DEGREE PROJECT IN SYSTEMS ENGINEERING,
SECOND CYCLE, 30 CREDITS
STOCKHOLM, SWEDEN 2024

Optimal Charge Scheduling of a BEV Fleet

Maheen Arfan

KTH ROYAL INSTITUTE OF TECHNOLOGY
ELECTRICAL ENGINEERING AND COMPUTER SCIENCE

Author

Maheen Arfan <maheen@kth.se>
Degree Programme in Aerospace Engineering (120 credits)
KTH Royal Institute of Technology

Place for Project

Gothenburg, Sweden

Examiner

Jan Kronqvist
Department of Optimization and Systems Theory
KTH Royal Institute of Technology

Supervisor

Viktor Larsson and Ahad Hamednia

Volvo Car Corporation

Gothenburg, Sweden

Abstract

As intermittent renewable energy integration rises, so does the demand for increased grid flexibility, particularly for frequency regulation to maintain stability amidst consumption and production fluctuations. The Swedish transmission system operator (TSO), Svenska Kraftnät, procures various frequency regulation services to manage these imbalances. This thesis identifies a significant opportunity for battery electric vehicle (BEV)s to participate in these services, creating revenue by selling flexibility.

The research focuses on optimizing unidirectional EV charging to support grid stability, examining participation in primary reserves FCR-D-Up and FCR-D-Down using synthetic EV fleet data. A non-convex optimization problem is formulated and solved using market data from 2023/2024, incorporating three on-board charger loss models. The findings reveal that FCR-D-Down revenue consistently exceeds 90% of the total revenue during both summer and winter months. Additionally, the optimal charging trajectory for day-to-day energy requirements suggests charging with small input power, typically around $1.1 - 1.7$ kW.

Keywords

Ancillary Services, Frequency Regulation, Energy Market, FCR-D, Battery Electric Vehicle, Virtual Power Plant, and Optimal Control.

Sammanfattning

I och med att andelen förnybar el växer, ökar även behovet av flexibilitet i elnätet. Flexibilitet är nödvändigt bland annat för att säkerställa frekvensreglering. För att skydda mot dessa obalanser upphandlar Svenska Kraftnät flera olika frekvensregleringstjänster. Denna studie undersöker potentialen för elfordon att delta i frekvensregleringstjänster och skapa intäkter genom att sälja flexibilitet. Fokus läggs på optimering av enkelriktad elbilsladdning, med särskilt fokus på deltagande i primära reserver FCR-D Upp och FCR-D Ned. Syntetiskt data från en elfordonsflotta används för att utvärdera potentialen, och ett icke-konvext optimeringsproblem formuleras och löses med prisdata från 2023/2024.

Resultaten visar att intäkterna från FCR-D Ned konsekvent överstiger 90% av de totala intäkterna både under sommar- och vintermånader. Vidare, studien visar att den optimala laddningsstrategin för dagliga energibehov föreslår laddning med låg laddeffekt, vanligtvis runt $1,1 - 1,7$ kW.

Nyckelord

Stödtjänster, frekvensreglering, elmarknad, FCR-D, elfordon, virtuellt kraftverk, och optimal styrning.

Acknowledgements

I extend my heartfelt gratitude to both Dr. Ahad Hamednia and Dr. Viktor Larsson for giving me this wonderful opportunity. I would not have enjoyed writing this thesis a tenth as much if it was not for your company.

I also want to express my gratitude to my academic supervisor and examiner, Professor Jan Kronqvist, for his invaluable feedback and guidance.

Acronyms

EV	electric vehicle
TSO	transmission system operator
DSO	distribution system operator
VPP	virtual power plant
FCR-D	frequency containment reserve disturbance
SVK	svenska kraftnät
mFRR	manual frequency restoration reserve
FFR	fast frequency reserve
AC	alternating current
LHS	latin hypercube sampling
DC	direct current
BEV	battery electric vehicle
aFRR	automatic frequency restoration reserve
BRP	balance responsible party
FCR-N	frequency containment reserve normal
ECU	electronic control unit
BSP	balancing service provider
MILP	mixed-integer linear programming
NLP	nonlinear programming
OBC	on-board charger
OBCA	optimal bid capacity allocation
SOE	state of energy

Contents

Chapter 1

Introduction

1.1 Background

The upcoming penetration of BEVs has drawn significant research interest, aiming at their efficient integration in today's energy systems. These electric vehicle (EV)s can be charged using fast charging stations, workplace chargers, and private home chargers, which will be supplied from the local distribution network. Recent research indicates that large scale, uncontrolled charging of BEVs can cause energy shortages, unacceptable voltage fluctuations, transformer overloading and increased energy losses in (local) distribution networks [1]. Such high electrical energy demand by BEVs within short time intervals can, can cause congestion in the distribution network. Consequently, it can create a need for substantial infrastructure upgrades. These upgrades are economically burdensome for utility companies and have long lead times.

In parallel, global efforts to address the climate crisis are driving a shift towards integrating variable energy sources, like wind and solar, into the power grid. However, these sources produce energy in patterns that vary significantly throughout the day and are challenging to predict accurately. For instance, the phenomenon of ”duck curves”, which illustrates the timing imbalance between peak solar energy production and peak household demand, has been observed in Sweden. Currently, this issue largely stems from electricity imports from other parts of Europe [2]. Nonetheless, Sweden itself is also committed to achieving a 100 % renewable energy supply [3], despite the challenges posed by the phasing out of nuclear energy, which is not classified as renewable. This shift is crucial as the demand for electricity in Sweden is expected to rise sharply, driven by investments in hydrogen-based green steel production in northern Sweden and the broader electrification of the transportation sector.

The evolving energy landscape, characterized by the uncertain future of plannable energy sources like nuclear power and the growing reliance on unpredictable energy production, highlights the urgent need for enhanced grid flexibility. This flexibility is crucial to maintain a stable grid frequency at 50 Hz and ensuring the delivery of high-quality power to consumers. Ancillary services, provided by flexible consumers, plays a vital role in achieving this stability. With production unpredictability, it is essential to ensure that at least consumption is well-scheduled.

The primary objective of a local distribution system operator (DSO), is to maintain a relatively flat demand curve throughout the day to avoid overloading the local transformers. While there will inevitably be peaks in the morning and evening, a promising way to minimize these fluctuations and achieve a flatter overall demand curve is through strategic BEV charging, as illustrated by the dashed line in Figure 1.1.1. Here, valley-filling may be done during peak solar hour when there is overproduction in the system given an EV is connected to the network.

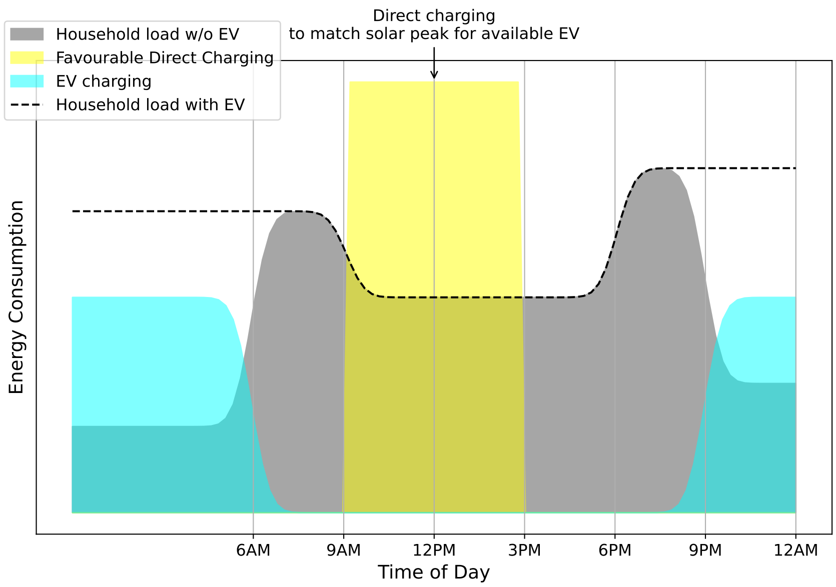


Figure 1.1.1: A flat demand curve is desirable from the DSO perspective.

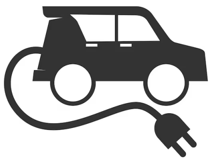
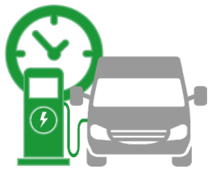
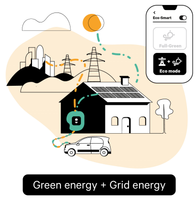
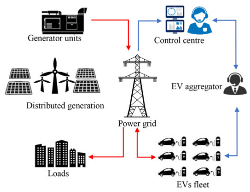
The EV battery is an ideal source for ancillary services due to its significantly faster response times compared to conventional thermal generators. Additionally, the cost for EVs to provide frequency regulation is practically null. While an EV is plugged in for charging, it can simultaneously offer regulation services to the grid by shifting its charging times according to grid needs. Unlike generators, which incur additional wear costs when participating in ancillary markets [4], EVs with unidirectional grid interaction do not experience these costs. Furthermore, the marginal cost of using the EV battery for regulation is close to zero, as the investment in the battery was made for the owner's transportation needs, not for providing regulation services.

To control EV charging optimally, several parameters must be considered, including the charging start time, charger rated power, charging location, battery capacity, and the initial state of energy (SOE) of the EV. Anticipating these uncertainties, many studies propose methods such as vehicle-to-grid (V2G) interactions, as well as vehicle-to-building (V2B) and vehicle-to-home (V2H) technologies. These methods help alleviate the burden on the energy grid by allowing EVs to discharge energy to the grid or use stored energy within buildings and homes during peak demand times, thus balancing supply and demand more effectively. This paves the way for innovative business models and charging strategies.

One common strategy is smart-charging, which involves charging EVs during off-peak hours to avoid household peaks and take advantage of cheaper spot prices. However, if all EVs begin charging simultaneously during these off-peak times, it can lead to congestion and increased stress on the local distribution network [5]. Therefore, there is a need for additional business models that manage EV charging more effectively, ideally shifting the charging to times that better support grid stability and efficiency, rather than merely focusing on spot price savings.

EV charging can be categorized into several stages, each representing a different level of integration with the grid [6]. These stages, as illustrated in Table 1.1.1, range from basic direct charging to advanced optimized charging strategies. The simplest form, direct charging, involves plugging in and starting to charge vehicles whenever required without considering timing or grid conditions. While this can be beneficial during periods of overproduction, it can also lead to increased stress on the grid during peak demand times. Manual charging timers mitigate this controlling the start and stop times of charging sessions, thereby avoiding peak hours.

Table 1.1.1: Stages of Electric Vehicle Charging.

Step 0	Step 1	Step 2	Step 3
Direct charging	**Manual charging timers**	**Smart home energy management**	**Optimized charging**
Plug-in when needed	Load-shifting	Fuse protection V2G	Aggregation V2G
			

Home energy management takes integration further by including V2G interactions and V2B or V2H technologies. These methods enable EVs to support local energy needs and contribute to grid stability during peak demand periods. Smart charging optimizes charging times by shifting them to off-peak hours, which reduces the load on the local distribution network and leverages lower electricity prices, though it requires careful management to avoid congestion. In this thesis, the focus will be on the most advanced stage, optimized charging, which involves an EV aggregator coordinating the charging process for multiple EV owners. The aggregator participates in day-ahead energy markets and ancillary service markets on behalf of the EV owners, strategically scheduling charging loads to minimize their costs and maximize profits. Additionally, by actively engaging in the frequency regulation market, the aggregator responds not only to spot prices but also compensation levels for the ancillary service market. This ensures overall grid health, also alleviating congestion limits on the national transmission lines.

The EV interaction with the grid can be either bidirectional or unidirectional. The bidirectional mode offers higher flexibility and profits but requires additional hardware, additional protection, and thus leads to increased wear of the battery. The unidirectional mode offers less flexibility and profits, but it does not face the above challenges and seems as the first step for EV participation in the regulation market.

1.2 Scope

This thesis explores the Swedish national frequency regulation market, focusing on the two primary reserves: FCR-D-Up and FCR-D-Down. The literature review in section 3.3 refines the research questions, ensuring the study's focus is distinct from previously explored topics. While many studies examine the economics of EV aggregation for frequency regulation in various European markets, few address asymmetrical regulation markets like FCR-D or the specific rules of the Swedish market.

The literature review also identified a knowledge gap in quantifying revenue from two auctions and understanding the charging trajectory for an EV participating in a virtual power plant (VPP). Additionally, there was no research investigating different modelling assumptions for the on-board charger (OBC) losses. Thus, it is crucial to understand both the economic feasibility and technical capability of EVs to meet the regulation market requirements to make informed investment decisions regarding EV aggregation in these markets.

To address such gap, this thesis investigates the potential for EV aggregation to provide flexibility services to the Swedish TSO svenska kraftnät (SVK). In this context, flexibility refers to the ability of an EV fleet to adjust their charging patterns to provide grid services, such as frequency regulation, in response to market prices. The research questions aim to determine the economic potential and technical viability of investing in EV aggregation for an automotive company. The primary objective is to investigate optimal charging strategies for an EV fleet.

The major research questions of this thesis are:

1. How can an optimization problem be formulated and solved for fleet-level charging, considering both electricity prices and revenue from FCR-D services?
2. Which scenario offers the highest revenue from FCR-D: Up regulation, Down regulation, auction 1, or auction 2?
3. What constitutes the optimal charging behavior for a VPP that participates in the FCR-D market?
4. How do different OBC loss models influence the behaviour of the optimal charging strategy?

1.3 Delimitations

This thesis is limited to certain aspects. It focuses solely on unidirectional charging and considers only the FCR-D service, excluding other regulation services such as aFRR and mFRR. The study does not account for the effects of battery temperature on the maximum allowed charging power. Additionally, it does not model or simulate the actual frequency deviations and their effects on charging during the intra-day period.

Moreover, this study only considers the spot price and FCR-D compensation in the objective function. However, there are additional costs associated with EV charging, such as taxes, transmission network fees, and other related expenses.

Given that the Swedish flexibility market is undergoing significant changes each year, the economic feasibility of EV aggregation depends on future market prices, which are determined by the supply and demand for regulation services. However, understanding optimal charging trajectory for a flexible EV, which is central to this study for minimizing on-board charger losses, remains relevant even as market prices change.

The optimization results presented in this thesis are based on historical prices from 2023/2024 and the market rules in place at the time of writing. Therefore, the findings may not remain applicable if market conditions change significantly in the future.

Chapter 2

Vehicle Model

2.1 Overview

This chapter introduces the vehicle model that characterizes the charging behaviour of an EV. The model combines the charging dynamics formulated in the power domain and incorporates three distinct models for OBC losses. Additionally, the individual vehicle usage is nodelled through probability density functions and the latin hypercube sampling (LHS) method. Moreover, the EVs participating in the VPP are assumed to be charged at home using alternating current (AC). Figure 2.1.1 illustrates a schematic representation of a VPP for a fleet size of M.

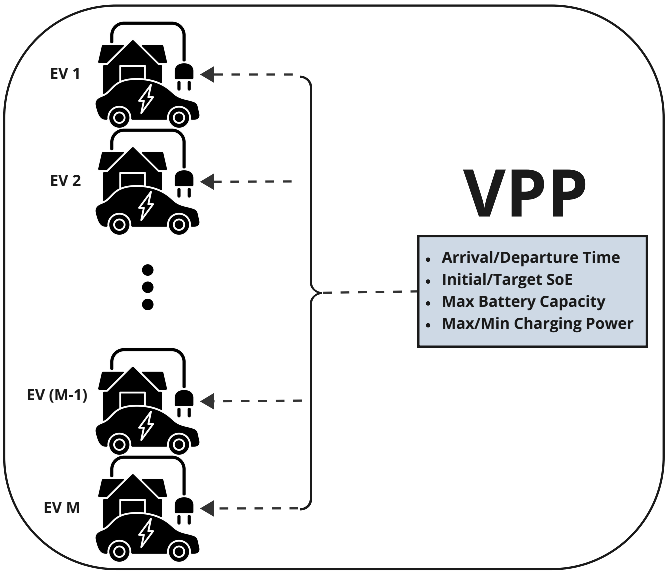


Figure 2.1.1: Schematic figure of a VPP and the key parameters for each vehicle.

EV charging can be done using either AC or direct current (DC) chargers, each with distinct efficiency considerations. AC charging involves converting AC from the grid into DC using an on-board charger, which then delivers the DC to the battery. The OBC, housed inside the vehicle (as shown in Figure 2.1.2), can introduce significant inefficiencies, especially at lower power levels. Typically, efficiency ranges from 75% to 95% [7]. Manufacturers often limit AC charging to power levels above 3.6 kW due to low efficiency that occur below this threshold [8]. DC charging bypasses the OBC, directly delivering DC to the battery, which results in higher efficiency. However, DC charging must manage high current levels, which can lead to high resistive losses and generate significant heat. In both cases, the flow of current involves several stages and components, including the conversion processes and thermal management systems respectively. When referring to wallbox power, it is the power as measured at the wallbox, i.e., before losses.

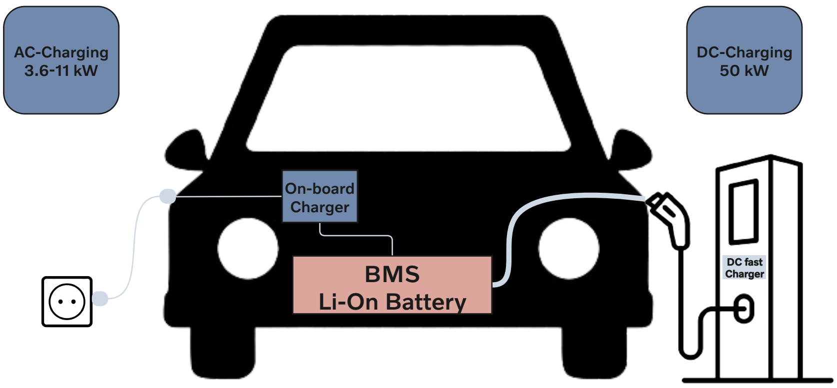


Figure 2.1.2: AC chargers deliver power to the EV's onboard charger.

Table 2.1.1: Notation Table.

Symbol	Definition	Unit
$P_{\text{wb, m}}(n)$	Wallbox power of EV m at time interval n as seen by the utility company	kW
$P_{\text{loss}}(n)$	OBC losses	kW
Δt	Duration of each time interval	h
P_{max}	Maximum charging power of each EV	kW
$\texttt{SOE}_{m,n}$	state of energy of EV m at time interval n	-
η	Charging efficiency	-
β	Energy consumption	kWh/km
$E_d(m)$	Daily commute distance of EV m	km
$E_{\texttt{max}}$	Maximum energy capacity of the EV battery	kWh

2.2 Battery and OBC model

In this study, three OBC models were investigated when studying EV charging for frequency regulation. The models vary in computational complexity and become more detailed in accounting for OBC losses. This research aims to investigate how sensitive the optimal charging strategy is to different modeling assumptions.

The battery SOE can be defined as the ratio of remaining residual energy to the maximum available energy. The SOE dynamics are assumed to be linear and are modelled by equation 2.1, with the relevant variables listed in Table 2.1.1.

$$\mathtt{SOE}_{m,n+1} = \mathtt{SOE}_{m,n} + \Delta t \cdot \frac{(P_{\text{wb, m}}(n) - P_{\mathtt{loss}})}{E_{\mathtt{max}}} \qquad \forall n, m, \tag{2.1}$$

$$P_{\mathtt{loss}} = (1-\eta) \cdot P_{\text{wb, m}}(n) \qquad \forall n, m. \tag{2.1b}$$

The battery and OBC losses are modelled by a constant efficiency. In reality, OBC efficiency is significantly reduced at low charging powers and depends on the current wallbox power as shown in Figure 2.2.1. Charging power depends on both the terminal voltage and the current flowing through the charging circuit, with the power increasing as the current increases. To further simulate battery and OBC losses,

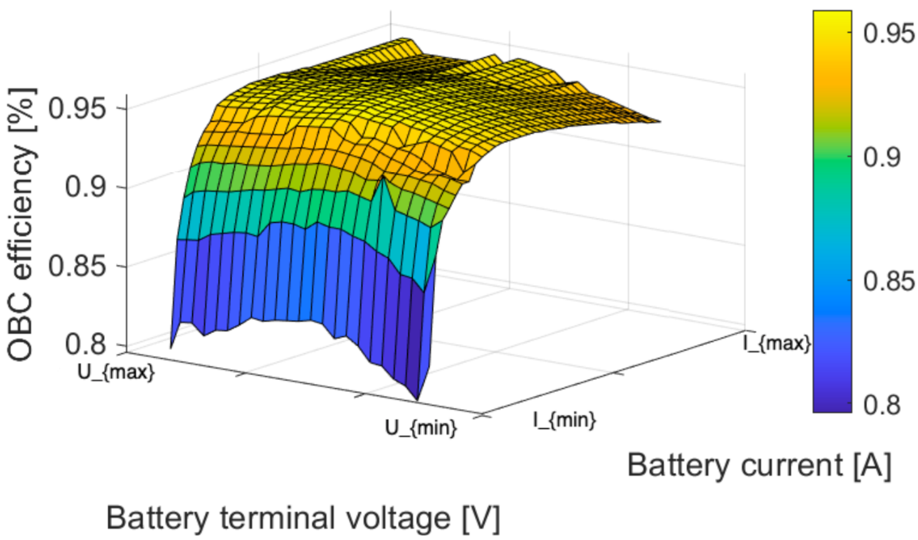


Figure 2.2.1: OBC efficiency as a function of battery terminal voltage and current [9].

two additional quadratic charging dynamics models were considered. The first is a convex model that incorporates the standby cost for each EV participating in a VPP.

Table 2.2.1: Coefficient values [9].

Coefficient	Value
η	0.9
α_0	90 W
α_1	10.9
α_2	3.1 W^{-1}
η_0	0.8
η_1	0.16

This standby cost represents the expense of keeping an EV's core systems active throughout the charging window to ensure a quick response to SVK's activation signal. The parameters for all three models are shown in Table 2.2.1. The convex loss model with standby cost α_0 is expressed by

$$P_{\mathtt{loss}} = \alpha_0 + \alpha_1 \cdot P_{\text{wb, m}}(n) + \alpha_2 \cdot P_{\text{wb, m}}(n)^2 \qquad \forall n, m. \tag{2.2}$$

Additionally, a third concave model was developed to reward higher charging input power by increasing efficiency linearly with increasing charging power as given by

$$P_{\mathtt{loss}} = \left(1 - \left(\eta_0 + \eta_1 \frac{P_{\text{wb, m}}(n)}{P_{\mathtt{max}}}\right)\right) \cdot P_{\text{wb, m}}(n) \qquad \forall n, m. \tag{2.3}$$

The theoretical loss models are plotted with respect to the decision variable P_{wallbox} in Figure 2.2.2.

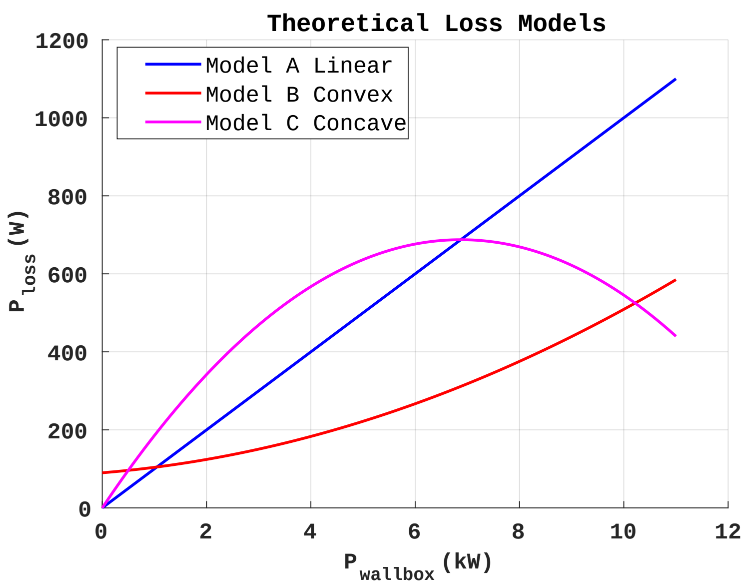


Figure 2.2.2: Theoretical loss models for EV charging.

Each EV can provide a specific amount of up regulation capacity and down regulation capacity, as illustrated in Figure 2.2.3. This model has been used in optimization to manage the provision for EVs who are plugged in throughout the charging window. However, uncertainties remain, such as the number of EVs connected at any given time and as a result the total capacity they can collectively offer. This thesis does not simulate these uncertainties in a stochastic manner.

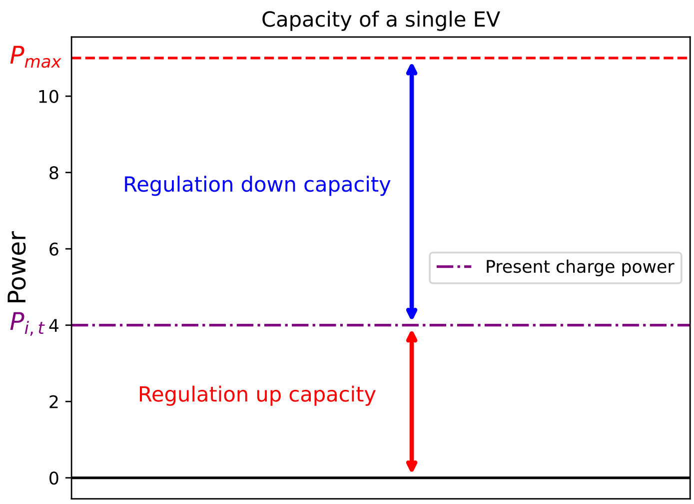


Figure 2.2.3: Capacity of a single EV.

2.2.1 Vehicle usage and energy requirements

To model this problem realistically, the random variability in input data is addressed using probability distributions. One crucial parameter is the arrival time $t_{\text{plug-in},m}$, representing when the EV owner arrives home and connects the vehicle to the grid. The other parameter is the departure time $t_{\text{plug-out},m}$, indicating when the EV is unplugged based on the owner's departure time. To capture these uncertainties, both arrival and departure times are modeled as lognormally distributed random variables, as suggested in [10].

Table 2.2.2: Log-Normal Distribution Parameters.

	Arrival Times	Departure Times
Mean	18 hours	7 hours
Std Dev	1.8 hours	1 hour

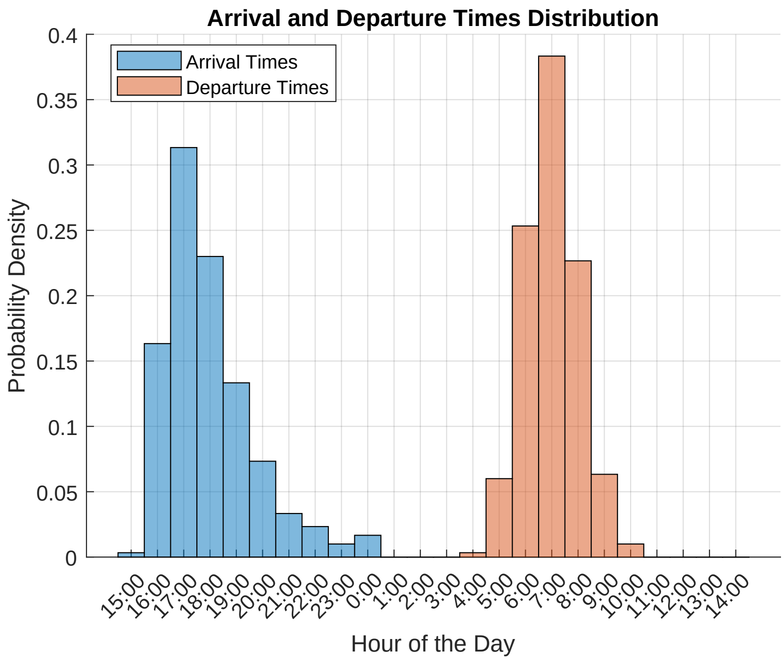


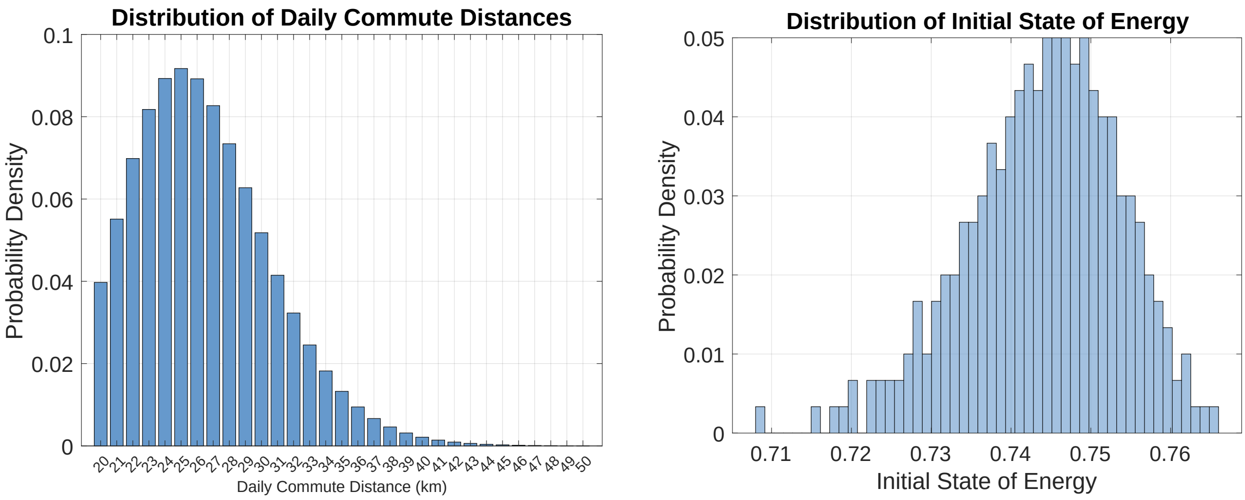
Figure 2.2.4: Histogram of arrival and departure times for EVs participating in VPP.

To generate samples that adhere to these distributions, LHS is employed, as detailed in [11]. The parameters of these distributions can be found in Table 2.2.2, and their probability distributions are depicted in Figure 2.2.4.

The initial state of energy of the m-th EV $\mathtt{SOE}_m^{\text{init}}$ is calculated by equation 2.4, which relies on the daily distance $E_d(m)$ traveled by the EV. This distance is a random variable following a log-normal probability distribution function, with mean and variance values of 25 km and 20 km, respectively [12] [13].

$$\text{SOE}_{\text{init}} = 1 - \frac{\beta \cdot E_d(m)}{E_{\max}}, \tag{2.4}$$

where $\beta = 0.238$ kWh/km, represnting the average energy consumption of the EV per kilometer driven.



(a) Histogram of daily commute distances.

(b) Histogram depicting initial state of energy distribution.

Figure 2.2.5

Chapter 3

Overview of the nordic regulation markets

3.1 Introduction

The power grid is a dynamic and complex system that is usually described as "a huge multi-variable process that works in an environment of constant change". Consumption and generation vary continuously, and so as parameters critical to the power system, such as current, voltage and frequency. The Swedish electricity grid consists of 58,900 km of cable, approximately 43,000 km of which is underground cable and 16,000 km is overhead [14]. The electricity grid can be divided into three levels: transmission grid, regional grid and local grid. The transmission grid transports electricity over long distances at high voltage levels. Svenska Kraftnät, is in charge of all main transmission lines in Sweden. Main transmission lines (220 or 400 kV), act together with regional lines (130 kV) and local lines (<40 kV) to distribute the electricity from producer to consumer. The regional grids transport electricity from the transmission grid to the local grids and in some cases directly to larger electricity users. The local grids connect to the regional grids and transport electricity to households and other end customers. Regional and local distribution lines are not owned by SVK, but rather by DSO. The transmission and distribution grid physically transmit electricity throughout the country, and to countries with which Sweden is electrically connected. However, to ensure that the electricity consumed can be supplied by the production, there exists multiple electricity markets.

Before delving further into the balancing markets within the electricity system, it is important to note certain safety measures that are not traded on day-ahead markets. Key measures include insuring against power shortages, complete blackouts, unexpected spikes in demand and other disruptions. To address this, power reserves (sv. Effektreserv) and disturbance reserves (sv. Störningsreserv) are procured to protect the electrical grid against persistent power imbalances. Although the above mentioned measures are important for the operational reliability, neither of them are sold or bought on daily markets [15]. They all lie outside the scope of the thesis.

In a stable power system, energy demand including system losses must be matched to generation (including import/export) in every instance, regardless of what events occur, such as a line, generator or major electricity user being disconnected. Accordingly, market actors play an important role in the system balancing. As mentioned before, the TSO is responsible for the overall performance of the grid. The DSOs are in charge of regional and local distribution grids. Moreover, there are also local flexibility markets to alleviate the burden on local transformers and cables, which could have the highest priority to the EV aggregator. However, since these markets are very new and are only open during peak consumption hours during winter months [16], prices are not as readily available. However, an actual implementation for the upcoming model would entail that the consumption bids of an aggregator who participates in the national flexibility market are approved by the local DSO. Since, it is the DSO that ultimately deliver the electricity for charging of a large fleet of EVs.

There exists a third party, i.e., a balance responsible party (BRP), that is responsible for balancing production and consumption in their designated area [17], which should not be confused with the four electrical areas in Sweden. The BRP ensures that the demand they oversee is matched by generation for every second of the day. There are numerous BRPs in Sweden [18]. When a discrepancy between production and consumption occurs in a BRP's area, the BRP must pay a penalty fee proportional to the difference to SVK. Therefore, BRPs always strive to balance their portfolios.

Any entity capable of providing flexibility on the frequency regulation markets is referred to as a balancing service provider (BSP). BSPs aggregate a variety of flexible assets, including EVs, solar parks, and batteries, to meet participation criteria established by SVK. These providers must initially collaborate with a BRP to enter these markets. In Sweden, numerous providers have emerged, such as Checkwatt, Flower, and Fever Energy, each selecting different BRPs based on their sources of flexibility.

SVK is currently revising regulations to allow BSPs direct access to the frequency regulation market by autumn 2024. Under this new framework, only BSPs will participate directly in the regulation market. However, BRPs will remain responsible for any imbalance fees incurred if BSPs fail to deliver promised flexibility during operational hours [19]. This restructuring aims to reduce economic risks associated with the BSP's participation in the regulation market [20].

3.2 Electricity markets

The Swedish market can be divided into a set of submarkets. These are the forward market, the day-ahead market, the intraday market, the frequency regulation markets, and finally the market for imbalances. These markets will be discussed further below. A summary of all markets can be seen in Figure 3.2.1. In this thesis, the EV aggregator participates exclusively in the day-ahead market, which consists of three auctions in total.

3.2.1 Financial Market

In the financial market, no physical transaction of electricity occurs. Instead, electricity derivatives are created and traded between parties to mitigate their exposure to risks associated with fluctuating electricity prices. This market allows for contracts up to 10 years before the delivery hour. For example, H2 Green Steel made a 7-year contract for 2 TWh of renewable energy per year with Norwegian Statkraft to secure electricity delivery for the period 2026-2032 [21].

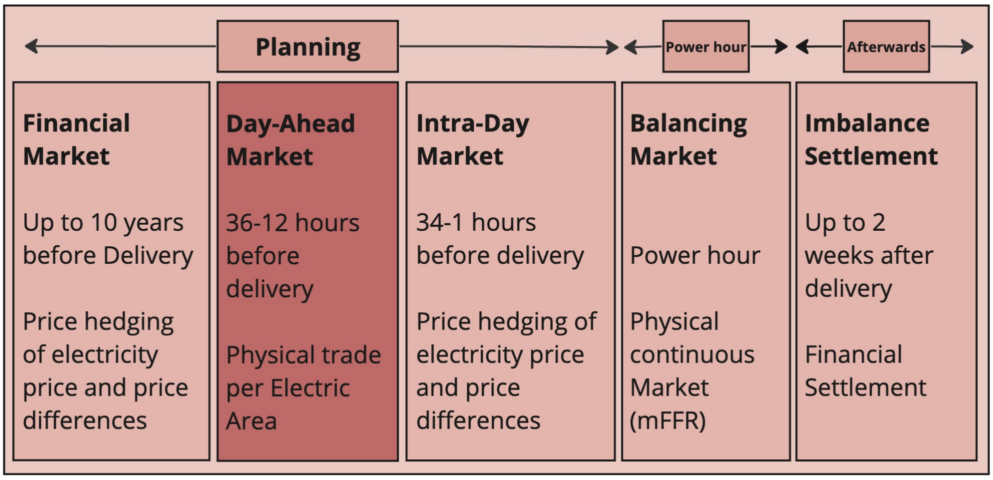


Figure 3.2.1: A summary of the Swedish electricity markets [22].

3.2.2 Day-Ahead Market

The day-ahead market is where most of the electricity is bought and sold. The market takes in bids in a closed auction, so participants are unaware of each other's bids. Every day before noon, producers specify how much electricity they wish to sell at different prices every hour for the next 24 hours. Similarly, electricity retailers and large industrial consumers submit bids for how much electricity they are willing to buy at different prices every hour for the next 24 hours. The network owners announce the capacity of the transmission grid for each hour.

A supply curve is then created for each hour of the next day by adding together all the bids received for that hour and a demand curve by summing up all bids for the same hour for all exchanges together, as shown in Figure 3.2.2. Bids from nuclear and wind power enter the supply curve at the lowest levels due to their low marginal costs, followed by heat and condensing plants. The system price for the hour in question is set at the level at which supply equals demand for the entire geographical market. At 12.00, the day before delivery, the market closes. The day-ahead market is using marginal pricing, also called pay-as-cleared. At 12.45 or later, prices for all hours the coming day are published [23].

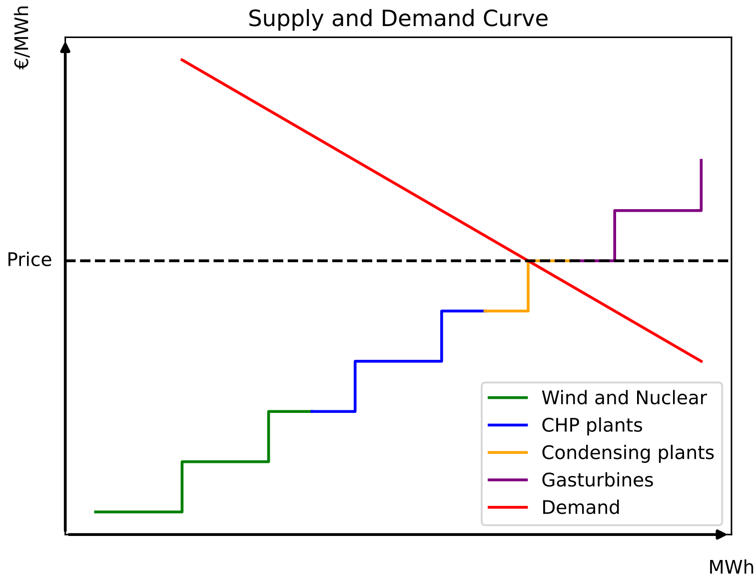


Figure 3.2.2: Renewable sources enter the supply curve at the lowest marginal price [24].

The prices of electricity set on the day-ahead market are generally referred to as the spot prices. Prices set on the day-ahead market differ within Sweden. More specifically they differ between the four different electrical areas. SVK as the network owner receives congestion revenue exporting cheap electricity from producers in the north to consumers in the south [25]. Moreover, the regulation capacities for any hour of the day D are contracted via two separate auctions, both pay-as-cleared structured, on D-2 and D-1 prior to the delivery day (see Figure 3.2.3). Approximately, 80 % of each FCR service is contracted on the D-2 auction, and the remaining in D-1.

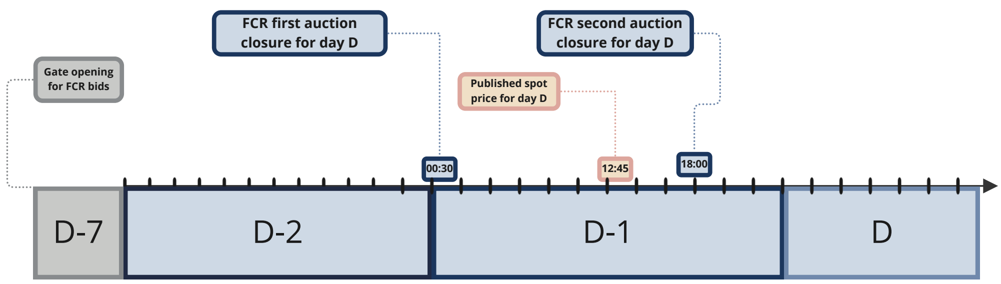


Figure 3.2.3: Timeline for FCR and spot markets in Sweden. There are two auctions for the FCR services, one closes before and one after the spot market [26] [27] [23].

The provision of FCR services entails two distinct stages, namely reserve contraction and activation. Reserve contraction occurs during the D-2 or D-1 auction, wherein the availability of the reserve noted in the FCR bid is approved by the TSO. Compensation for the FCR service in hour n is based on the reserve quantity $r(n)$ (MW) and the submitted bid price $\lambda(n)$ (€/MW), resulting a revenue, the so-called reserve payment. Moreover, the actual payment is based on the pay-as-cleared pricing model. When flexibility suppliers submit their bids and corresponding prices. SVK sorts them in ascending order. The last bid to make SVK's capacity quote sets the marginal price. All bids that are included in the quote are priced with the same marginal price. Figure 3.2.4 aims to describe pay-as-cleared. All bids are paid according to the price of the highest bid, thus SVK has to pay the total demand multiplied with the price of the highest bid.

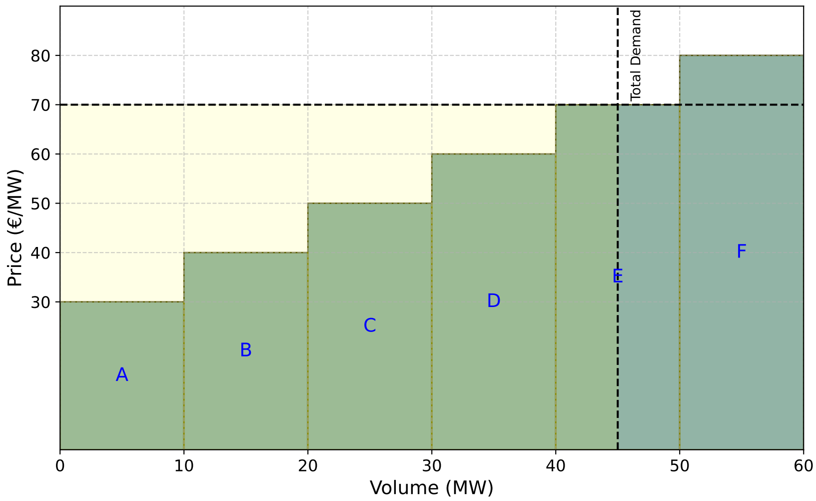


Figure 3.2.4: Pay-as-cleared.

3.2.3 Intra-Day Market

The intraday market allows market players to adjust their positions after the day-ahead market closes. Participants might bid in the intraday market due to revised production forecasts, increased electricity demand, or unaccepted bids from the day-ahead market.

The intraday market is expanding, largely due to the rise in intermittent electricity production, which is weather-dependent and thus has uncertain predictions. As the delivery hour approaches, this uncertainty diminishes, making the intraday market essential for adjusting forecasts for variable production.

The intraday market opens two hours after the day-ahead market closes, at 14:00, and closes one hour before delivery. It operates similarly to a stock market, with continuous trading allowing prices to vary throughout the trading period, even for electricity contracted for a specific operating hour.

3.2.4 Balance hour

Balancing markets are markets that are put in place to provide stability during the hour of delivery. On the frequency regulation market, a total of seven services are bought by SvK, and provided through the BRPs. These services act to keep the frequency in the grid at its nominal value, i.e., 50 Hz in Sweden. Whenever the frequency differs from 50 Hz, one, or multiple services are activated to correct the frequency. They have different properties to provide support in different situations.

The frequency regulating services in Sweden are fast frequency reserve (FFR), frequency containment reserve normal (FCR-N), frequency containment reserve disturbance (FCR-D), automatic frequency restoration reserve (aFRR), and manual frequency restoration reserve (mFRR). Their names, and how they differ from one another, is depicted in Figure 3.2.5. A service name that ends with up only performs up regulation. Up regulation refers to services that are activated to push the frequency upwards. Up regulating services act by injecting energy to the grid, or remove consumption from the grid. The opposite is true for down regulation. Henceforth, these expressions will be used in the thesis. The terminology used to describe frequency regulating services varies between different markets and countries. Another set of terms is primary, secondary and tertiary reserves. Primary reserves refer to the FFR and FCR services, secondary reserve to the aFFR services, while tertiary reserve to mFRR services. Primary reserves acts as the primary tool to hinder a change in frequency and, at best, to restore it. Secondary reserves are activated as the primary reserves are depleting, and aims to restore the frequency to its nominal value. Tertiary reserves such as mFRR are activated at last and with longest durability.

Suppliers of frequency regulating services can receive revenues in two ways: through availability and through activation. All services provide remuneration for availability, while some services provide remuneration for both availability and activation. For availability the suppliers are paid to be available with their resources. Regardless of if a supplier's resource is activated or not, the supplier will be reimbursed either way. Availability is essentially an insurance, it is not certain that the insurance will be needed. It is, in short, the SVK buying insurance for unexpected imbalances. It is emphasized that SVK is the only buyer on all frequency regulation markets. For the services that offer payments for activation, from this point on referred to as activation remuneration, an additional revenue is gained by the supplier in the case that their resource is actually activated for frequency regulation. In that case, the supplier can see two revenues: remuneration from availability and activation.

Remedial action	Frequency containment reserves			Frequency restoration reserves	
FFR	**FCR-N**	**FCR-D Up**	**FCR-D Down**	**aFFR**	**mFFR**
Fast Frequency Reserve	FCR-Normal Reserve	FCR-Disturbance Upward Reserve	FCR-Disturbance Downward Reserve	Automatic Frequency Restoration Reserve	Manual Frequency Restoration Reserve
Upward Regulation	Symmetrical upward and downward regulation	Upward Regulation	Downward Regulation	Upward and/or downward regulation	Upward and/or downward regulation
Procurement Bids on capacity market	**Procurement** Bids on capacity market	**Procurement** Bids on capacity market	**Procurement** Bids on capacity market	**Procurement** Bids on capacity market	**Procurement** Bids on capacity market and energy activation market
Minimum bid size 0.1 MW	**Minimum bid size** 0.1 MW	**Minimum bid size** 0.1 MW	**Minimum bid size** 0.1 MW	**Minimum bid size** 1 MW	**Minimum bid size** Capacity market: 1 MW Energy activation market: 5MW
Capacity remuneration. Pay as cleared.	Capacity remuneration. Pay as cleared.	Capacity remuneration. Pay as cleared.	Capacity remuneration. Pay as cleared.	Capacity remuneration. Pay as cleared.	Capacity remuneration. Pay as cleared.
No energy remuneration	Energy remuneration.	No energy remuneration	No energy remuneration	Energy remuneration.	Energy remuneration.
Activation: Automatic activation	**Activation:** Automatic linear activation within the frequency interval 49.90-50.10 Hz	**Activation:** Automatic linear activation within the frequency interval 49.90-49.50 Hz.	**Activation:** Automatic linear activation within the frequency interval 50.10-50.50 Hz.	**Activation:** Automatic activation for frequency deviations from 50.0 Hz	**Activation:** Manual activation when requested by Svenska kraftnät
Activation time Three alternatives for 100% • 0.7 seconds (at 49.50 Hz) • 1.0 seconds (at 49.60 Hz) • 1.3 seconds (at 49.70 Hz)	**Activation time** 63% within 60 seconds 100% within 3 min	**Activation time** 50% within 5 seconds 100% within 30 seconds	**Activation time** 50% within 5 seconds 100% within 30 seconds	**Activation time** 100% within 5 minutes	**Activation time** 100% within 15 minutes
Endurance 5 seconds alternatively 30 seconds	**Endurance** 1 hr	**Endurance** At least 20 minutes	**Endurance** At least 20 minutes	**Endurance** 1 hr	**Endurance** 1 hr

Figure 3.2.5: Overview of the requirements for reserves [28].

3.3 Related Work

Electric vehicle (EV) fleet management involves a variety of complex decision-making processes, particularly in the context of charging scheduling. These processes are influenced by numerous constraints specific to the problem at hand. In the case of workplace and public charging, the limited number of chargers, and constrained charging windows require the application of advanced mathematical tools to optimize resource allocation. An important survey [29] provides a comprehensive review of the operational decisions involved in fleet charging, highlighting the prevalent use of mixed-integer linear programming (MILP) for addressing these challenges.

Fleet charging involves charging all fleet vehicles during off-peak periods while interacting with the regulation market through so called optimal bid capacity allocation (OBCA). A notable study in this area is [30], which investigates the role of an EV aggregation agent in the Iberian secondary reserve market from 2009 to 2010. This market setup allows for separate bids for upward and downward reserves for each hour of the following day, providing unidirectional flexibility to the grid. Their findings emphasize that revenue is largely driven by intraday market participation, as remuneration depends on the activation of promised capacities. Their model incorporates a 10 % dispatch factor—providing flexibility back to the grid upon activation—thereby generating additional revenue while still meeting full recharge needs for EVs.

The above study is particularly well-suited for markets akin to mFRR down, which compensate based on similar mechanisms. However, it is ill-suited for both the Nordic primary and secondary capacity markets in Sweden, where remuneration does not depend on the activation of bids. A fundamental limitation with secondary and tertiary reserves, such as aFRR and mFRR respectively, is duration requirements in case of activation. When the TSO requires flexibility activation from these reserves—typically an hour or more — the feasibility for aggregators to ensure a reliable connection of enough EVs diminishes. Consequently, while the above model may prove effective for mFRR down reserve with activation taken into account, its actual implementation is constrained in Sweden by the rigorous duration requirements imposed by Svenska Kraftnät for these reserves.

When it comes to a large number of EVs participating in a VPP, on a micro-level, lower-level optimization problems or heuristics make participation decisions based on variables like location, battery state, and vehicle status (e.g., awake, sleep, standby), determining a vehicle's eligibility for inclusion in a VPP. At a macro-level, broader constraints dictate market participation, such as the need for an aggregator to have sufficient capacity to meet the minimum bid size for day-ahead forecasts. This complex binary decision-making framework was explored in a study by [31], which simulates VPP participation hour-by-hour in a deterministic setting. Their research, set in the French electricity market, examines how an aggregator can balance buying electricity in the day-ahead and intra-day markets while also engaging in the ancillary services market. The study identifies a significant motive for participating in the intra-day market: the risk of overcommitting to the ancillary services market to maximize revenues, which could result in resource shortages if not enough EVs are connected.

Surprisingly, the findings reveal that the optimizer prioritizes energy arbitrage as a secondary advantage. Primarily, it reserves a portion of the EVs' capacities for ancillary services. This approach takes into account the bidirectional nature of the bids. Furthermore, the model proposes placing upward bids hourly to maximize revenue; however, such a strategy is constrained by the current SOE, highlighting the practical limitations of real-world application. This limitation accentuates the importance of modelling TSO activation through a binary signal variable, which helps mitigate risks associated with failing to meet energy commitments. Additionally, the findings suggest cautious approaches to downward capacity bids, particularly when deployment requires purchasing energy at higher intra-day market prices. This strategy could constrain opportunities in markets like the Nordic region's primary reserves, such as FCR-D-Down. In these markets, energy used during TSO activation does not create imbalances, and the associated energy costs are often negligible or even negative.

In contrast, for unidirectional up regulation, a model that incorporates a dispatch ratio—tailored to address specific market penalties and operational limitations—would be more effective. This insight leads us into another domain within optimal bid allocation: stochastic programming. Through energy arbitrage and participation in up-regulation, an aggregator, based on favorable price differentials between day-ahead and intra-day markets, might sell their total energy demand for charging during intra-day. This can lead to uninstructed deviation, further explored in [32], of real-time energy consumption from day-ahead bid. This shall naturally result in penalties due to the imbalances created if an activation occurs and charging cannot be halted, as the EVs must still meet their target States of Energy (SoEs). A pivotal study in the nordic market [33] utilizes stochastic optimization to enhance revenue from energy arbitrage while participating in regulation markets and reducing the risk of penalties from bid non-fulfillment, such as those incurred during imbalance settlement. The paper models that aggregator can participate in only one of the FCR markets at a time (either FCR-N or FCR-D). FCR-N bids are symmetrical which means that the same volume for up- and down-regulation is offered. However, FCR-

N requires quick response times, which could be challenging due to communication delays and other technical issues related to EV infrastructure. Nonetheless, the study concludes that there is often more value in energy arbitrage than in promising FCR-D-Up capacity in the day-ahead bid. Therefore, EV aggregator identifies FCR-N as a more profitable option under the study's assumptions.

3.4 Research gap

While existing studies have significantly advanced the field of EV fleet management and regulation market participation, there remains a pivotal research gap in the operational optimization for a large fleet of EVs participating in the Nordic balancing market, particularly post-2022. A novel reserve market, FCR-D-Down, offers fresh opportunities for investigation, especially since capacity bids in this context do not require symmetrical placement for unidirectional cases where both up and down regulation are available. This study seeks to focus solely on aiding the grid stability rather than pursuing energy arbitrage, aiming to clearly quantify the potential revenues from FCR-D in the Nordic market within the year 2023/2024.

Furthermore, to enhance computational efficiency in solving the aggregator problem, this research proposes a methodological shift from the traditional MILP approach to a more flexible nonlinear optimization framework. The nonlinear approach scales much better than MILP-based methods, allowing for the consideration of a larger number of vehicles and more time steps. While the nonlinear approach typically yields a local optimum rather than a global optimum, it offers significant advantages in other areas. Notably, it can incorporate nonlinear effects that are critical for managing OBC losses among large EV fleets. By employing off-the-shelf nonlinear solvers, this approach extends the modeling capabilities to embrace more complex operational dynamics, thereby filling a crucial gap in current research.

Chapter 4

Method

4.1 Methodology

This chapter presents the general Mixed-Integer Linear Programming (MILP) optimization problem formulation and explains the associated notation. Additionally, it introduces the relaxed non-linear problem, which is implemented and solved in this thesis along OBC loss models. The flow diagram for the implemented optimization framework is shown in Figure 4.1.1.

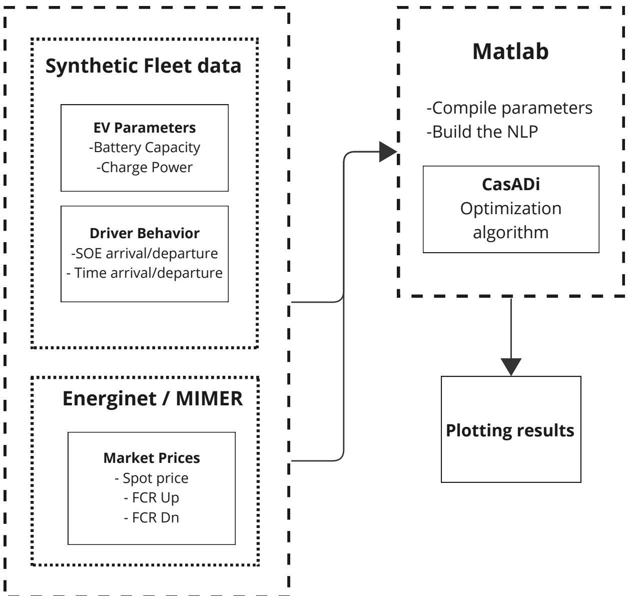


Figure 4.1.1: Data flowchart diagram.

Table 4.1.1: Notation Table.

Symbol	Definition	Unit
F	Binary charging-interval matrix	-
$\mathcal{M}$	Number of electric vehicles (EVs)	-
$\mathcal{N}$	Number of time intervals	-
f_{mn}	Element of the charging-interval matrix F	-
$z^{\mathbf{Up}}$	Binary vector denoting participation in Up-regulation	-
$z^{\mathbf{Dn}}$	Binary vector denoting participation in Down-regulation	-
T_m	Charging period of EV m	-
$\Pi^{\text{DA cost}}$	Day-ahead cost	-
$\Pi^{\text{FCR-D-Up revenue}}$	Revenue from FCR-D Up	-
$\Pi^{\text{FCR-D-Dn revenue}}$	Revenue from FCR-D Down	-
$C_{\text{spot}}(n)$	Spot price at time interval n	€ /MWh
Δt	Duration of each time interval	h
$\lambda(n)$	Compensation for FCR-D Up at time interval n	€ /MW
$\rho(n)$	Compensation for FCR-D Down at time interval n	€ /MW
r_n^{Up}	Aggregate power for FCR-D Up at time interval n	MW
r_n^{Dn}	Aggregate power for FCR-D Down at time interval n	MW
Q^{FCR}	Minimum bid size requirement	-
$\mathtt{SOE}_{t^{\text{start}},m}$	State of Energy of EV at simulation start m	-
$\mathtt{SOE}_m^{\text{init}}$	State of Energy of EV m at start of the charging session	-
$\mathtt{SOE}_{N,m}$	Final State of Energy of EV m at the end of simulation	-
$\mathtt{SOE}_m^{\text{target}}$	Target State of Energy of EV m	-
$\text{Sigmoid}(x, k)$	Sigmoid function with input x and steepnes parameter k	-
$t_{\text{plug-in},m}$	Plug-in time of EV m	h
$t_{\text{plug-out},m}$	Plug-out time of EV m	h

4.2 Description of the mathematical formulation

We define a binary charging-interval matrix $F \in \{0, 1\}^{\mathcal{M} \times \mathcal{N}}$, where $\mathcal{M}$ and $\mathcal{N}$ denote the number of EVs and time intervals, respectively. The element f_{mn} of matrix F is defined as follows

$$f_{mn} = \begin{cases} 1 & \text{if interval } n \text{ falls within the charging period } T_m \text{ of EV } m, \\ 0 & \text{otherwise.} \end{cases}$$

In essence, this matrix captures the charging schedule of each EV in the fleet. A value of 1 indicates that a specific EV is plugged in during a particular time interval, while 0 signifies that it is not connected to the grid. Let $z^{\text{Up}}(n)$ be a binary variable indicating up-regulation participation of the EV fleet during time interval n, defined as

$$z^{\mathrm{Up}}(n) = \begin{cases} 1 & \text{if participating in up-regulation (reducing power consumption),} \\ 0 & \text{otherwise.} \end{cases}$$

Similarly, $z^{\mathrm{Dn}}(n)$ is given by

$$z^{\mathrm{Dn}}(n) = \begin{cases} 1 & \text{if participating in down-regulation (increasing power consumption),} \\ 0 & \text{otherwise.} \end{cases}$$

Then, the decision variables vector on the fleet level, denoted by $\mathbf{u}$, is given as

$$\mathbf{u} = \begin{bmatrix} z^{\mathrm{Up}}(1) \cdots z^{\mathrm{Up}}(N) & z^{\mathrm{Dn}}(1) \cdots P_{\mathrm{wb,\ 1}}(1) \cdots P_{\mathrm{wb,\ 1}}(N) & P_{\mathrm{wb,\ 2}}(1) \cdots\cdots\cdots P_{\mathrm{wb,\ m}}(N) \end{bmatrix}^{\mathrm{T}}.$$

The MILP formulation offers several advantages. It allows the optimizer to select the most favorable hours for participation based on regulation prices and the availability of participating EVs. Furthermore, MILP guarantees finding the global optimum, facilitating the meeting of bid size requirements. However, MILP is computationally demanding and does not scale well with non-linear charging dynamics. Therefore, section 4.3 presents a non-linear relaxation of the original problem.

The mathematical objective for the MILP can be formulated as

$$
\begin{aligned}
\min_{\mathbf{u}} \quad & \Pi^{\text{DA cost}} - \Pi^{\text{FCR-D-Up revenue}} - \Pi^{\text{FCR-D-Dn revenue}} && (3.1)\\
\text{subject to} \quad & \Pi^{\text{DA cost}} = \sum_{n=1}^{N}\sum_{m=1}^{M} P_{\text{wb, m}}(n) \cdot C_{\text{spot}}(n) \cdot \Delta t, && (3.1a)\\
& \Pi^{\text{FCR-D-Up revenue}} = \sum_{n=1}^{N} \lambda(n) \cdot r_n^{\text{Up}}, \cdot z^{\text{Up}}(n), && (3.1b)\\
& \Pi^{\text{FCR-D-Dn revenue}} = \sum_{n=1}^{N} \rho(n) \cdot r_n^{\text{Dn}} \cdot z^{\text{Dn}}(n), && (3.1c)\\
& r_n^{\text{Up}} = \sum_{m=1}^{M} f_{mn} \cdot P_{\text{wb, m}}(n) \quad \forall n, && (3.1d)\\
& r_n^{\text{Dn}} = \sum_{m=1}^{M} f_{mn} \cdot \big(P_{\max} - P_{\text{wb, m}}(n)\big) \quad \forall n, && (3.1e)\\
& r_n^{\text{Up}} \geq Q^{\text{FCR}} \cdot z^{\text{Up}}(n) \quad \forall n, && (3.1f)\\
& r_n^{\text{Dn}} \geq Q^{\text{FCR}} \cdot z^{\text{Dn}}(n) \quad \forall n, && (3.1g)\\
& 0 \leq P_{\text{wb, m}}(n) \leq P_{\max} \quad \forall n, m, && (3.1h)\\
& \texttt{SOE}_{m,n+1} = \texttt{SOE}_{m,n} + \Delta t \cdot \frac{(P_{\text{wb, m}}(n) - P_{\text{loss}}) \cdot f_{mn}}{E_{\texttt{max}}}, && (3.1i)\\
& P_{\texttt{loss}} = \begin{cases} (1-\eta) \cdot P_{\text{wb, m}}(n) & \text{Model A} \\ \alpha_0 + \alpha_1 \cdot P_{\text{wb, m}}(n) + \alpha_2 \cdot P_{\text{wb, m}}(n)^2 & \text{Model B} \\ \left(1 - \left(\eta_0 + \eta_1 \frac{P_{\text{wb, m}}(n)}{P_{\texttt{max}}}\right)\right) \cdot P_{\text{wb, m}}(n) & \text{Model C,} \end{cases} && (3.1j)\\
& \texttt{SOE}_{t^{\text{start}},m} = \texttt{SOE}_m^{\text{init}} \quad \forall m, && (3.1k)\\
& \texttt{SOE}_{N,m} \geq \texttt{SOE}_m^{\text{target}} \quad \forall m, && (3.1l)\\
& t_{\text{plug-in},m} \leq t_{\text{plug-out},m} \quad \forall m. && (3.1m)
\end{aligned}
$$

4.3 A relaxation to NLP problem

The original MILP is relaxed by incorporating an exponential activation function known as the sigmoid function. Throughout the optimization results detailed in section 5, the steepness parameter $k = 40$ remains constant. The minimum bid size for FCR-D, applicable to both up and down regulation, is set at 0.1 MW, which is reflected in the sigmoid function below

$$\text{Sigmoid}(x, k) = \frac{1}{1 + e^{-k\cdot(x-0.1)}}.$$

The mathematical objective can be formulated as

$$\begin{aligned}
\min \quad & \Pi^{\text{DA cost}} - \Pi^{\text{FCR-D-Up revenue}} - \Pi^{\text{FCR-D-Dn revenue}} && (4.1)\\
\text{subject to} \quad & \text{3.1a, 3.1d, 3.1e, and 3.1h - 3.1m,} \\
& \Pi^{\text{FCR-D-Up revenue}} = \sum_{n=1}^{N} \lambda(n) \cdot r_n^{\text{Up}} \cdot \text{Sigmoid}(r_n^{\text{Up}}, k), && (4.1a)\\
& \Pi^{\text{FCR-D-Dn revenue}} = \sum_{n=1}^{N} \rho(n) \cdot r_n^{\text{Dn}} \cdot \text{Sigmoid}(r_n^{\text{Dn}}, k). && (4.1b)
\end{aligned}$$

Chapter 5

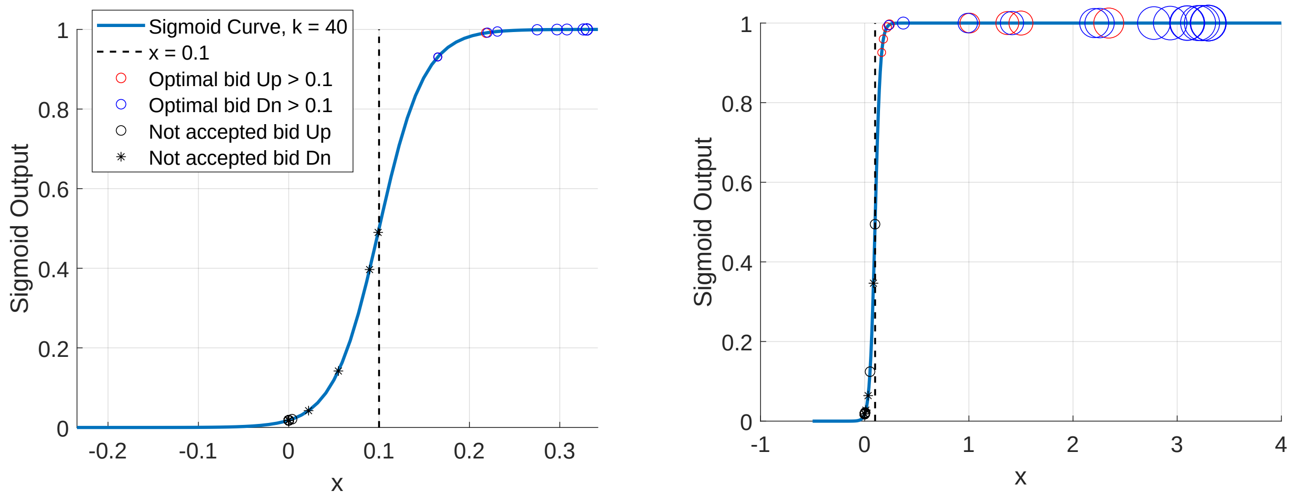
Results

This chapter discusses the simulation results derived from the NLP formulation, the effectiveness of relaxation methods, case studies demonstrating seasonal variations, and analyses of optimal charging trajectories under various OBC loss models.

5.1 Quality of relaxation

This section presents results of a single optimization horizon i.e. one overnight charging session, emphasizing OBCA to address research questions Q1, Q2, and Q3 as outlined in Section 1.2. The analysis assumes an initial SOE of 60% and targets a SOE of 80%, utilizing the dynamics of model A. Additionally, the findings are based on electricity prices specific to the SE3 region in Sweden.

The effectiveness of relaxation diminishes with smaller fleet sizes because even bids that are not accepted contribute to total revenue. This is due to the sigmoid output not being precisely zero for small bid sizes, but rather varying between 0 and 0.5 (see Figure 5.1.1a). For accepted bids, the sigmoid output ranges from 0.5 to 1. Moreover, the non-convex nature of the exponential function makes the NLP objective non-convex. Using IPOPT, which employs an interior point method, does not guarantee a global optimum. However, the quality of the relaxation improves with larger fleet sizes, as illustrated in Figure 5.1.1b.



(a) EV fleet consisting of 30 cars. *(b) EV fleet consisting of 300 cars.*

Figure 5.1.1: Sigmoid curve with steep $k = 40$.

Figure 5.1.2 demonstrates the OBCA for a single optimization horizon applied to a fleet of 200 electric vehicles (EVs) during December 2023, a winter month characterized by negligible down-regulation prices. The top section of the figure highlights more favorable up-regulation prices. As a result, the entire fleet initiates charging during the early plug-in hours due to the high revenue from up regulation. Once the fleet reaches an 80% charge level, bids for down-regulation are submitted until each EV's departure.

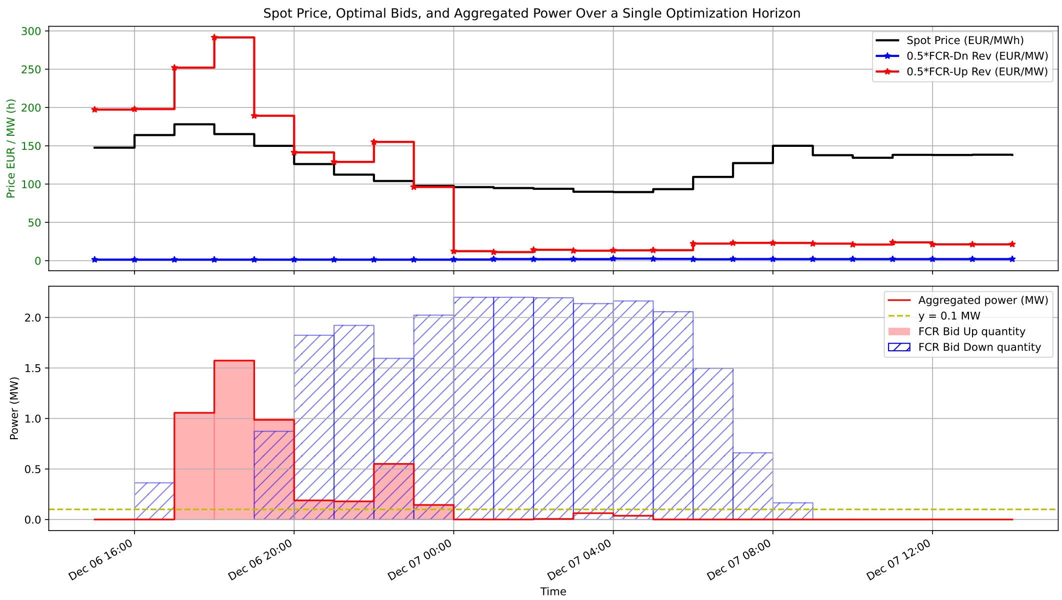


Figure 5.1.2: Aggregated charging and OBCA for a fleet of 200 EVs, each with 20% energy demand on a winter day, highlighting the impact of participating in FCR-Up.

In contrast, during April 2024, significant amount of intermittent renewable energy production in the electricity transmission system caused substantial fluctuations in down-regulation prices. The optimization results (see Figure 5.1.3) show that during peak hours, the optimizer refrains from charging the fleet entirely. Instead, it places large capacity bids due higher FCR-D compensation for down regulation. In the event of activation, each EV can ramp up from 0 to $P_{\max}$ to deliver the promised capacity.

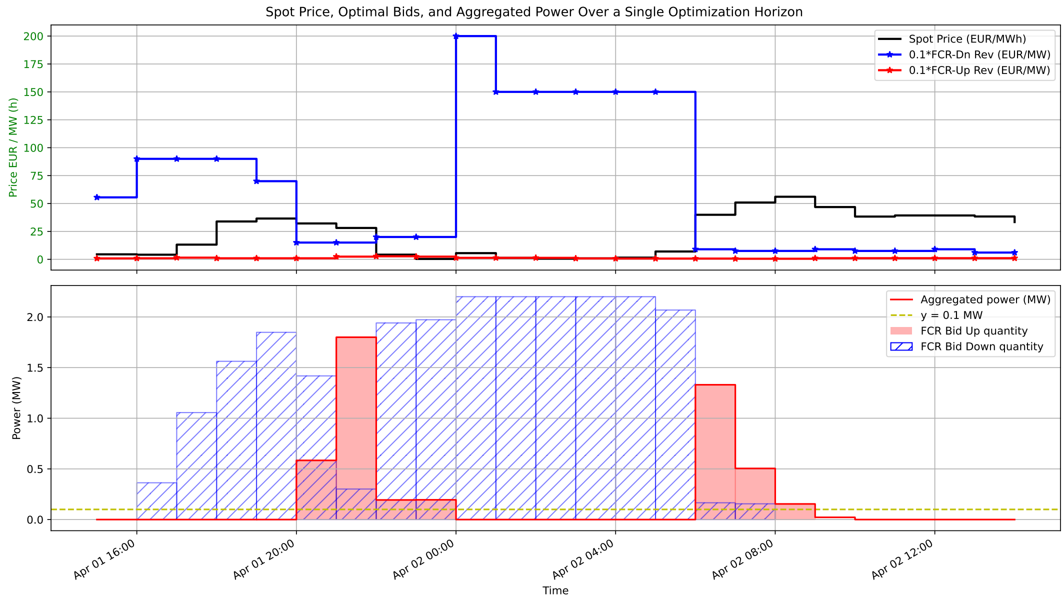


Figure 5.1.3: Aggregated charging and OBCA for a fleet of 200 EVs, each with 20% energy demand on a summar day, highlighting the impact of participating in FCR-Dn.

Notably, on both summer and winter days, the majority of revenue comes from FCR-D Down due to the ability to place these bids as long as EVs remain connected to the grid and provided that the vehicle electronic control unit (ECU)s are kept awake. Activation for FCR-D Down occurs only 1-2% of the time and lasts for a maximum duration of 20 minutes [34]. The selection of EVs that can increase their charging power during activation depends largely on availability.

For scenarios where the charging energy demand is 20% or higher, there are instances when the optimizer opts for relatively high charging power for each EV, as depicted in Figure 5.1.4, where arrows indicate the charging windows of selected vehicles. However, this decision relies heavily on the prices for up and down regulation. When up-regulation prices are high, the entire fleet charges at relatively high power levels. Conversely, during periods of favourable down-regulation prices, the fleet charges at very low power levels to preserve capacity for bidding in down-regulation markets. This latter scenario becomes particularly challenging if energy demand decreases, specifically when the initial state of energy follows the daily commute distributions outlined in Section 2.2.1. Therefore, the following section investigates different OBC loss models, to penalize charging at low power in order to improve efficiency, focusing on optimizing day-to-day energy demand as given in Figure 2.2.5.

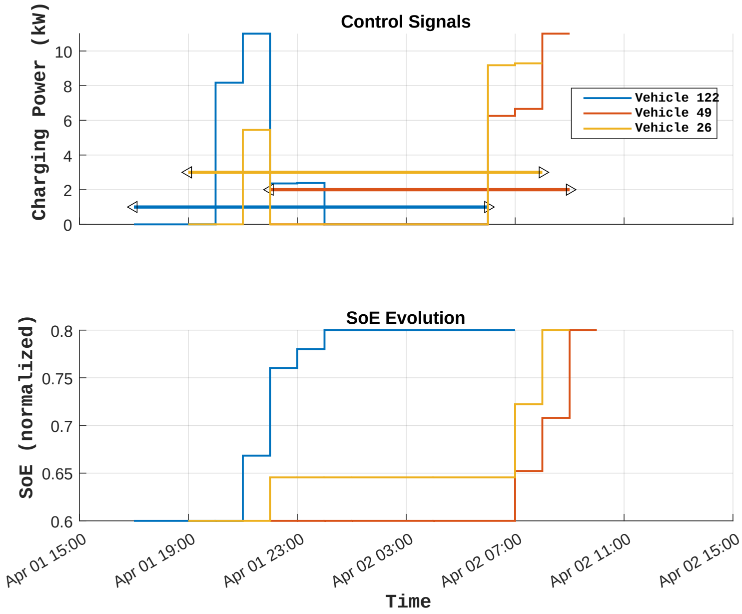


Figure 5.1.4: The simulated SOE evolution of selected EVs in the fleet with 20 % energy demand, alongside their corresponding control signals and charging windows.

5.2 Evaluation of OBC loss models

This section presents the optimization results for July 2023, chosen for its particularly favorable FCR-D Down prices. These conditions offer an ideal opportunity to analyze OBC losses and significant participation in the FCR-D Down market. Additionally, this analysis examines how the inclusion of a stand-by cost in the OBC loss model impact the overall objective. The focus is on determining the optimal charging trajectory necessary to meet daily commute distances.

5.2.1 Model A

The optimization results for Model A, utilizing linear dynamics, are presented in Table 5.2.1 and visualized in Figure 5.2.1. For the single day of July 19, 2023, the optimization process required 21 iterations and 60 seconds in IPOPT. Over the entire month, the average charging power was 1.1 kW. The total objective, summed up for each optimization horizon, amounted to -11 230 SEK per car.

The results show that the OBC loss model results in a strategy focused on minimizing energy costs while strategically bidding the remaining power in down regulation. However, operating at low charging power levels lead to increased OBC losses, thereby reducing overall system efficiency. The heatmap in Figure 5.2.1 shows significant fluctuations in charging power throughout the month, indicating frequent operation below the threshold 3.6 kW which is a typical lower limit for BEV charging power, i.e. to avoid the low efficiency region. The grey areas on the heatmap indicate times when the EV is unavailable for charging.

Table 5.2.1: Optimization Results for Model A.

(a) Single Horizon (19 July 2023).

Model A	
Number of iterations	21
Time in IPOPT	60 s

(b) Monthly Horizon (July 2023).

Model A	
Avg charging Power	1.1 kW
Cost	-11 230 SEK

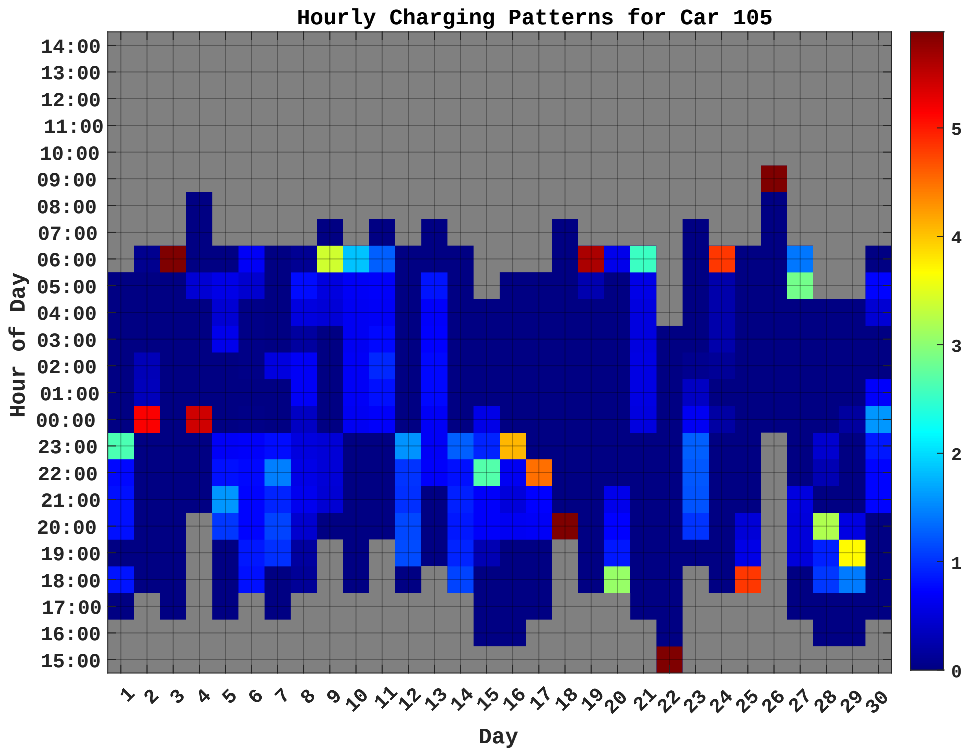


Figure 5.2.1: Charging power as seen from wallbox during month of July 2023 with Model A.

5.2.2 Model B

The same investigation as above was carried out using Model B dynamics and the same input parameters as above. This model incorporates stand-by cost incurred whenever the EV is connected to the grid, and therefore account for decrease in SOE before start of the charging session. The introduction of quadratic dynamics provides a more detailed and realistic representation of EV charging and OBC losses for each power input.

The optimization results, shown in Table 5.2.2 and Figure 5.2.2, indicate a marginal increase in average charging power, accompanied by a rise in the overall objective cost. In this case, the cost increase is mainly due to increased losses at zero charging power that must also be charged and paid for. However, quadratic dynamics could lead to lower costs in other months, highlighting the sensitivity to price fluctuations when using a more detailed model.

Table 5.2.2: Optimization Results for Model B.

(a) Single Horizon (19 July 2023).

Model B	
Number of iterations	40
Time in IPOPT	101 s

(b) Monthly Horizon (July 2023).

Model B	
Mean wallbox power	1.7 kW
Cost	-11 156 SEK

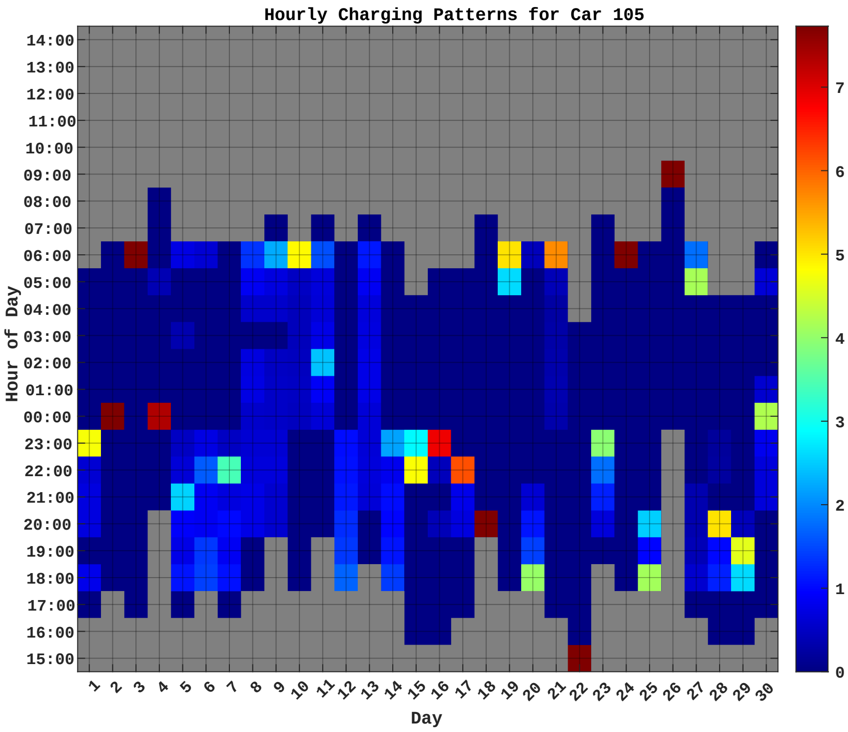


Figure 5.2.2: Charging power as seen from wallbox during month of July 2023 with Model B.

5.2.3 Model C

Following the evaluation of Model A and Model B, this section presents results of concave dynamics, which are intended to penalize low charging power inputs by decreasing efficiency to levels depicted in Figure 2.2.1. Utilizing the same input parameters as in the previous sections, the optimization results reveal a distinctive pattern: the optimizer consistently opts for charging power values of either zero or 6 kW. Moreover, the overall objective value remains comparable to that achieved with model A and model B. This indicates that the optimizer, after a large number of iterations, may be influenced by the optimization landscape and settle for a local minimum, or it may strategically target specific hours with low spot prices to effectively meet energy requirements and maximize revenue. Nonetheless, a crucial takeaway is that for an EV participating in a VPP, the optimal charging trajectory could involve either Model B dynamics, where the EV remains active most of the time, or Model C dynamics, involving near bang-bang control approach. Despite the strategy differences, the contribution from FCR revenue remains consistent.

Table 5.2.3: Optimization Results for Model C.

(a) Single Horizon (19 July 2023).

Model C	
Number of iterations	603
Time in IPOPT	2.04 ks

(b) Monthly Horizon (July 2023).

Model C	
Mean wallbox Power	6 kW
Cost	-11 156 SEK

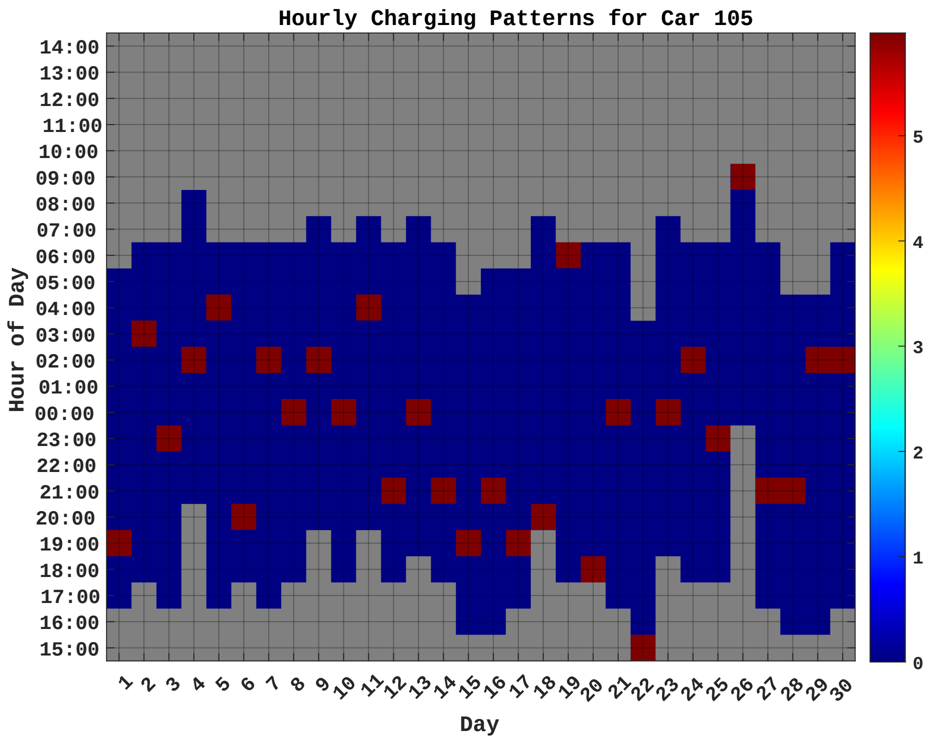


Figure 5.2.3: Charging power as seen from wallbox during month of July 2023 with Model C.

Additionally, Figure 5.2.4 shows a scatter plot of all the the simulated OBC losses for July 2023 related to daily commute energy requirements. For both Model A and Model B, the optimizer indicates that most of the charging input power is concentrated between 0 and 1.5 kW.

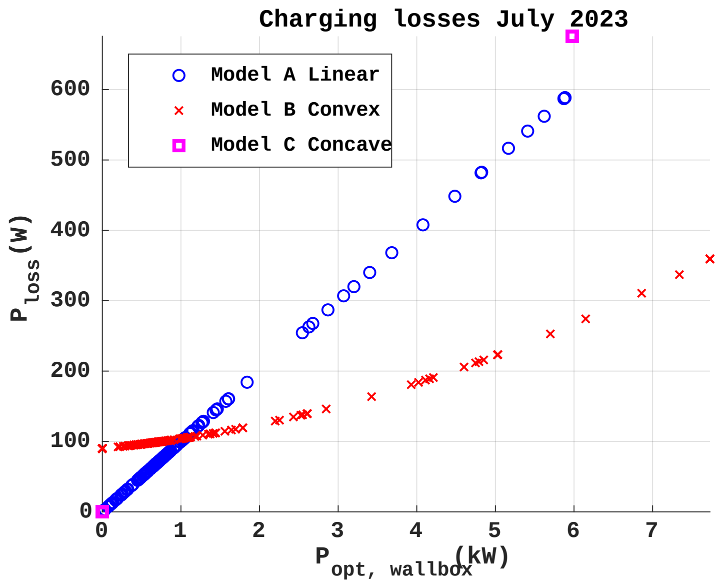


Figure 5.2.4: Simulated OBC losses for daily commute energy requirements in July 2023.

5.3 Seasonal impact on SE3 FCR Revenue: Winter vs. Summer Case Studies

This section presents the optimization results for the summer and winter months of 2023 and 2024. Model A dynamics was chosen for its computational efficiency, and daily commute distances were used as the initial condition in the analysis. The optimization was conducted for each month, first by solely participating in Auction 1 and then solely participating in Auction 2. The tables below display key revenue parameters, offering a detailed comparison of the financial outcomes under different seasonal conditions and auction scenarios.

Table 5.3.1: Summer Monthly Optimization Results Auction 1.

Month	Spot Price Cost per EV [SEK]	FCR Revenue per EV [SEK]	Daily Min obj per EV [SEK]	Daily Max obj per EV [SEK]	FCR-Up [%]	FCR-Dn [%]	FCR-revenue from 5% of bidding hours [%]
April	116	-2 880	-231	-25	4	96	24.3
May	47	-5 030	-325	-126	3	97	17
June	87	-5 450	-224	-145	2	98	12
July	72	-8 880	-354	-218	1	99	11.3
August	37	-5 750	-247	-104	2	98	11.4
September	12	-3 011	-115	-85	2	98	10.9

Table 5.3.2: Summer Monthly Optimization Results Auction 2.

Month	Spot Price Cost per EV [SEK]	FCR Revenue per EV [SEK]	Daily Min obj per EV [SEK]	Daily Max obj per EV [SEK]	FCR-Up [%]	FCR-Dn [%]	FCR-revenue from 5% of bidding hours [%]
April	133	-5 940	-743	-15	2.3	97.7	34.1
May	52.4	-5 555	-583	-75	3	97	27.1
June	98	-10 207	-1 406	-118	1	99	33.5
July	81	-11 230	-955	-136	0.6	99.4	22.3
August	41	-7 661	-975	-86	1.7	98.3	32.8
September	19	- 3 728	-291	-54	1.5	98.5	27

During the summer months, notable fluctuations are observed in the daily minimum and maximum values of the objective function, particularly evident in Auction 2 (see Table 5.3.2). Moreover, the FCR revenue derived from the top 5% of bidding hours indicates the substantial contribution from peak periods in both FCR-D Up and FCR-D Down throughout the month.

Table 5.3.3: Winter Monthly Optimization Results Auction 1.

Month	**Spot Price Cost per EV** [SEK]	**FCR Revenue per EV** [SEK]	**Daily Min obj per EV** [SEK]	**Daily Max obj per EV** [SEK]	**FCR-Up** [%]	**FCR-Dn** [%]	**FCR-revenue from 5% of bidding hours** [%]
October	21	-1 650	-82	-21	3	98	22
November	102	-617	-42	-5	6.3	93.68	21
December	126	-1 590	-124	-5	4	96	25.4
January24	111	-1 520	-90	-20	1.7	98.3	20
February24	79	-1 600	-198	-17	2	98	28
March24	106	-1 110	-121	-6	2	98	31.5

It is evident that for both summer and winter months, a significant portion of the revenue is derived from FCR-D Down and auction 2. Historically, prices during auction 2 have shown greater fluctuation due to proximity to operational hours. Furthermore, during winter months, an even larger share of the total revenue comes from the top 5% of bidding hours, as indicated in the last column of Table 5.3.4. This underscores the observation that regulation prices tend to remain flat for most of the time, with occasional peaks occurring each month.

Table 5.3.4: Winter Monthly Optimization Results Auction 2.

Month	**Spot Price Cost per EV** [SEK]	**FCR Revenue per EV** [SEK]	**Daily Min obj per EV** [SEK]	**Daily Max obj per EV** [SEK]	**FCR-Up** [%]	**FCR-Dn** [%]	**FCR-revenue from 5% of bidding hours** [%]
October	25.7	-1 212	-88	-15	2.8	97.2	21.5
November	112	-1 230	-322	-1.5	5	95	65.8
December	142	-3 022	-459	0.4	6	94	48
January24	132	-1 430	-162	-14	5	95	35.3
February24	90	-3 150	-1 260	-7	3	97	61.3
March24	117	-3 314	-815	0.6	1.4	98.6	65

Chapter 6

Discussion and Conclusions

6.1 Discussion

In this section, the results presented in Section 5 will be discussed in relation to the research questions. The decision to formulate a non-linear optimization problem with an activation function approximating the binary decisions proved beneficial in this context. This method diverges from conventional approaches to solving frequency regulation problems, which typically involve numerous binary variables to model participation [31]. However, a non-linear formulation aligns well with other detailed models that are commonly used for charging a single EV, which extensively account for non-linear effects such as battery temperature dependencies [35] and use polynomial approximations for battery open-circuit voltage, as described in [36]. By using a non-linear optimization for a fleet, it becomes feasible to incorporate additional non-linear phenomena as required. In this study, the charging dynamics were further refined without significantly increasing computational complexity. While non-linear relaxation does not guarantee a global minimum in terms of optimality, its impact on the objective function becomes negligible for large EV fleet sizes. Consequently, incorporating additional non-linear effects at the fleet level scales much more efficiently with non-linear relaxation.

The results suggest that participation in FCR-D Down should be the first step for EV aggregation, at least in terms of revenue maximization. This market is relatively new and thus vulnerable to fluctuations in the Swedish market, where SVK often requires assistance, especially during the summer months due to overproduction.

Moreover, starting with unidirectional FCR-D is less intrusive for EV owners and also enables the evaluation of EVs' readiness to offer flexibility to the grid.

The optimal charging trajectories provided by Model A and Model B indicate that charging should ideally occur with low input power given historic prices, around $1.1 - 1.7$ kW/h. However, Model C demonstrates that the overall objective is not highly sensitive to the precise charging trajectory, suggesting that heuristic methods could also effectively determine EV charging strategies.

6.1.1 Future Work

During the writing of this thesis, interesting topics for future research has been gathered. Two possible ideas for future research are presented below.

- Data-driven investigation for predicting number of EVs that are connected to the grid during a charging window.
- Application of machine learning methods to predict FCR regulation prices.

The first topic involves using large datasets to forecast EV user behavior accurately. By predicting the number of EVs connected to the grid, more informed bids can be placed in capacity markets.

The second topic focuses on using machine learning techniques to predict FCR regulation prices. By analyzing historical price data and relevant market factors, machine learning models can offer accurate price forecasts. These predictions can help optimize bidding strategies, improve revenue generation, and ensure participation during peak price periods.

Bibliography

[1] Nour, Morsy, Chaves-Ávila, José Pablo, Magdy, Gaber, and Sánchez-Miralles, Álvaro. “Review of positive and negative impacts of electric vehicles charging on electric power systems”. In: *Energies* 13.18 (2020), p. 4675.

[2] Tidningarnas Telegrambyrå (TT). *Svenska Kraftnät bevar för ankarkurvan – Solceller utmanar elsystemet*. insert year. URL: https://www.tn.se/naringsliv/36829/svenska-kraftnat-bavar-for-ankkurvan-solceller-utmanar-elsystemet/ (visited on 05/12/2024).

[3] Government of Sweden. *Sweden's Draft Integrated National Energy and Climate Plan*. insert year. URL: https://www.government.se/contentassets/e731726022cd4e0b8ffa0f8229893115/swedens-draft-integrated-national-energy-and-climate-plan/ (visited on 05/12/2024).

[4] Kirby, Brendan J. “Frequency regulation basics and trends”. In: (2005).

[5] Sandström, Maria. *Evaluation and variability of power grid hosting capacity for electric vehicles: Case studies of residential areas in Sweden*. 2024.

[6] Power Circle. *Smartladdning*. https://powercircle.org/smartladdning.pdf. Accessed: June 9, 2024. 2021.

[7] August, Brandon. *Is your EV battery getting all the energy you pay for?* Accessed: 2024-06-30. 2023. URL: https://www.recurrentauto.com/research/why-doesnt-your-battery-get-all-the-energy-you-pay-for.

[8] Boulanger, Albert G, Chu, Andrew C, Maxx, Suzanne, and Waltz, David L. “Vehicle electrification: Status and issues”. In: *Proceedings of the IEEE* 99.6 (2011), pp. 1116–1138.

[9] Group discussion with a senior simulation engineer at Volvo Cars Corporation. Data provided during a group discussion. 2024.

[10] Shaaban, Mostafa F, Atwa, Yasser M, and El-Saadany, Ehab F. "PEVs modeling and impacts mitigation in distribution networks". In: *IEEE Transactions on Power Systems* 28.2 (2012), pp. 1122–1131.

[11] Liu, Hui, Huang, Kai, Wang, Ni, Qi, Junjian, Wu, Qiuwei, Ma, Shicong, and Li, Canbing. "Optimal dispatch for participation of electric vehicles in frequency regulation based on area control error and area regulation requirement". In: *Applied energy* 240 (2019), pp. 46–55.

[12] Trafikanalys. *Commuting in Stockholm, Gothenburg, and Malmö - A Current State Analysis*. Accessed: 2024-06-29. 2011. URL: `https://www.trafa.se/globalassets/rapporter/summary-report/2011-2015/2011/summary-report-2011_3-commuting-in-stockholm-gothenburg-and-malmo---a-current-state-analysis.pdf`.

[13] Numbeo. *Traffic in Stockholm*. Accessed: 2024-06-29. 2024. URL: `https://www.numbeo.com/traffic/in/Stockholm`.

[14] Energi Information Agency. "Sweden's Electricity and Natural Gas Market 2022". In: (2023). URL: `https://ei.se/download/18.2b54186118afe6e6d30ede/1696496742338/Sweden%E2%80%99s-electricity-and-natural-gas-market-2022-Ei-R2023-13.pdf` (visited on 05/12/2024).

[15] Svenska kraftnät. *Svenska kraftnät System Development Plan 2018-2027*. 2018. URL: `https://www.svk.se/siteassets/om-oss/rapporter/2018/svenska-kraftnat-system-development-plan-2018-2027.pdf` (visited on 05/12/2024).

[16] Svenska kraftnät. *Lokala flexibilitetsmarknader*. Year Accessed. URL: `https://www.svk.se/utveckling-av-kraftsystemet/systemansvar--elmarknad/lokala-flexibilitetsmarknader/` (visited on 05/13/2024).

[17] *Balansansvarig part*. URL: `https://www.svk.se/aktorsportalen/balansansvarig-part/` (visited on 05/13/2024).

[18] *Becoming Balance Responsible*. URL: `https://www.svk.se/en/stakeholders-portal/electricity-market/balance-responsibility/becoming-balance-responsible/` (visited on 05/13/2024).

[19] Stödtjänster. *Hur kommer det nya balansansvaret påverka aggregatorerna?* https://stodtjanster.se/hur-kommer-det-nya-balansansvaret-paverka-aggregatorerna/. (Visited on 05/13/2024).

[20] Stödtjänster. *Hur kommer det nya balansansvaret påverka aggregatorerna?* Year Accessed. URL: https://stodtjanster.se/hur-kommer-det-nya-balansansvaret-paverka-aggregatorerna/ (visited on 05/13/2024).

[21] Steel, H2 Green. *H2 Green Steel partners with Statkraft for 1.4 TWh of renewable electricity.* https://www.h2greensteel.com/latestnews/h2-green-steel-partners-with-statkraft-for-14-twh-of-renewable-electricity. Year. (Visited on 05/13/2024).

[22] Energiforsk. *Intradagmarknaden.* 2021. URL: https://energiforsk.se/media/30200/intradagmarknaden-energiforskrapport-2021-797.pdf (visited on 05/09/2024).

[23] *Nord Pool Day-Ahead Market.* Available online. URL: https://www.nordpoolgroup.com/en/the-power-market/Day-ahead-market/.

[24] *Wind Energy - The Facts: Power Markets.* https://www.wind-energy-the-facts.org/power-markets-7.html. (Visited on 05/13/2024).

[25] Holmberg, Pär and Tangerås, Thomas P. *The Swedish Electricity Market: Today and in the Future.* Accessed on 26th May 2024. Riksbank. 2023. URL: https://www.riksbank.se/globalassets/media/rapporter/pov/artiklar/engelska/2023/230512/2023_1-the-swedish-electricity-market--today-and-in-the-future.pdf.

[26] *Villkor FCR.* Svenska kraftnät. URL: https://www.svk.se/siteassets/aktorsportalen/balansansvarig/balansansvarsavtal/aktuella-balansansvarsavtal/avtal-4620-8-bilaga-3-villkor-fcr.pdf (visited on 05/09/2024).

[27] Energimarknadsinspektionen. URL: https://ei.se/download/18.6ac6e41d18093f316201817e/1653997945321/EB-Artikel-33(1)-svenska-kraftn%C3%A4t-metod.pdf (visited on 05/09/2024).

[28] Svenska kraftnät. *Overview of the Requirements for Reserves.* Available online. May 2024. URL: https://www.svk.se/siteassets/english/stakeholder-portal/provision-of-ancillary-services/overview-of-the-requirements-for-reserves-may-2024.pdf (visited on 05/09/2024).

[29] Tai-Yu Ma, Yumeng Fang. “Survey of charging management and infrastructure planning for electrified demand-responsive transport systems: Methodologies and recent developments”. In: *European Transport Research Review* 14.1 (2022), p. 36.

[30] Bessa, Ricardo J, Matos, Manuel A, Soares, Filipe Joel, and Lopes, João A Peças. “Optimized bidding of a EV aggregation agent in the electricity market”. In: *IEEE Transactions on Smart Grid* 3.1 (2011), pp. 443–452.

[31] Genidy, Abdelrahman, Dahmane, Yassir, and Hamida, Mohamed Assaad. “Electric Vehicles Charging Strategy for Optimal Bidding in the Wholesale Energy Markets”. In: *IFAC-PapersOnLine* 56.2 (2023), pp. 2540–2545.

[32] Vagropoulos, Stylianos I and Bakirtzis, Anastasios G. “Optimal bidding strategy for electric vehicle aggregators in electricity markets”. In: *IEEE Transactions on power systems* 28.4 (2013), pp. 4031–4041.

[33] Herre, Lars, Dalton, Jacob, and Söder, Lennart. “Optimal day-ahead energy and reserve bidding strategy of a risk-averse electric vehicle aggregator in the nordic market”. In: *2019 IEEE Milan PowerTech*. IEEE. 2019, pp. 1–6.

[34] Svenska Kraftnät. *Bidra med reservkraft: FCR-D ned och MFRR ned - Räkneexempel*. 2023. URL: `https://www.svk.se/siteassets/aktorsportalen/bidra-med-reserver/fcr-d-ned-och-mfrr-ned-rakneexempel.pdf` (visited on 06/30/2024).

[35] Ahad Hamednia, Nikolce Murgovski, Jonas Fredriksson, Jimmy Forsman, Mitra Pourabdollah, and Viktor Larsson. “Optimal thermal management, charging, and eco-driving of battery electric vehicles”. In: *IEEE Transactions on Vehicular Technology* (2023).

[36] Lee, Chih Feng, Bjurek, Kalle, Hagman, Victor, Li, Yang, and Zou, Changfu. “Vehicle-to-grid optimization considering battery aging”. In: *IFAC-PapersOnLine* 56.2 (2023), pp. 6624–6629.