_{(t)} - C_d)\right]P^{SP}_{(t)} + \left[\pi^{NSP}_{(t)} + \gamma_{nsp}(\pi^{RT}_{(t)} - C_c)\right]P^{NSP}_{(t)} \Big\} \cdot \Delta t \tag{5.11a}$$

s.t.

$$0 \leq P^D_{(t)} + P^{SP}_{(t)} + P^{NSP}_{(t)} \leq P^{max}_{disch(t)} \cdot \mu_{(t)} \qquad \forall t \in T, \tag{5.11b}$$

$$0 \leq P^C_{(t)} \leq P^{max}_{charg(t)} \cdot (1 - \mu_{(t)}) \qquad \forall t \in T, \tag{5.11c}$$

$$0 \leq P^D_{(t)}, P^{SP}_{(t)}, P^{NSP}_{(t)}, P^C_{(t)} \leq P^b_{cap} \qquad \forall t \in T, \tag{5.11d}$$

$$0 \leq P^D_{(t)} + P^{SP}_{(t)} + P^{NSP}_{(t)} \leq P^b_{cap(t)} \qquad \forall t \in T, \tag{5.11e}$$

$$SoC_{(t)} = SoC_{(t-1)} + \frac{\eta_c P^C_{(t)} \Delta t}{E^b_{cap}} - \frac{P^D_{(t)} \Delta t}{E^b_{cap}\eta_d} - \frac{\gamma_{sp} P^{SP}_{(t)} \Delta t}{E^b_{cap}\eta_d} - \frac{\gamma_{nsp} P^{NSP}_{(t)} \Delta t}{E^b_{cap}\eta_d} \qquad \forall t \in T, \tag{5.11f}$$

$$SoC_{min} \leq SoC_{(t)} \leq SoC_{max} \qquad \forall t \in T. \tag{5.11g}$$

Mathematical Validation

Figure 5.4 illustrate the BESS operation. The battery bids only in two markets in the week analyzed. The reason has been that both RSS and NSPIN market requires the battery to discharge energy. Thus, the operation decision is based on which market presents the higher price. From the second plot, top to bottom, it can be observed how the prices in the markets fluctuate. NSPIN prices are quite small compared with the other markets. Therefore, for this bid scheme, in this week, is better to bid in the DAM and RSS only. The battery SOC and Power rating are within the predefined limits.

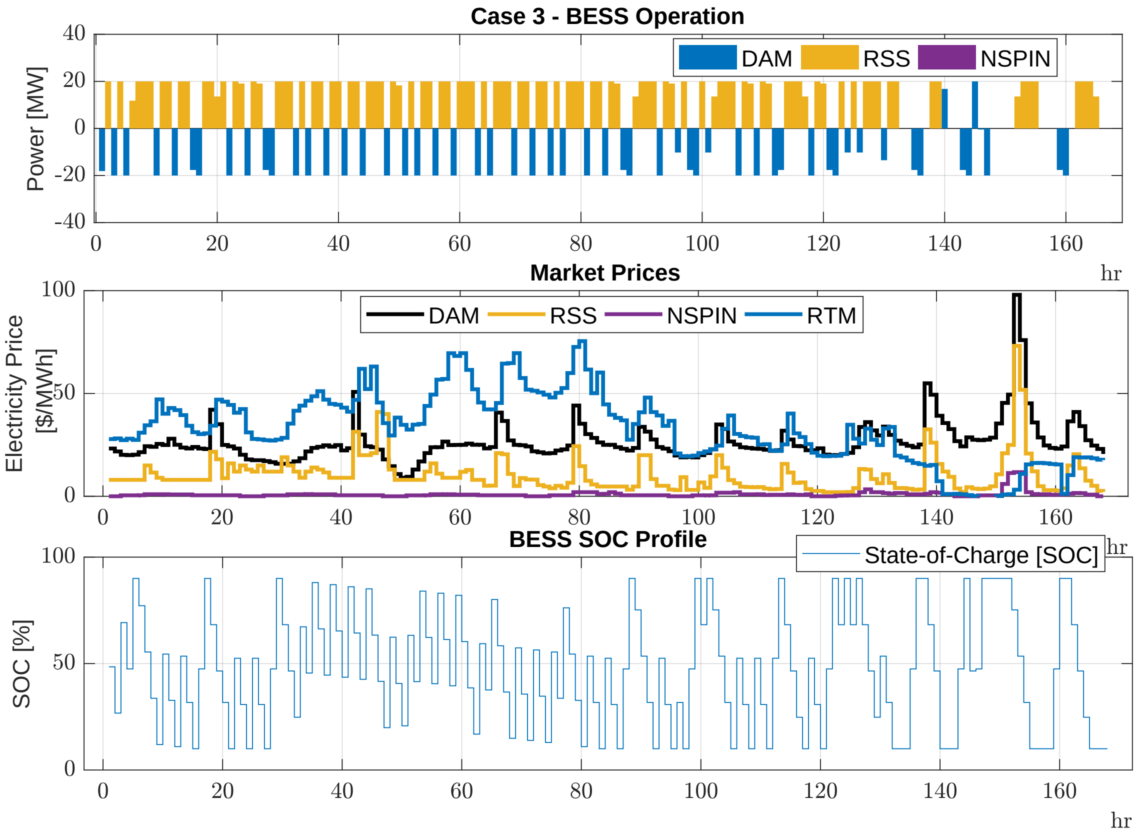

Figure 5.4 BESS Operation for Case 3.

Battery SOC profile is shown in the last plot of Figure 5.4, once again the profile shows rapid variations of SOC to accommodate the price changes.

Case 4 - All markets

For the final case all markets are considered, the problem formulation is presented in Equations 5.12a-5.12h as a combination of previous cases.

$$\max_{P^{D}_{(t)},P^{RU}_{(t)},P^{SP}_{(t)},P^{NSP}_{(t)},P^{C}_{(t)},P^{RD}_{(t)},\mu_{(t)}} \sum_{t=1}^{T} \Bigg\{ (\pi^{DAM}_{(t)} - C_w)P^{W}_{(t)} + (\pi^{DAM}_{(t)} - C_d)P^{D}_{(t)} - (\pi^{DAM}_{(t)} + C_c)P^{C}_{(t)} + \left[\pi^{RU}_{(t)} + \gamma_{ru}(\pi^{RT}_{(t)} - C_d)\right]P^{RU}_{(t)} + \left[\pi^{RD}_{(t)} - \gamma_{rd}(\pi^{RT}_{(t)} + C_c)\right]P^{RD}_{(t)} + (\pi^{SP}_{(t)} + \gamma_{sp}(\pi^{RT}_{(t)} - C_d))P^{SP}_{(t)} + (\pi^{NSP}_{(t)} + \gamma_{nsp}(\pi^{RT}_{(t)} - C_c))P^{NSP}_{(t)} \Bigg\} \cdot \Delta t \tag{5.12a}$$

subject to

$$0 \le P^{D}_{(t)} + P^{RU}_{(t)} + P^{SP}_{(t)} + P^{NSP}_{(t)} \le P^{max}_{disch(t)} \cdot \mu_{(t)} \tag{5.12b}$$

$$0 \le P^{C}_{(t)} + P^{RD}_{(t)} \le P^{max}_{charg(t)} \cdot (1 - \mu_{(t)}) \tag{5.12c}$$

$$0 \le P^{D}_{(t)} + P^{RU}_{(t)} + P^{SP}_{(t)} + P^{NSP}_{(t)} \le P^{b}_{cap(t)} \tag{5.12d}$$

$$0 \le P^{C}_{(t)} + P^{RD}_{(t)} \le P^{b}_{cap(t)} \tag{5.12e}$$

$$0 \le P^{D}_{(t)}, P^{RU}_{(t)}, P^{SP}_{(t)}, P^{NSP}_{(t)}, P^{C}_{(t)}, P^{RD}_{(t)} \le P^{b}_{cap} \tag{5.12f}$$

$$SoC_{(t)} = SoC_{(t-1)} + \frac{\eta_c P^{C}_{(t)} \Delta t}{E^{b}_{cap}} + \frac{\gamma_{rd}\eta_c P^{RD}_{(t)} \Delta t}{E^{b}_{cap}} - \frac{P^{D}_{(t)} \Delta t}{E^{b}_{cap}\eta_d} - \frac{\gamma_{ru} P^{RU}_{(t)} \Delta t}{E^{b}_{cap}\eta_d} - \frac{\gamma_{sp} P^{SP}_{(t)} \Delta t}{E^{b}_{cap}\eta_d} - \frac{\gamma_{nsp} P^{NSP}_{(t)} \Delta t}{E^{b}_{cap}\eta_d} \tag{5.12g}$$

$$SoC_{min} \le SoC_{(t)} \le SoC_{max} \tag{5.12h}$$

Mathematical Validation

Figure 5.5 illustrate the BESS operation when included in all markets. A mixed of strategies can be seen; similarly to Case 2 the BESS bids "charging" energy in the DAM when the RTM price is high to avoid penalty. When RTM prices are lower than DAM prices, the BESS bids on the REGDN market instead. The BESS does not bid in the NSPIN market for the week analyzed, this market does not present revenue for the battery once its prices are low. The

BESS uses a strategy between ASM and DAM to decided between the markets available to discharge energy. A price spike appears around 30 hours in the REGUP market, the battery uses the possible profit from this market to discharge. The BESS uses most of the time the RRS market to bid capacity due to its high prices, once the RTM price is lower than the DAM prices the battery uses a conjoint strategy between DAM and RRS market to bid energy.

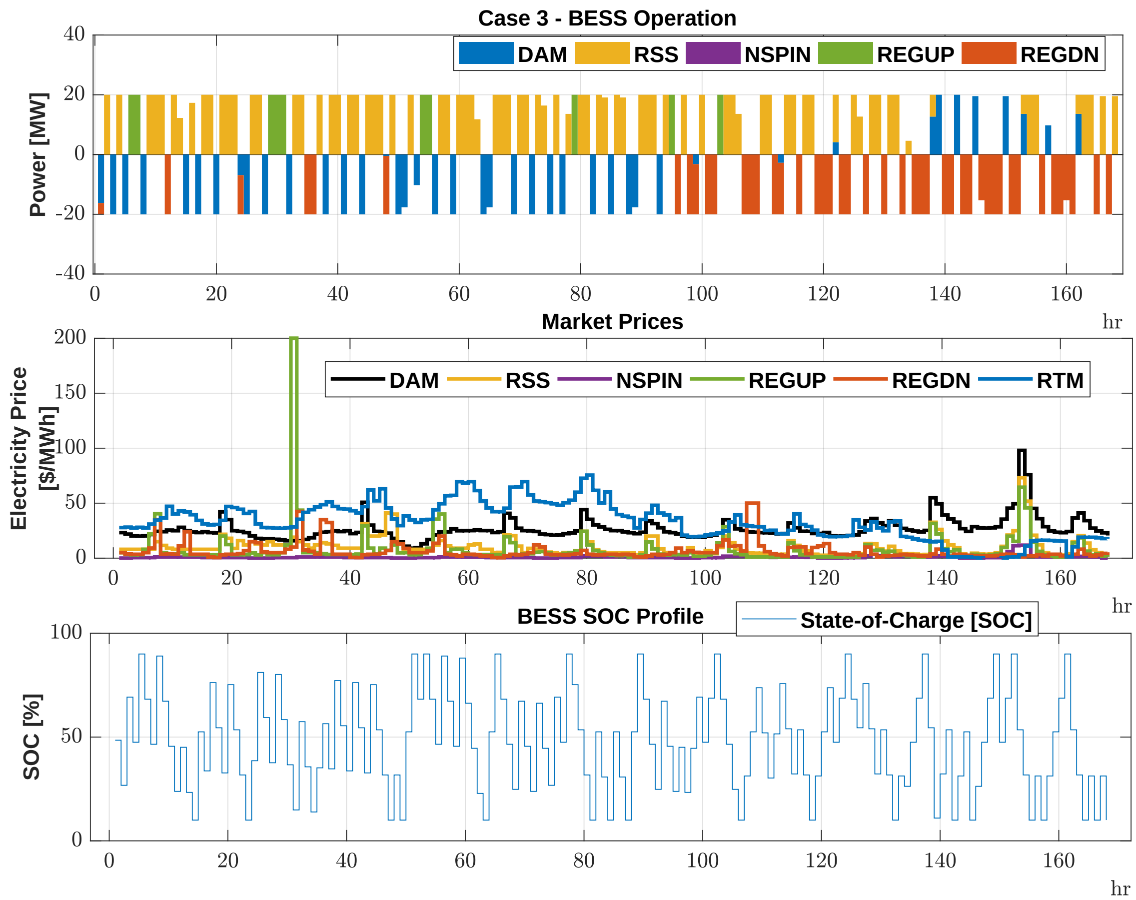

Figure 5.5 BESS Operation for Case 4.

The SOC profile, given in the last plot in Figure 5.5, shows the rapid changes the battery has to employ to be able to capture all markets variations.

With the BESS unit commitment described and validate for each case defined is possible to explain the second stage of the optimization procedure.

5.1.2 Second Stage Optimization Problem

The second stage of the optimization problem deals with the BESS optimum sizing considering economic terms. However, as mentioned in the begin of this chapter another BESS term is added in the second stage optimization. The SOC range, as seem before this parameter can greatly affect the degradation cost. Therefore, in order to carry a sensitivity analysis later in Chapter 6 this term is added to the second stage optimization.

To find the optimum BESS size and SOC range a Net Present Value (NPV) maximization approach is used. This approach is used to have a better understating of which case presents the best project implementation. It should be stated that this economic evaluation is not aiming a business case implementation, but rather presenting various assessments of the economic effects of the different cases defined in previous sections.

Therefore, by combining economic theory and genetic algorithms is possible to search and identify which BESS size and SOC range would give the best project profitability for each case defined. To better understand the second stage procedure, a brief description of the economic terms used is given.

Net Present Value

The NPV is the difference between the present value of cash inflows (such as revenue or income) and the present value of cash outflows (such as costs) over a period of time. NPV is used to analyze the profitability of a project. Equation 5.13 is used for calculating NPV:

$$NPV = \sum_{k=0}^{20} \frac{Net\ Cash\ Flow}{(1+r)^k} \tag{5.13}$$

where $Net\ Cash\ Flow$ is the difference between present value of the cash outflow and cash inflow, r is the annual required rate of return and k is the time in future, in this circumstance, number of years.

A positive NPV indicates that the earnings generated by a project exceed the anticipated costs at a specified required rate of return [47].

The BESS cash inflow is represented by revenue which is calculated for each case in the MILP formulation. On the other hand, cash outflow considers Capital Expenditures (CapEx) and Operating Expenses (OpEx). The CapEx consists of BESS purchase cost and Engineering and Construction (E&C). The purchase cost is given by Equation 5.14

$$C_{bess} = P^b_{cap} \cdot C_P + E^b_{cap} \cdot C_E \tag{5.14}$$

where C_P and C_E are power and energy costs, respectively. The OpEx consist of Operation and Maintenance (O&M), and the degradation cost or replacement cost. The degradation cost is used to quantify the degradation related to battery operation. The assumption used is that once the capacity of the BESS degrades it will be replaced at a cost. The two types of capacity fade: idling and cycling, are added to provide a total capacity fade. Accounted for BESS degradation. The total capacity fade $C_{total\%}$ is the sum of Equations 3.2 and 3.3 presented in Chapter 3. Therefore the degradation cost is defined by the following equation:

$$DegCost = E^b_{cap} * C_{total\%} * Cell_{cost} \tag{5.15}$$

where E^b_{cap} stands for battery energy capacity rating, $C_{total\%}$ is the total capacity fade in percentage and $Cell_{cost}$ is the battery cell replacement cost.

With the NPV equation formulated, the Particle Swarm Algorithm (PSO) can be used. The PSO is one of the most successful optimization approaches and is inspired by nature [48]. The algorithm is formulated based on the performance of a swarm such as; a flock of birds, a shoal of fish. Generally speaking, various particles are generated and a fitness function is given to each. The particles exchange information among each other to define which path to follow in order to find the best fitness function e.g. NPV value.

The PSO is used to find the optimal BESS size and SOC range that maximizes NPV for each defined case. However, these two parameters are decoupled: two PSOs will be used..

The first PSO will disregard the degradation cost in the NPV calculation, ensuring that the BESS size found gives the best profitability of potential investments. This optimum size is then used as input for the next PSO, which will consider the degradation cost in the NPV calculations. This decoupling is done in order to later be used in a sensitivity analysis. Therefore, the second stage in the optimization procedure is used to find the BESS size and SOC range while maximizing the NPV.

With both stages explained is possible to combine them and formulate the full optimization procedure and a Benchmark case to validate it.

5.2 Optimization Procedure and Benchmark Case

The first PSO algorithm is written and executed in MATLAB®, two variables are randomly generated between [1W, 1Wh] and [200MW, 400 MWh][2], as power and energy capacity. These two generated variables are provided as input to each MILP previously formulated.

The first stage optimization is then modeled taking into consideration the objective function and constraints for the defined case. The optimization modeling toolbox YALMIP® [30] is used in the MILP formulations. With the MILP developed the solver Gurobi [31] is used to find the maximum revenue.

The output of the solved MILP is revenue and battery SOC profile. The SOC profile is then separated between idling and cycling mode to calculate degradation cost. The degradation cost and BESS revenue are used to calculate the NPV which is the fitness function to the PSOs. For the first PSO, the degradation cost is disregarded from the NPV calculations. This PSO will then try to maximize NPV by changing the BESS size. The process is repeated until the fitness function has no significant improvement between iterations or reach the maximum number of iterations predefined.

The output of the first PSO: optimum BESS size, is then used as input for the second PSO. The procedure is the same as explained before. The difference, in this step, is that the BESS size is fixed as the optimum size. The decision variables are SOC_{min} and SOC_{max} and the degradation cost is considered in the NPV calculation. Figure 5.6 make this procedure more clear.

[2]The lower bound is chosen as 1 so it is possible for the second PSO to find the best SOC range. The upper bound is chosen to increase the PSO performance.

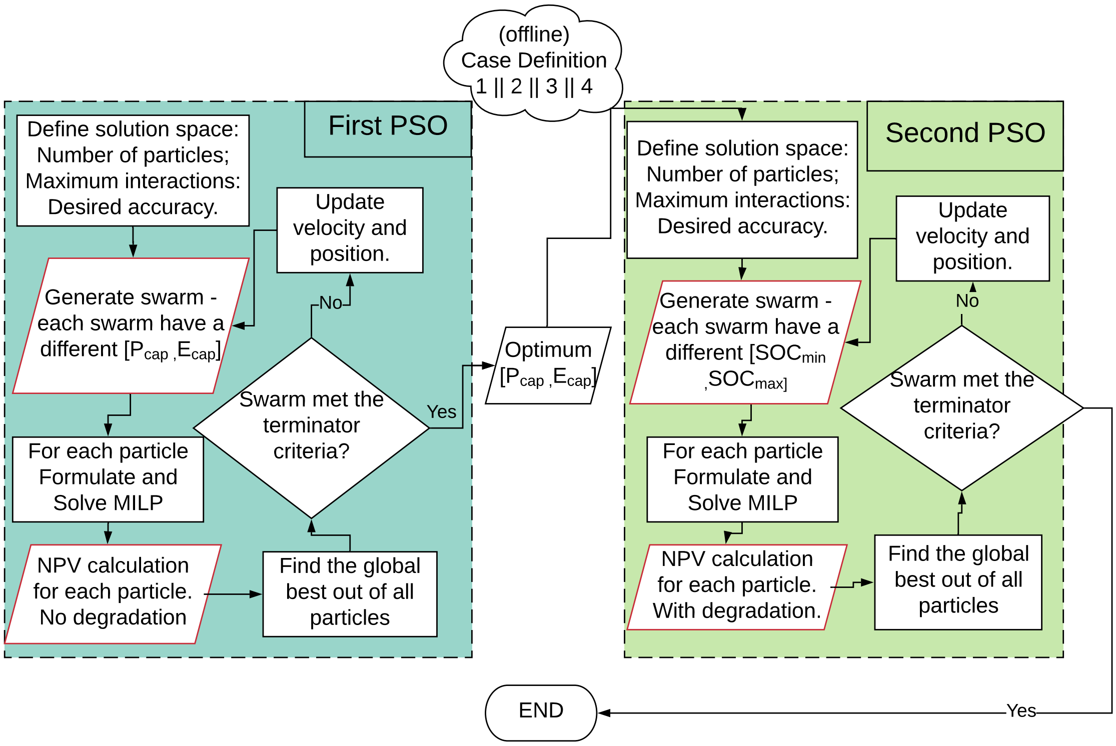

Figure 5.6 Full Optimization Procedure Flowchart.

Having the full optimization procedure formulated and explained. A Benchmark case is defined below, to evaluate the optimization procedure.

5.2.1 Benchmark Case

Case 1 will be used as a Benchmark. A deterministic approach is used to define the best possible operation scenario for a battery providing energy arbitrage only. This implies a perfect price forecast in a one-year optimization window.

Figure 5.7 show the first PSO operation. This PSO will evaluate the best "Fitness value" i.e. the NPV value in 20 years, disregarding degradation. From the figure is possible to observe the PSO process. Until the fifth iteration, the swarm is still searching for the optimum BESS value. There is no significant NPV improvement between iteration 6 and 30, so the operation is finalized.

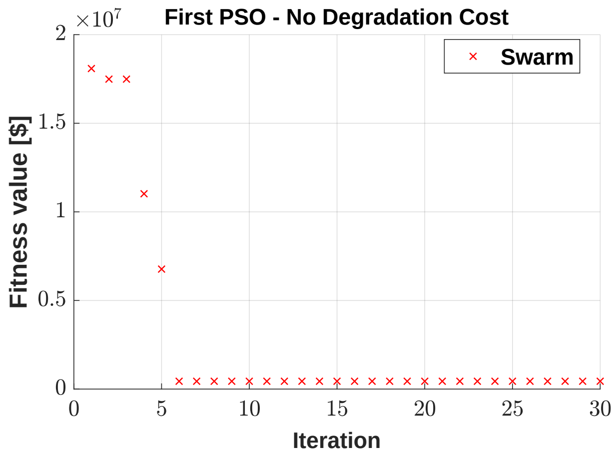

Figure 5.7 First PSO BESS size Search Process.

The final value found by the first PSO is its lower bound, 1W / 1Wh. Implying that no BESS will bring profitability in Case 1 i.e. the possible revenue accrue from having a BESS participating in arbitrage only does not suffice a project implementation. Provided that even if the degradation cost is disregarded, there is no optimum size. The second PSO considering such cost is not evaluated.

This result is supported by other papers evaluating a Li-ion BESS profitability participating in arbitrage only in the same market [19]. This, however, does not mean that a BESS is not a profitable revenue stream in the energy arbitrage the only case. As stated in Chapter 2, in the energy arbitrage market the energy bids are not financially bonded. The revenue comes from the RTM, each settle prices every 15 min. This market as shown in Chapter 4 have high prices leading to higher revenue than the one for Case 1, just analyzed.

The key points of this chapter are summarized in the following section.

5.3 Summary

This chapter dealt with the optimization procedure used to define the BESS size. Firstly, four cases were defined to assess the different bidding schemes in which a BESS can participate. The optimization procedure is divided into two stages to deal with non-linearity problems. The first procedure deals with the BESS unit commitment problem. For each case predefined a MILP problem is formulated and validated with a week of BESS operation. This formulation takes into consideration grid and battery constraints while maximizing the revenue. The second stage of the optimization deals with the optimum BESS size. At this stage, two PSOs algorithms are used to evaluate the BESS size while maximizing NPV with and without degradation cost. Lastly, Case 1 is used as a Benchmark to verify the full optimization procedure combining stage one and two previously mentioned.

With the forecast methodology and the BESS optimization procedure formulated. Is possible to define a practical operation schedule for the BESS in the following chapter.

Chapter 6

Operating Schedule Strategy

This chapter will bring together the forecast method and the optimization procedure to provided a practical operation strategy to BESS. Firstly, the operational strategy is described taking into consideration forecast and optimization. Secondly, the defined operational strategy is evaluated. Furthermore, the strategy is used to economically evaluate the different cases defined in the last chapter. Lastly, a sensitivity analysis is presented.

6.1 Receding Horizon Control

In reality, the BESS operation does not possess a deterministic view like the one defined for the Benchmark case. Therefore, in order to evaluate the real profitability of such system, a practical operation strategy must be used. A Receding Horizon Control (RHC) strategy often used as a scheduling procedure, which can be used in real-world operations, is selected [49].

RHC or model predictive control can be considered as a type of feedback control [49]. The RHC shows a good performance for stochastic and nonlinear problems. However, the RHC is an inappropriate control method for real-time applications, where it increase the size of an optimization problem and requires data estimations. Therefore, the RHC can be considered as a viable option to control systems with sample times like the one analysed [7].

The RHC concept is illustrated in Figure 6.1. Basically, the optimization problem, at each time step, is solved over a fixed time horizon. Then, the decision variables from this horizon are used. The prediction horizon, consequently, moves forward and the same procedure is repeated[1]. Then, the market price data used for each case is forecasted, over the prediction horizon. The optimization problem is solved based on forecasted prices to maximize revenue. All constraints should be satisfied at each iteration to guarantee the feasibility of the solution [7, 49]. The energy content in the battery by the end of the time horizon ($E^{(End)}$) is used as input for the next time horizon, ensuring operational continuity.

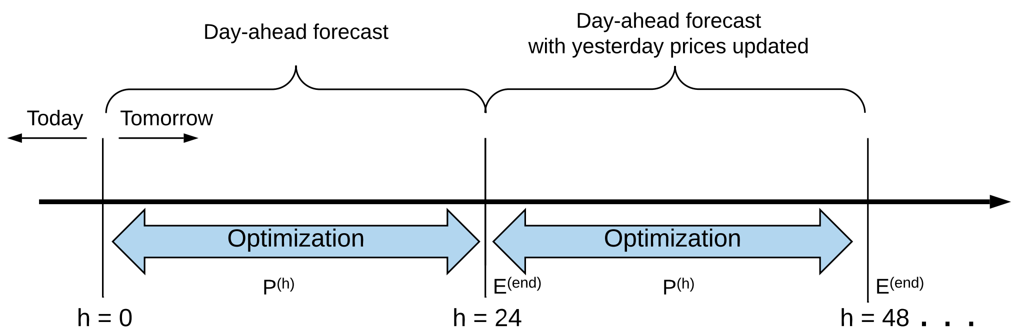

Figure 6.1 Schematic of Receding Horizon Control (RHC).

Five markets are forecasted and used in the RHC approach, REGUP, REGDN, RRS, NSPIN, and DAM. Each market is forecasted using the ANN methodology defined in Chapter 4. Table 6.1 show the forecast errors for each of these markets. The high error percentage is due to price spikes, forecast improvement is not the main focus of this thesis, thus these forecasted values will suffice [2].

Table 6.1 Forecast error for each market used in the forecast.

Market	MAPE [%]	MAE [$]	Daily Peak MAPE [%]
DAM	38.83	4.30	18.98
REGUP	64.49	3.65	46.57
REGDN	69.70	2.79	36.76
RRS	45.67	3.51	26.86
NSPIN	768.01	1.99	240.55

[1] It is worth noting that all previous wind and price information is available for the optimization problem at each iteration.

The prediction horizon window is chosen to be 24 hours to simulate the day-ahead market operations. The day-ahead forecast is used to solve the MILP for each case in Table 5.1. The horizon is moved, prices are forecasted for the next 24 hours and the procedure repeated. This is done until the end of the year. The annual revenue is calculated using the predicted battery schedule and the real market prices. The degradation is calculated using the battery charge/discharge profile. The full optimization procedure defined in section 5.2 is used, where two PSOs are used. The first step the PSO will generate battery sizes in order to maximize NPV disregarding degradation, for every combination of battery size the RHC strategy is performed until the optimum size is found. The optimum size is then used as input to the second step, where the PSO will find the optimum SOC range for the optimum size found considering degradation in the NPV calculations. The RHC procedure is the same as before. Figure 6.2 captures this entire procedure.

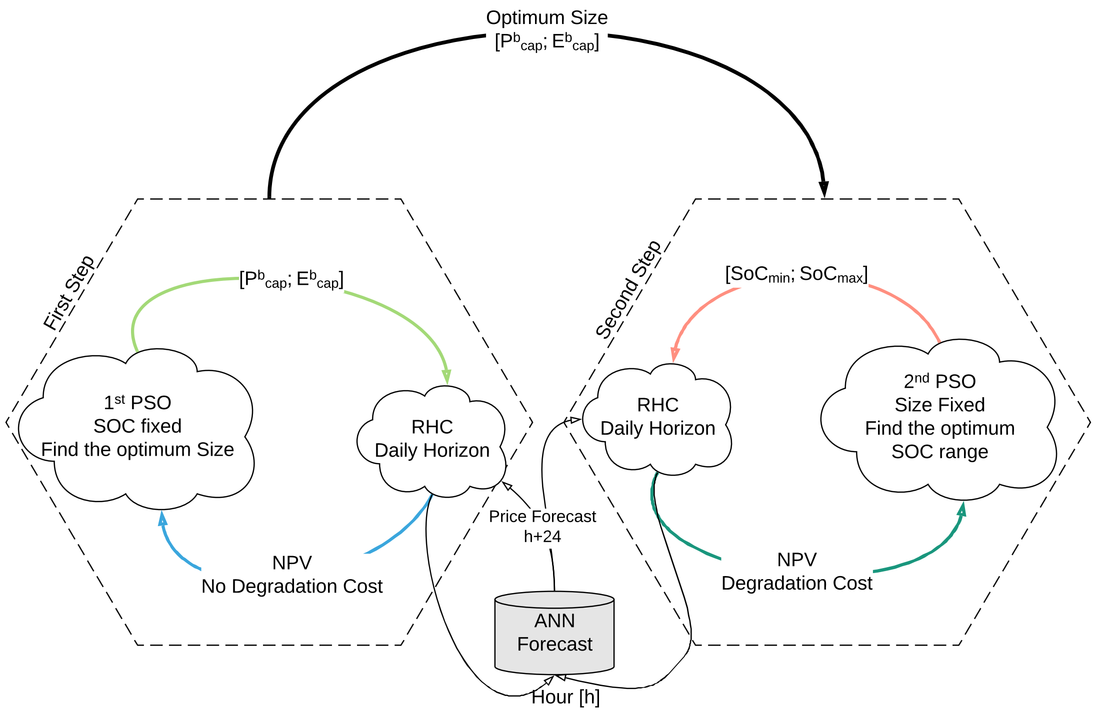

Figure 6.2 Combined RHC and PSO Strategy to find Optimum Battery Size and SOC Range.

This procedure is done for Case 2, 3 and 4. Case 1 is disregarded from this analysis once its was found that for the best operational case (perfect foresight), the battery was deemed unprofitable. The procedure is done twice for cases 2 to 4. One simulation is done using the forecasted prices, called stochastic RHC. The other simulation is done using perfect foresight, called deterministic RHC. The later is used as an upper bound for the RHC strategy. Different results from the simulations will be described in the following section.

6.2 Results Examination

The results presented in this section are divided to better visualization. Firstly, the RHC strategy results will be presented to evaluate its ability as a practical operation strategy. Secondly, the economic results will be evaluated, to verify the BESS profitability.

6.2.1 Practical Operating Schedule

The first set of results will show the RHC ability in providing a practical operation scheme to the BESS operator. In Figure 6.3 is seem the annual revenue for each case evaluated. The figure illustrates the ability a RHC strategy has. The revenue values found using the RHC methodology are rather close to the upper bound.

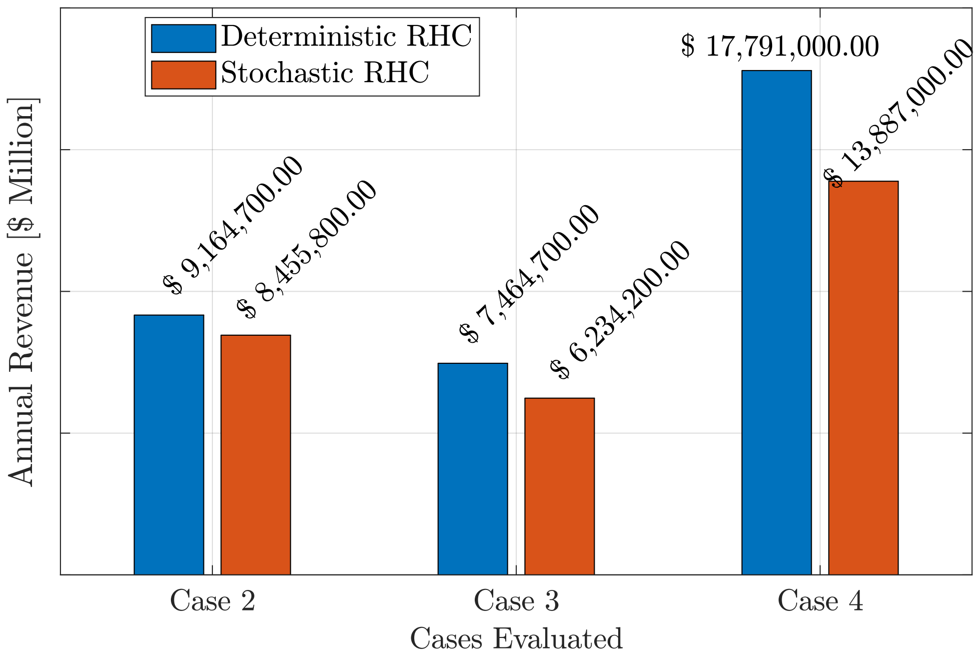

Figure 6.3 Revenues from Each Formulated Case Using Deterministic and Stochastic RHC.

The highest revenue discrepancy is observed in Case 4, with a 22% difference between stochastic and deterministic RHC. Case 1 presents the lowest with 8% followed by Case 3 with 16%. Case 4 has the highest revenue in both RHC simulations. With values close to 18 Million. Is important to point out that with an increase in forecast horizon this revenue could be increased.

Table 6.2 reveals the BESS sizes found by the optimization procedure. These values show another strength of the RHC strategy. The stochastic and deterministic BESS size values are close to each other. In fact, in Case 2, the BESS optimum size is the same for both RHC simulations.

Table 6.2 BESS Optimum Size for each Case Studied, Considering RHC Planning.

	Power		Energy	
RHC	Deterministic	Stochastic	Deterministic	Stochastic
Case 2	100 MW	100 MW	108 MWh	108 MWh
Case 3	119 MW	110 MW	147 MWh	125 MWh
Case 4	200 MW	177 MW	210 MWh	189 MWh

Case 4 presents the highest size. Being the case where all markets are considered, the optimization seems to define a large capacity in order to fully used the available revenue streams. Is useful to remember that these values are found without considering the degradation cost in the NPV calculations. In reality, the degradation effect shown in Table 6.3 is quite severe. To avoid redundancy, only the deterministic RHC values are used in the following analysis.

In all cases the BESS has high capacity fade due to cycling. As demonstrated in the MILPs validations. The BESS performs high discharge/charge cycles in order to obtain such high revenues. This leads to high capacity fading. In Case 4 the fading is so high that the replacement cost surpass the actual revenue seen in Figure 6.3.

Table 6.3 BESS Capacity Fade for each Case Studied along with its Total Replacement Cost and the Actual Revenue.

	Case 2	Case 3	Case 4
Cap. Fade Idling	0.068 %	0.7083 %	0.07 %
Cap. Fade Cycling	22.54 %	18 %	51.61 %
Replacement Cost	$ 4.88 Million	$ 5.32 Million	$ 21.17 Million
Percentage of Actual Revenue Earn	47 %	29 %	- 22 %

If the degradation cost were to be accounted for in the revenue. The actual revenue earn would be less than the ones previously observed. In Case 2 for example, a 47% decrease in revenue would be observed. Case 3 has the lowest lost in actual revenue, due to its lowest capacity fade out of the three cases evaluated. This is explained by the markets used in this case. The BESS has fewer options to charge from. Therefore, it decides to wait for high prices to discharge, leading to longer idling time. This can be corroborate by the fact that Case 3 has the highest capacity fade due to idling out of all the three cases.

The degradation looks severe in some cases such as 4. But it may be that in cases like 2 or 3 the lost in revenue due to degradation is not severer enough to stop project implementation. In addition to that the following economic analysis also gives which of the three cases presents a potential project implementation.

6.2.2 Economic Analysis

The BESS project is assumed to have 20 years, the same as a WF. Therefore, the NPV after 20 years of project development will be assessed. A second economic term is defined to better comprehend the results to be presented. The NPV ratio (NPV_{ratio}) gives the amount of money returned for each dollar invested in the project. For example, if the NPV ratio of a project is 10/$, that means the project returns 10 dollars for each dollar invested. This ratio gives a better comparison between projects once it only takes into consideration the profitability of each project [47].

Table 6.4 presents the NPV in 20 years and the NPV ratio of each case evaluated in this chapter. Without the degradation cost, the best market bid scheme is the one presented in Case 2. Case 4 presents the highest NPV (86 Million), however, the large BESS (200 MW/ 210 MWh) makes the project less attractive than Case 2.

When considering the degradation cost, none of the market schemes has a positive NPV. For such condition, Case 4 shows the worst performance. Again Case 2 presents as the most attractive out of all three.

Table 6.4 Economic Evaluation of each Case.

Projects Economic Analysis				
	No Degradation Cost		With Degradation Cost	
Economic term	$NPV_{t=20}$	NPV_{ratio}	$NPV_{t=20}$	NPV_{ratio}
Case 2	$ 46 Million	+ 0.789/$	- $14.81 Million	- 0.234/$
Case 3	$ 3.41 Million	+ 0.044/$	- $ 62 Million	-0.759/$
Case 4	$ 86 Million	+ 0.748/$	- $183 Million	- 1.337/$

From a purely projects implementation perspective, Case 2 has presented the most attractive values out of all the cases analyzed. The degradation has quite a large effect on the project implementation. None of the cases presents positive NPV if degradation cost is considered.

Having that in mind, a sensitivity analysis is carried out in the following section to verify if the using less energy capacity could lead to better profit implementation.

6.3 Sensitivity Analysis

The sensitivity analysis is carried out from the second PSO defined in the optimization procedure. Therefore, the BESS values are the ones presented in Table 6.2. To recapitulate, the second PSO will find the best SOC range while maximizing revenue.

The sensitivity analysis is presented in Table 6.5, where the optimum SOC range found is given for each case. Except for Case 4, all the other cases have SOC range in the upper half percentage. In all cases, however, the actual BESS capacity used is close to 20% of total energy capacity.

The capacity fade is reduced significantly. Cases like Case 4, which presented 51% capacity fade due to cycling now presents 7%. On the other hand, the capacity fade due to idling has an increase in each case. The replacement cost due to degradation follows the decreasing trend. Degradation cost is presented in the thousands for Case 2 and 3, where before it was in the millions.

The fewer energy availability is perceived in the annual revenue stream. Revenue, as expected, is less than in previous cases with larger energy capacity for use.

Table 6.5 Sensitivity Analysis for Change in SOC Range.

		Case 2	Case 3	Case 4
SOC Range		54 - 77 %	53 - 70 %	0 - 27 %
Annual Cap. Fade	Idling	0.288 %	0.851 %	0.2192 %
	Cycling	0.549 %	0.778 %	6.978 %
Replacement Cost		$ 180,690.00	$ 478,960.00	$ 3,022,800.00
Annual Revenue		$ 4,266,700.00	$ 2,943,500.00	$ 10,627,000.00
Project Analysis	$NPV_{t=20}$	- $ 21.8 Million	- $ 63 Million	- $ 47 Million
	NPV_{ratio}	- 0.343/$	-0.764/$	-0.3723/$

However, despite the decrease in degradation cost, when constrained SOC is used, the NPV is still negative. Looking at the NPV ratio, Case 2 still present the best project implementation attractiveness out of the three. However, Case 4 has a better NPV ratio than Case 3. As a matter of fact, Case 3 NPV ratio is worst than before. Case 4 seems to benefit the most from the SOC constrain.

Table 6.6 helps to visualize this improvement. The percentage decrease for each parameter presented before is given. As observed before, the BESS for all cases has a 80% capacity decrease i.e. 80% of the BESS capacity is not used. In all cases the replacement cost is decreased, presenting values such as 96% in Case 2, for instance. The annual revenue is also decrease, with Case 3 presenting the highest lost in revenue. However, the lost in revenue seems to balance with replacement cost in the project analysis. For Case 3 the NPV ratio has a small increase. Contrary to Case 2, where the lost in revenue has a big impact in project implementation. The NPV has a 47% increase.

Table 6.6 Percentage Decrease in Parameters when SOC Range is Constraints

Parameters Percentage Decrease				
		Case 2	Case 3	Case 4
BESS Energy Capacity			∼80 %	
Replacement Cost		96 %	91 %	86 %
Annual Revenue		53 %	60 %	40 %
Project Analysis	$NPV_{t=20}$	-47 %	-0.2 %	74 %
	NPV_{ratio}	-46 %	-0.6 %	72 %

Case 4, however, has the best improvement out of the three cases. Its replacement cost declined to 86%, while revenue had a 40% decrease. Its project implementation increased to 72%. A summary of the chapter is given in the following section to identify key element points introduced in this chapter.

6.4 Summary

This chapter combined the the forecast methodology and the optimization procedure to provided a practical operation schedule for the BESS. A receding horizon control strategy was used to evaluate the actual profitability of the BESS in three different cases. Firstly, the RHC strategy was simulated with perfect foresight to predefined an upper bound. This upper bound was used to evaluated the RHC strategy with forecasted markets. The performance was deem satisfactory, as the forecast and the perfect foresight results were close. Subsequently, the RHC operation was used to evaluate the BESS project implementation. Revenue streams up to 18 Million were found using a 200 MW / 210 MWh battery. This, however, lead to high degradation costs. Even though projects showed positive NPV values if degradation was not considered, no project showed the same if degradation was considered. Overall Case 2 presents to have the highest project implementation of all cases evaluated. Eventually, a sensitivity analysis was carried out. The BESS SOC range was constrained and the results founds point to a high decrease in degradation cost. The revenue, however, also decreases. Again no project showed positive NPV and Case 2 present to have the best NPV ratio. The conclusion and future work are presented in the next chapter.

Chapter 7

Conclusion and Future Work

7.1 Conclusion

In this thesis, a key focus is put on investigating on the BESS profitability in multiple market services provision. Wind power generation has had an increase in deployment in recent years. Nevertheless, its share in the electricity market is still small when compared with the non-renewable generation. Largely due to its inability to provided multiple market services. BESS is presented as a prominent solution. Its installation is supposed to add different services provision to wind power portfolio leading to an increase in its share in the generation mix.

In order to evaluate such a scenario, an practical operation scheduling procedure for the BESS was defined in this thesis. In the interest of having such operation in place key elements needed to be addressed. Firstly, the ERCOT electricity market and its rules and regulation were presented. Furthermore, the conjoint BESS and Wind Farm system was described as a hybrid system. A BESS degradation model was defined and the wind farm structure develop. Subsequently, a price forecast methodology for different markets was found. Afterward, the optimum BESS operation was addressed through an optimization procedure. Eventually, with all the information necessary, the practical operation schedule was addressed. The RHC strategy was used combining the forecast of 5 different markets and the optimization procedure. The RHC strategy performed with satisfactory results, presenting as a good practical operation strategy.

Finally, BESS profitability was analyzed. The main conclusions suggest that a combination of regulation services and energy arbitrage presents as preferred project implementation out of the cases analyzed. When considering all the market scheme the annual revenue can reach values close to 18 Million. However, the battery has to perform high charge/discharge cycles leading to high degradation cost. Nevertheless, the RHC presented as a good strategy for operations in the electricity market, if combined with a real-time operation strategy the revenue could increase. Another key outcome was how BESS degradation behavior is connected to constrain SOC. Therefore, this behavior must be considered inside the unit commitment problem. The BESS showed positive NPV values if no degradation was considered leading to the assumption that if such parameter could be improved or diminished the BESS project attractiveness most certain would increase.

To conclude the BESS operation showed its rapid response to price changes, fast changes that few systems can provide. If the BESS were to be paid for its performance, its revenue would also increase. Therefore, there is still exists a gap between the optimum amount of degradation and revenue to be considered to define if a BESS can help increase wind power penetration in future work.

7.2 Future Work

In the further part of the text, future work verifying and improving the results of the work carried out in this thesis is suggested. The focus is put on investigation of different scenarios which, due to the limited time period of a semester, have not been investigated.

Task are listed as follow:

- Implement a degradation model inside the unit commitment problem.
- Investigate the profitability of different horizons in the RHC strategy.
- Investigate real-time operation scenarios.
- Investigate BESS project profitability accounting with wind farm revenue.
- Use different search algorithms strategy to identify best BESS parameters.
- Evaluate different batteries with less degradation effect.

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