Large-Scale Setpoint Tracking Controller for Co-regulation of Electric Vehicle Charging Stations

Coordinating Charging with Energy Market Dynamics

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Master of Science Thesis

Delft University of Technology

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Large-Scale Setpoint Tracking Controller for Co-regulation of Electric Vehicle Charging Stations

by

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Abstract

This research explores the feasibility of building a large-scale setpoint tracking controller for the co-regulation of Electric Vehicle (EV) charging stations, aiming to coordinate charging with energy market dynamics and minimize the error between a power setpoint and the aggregated consumption of charging stations while capitalizing on developments in the imbalance market. The study examines the roles of actors in the energy market, the characteristics of the EV charging infrastructure, and the information provided by TenneT regarding the imbalance market. Using historical charging data and information provided by TenneT regarding the imbalance market, an optimization problem is formulated and a method for coordinating EV charging is proposed. Our sensitivity analysis of the weight parameters and reduction factor shows their significant impact on the performance of the controller.

In this study, we evaluate the performance of the proposed co-regulation controller by tuning the weight parameters to find the optimal balance between financial benefits and customer satisfaction. Our sensitivity analysis of the weight parameters demonstrates that changing them can have a significant impact on the performance of the controller. We also consider the impact of the reduction factor on the performance of the controller and find that increasing it enhances financial benefits but reduces customer satisfaction. Our simulation results indicate that the proposed co-regulation controller can effectively balance financial benefits and customer satisfaction by using appropriate weight parameters. We estimate a yearly profit of €266.45 per EV user, which is equivalent to 13.2% reduction in cost.

In conclusion, our research demonstrates the feasibility and effectiveness of using co-regulation to manage the charging demand of electric vehicles in a cost-effective and sustainable way. Our findings provide valuable insight for the development of smart charging strategies that balance the needs of the EV driver, the grid, and other stakeholders, and have important implications for the energy market. Further research is needed to evaluate the effectiveness and robustness of the proposed solution under varying degrees of uncertainty in the input data. Our proposed solution provides a practical and scalable method for managing the charging demand of electric vehicles and has the potential to contribute significantly to global efforts to reduce carbon emissions.

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Preface

This thesis represents the culmination of a long and challenging journey, where I navigated a complex and intricate simulation environment with unforeseen challenges at every turn. Nevertheless, I take great pride in the final results and have learned that hard work does pay off.

I am deeply thankful for all the support and guidance I received along the way. I would like to convey my sincere gratitude to my supervisor, Prof. Peyman Mohajerin Esfahani, who provided me with invaluable feedback and insights during our monthly hour-long meetings. His easy-going nature and high standards made each meeting a combination of enjoyable and motivating.

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Above all, I want to express my heartfelt thanks to my girlfriend, Loucka, and my mother, Machteld, for their unwavering support throughout my academic journey, especially during the completion of this thesis. They were always there for me, and even when I was pushing the deadline, they worked through the night without hesitation when I asked them to proofread my thesis. I feel blessed to have them in my life.

I am especially grateful for Louckas (somewhat unexpected) exceptional academic writing skills. Even when others could not find any mistakes, she provided extensive feedback on how to improve my writing. I cannot express how much I appreciate her support and contributions. Masha danki, Dushi!

And finally, I would also like to express my gratitude to my friend and former classmate, Emiel Legrand, who unfortunately will never read this, but his expertise had taught me a great deal over the years and inspired me to push beyond my limits.

In the end, I hope that the reader finds my thesis interesting and informative. Thank you for taking the time to read it.

Fères Pepijn Hassan

Amsterdam, 25-02-2023

仕方がない

— *Shikita ga nai; let go of what you cannot change.*

— *The greater the obstacle, the more glory in overcoming it.*

Molière

Chapter 1

Introduction

This thesis examines the feasibility of aligning the charging of Electric Vehicles (EVs) with the dynamics of the energy market. With the increasing market share of EVs, the current energy infrastructure is struggling to meet the growing energy demand. Both challenges and opportunities have arisen for the energy market. This research aims to address the challenges and seize the opportunities by developing a large-scale setpoint-tracking controller that minimizes the difference between a power setpoint and the aggregated capacity of charging stations while leveraging the flexibility of EVs to regulate the energy market. The introduction of this report is structured into four sections.

In the first section, we discuss the relevance of this research and emphasize the importance of coordinating the charging of EVs with the energy market. In the second section, we explore the flexibility of EVs as energy consumers and their potential for balancing the energy market In the third section, we discuss the services provided by GreenFlux and their contributions to this research. Third, we discuss the services of GreenFlux and their contribution to this research. Finally, we present the problem statement, outlining the focus and objectives of this research.

1-1 Relevance; Solving a Real World Problem

According to a report by International Energy Agency [1], EVs accounted for nearly 10% of global car sales in 2021, which is four times the market share in 2019. This increase in the adoption of EVs presents both challenges and opportunities for the energy sector. Replacing traditional combustion engines with electric powertrains and battery packs has several benefits for society, including reducing greenhouse gas emissions and improving air quality in densely populated areas [2]. While the transition appears promising, the growing market share of EVs posed significant challenges to the current energy infrastructure as the grid is insufficiently equipped to handle the rising demand for energy. In addition to the challenges, the increase also offers opportunities for the energy sector. The feedback controller developed in this research enables the coordination between EV charging stations and the dynamics of the energy market.

Castrol's research on the widespread adoption of EVs has highlighted the charging problem as one of the biggest challenges [3]. As the Netherlands has taken the lead in the introduction of electric vehicles, with a share of 19.8% of fully electric vehicles sold in 2021, the charging problem is becoming more pressing [4]. Several studies have shown how uncontrolled charging of EVs can jeopardize the stability and reliability of the electricity grid [5, 6, 7, 8, 9]. Traditionally, the solution to this problem was the physical expansion of the energy infrastructure, but as the development is happening much faster than the energy and utility sectors are accustomed to, this is not sustainable, making it a costly and labor-intensive solution. Instead, the focus should be on developing a smarter energy system through the utilization of the the flexible capacity of electric vehicles [10, 11].

Making the energy system "smarter" offers opportunities. Based on Price Waterhouse Coopers' forecast for the passenger vehicle fleet in 2030, there will be 1.9 million fully electric cars on the road in 2030 [12]. This equated to a capacity 20.9 GW when they are fully electric with an average charging rate power of 11 kW. To put that into perspective, the combined output of all coal-fired power plants, solar and wind farms, and other sources was 43 GW in 2020 [13]. However, cars will not always be parked at charging points, but even if only 20% are connected to the grid, that would still provide about 4.18 GW of flexible capacity, or about 10% of the total production capacity in the Netherlands. This flexible capacity may play an important role in stabilizing the grid. This research may be of importance to the industry, policymakers, and society as a whole, as it has the potential to shape the future of sustainable energy and energy balancing.

1-2 Flexibility of Electric Vehicles

The flexible capacity of EVs refers to the ability to charge and discharge the vehicles' batteries as needed. In addition to the conventional use of EVs as personal transportation, EVs can be integrated into the energy system as units for energy storage. Given that the charging and discharging of EVs can be managed and controlled, they are a valuable source of flexibility for the energy system and an interesting asset for grid management. The potential of EVs to provide grid services has been extensively studied and demonstrated in literature, Sortomme and El-Sharkawi [14], Codani et al. [15], Druitt and Früh [16].

The quick response times, low costs, and scalability of EVs make them a promising technology for supporting the stability and reliability of the grid. EVs can be charged during periods of low energy demand, and during periods of high energy demand, their energy consumption can be reduced, or their energy can be used to supply the grid. This way, the flexibility of EVs can support the energy grid, especially during peak periods of energy demand. However, the full potential of EV flexibility can only be realized if charging and discharging are effectively managed and coordinated. This requires the development of control and optimization algorithms to balance energy supply and demand, while taking into account real-time constraints of the energy grid and customer needs.

In summary, the adoption of EVs has the potential to significantly reduce greenhouse gas emissions and promote decarbonization. Furthermore, smart charging solutions that effectively manage and coordinate the charging of EVs can enhance the stability and reliability of the energy grid, particularly during peak periods of energy demand

1-3 GreenFlux

GreenFlux is a cloud-based platform provider based in Amsterdam. They offer solutions for charging operations, including roaming and billing services, fleet management, and smart charging. Smart charging is an essential part of their services, allowing more charge points to be connected to the same grid connection without requiring upgrades to the grid. GreenFlux's customers (e.g., Charge Point Operator (CPO), Balance Responsible Party (BRP), or Balancing Service Provider (BSP)) have a vested interest in using EV charging to optimize their daily energy portfolio. The goal is to reduce costs or generate additional revenue. This is an important business opportunity for GreenFlux, as it can provide flexibility on a large scale to these customers, generating income and strengthening GreenFlux's market position.

Smart charging is necessary for utilizing the flexibility of EVs. Although a significant amount of literature shows that this flexibility can be used through balancing markets, most research assumes that the driving parameters and charging characteristics are known, while this is usually not the case.

For the research of this thesis, the knowledge and experience of GreenFlux regarding EV charging are valuable resources. As a leading provider of smart charging solutions, GreenFlux offers unique perspectives on the practical challenges facing the industry. The relevance of GreenFlux to this thesis is also highlighted by their enormous amount of data. To understand the trends, charging behavior, and charging landscape of EVs, tens of millions of charging sessions from their databases were available. This has enabled the development of a more realistic charging controller that takes into account the uncertainties in charging characteristics and driving parameters, in contrast to what is often assumed in the current literature. Providing this valuable data for this research has been a testament to GreenFlux's commitment to advancing the field.

The literature study in this report is crucial as it provides a comprehensive understanding of the energy and balancing markets and the associated requirements and limitations. This information is essential in making informed decisions on the implementation of smart charging, to ensure that the flexibility potential of EVs is utilized to the fullest extent. For instance, the uncertainty in the inputs used for smart charging presents challenges for balancing markets, which have strict regulations and do not tolerate uncertainty.

1-4 Problem Statement

The focus of this research is on the feasibility of building a large scale setpoint-tracking controller to regulate EV charge points and coordinate charging with energy market dynamics through co-regulation. This research aims to develop and evaluate the performance of this controller and provide insight into the impact of the proposed solution on the energy market. To achieve this goal, the roles of the actors in the energy market, the characteristics of the EV charging infrastructure, and information provided by TenneT about the imbalance market have been thoroughly investigated. By utilizing the flexibility of EVs, the proposed method has the potential to revolutionize the energy market and contribute to the global effort to reduce carbon emissions. The proposed solution uses information that is available in practice, thus providing a practical and scalable solution for a rapidly growing problem.

1-4-1 Research question

Is it possible to develop a large scale setpoint-tracking controller that optimizes the balance between the power setpoint and the aggregated consumption of electric vehicle charge points while aligning with the dynamics of the energy market?

1-4-2 Sub-questions

1. How can smart charging be effectively implemented within the context of the energy market?
2. How can a simulation environment be developed to test the performance of a controller using real-world electric vehicle charging session data?
3. How can a feedback controller be designed to track a power setpoint in real-time while accounting for the potential impact of flexible charging schedules on future events, without relying on assumptions about travel patterns or charging characteristics?
4. What are the challenges and limitations of the proposed solution, and what recommendations can be made for future research in this area?

The findings of this research contribute to the Systems & Control and Electrical Engineering fields by presenting a method for aligning EV charging with the fluctuation of the energy market.

1-5 Report Outline

The remainder of this report is structured into several chapters. Chapter 2 introduces the electricity markets and balancing markets, exploring the best use case for using EV flexibility to restore system imbalances and generate revenue. Next, Chapter 3 describes the research design, including the methods and techniques used to collect and analyze data for the simulation environment. Moreover, the steps taken to conduct the research and the reasoning behind the choices made are explained. Next, the algorithm and controller design are explained in Chapter 4. Additionally, the findings of the research, including tables, graphs, and images, are presented in Chapter 5. Chapter 6 will interpret the results and discuss their implications, including limitations and areas for future research. It will provide a critical evaluation of the findings and assess their validity. Finally, the conclusions of the research are presented in Chapter 7.

Chapter 2

Smart Charging and balancing Services for Electric Vehicles

Integrating Electric Vehicles (EVs) into the power grid could revolutionize the way electricity is generated, distributed and consumed. Smart charging, which is a way of controlling EV charging patterns, can optimize the use of EVs as a distributed energy source. However, the most efficient and cost-effective implementation is still debatable, as many different control strategies have been proposed in literature. Formalizing an optimization strategy requires a thorough understanding of the different use cases for smart charging and the key technologies, protocols and market mechanisms that enable it.

This chapter is divided into several sections, each covering a specific aspect of the energy ecosystem and smart charging. Navigating the energy market can be overwhelming, as it involves multiple technical terms and various stakeholders. To make it easier for readers, we have compiled several glossary tables per topic in Section 2-1, including the key terminologies, the different parties involved in the electricity market, and the various balancing markets. With this glossary, we hope to provide a clear and concise reference guide for readers to better understand the intricacies of the energy industry. In Section 2-2, a comprehensive and clear overview of the energy market is provided, highlighting clear interrelationships between actors. Section 2-3 then introduces the topic of smart charging and explains why the choice between ancillary services and co-regulation is important. Moving on to Section 2-4, potential revenues for each use are discussed. Finally, the chapter concludes with a discussion of the practicalities of implementing smart charging, including the trade-offs and challenges to consider, in Section 2-5 and Section 2-6.

Overall, this chapter serves as a comprehensive introduction to the topic of smart charging controllers for balancing services with EVs and provides a clear understanding of the research objectives.

2-1 Glossary

Actor	Acronym	Description
Transmission System Operator	TSO	Is accountable for the management and stability of the high-voltage grid, as well as the functioning of the market and the integration of sustainable energy.
TenneT		TSO of the Netherlands.
Balance Responsible Party	BRP	Is responsible for maintaining the balance between the energy they produce or consume and the amount of energy they sell or purchase on the energy market.
Balancing Service Provider	BSP	is responsible for delivering balancing services to BRPs to assist them in maintaining their energy balance.
Charge Point Operator	CPO	A company that operates and manages charging stations for electric vehicles.
GreenFlux	GFX	Company that provides cloud-based back-office capabilities to its clients. They are now expanding their smart charging business. This research is done in collaboration with GreenFlux.

Table 2-1: Glossary of Electricity Market Related Actors.

Terms	Acronym	Description
Balancing market		A platform where grid operators can buy or sell energy reserves to balance electricity supply and demand in real-time.
Day Ahead Market	DAM	The Day Ahead Market is an energy market where electricity transactions are concluded for the delivery of electricity on the following day.
Intraday market		Is an energy market where electricity transactions are concluded for the delivery of electricity on the same day as the transaction. The market also corrects the imbalance created in the DAM.
Imbalance settlement Period	ISP	A period of 15 minutes during which the actual energy production and consumption are measured and compared with the planned energy production and consumption for settlement of any deviations.

Table 2-2: Glossary of Electricity Market Related Terms.

Services	**Description**
Ancillary services	Services purchased by Transmission System Operators (TSOs) to ensure the reliability and stability of the electricity network. Only Balancing Service Provider (BSP)'s.
Co-regulation	The ability of a consumer to adjust their own energy demand in response to signals from the energy market or grid operator in order to balance supply and demand and maintain the stability of the electricity system.

Table 2-3: Glossary of Balancing services. This table provides definitions for the two types of balancing services, ancillary services and co-regulation, that are relevant to the use of Electric Vehicles as a distributed energy source in the electricity market.

Prices	**Description**
Capacity price	Price paid to guarantee the availability of energy capacity.
Energy price	Price paid for the actual delivery of energy.
Upward regulation price	Price paid for the contribution to inject energy in the network (or withdraw in a lesser extent).
Downward regulation price	Price paid for the contribution to withdraw energy from the network (or inject to a greater extent).
Regulation price	The price for imbalances in an imbalance settlement period.
Regulation state	State in which the electricity market is when the production and consumption of electricity are balanced.

Table 2-4: Glossary of Electricity Market Prices.

2-2 Electricity Market Operations

The integration of renewable energy sources into the power grid has brought new challenges to maintaining a stable and reliable electricity system. One of these challenges is balancing electricity supply and demand in real time. The wholesale electricity market plays a role in this, but it is not sufficient on its own. The power grid relies on a combination of wholesale electricity markets, balancing markets and a market mechanism called imbalance settlement to balance the market. Each of these mechanisms plays a distinct role in maintaining balance in the power grid. This section provides an overview of all electricity market activities, including the day-ahead and intraday markets, the different types of balancing services, the imbalance settlement system, and a schematic overview of the energy market and its different actors. It is important to note that in this context, the terms '(wholesale) electricity market' and 'energy market' are often used interchangeably, but they do have a subtle difference in meaning. The (wholesale) electricity market refers specifically to the market for buying and selling electricity among electricity generators, traders, and suppliers. While these mechanisms work together to balance the market, this section focuses on providing an overview of all electricity market activities, including the day-ahead and intraday markets, the different types of balancing services, the imbalance settlement system, and a schematic overview of the energy market and its different actors

Balancing markets are an important mechanism used to maintain the stability of the power grid by balancing the electricity supply and demand in real time. These markets allow for the procurement of balancing services, which help to regulate the grid and ensure that the electricity supply matches the demand at any given time. These balancing markets are an essential component of the electricity market, as they help to ensure that the electricity grid remains stable and reliable.

2-2-1 Energy system diagram

The energy market is a complex system with many actors from the financial, energy and technical sectors, each with their own objectives and motivations, however its functioning relies on their cooperation and coordination. Figure 2-1 provides a clear and understandable representation of the organization of the energy market where the interdependence between the actors and the time factor involved are emphasized through the use of color coding and clear illustrations of the interrelationships. The figure presents the complex web of actors in an accessible and informative way.

However, the dynamics of the energy market can be difficult to grasp without prior knowledge. The schematic and colored overview is accompanied by detailed explanations in Section 2-2. Because each individual explanation may not provide complete clarity, it is recommended that both the figure and accompanying text be studied together for a full understanding of energy market dynamics.

The different colors in the figure are used to distinguish the main components of the energy system. The colors and components of the figure are explained below:

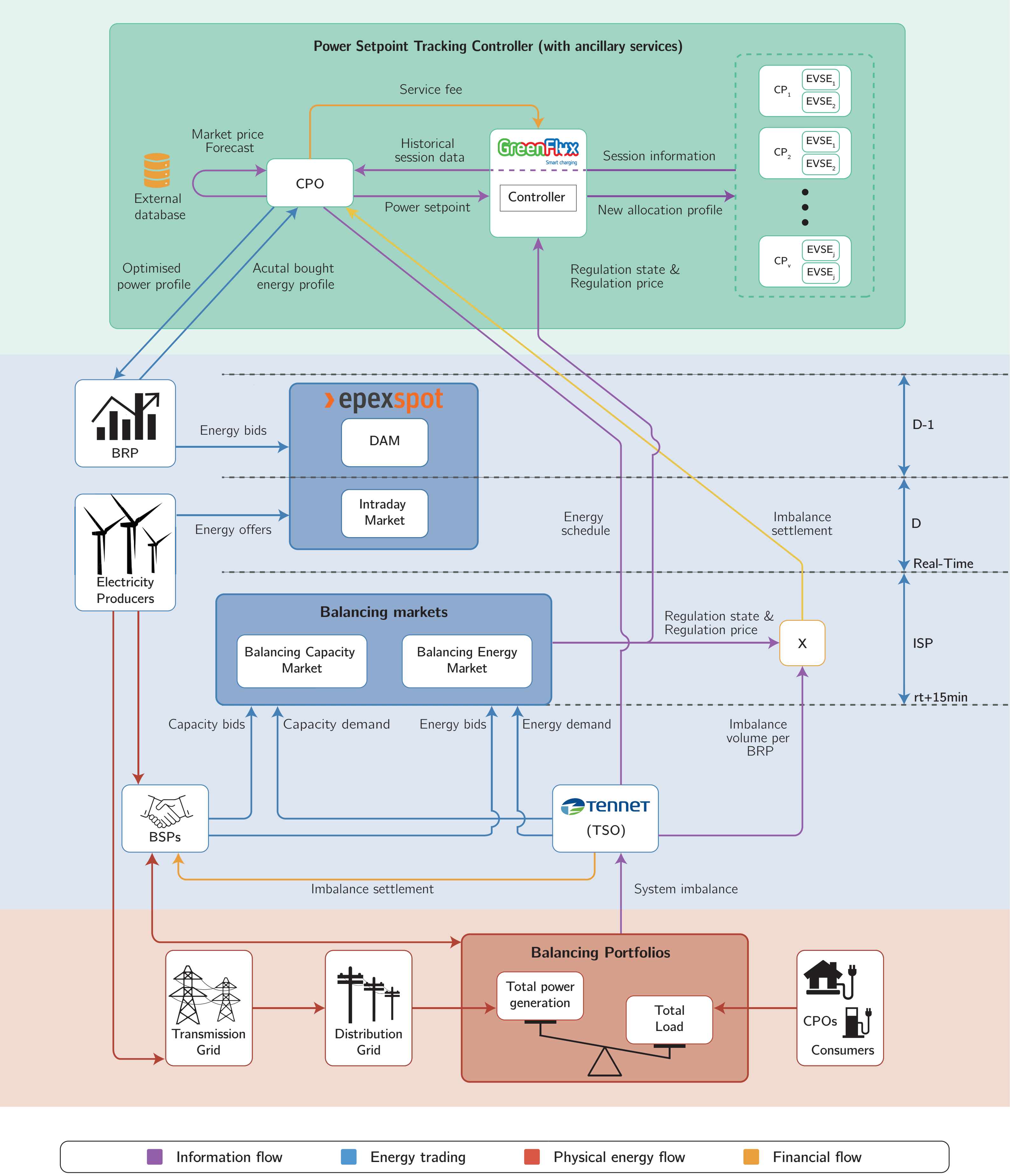
- The green top layer shows the relationship between GreenFlux, its customers, and the energy market.
- The blue part includes all energy and balancing markets, which are discussed further in Section 2-2-3.
- The bottom red layer represents the physical layer of the electricity grid.
- The color-coded arrows indicate the flow of information, energy (both trading information and physical energy), and money within the system.
- The timeline on the right illustrates the activation time of the markets. Three activation times are distinguished: the day-ahead (D-1), real-time, and ISP.

The Epexspot market serves as a centralized platform for wholesale electricity trading. It enables electricity producers to match their supply with the demand of consumers. At gate closure (noon of the day-ahead), each producer is notified of the amount of electricity they are required to provide to consumers. Through the real-time assessment of the system imbalance TenneT calculates the balancing volume required in each balancing market to bridge the difference between total power generation and total load. The regulation state and price reflect the current market conditions. The settlement of the system imbalance is based on the state of the market and the discrepancy between the commercially agreed trade schedule and the actual load per Balance Responsible Party (BRP).

In the figure, GreenFlux and the controller are represented as part of the same block. That is because the controller would be a product of GreenFlux or a similar actor that helps it achieve its objectives. The necessary operations for the effective functioning of the controller, typically performed by GreenFlux, a similar actor or the Charge Point Operator (CPO), are outlined as follows:

- GreenFlux collects sessions information from the Charge Points (CPs), including session duration and total energy consumption.
- This information is processed and sent to the CPO.
- A forecast of the unsteered demand for the day-ahead is generated based on this information.
- Based on a day-ahead market price forecast, an optimization problem is solved to create an energy profile that meets the needs of each charge session at the lowest possible cost. A simplified optimization was performed in Section 3-2-6 for simulation purposes.
- Based on this profile, the CPO submits energy bids to the day-ahead market and receives the contracted amount of energy at gate closure.
- GreenFlux turns this power setpoint into a new allocation profile with individual control signals for each charge point.

It is important to note that the operations described in the list above may not always be performed by the specific actors mentioned. This representation is the most common structure, and provides a general understanding of how the CPO and GreenFlux operate.



List of Acronyms					
CP(O)	Charge Point (Operator)	**D**	Day	**ISP**	Imbalance Settlement Period
EVSE	Electric Vehicle Supply Equipment	**BSP**	Balancing Servicing Party	**DAM**	Day Ahead Market
		BRP	Balancing Responsible Party	**TSO**	Transmission System Operator

Figure 2-1: A high-level overview of the Dutch electricity balancing markets and GreenFlux's role. Blue indicates the electricity market and its relationship to electricity markets. The grid's physical layer is shown in red. The research's focus on the setpoint-tracking controller is marked in green.

2-2-2 Wholesale electricity market

The electricity market is a platform for buying and selling electricity, where market participants can trade energy based on their forecasts for supply and demand. The day-ahead market is used to secure the necessary amount of electricity for the following day by balancing supply and demand through the auction of available capacity. The intraday market is used to balance supply and demand in real-time and correct any imbalances that occurred in the day-ahead market. The prices for electricity in these markets are determined by the market, providing a mechanism for energy scheduling and incentivizing market participants to optimize their production and consumption. The day-ahead market and intraday market are explained below

Day-ahead Market The day-ahead market is used to secure the necessary amount of electricity for the following day. This market is used to balance supply and demand through the auction of available capacity. On the day-ahead market, market participants can buy and sell one-hour electricity contracts in a pan-European auction for the next day. Producers and consumers submit their offers and bids respectively, based on their expected production and consumption. The day ahead price is based on a marginal pricing system, resulting in the same price per MW h during that time frame for everyone. After market closing, the market participants have to send their contracted power schedule to the TSO themselves or through a chosen BRP. After handing in the commercial trade schedule, the BRP is responsible for abiding by their contracted volume.

Intraday Market The intraday market is another important component of the electricity market, which allows for the balancing of electricity supply and demand on the day of delivery. The prices in the intraday market tend to be higher than in the day-ahead market, due to the increased complexity and expense of short term energy delivery. The intraday market provides a mechanism for market participants, such as generators and retailers, to adjust their positions in the market by buying or selling electricity to align their schedules with their expected production and consumption. This helps to ensure that the electricity supply and demand are more evenly balanced in real time. The 15-minute energy contracts available in the Dutch market can be traded up to 5 minutes before delivery, providing increased flexibility in energy trading and supporting the balancing of the grid.

For further clarity and to aid understanding of the energy market concepts discussed in this section, intuitive examples have been provided in Appendix A. Readers are encouraged to refer to this appendix, particularly if these general concepts require further explanation.

2-2-3 Balancing services and imbalance settlement system

Energy trading on the electricity markets is based on predictions, which can lead to imbalances in real time. To address these imbalances, balancing markets come into play, where balancing capacity can be bought from pre-qualified BSPs [17]. The pre-qualification process is explained in Section 2-6. Balancing services are typically provided by conventional generators. However, with the increasing penetration of renewable energy, it has become more challenging to adjust generation, making it necessary to shift balancing services to the demand side. Balancing services are generally divided into two main categories: ancillary services, which actively balance the grid, and co-regulation (also known as passive steering), which uses demand-side resources such as electric vehicles EVs.

Ancillary services include services such as frequency control, voltage control, and reserve capacity, and are typically provided by conventional power plants. Detailed descriptions on how these specific balancing market work are given in Appendix B. On the other hand, co-regulation services, such as demand response, use demand-side resources to adjust consumption to match supply.

As the penetration of renewable energy sources continues to increase, the demand for balancing services is likely to shift towards the demand side, as renewable energy resources such as wind and solar power are more difficult to adjust. This trend has led to new market opportunities for demand-side response services, including the use of EVs as mobile storage devices.

Ancillary services The TSO, TenneT in the Netherlands, is responsible for maintaining a country's grid's power balance, and procure balancing capacity from pre-qualified BSPs to maintain the balance. Several balancing markets, primarily distinguished by their activation method and response time, cooperate to restore imbalances in the power system. The order in which the different products are activated is shown in Figure 2-2.

In continental Europe, the target frequency is set at 50 Hz. Note that "frequency" in the context of the power grid refers to the rate at which the alternating current in the grid, changes direction and frequency deviations can occur when there is an imbalance between electricity supply and demand in the power grid. To maintain this frequency, BSPs must continuously measure it and adjust their output power automatically to compensate for deviations from the target frequency. The balancing market responsible for frequency containment is the Frequency Containment Reserve (FCR), which is also known as primary reserve. It is the first line of defense for TenneT in maintaining balance in the grid, and BSPs are required to have their contracted reserves fully activated within 30 seconds. The FCR helps to stabilize the frequency across borders for the entire synchronous grid of continental Europe.

The FCR product has the fastest response time and must therefore be available for future imbalances. Secondary control is used to balance the power system over longer timescales. The automatic Frequency Restoration Reserve (aFRR) gradually replaces the FCR when imbalances are expected to last longer than 15 minutes. The ramp rate for aFRR is at least 20%/min, resulting in full activation within 5 minutes. The aFRR is the most frequently activated market to restore regional grid imbalances. A part of the imbalance is automatically regulated by activating aFRR, which is available after 30 seconds. If the available aFRR falls below a threshold or the imbalance is expected to remain longer than a few Imbalance Settlement Periods (ISPs), additional measures are required. Through a manual procedure, TenneT can activate manual Frequency Restoration Reserve scheduled activated (mFRRsa) to support or partially substitute the aFRR until sufficient aFRR capacity becomes available or the balance is sufficiently restored. And finally, the manual Frequency Restoration Reserve direct activated (mFRRda) is used in the event of an emergency when all mFRRsa and aFRR reserves have been depleted.

The payment for balancing services in the Netherlands, as well as in most European countries, is based on two forms of remuneration: capacity price for keeping capacity available and energy

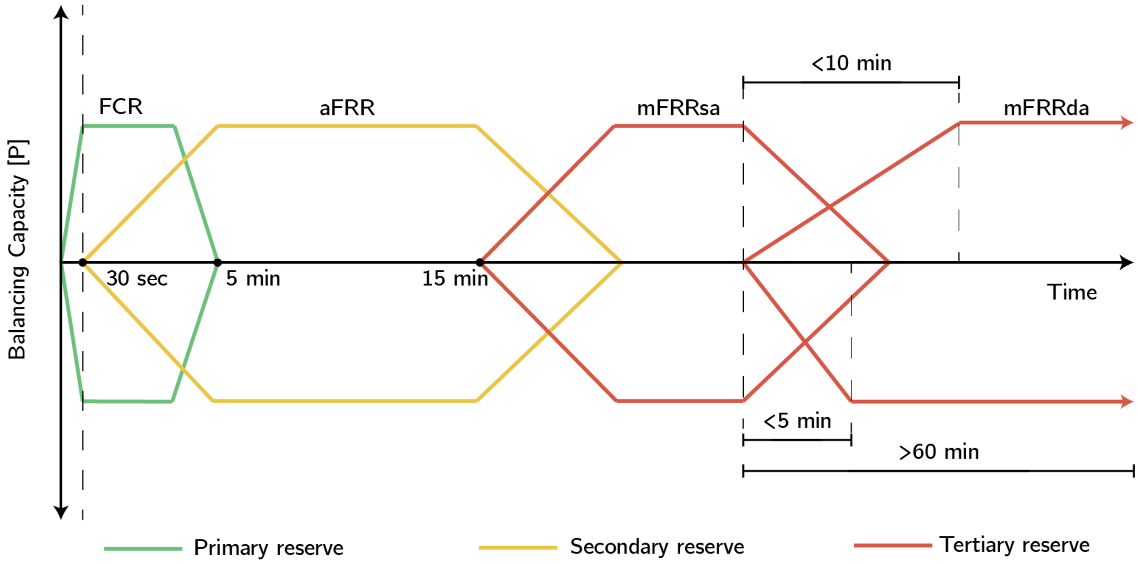


Figure 2-2: Activation schedule for different balancing markets. Note that symmetrical activation is illustrated to accentuate the symmetrical nature of balancing markets, but actual activation will always be one-sided.

price for actually providing the balancing energy. The merit order list is used to rank bids and determine which bids will be accepted, with the most competitive bids having a higher likelihood of being activated. This system encourages competitive bidding.

When smaller end-users participate in balancing services, their demand is aggregated [18]. Numerous research initiatives have shown that EVs can provide ancillary services through balancing markets [14, 15, 16, 19, 20, 21, 22, 23, 24, 25]. On the other hand, the reality may be more challenging than what is presented in literature and this will be discussed in Section 2-6.

Imbalance settlement The imbalance settlement system works by comparing the amount of energy that each BRP contracted to deliver or consume with the actual amount of energy that was consumed or produced. If there is an imbalance between the contracted and actual amounts of energy, the TSO will activate the balancing markets to correct the imbalance. After the imbalance has been settled, TenneT calculates the imbalance settlement price using marginal-cost pricing, which ensures that all BSPs are charged equally per energy volume per imbalance settlement period. The BRP is then responsible for settling any imbalances between the contracted and actual energy consumption or production with their customers. This system transfers some balancing responsibilities to BRPs. The imbalance settlement price serves as an incentive for BRPs to balance their portfolio using their assets and electricity markets.

The imbalance settlement is determined by the combination of the current market conditions and the surplus or deficit of energy, which is represented by the regulation state. When the BRPs's imbalance reduces the overall system imbalance, the imbalance price is paid out to the BRP.

When both upward and downward regulation occurs during an ISP, the series of balance deltas determines the regulation state. The balance delta is the power of the activated upward bids minus the power of the activated downward bids. The different regulation states are:

- Regulation state 0 : No regulation.
- Regulation state -1 : Only downward regulation or continuously decreasing or constant series of balance deltas.
- Regulation state +1 : Only upward regulation or continuously increasing or constant series of balance deltas.
- Regulation state 2: : If the series of balance deltas both decreases and increases.

Co-regulation Co-regulation, also known as passive steering, is a type of balancing service that refers to the process of changing consumer energy consumption to balance the grid Warren [26]. TenneT, the transmission system operator in the Netherlands, publishes live information about the regulation state and regulation price, which enables BRPs to offer balancing services without actively participating in the official imbalance markets [17]. Strategies to promote co-regulation include financial incentives and education to encourage changes in consumer behavior and reduce demand and supply peaks [27]. Financial incentives have been shown to be effective in promoting consumer participation in co-regulation and achieving the desired changes in energy demand, which helps to balance the grid and maintain grid stability [28, 29].

2-3 Smart Charging Use Cases

The section aims to explore the potential use cases of smart charging for the power grid and discuss different communication protocols for smart charging. Smart charging has gained increasing attention, especially due to the fast increase of EVs on the roads. Essentially, smart charging optimizes the charging of EVs through advanced technologies and algorithms to balance different objectives. Aggregators have a vital role in providing balancing services by grouping a large number of EVs and offering them as a single entity to Tennet, known as a Virtual Power Plant (VPP). As EV integration into the power grid continues to progress, standardizing communication protocols is crucial to ensure compatibility between parties involved in EV charging. The most relevant protocols for smart charging are Open Charge Point Protocol (OCPP), Open Smart Charging Protocol (OSCP), and IEC 15118.

- The OSCP is an open-source communication protocol that CPOs use to communicate with the local electricity grid operator. It aims to prevent grid overloading by providing capacity forecasts for the local grid. Developed by Enexis and GreenFlux, the OSCP is an essential protocol for smart charging.

- The OCPP is the most widely used protocol for smart charging. It enables CPOs to manage and control charge station operations remotely, and it is hardware-agnostic, which means it can be used with a wide range of charging station types. The protocol allows for the sending of real-time charging session data, such as charge point status, total energy consumed, and total connection time.

- The International Electrotechnical Commission (IEC)15118 is a more advanced communication protocol that enables high-level bi-directional communication between the EV and the charge point. It allows for the transfer of information such as the vehicle's (acSoC and maximum charging rate. The standard also includes provisions for secure payment, load management, and load balancing to help prevent grid overloading. However, the use of the more advanced IEC 15118 is not yet widespread in the industry, and it is common for information about the battery characteristics of the EV to not be exchanged between the charge point and the grid operator.

The Dutch energy system is complex due to its various interrelated trading and balancing markets.The system is designed to incentivize all actors to maintain the balance. An aggregator of a fleet of EVs can offer balancing capacity in several ways, such as::

1. **Power setpoint-tracking:**
   Controlling the charging rate of EVs to adjust aggregated power consumption and follow contracted power from the day-ahead to avoid creating an imbalance and incurring fines.

2. **Ancillary services:**
   Offering flexibility in one or more balancing markets and receiving payment in the form of a capacity fee for making capacity available and an energy fee for actual activation.

3. **Co-regulation:**
   Adapting the aggregated charging power of the EV fleet in near real-time based on the regulation state and regulation price.

Conventional power plants typically provide ancillary services. However, simulations have shown that EVs acting as smart storage can provide fast and accurate responses for frequency regulation [30, 31, 32]. Using EVs for ancillary services offers several advantages over conventional generators, including fast response time, low operating costs, and increased utilization of battery capacity that can reduce the overall cost of EV ownership. Through co-regulation, EVs can provide accurate and fast grid balancing by adjusting their charging in near real-time. Co-regulation is a proactive approach to managing the power grid that involves coordinating the activities of grid participants, including EVs, to regulate energy consumption. CPOs can offer co-regulation services by combining this information to understand how to use their assets in order to receive the imbalance price.

However, it is important to consider the trade-offs and practicalities of implementing both use cases for smart charging, which will be discussed in further detail in Section 2-5 and Section 2-6.

2-4 Economic Viability of Smart Charging

The economic viability of smart charging is an important aspect to consider when determining its most valuable and promising use case. In this section, we will analyze the costs and benefits of providing ancillary services and co-regulation with EVs. Unlike generators, EV batteries have virtually zero fixed costs as they have already been purchased for the owner's transportation needs and they have fewer moving parts, which means they have lower maintenance costs. Furthermore, while plugged in, EV batteries can provide regulation services with relatively low additional operating cost. Most studies have shown that batteries, including those in electric vehicles, are well-suited for providing regulatory services, particularly primary reserves such as FCR, due to their high revenue potential.

Studies conducted in different countries have estimated the potential profits from utilizing EVs for ancillary services. In the United States, a large-scale study conducted by Sortomme and El-Sharkawi [14], predicted an annual profit between $161 and $635 per EV. In France, the potential profit is estimated to be between €193 and €593 per year per EV according to Codani et al. [15]. In the United Kingdom, research by Pavić et al. [23] found that using EVs to balance the energy system benefits not only the EV driver and aggregator, but also the entire system by reducing the overall price of energy. The study showed that when EVs provide balancing capacity to the secondary reserves, they can do so at competitive prices, reducing the total cost of the secondary reserve by an estimated €122 to €540 per EV. This means that with an increasing number of EVs used for balancing services, the total cost of the secondary reserve can be significantly reduced, making the system more efficient and cost-effective. Druitt and Früh [16]'s research concluded that depending on the number of EVs the benefits of balancing range from £150 to £400. In summary, utilizing EVs for balancing services has been shown to be a profitable and cost-effective solution in various countries.

Utilizing electric vehicles for co-regulation has the potential to generate revenues similar to those obtained through ancillary services as all the flexibility can be used when it is available. However, co-regulation misses out on the capacity fee and steering in regulation state 2 can be challenging. It is important to evaluate the regulatory frameworks, technical requirements, and practical considerations of the targeted markets, as these factors can have a major impact on expected revenues and must be taken into account when determining the most valuable and promising use case. These will be discussed in Section 2-5 and Section 2-6.

The effectiveness of utilizing Co-regulation as a profitable and cost-effective solution for balancing services using EVs remains uncertain. This study aims to investigate the potential profits and practicalities of implementing Co-regulation and its trade-offs compared to ancillary services.

2-5 Trade-offs of Smart Charging

Although implementing smart charging presents benefits for ancillary services and co-regulation, it also involves a series of trade-offs that must be carefully considered when building a controller, in order to ensure the best possible outcome for the energy grid, CPOs, and EV user

First trade-off Smart charging for electric vehicles involves a trade-off between the needs of the power grid and the needs of EV users. On the one hand, smart charging can improve grid stability by spreading out demand for electricity and providing balancing services on a smaller scale. However, on the other hand, smart charging requires some control over the charging process, which can sometimes conflict with the preferences of EV users. For example, users may want to charge their vehicles at specific times or locations that are not optimal for grid stability. In some cases, it may be necessary to prioritize user satisfaction over grid stability. Therefore, it is important to develop smart charging systems that strike the right balance between these competing demands.

Second trade-off The use of bidirectional power flow between EVs and the grid, known as Vehicle to grid (V2G) technology technology, is a popular option for providing ancillary services [14, 16, 20, 21, 22, 24]. However, V2G has some drawbacks, such as battery degradation, hardware costs, and conversion losses. Alternatively, unidirectional charging can achieve similar benefits without these issues. When the charging of EVs is reduced or stopped, the overall demand on the grid decreases, which is similar to the effect of discharging power back to the grid. According to Fasugba and Krein [33], almost all the benefits of V2G can be obtained through unidirectional charging if the VPP of charging stations is large enough. In addition to avoiding conversion losses, unidirectional charging also minimizes the negative impact of frequent charging and discharging cycles on the battery's lifespan and performance, leading to decreased maintenance costs.

Overall, while bidirectional charging through V2G may sound promising, unidirectional charging can achieve similar effects while avoiding some of the associated drawbacks.

2-6 Practicalities of Smart Charging

The implementation of smart charging for EVs involves a range of technical and regulatory requirements that need to be carefully considered to ensure practicality and efficiency. Some of the practical considerations for implementing smart charging for ancillary services and co-regulation include the following:

- Capacity availability. Only the minimum expected capacity can be offered, and it must always be available.
- Ancillary services involve making agreements with TenneT on the amount of capacity made available. If the agreed-upon capacity cannot be delivered, penalties must be paid.
- To account for uncertainty, an uncertainty buffer must be included to make sure that in the event of unforeseen circumstances (e.g, unexpected events such as major public events, road closures, or accidents may divert traffic away from the charge points, resulting in lower demand). According to [34], a buffer of 25% should be factored in to deliver the required capacity.
- Symmetrical bidding requirements. For ancillary services the system should be able to deliver and retrieve the capacity offered. This can be a challenge for EVs, as charging is often a priority. To be able to take energy from the grid, the EV charge rate as to be structurally below the maximum to be able to increase the charging rate.

In addition to the above considerations, there are specific requirements that TenneT imposes to meet the pre-qualification status. For instance, Infrastructure must be in place to measure the frequency of the network accurately and quickly, and communication with TenneT's systems must be possible. Furthermore an algorithm must be approved that demonstrates the ability to deliver the capacity. Failure to deliver the agreed-upon capacity may result in the withdrawal of the pre-qualification status.

Another practical issue is that there is considerable academic attention on smart charging, yet industry collaboration is limited. Assumptions of availability of information on vehicle attributes (e.g., State of Charge (SoC), maximum charge rate, and required energy) and travel data parameters (e.g., departure time and arrival time). The most common assumptions are that the SoC is known in advance [14, 35, 36, 37] and that the driving profiles or (expected) arrival and departure time are known [38, 39, 40, 41, 42].

Implementing smart charging for EVs requires managing various practical considerations. By taking into account trade-offs and regulatory requirements, it is possible to optimize the use of smart charging technology for ancillary services and co-regulation.

2-7 Conclusion

In conclusion, this chapter has provided a detailed examination of the various use cases for smart charging. Through the analysis of literature and examination of the potential revenue, trade-offs, and practicalities, it has become clear that co-regulation presents the most promising opportunity for smart charging in a practical and beneficial way for both consumers and the power grid.

The trade-offs that were considered are; balancing grid stability and EV user satisfaction, and optimizing energy use versus maximizing profit. While V2G has the potential to provide additional benefits, the trade-offs in terms of potential impact on battery life and degradation, as well as the lost energy due to conversion losses, make it clear that the benefits do not outweigh the downsides in this particular case with a large VPP. Therefore, this study will focus on the benefits and challenges of unidirectional co-regulation for smart charging.

While ancillary services and co-regulation both have the potential to provide grid balancing services, despite slightly lower profits per EV, co-regulation has the potential to provide more accurate and faster grid balancing. Therefore, for an aggregator looking to provide balancing services with a fleet of EVs, co-regulation may be the more attractive option. When it comes to co-regulation, there are a number of practical implications that must be taken into account, including the need for standardized communication protocols, and the need to balance the interests of various parties involved in EV charging. Despite these challenges, o-regulation has several advantages over ancillary markets, including no penalties for failing to supply contracted capacity, no additional infrastructure investment or pre-qualification requirements, and real-time decision-making. Co-regulation eliminates the need for an uncertainty buffer and allows the aggregator to focus solely on their goals. As a result, co-regulation can be an effective solution for managing the increasing demand for electricity from EVs while also providing benefits to the grid and EV users.

Chapter 3

Modeling the Simulation Environment: Methodology and Implementation

This chapter provides a detailed overview of the methodology used to create the simulation environment. The simulation environment was an essential component of this study, where the data collected from Greenflux and TenneT was processed and analyzed to model the interaction of Electric Vehicles (EVs) with the charging infrastructure and the Charging Management System (CMS). The simulation environment was created using Azure Data Studio, Excel, and MATLAB and was based on data collected from real-world sources such as Greenflux and TenneT. The data was pre-processed to meet specific requirements, including filtering based on charge session duration, volume charged, time period, and location. The components that had to be modeled were:

1. User behavior
2. Charge characteristics
3. Unsteered Power Profile
4. Unsteered Energy Profile
5. Contracted power setpoint
6. Energy market information
7. Battery model

These components were combined to form a simulation environment capable of simulating the interaction of EVs with the charging infrastructure and the CMS.

The chapter contains several sections, each addressing a specific aspect of the simulation environment. Section 3-1 provides an outline of the data collection and processing steps. Section 3-2 focuses on modeling the charge sessions, including sampling a set of representative sessions from the data, generating the unsteered power and energy profiles, computing the contracted power setpoints, and energy market information. The EV charging model and battery model are discussed in Section 3-2. Finally, the models are validated in Section 3-3.

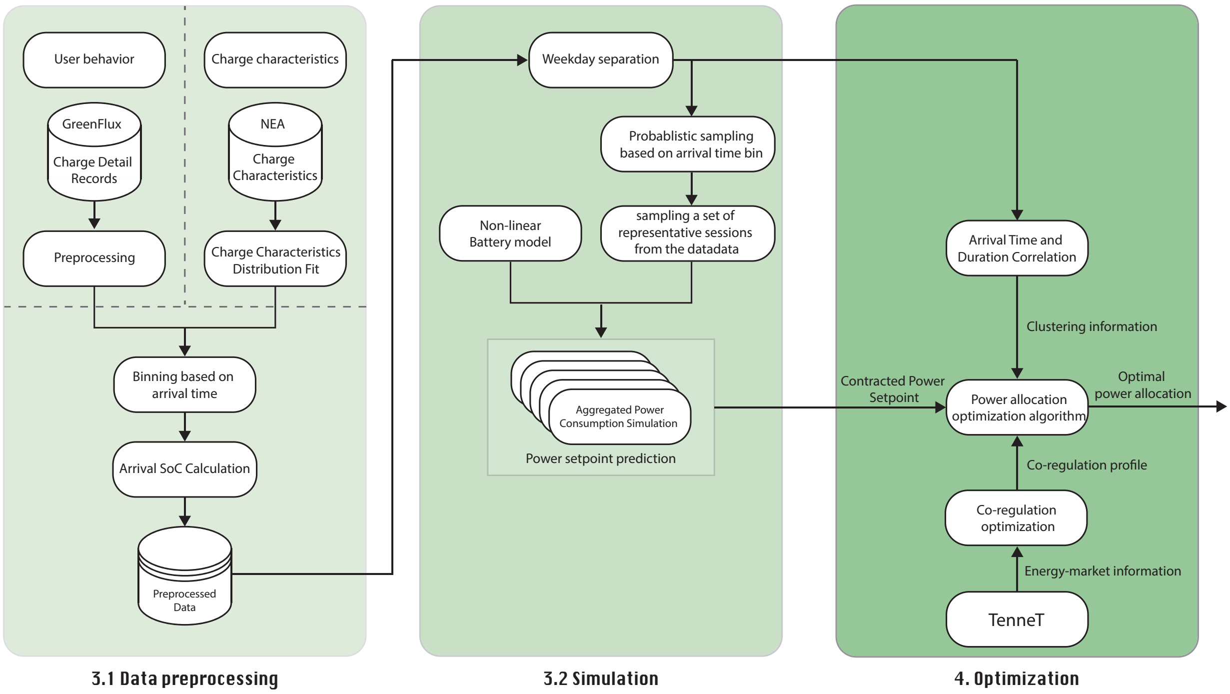


Figure 3-1: Data Processing, Simulation, and Optimization for Energy Market Analysis.

The aim of this chapter was to provide a comprehensive and transparent explanation of the simulation environment to allow for easy replication and extension of the study. For reference, a schematic of the simulation environment is shown in Figure 3-1, with the section numbers indicating in which section that part of the simulation environment will be discussed.

3-1 Data Collection and Processing

To create a comprehensive understanding of EV charging behavior and its impact on the energy market, this study utilized real-world data obtained from GreenFlux and energy market information from TenneT. The GreenFlux data provided details on arrival and departure times, charged energy, ChargePointID, and AuthenticationID. Meanwhile, the energy market information from TenneT furnished data on the energy market in the Netherlands, including day-ahead price, regulation state, and regulation price.

Information on the number of EVs of each type in the Netherlands and their market share was sourced from the Netherlands Enterprise Agency [4]. To accurately model the charging behavior of these EVs, charge characteristics for each model were obtained from technical specifications, and manufacturers' datasheets.

The data has been preprocessed to meet specific criteria to ensure its representativeness. The preprocessing step involved the following filters:

- Charge session duration between 15 minutes and 36 hours.
- Volume charged between 1 and 100 kWh.
- Charge sessions between 01-08-2021 and 31-07-2022.

- Charge sessions within the Netherlands.
- Removal of fast chargers, as they cannot use the same smart charging algorithms.

3-1-1 User Behavior

The GreenFlux database contains a wealth of information on EV charging sessions dating back to 2012. The Charge Detail Record (CDR) table, in particular, is of interest as it provides information on a single session level. The parameters that are relevant for this study are listed in Table 3-1. The goal of processing and interpreting EV charging data from CDRs is to gain valuable insights into user behavior and charging patterns. To accurately simulate these patterns in charging sessions, it is crucial to maintain the correlation between the arrival time, duration, and volume charged. This reflects real-life patterns and relationships present in the data. If these correlations are lost, the resulting model will not be representative of actual user behavior, which will negatively impact the accuracy of the results.

To simulate user behavior in charging sessions, a probabilistic approach was used to generate the arrival times. The resulting CDRs have been validated in Section 3-3.

Parameter	**Example**	**Explanation**
dStart	2019-01-08 09:04:53.000	Start of the session
dEnd	2019-01-08 16:04:18.000	End of the session
Duration	06:59:25	Session duration
Volume	16,6570	Charged energy in kWh
AuthenticationId	970DF570EAC8F	Unique ID of charge card

Table 3-1: Charge Detail Records.

3-1-2 Charge Characteristics

In order to reflect the diversity of charging characteristics among different EVs, the most commonly registered EV types in the Netherlands were analyzed. Data on battery capacity, number of phases (n_{phase}), maximum current (I_{max}), and maximum power (P_{max}) were collected from [43]. This information was then used to create a categorical distribution of EV types. The top 10 most registered EVs in the Netherlands on 15-08-2022, along with their respective charge characteristics, are presented in Table 3-2.

To simulate a charge session, the number of registrations for each EV model was first normalized to calculate its market share. Then, an EV model was selected based on its market share. If the selected EV's battery size was less than the volume charged in the charge session, the process was repeated until a suitable EV model was found and added to the charge session.

Model	Registrations	Battery [**kWh**]	$\mathbf{n}_{\text{phase}}$	$\mathbf{I}_{\max}$[**A**]	$\mathbf{P}_{\max}$[**kW**]
Tesla Model 3	42235	70	3	16	11
Kia Niro	18367	65	1	31	7.2
Hyundai Kona	16588	57	3	16	11
Volkswagen ID.3	3585	68	3	16	11
Renault ZOE	12618	38	3	32	22
Nissan Leaf	12087	40	1	16	3.6
Tesla Model S	11382	80	3	24	16.5
Skoda Enyaq	10633	76	3	16	11
Audi E-Tron	10489	89	3	16	11
VW Golf	5047	36	2	16	7.2

Table 3-2: Top 10 most registered EVs in the Netherlands on 15-08-2022, along with their respective charge characteristics.

3-2 Simulation modeling

3-2-1 Clustering

We used a Gaussian Mixture Model (GMM) to cluster charging sessions into three main clusters: short stay, daytime/business, and overnight charging. We evaluated several clustering techniques and found that the GMM produced the best results, in line with prior literature [44, 45].

Clustering is a useful technique to gain additional knowledge. It was employed for two main purposes:

1. To realistically emulate the charging behavior: It has been an important component to determine the arrival State of Charge (SoC) [see Section 3-2-2], which was crucial for the battery modeling. Once the arrival SoC was determined, the battery development could be simulated using the battery model from Section 3-2-4.

2. To use historical charge session information for controller decision making: In the clusters, it was determined whether a certain relationship exists between the arrival time and duration. The goal of utilizing solely EVs with adequate steering flexibility is to be able to lower the charging rate while still ensuring that the vehicle can be fully charged later in the session. This so-called flexibility represents the idle time within a charging session, which implies the period during a charging session when an EV is not actively charging.

Several clustering techniques were evaluated, ultimately the GMM was selected as it produced the best results, in line with prior literature [44, 45]. GMM is particularly suitable for modeling complex data distributions. It outperforms k-means clustering, as it offers greater flexibility in cluster shape and thereby better captures the variability of charging sessions.

A GMM assumes that the data is generated by a mixture of K Gaussian distributions, with each distribution corresponding to a different cluster. The probability density function of a

GMM is defined as:

$$p(\mathbf{x}) = \sum_{k=1}^{K} \pi_k \mathcal{N}(\mathbf{x}|\boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k),$$

where π_k is the mixing coefficient for the kth component, which represents the proportion of data points that belong to the kth cluster. The parameters $\boldsymbol{\mu}_k$ and $\boldsymbol{\Sigma}_k$ are the mean vector and covariance matrix of the Gaussian distribution for the kth cluster, respectively. The symbol $\mathcal{N}(\mathbf{x}|\boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k)$ represents the probability density function of a multivariate Gaussian distribution with mean $\boldsymbol{\mu}_k$ and covariance matrix $\boldsymbol{\Sigma}_k$.

The goal of clustering using a GMM is to estimate the parameters $\boldsymbol{\vartheta} = \pi_1, \boldsymbol{\mu}_1, \boldsymbol{\Sigma}_1, ..., \pi_K, \boldsymbol{\mu}_K, \boldsymbol{\Sigma}_K$ that maximize the log-likelihood function of the data, which is given by:

$$\log p(\mathbf{X}|\boldsymbol{\vartheta}) = \sum_{i=1}^{n} \log \sum_{k=1}^{K} \pi_k \mathcal{N}(\mathbf{x}_i|\boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k),$$

where $\mathbf{X}$ is the set of observed data points. This objective function was then optimized using the Expectation-Maximization (EM) algorithm, which is an iterative algorithm that alternates between computing the posterior probabilities of the data points given the current estimates of the parameters (E-step) and updating the parameters based on the posterior probabilities (M-step).

The implementation of the GMM clustering involved selecting the optimal number of clusters by balancing model complexity and cluster separation. We fit GMM models with varying numbers of components and used the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) to determine the optimal number of clusters. Subsequently, the parameters of Gaussian distributions were estimated for each cluster, yielding the means and standard deviations of arrival time and charge duration variables within each cluster.

In Chapter 5 the clustering results are shown and discussed.

3-2-2 Determining the arrival State of Charge

As mentioned in the previous section, the Constant Current Constant Voltage (CCCV) charging strategy is commonly used for charging Lithium-ion batteries. This method involves dividing the charging process into two stages: a constant current stage followed by a constant voltage stage. During the constant current stage, the charging current is kept constant until the battery reaches a certain voltage level. The charging process switches to the constant voltage stage once the desired voltage level is reached, where the charging voltage is kept constant and the charging current gradually decreases. By using the CCCV charging profile, the battery can be charged efficiently and safely, while minimizing the risk of overcharging.

Because the charging rate depends on the SoC, it is important to accurately determine the SoC at the time of arrival at a charging station. However, because the SoC could not be measured or communicated to the charge station, this information was not present in the CDRs provided by GreenFlux. To overcome this challenge, a mathematical method was developed to assign an estimated arrival SoC to each EV.

First, we determine which EVs in the GreenFlux database are "hot unplugs." A hot unplug occurs when a vehicle stops charging before the battery is fully charged. To determine hot unplugs, the following steps were taken:

1. The average power for each charging session was calculated by dividing the charged volume by the duration of the session.
2. The maximum power was determined for each Authentication ID, while removing IDs with less than 30 charging sessions to increase the accuracy of identifying the max charging power. This maximum power value was used to determine when a charge session was a hot unplug.
3. The most common charge rates in the market data on EV types were then identified; 3.6 kW, 6.6 kW, 7.2 kW, 7.4 kW, 11 kW, and 22 kW.
4. A charging session was labeled a hot unplug when it charged at its maximum power and also at a common charge rate.

After performing the above steps to determine the hot unplugs, we analyzed the results to identify the percentage of hot unplugs for each cluster session. The number of hot unplugs for each cluster session is shown in Table 3-3. We found that the percentage of hot unplugs varied significantly across different cluster. The Cluster Short Stay had the highest percentage of hot unplugs at 24.49%, while the Cluster Overnight had the lowest at 0.27%. These results indicate that hot unplugs are not evenly distributed across different charging sessions, and that some clusters have a higher risk of hot unplugs than others.

Cluster	Hot Unplugs (%)
Cluster Daytime	3.91
Cluster Overnight	0.27
Cluster Short Stay	24.49

Table 3-3: Number of hot unplugs per cluster session.

Because we knew the other group was fully charged, we could determine the arrival SoC with the following formula.

$$\text{ArrSoC} = \left\lfloor 100 \cdot \frac{\text{battery capacity} - \text{VolumeKwh}}{\text{battery capacity}} \right\rfloor$$

In this formula, the $\lfloor \cdot \rfloor$ notation represents the floor function that rounds down to the nearest integer.

From this group, we calculated the arrival SoC distribution, which was then used to assign the arrival SoC to the hot unplug group. We took the arrival SoC per cluster, as we expect it to differ due to differences in charging behavior between clusters, which was visually confirmed in Figure 3-2. For the hot unplugs, the Arrival SoC distribution from the fully charged sessions was used and randomly assigned to the hot unplug sessions.

3-2-3 Final charge session simulation

To model a day of charging, the N individual charge sessions needed to be generated. These were created by following the steps explained in this section and a consist of the following information:

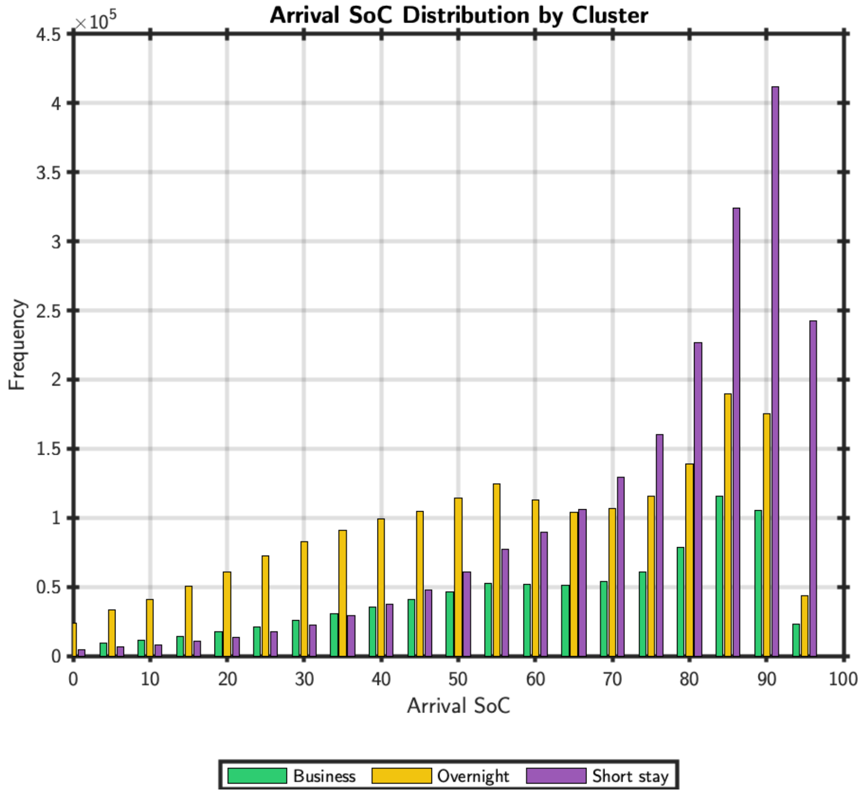


Figure 3-2: Arrival State of Charge distribution by cluster.

- Arrival time
- Charge duration
- Volume charged
- Arrival SoC
- Battery size
- Number of phases for charging
- Max current

The unsteered energy profile and unsteered power profile can be generated using the information listed above. The term "unsteered" refers to the charging strategy where the EVs are charged at full rate until they are fully charged or leave the charging station. The energy profile refers to the amount of energy charged in each session at each time step, while the power profile represents the accumulated energy from all the charging sessions. For these profiles we did also use the battery model discussed in Section 3-2-4.

3-2-4 EV Charging Model

To calculate the battery SoC over time, you would need to take into account the battery's current state of charge, the amount of energy being added to the battery, and the time over which this energy is being added. A common approach to modeling the battery SoC is to use the following formula:

$$SoC(k+1) = SoC(k) + \frac{\Delta E}{Q_{nom}},$$

where $SoC(k)$ is the current state of charge at time k, Q_{nom} is the nominal battery capacity, and ΔE is the energy added or removed from the battery over the time period Δk. The energy ΔE can be calculated from the current I and voltage V of the battery, as well as the charging efficiency η:

$$\Delta E = I \cdot V \cdot \eta \cdot \Delta k.$$

So the final equation to calculate the updated SoC is:

$$SoC(k+1) = SoC(k) + \frac{I \cdot V \cdot \eta \cdot \Delta k}{Q_{nom}}.$$

I is the current assigned by the controller. But in practice the actual consumed current during the charging process also depends on the SoC. If the assigned current is below the maximum current capacity of the battery, then the consumed current is equal to the assigned current. However, if the assigned current is higher than the maximum current capacity, then the consumed current is limited by the upper bound, which is based on the SoC of the battery. The upper bound is calculated using the formula:

$$I = \min(I, f_{cccv}(SoC)),$$

where f_{cccv} is a functions that are used to model the relation between the battery state of charge and the maximum charging current. One common formula for this relation is given by [46]:

$$f_{cccv}(SoC) = \frac{I_{max}}{1 + e^{-k(SoC - SoC_{50})}},$$

where I_{max} is the maximum charging current, k is a constant that controls the steepness of the function, SoC_{50} is the state of charge at which the function reaches half its maximum value, and e is the natural logarithm base.

This function models a sigmoidal relation between the battery SoC and the maximum charging current as shown in Figure 3-3. It is important to note that the form of the function depends on the specific battery chemistry, charging conditions, and other factors, and as such, the best form of the function may vary between different systems.

The following assumptions are made:

- The battery cell voltage is constant.
- No Peukert effect on the capacity of the battery as a result of charge current.
- No impact of temperature or humidity on battery behavior.
- No self-discharge present in the model.
- CCCV relation is the same for each EV model.

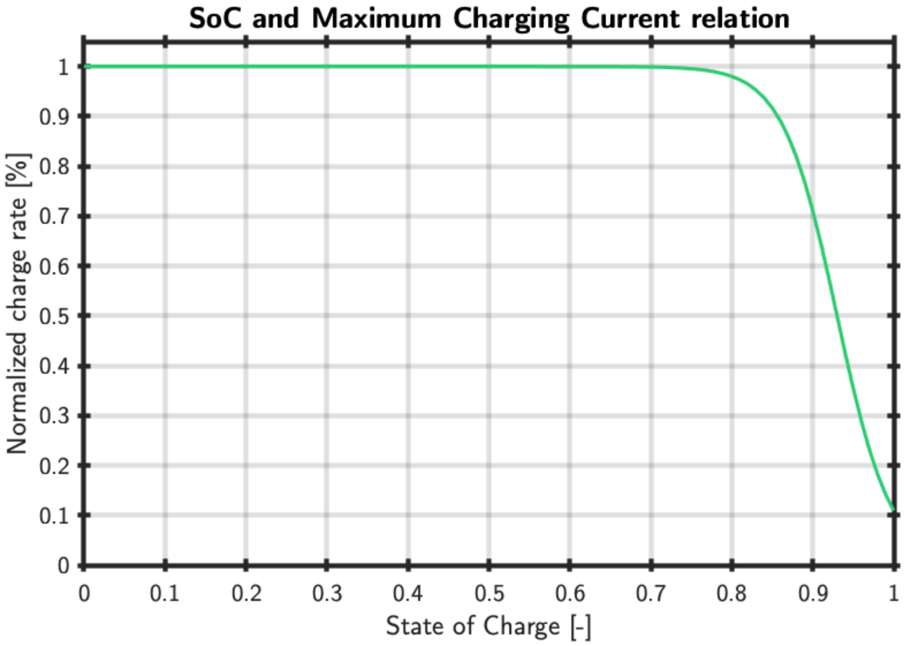


Figure 3-3: Arrival time distribution with a bin size equal to the Sampling time.

It should also be noted that this equation assumes a constant current and voltage during the time period Δk. In practice, the current and voltage may vary, and more complex models may be necessary to accurately capture the behavior of the battery over time. However, it is sufficiently accurate for this study.

3-2-5 Energy market and contracted power setpoint simulations

This section provides details how information about the energy market and the contracted power setpoint were retrieved and calculated. Historical data of the energy market was available from TenneT to test the controller. Figure 3-4 presents the Day-ahead price of energy and all the information required for the imbalance settlement The figure provides a visualization of the market conditions during one day. Further details can be found in the figures caption.

3-2-6 Contracted Power Setpoint

The contracted power setpoint is the energy that will be bought on the day-ahead market based on the expected charging profile for the next day. The contracted power setpoint was determined by optimizing the charging process to minimize costs while ensuring that the client's charging demands were met (Time of Use (ToU) optimization). The forecasts for the energy prices are out of scope of this research and therefore not included, but instead, the prices for the particular simulation day are retrieved from the day-ahead market and used in the cost function of the optimization problem.

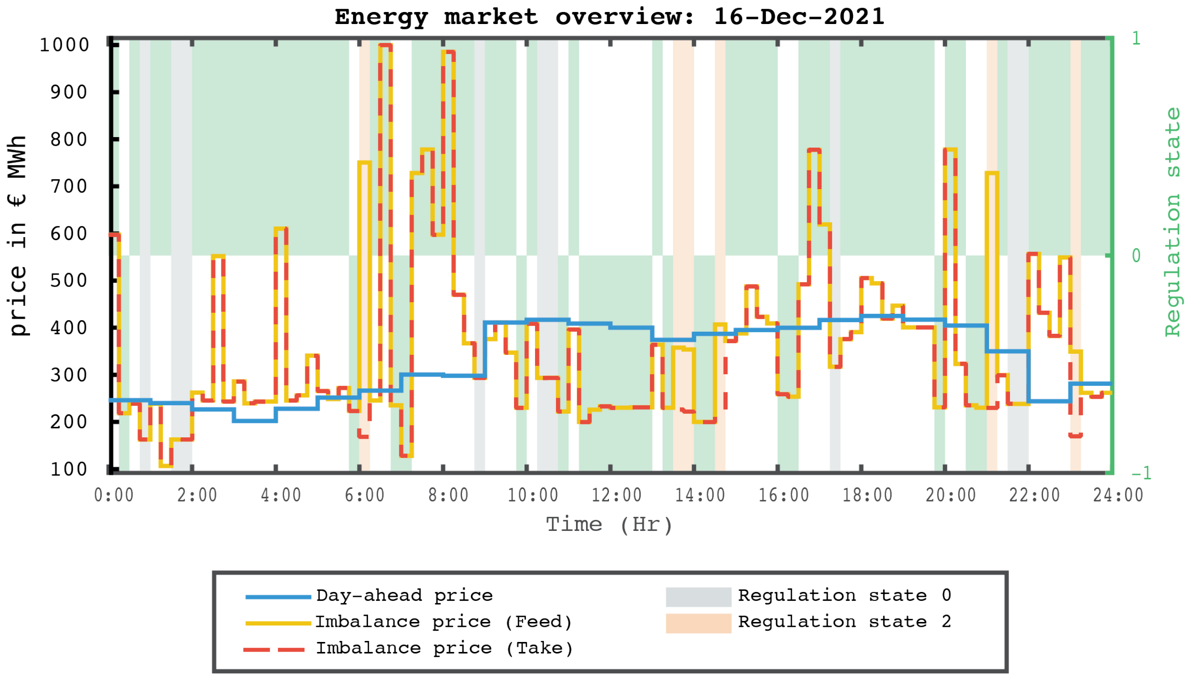


Figure 3-4: An orange rectangle in the plot represents regulation state 2. A grey rectangle indicates regulation state 0. Green up and down backgrounds correspond to regulation state 1 and -1 respectively.

Note that the optimization problem is a simplified approximation of the real-life optimization that considers multiple factors such as power constraints, charging preferences, and grid constraints. The final contracted power setpoint would normally be supplied by a third party or the customer itself. In the simplified optimization, only the Day Ahead Market (DAM) price forecast is taken into account to create an energy profile that meets the needs of each charge session at the lowest possible cost. Without a price optimization component, the optimal solution would be to charge the EVs at full charge rate from the moment they arrive. This is known as the unsteered power profile, and it represents the maximum amount of power that can be supplied to the EV without violating any constraints. By incorporating the price optimization component, the optimization algorithm considers both the energy consumption of the EVs and the energy prices, and adjusts the power setpoint accordingly. This results in an overall cheaper charging profile, while still ensuring that the EVs are sufficiently charged. The price optimization component provides a more realistic scenario for testing the smart charging controller.

For the optimization problem, Let there be $n = \{1 \dots N\} \in \mathbf{N}$ charge sessions and $h = \{1 \dots H\} \in \mathbf{H}$ time slots, where every time slot represents 15 minutes. Then for a full day, we have $H = 96$ time slots. As a result, our decision variable vector scales proportionally to N and is given by:

$$\mathbf{P} = [p_1^n, p_2^n \dots p_H^n \dots p_1^N, p_2^N \dots p_H^N] \in \mathcal{R}^{NHx1}.$$

A complete list of the variables is give in Table 3-4. The optimization problem formulation is:

$$\begin{aligned}
\underset{\mathbf{P}}{\text{minimize}} \quad & \sum_{n=1}^{N} \sum_{h=1}^{K} P_h^n \psi_h^n T^s \lambda_h \\
\text{subject to} \quad & P_h^n \geq P^{lb}, \\
& P_h^n \leq P^{\max} \quad n = 1, \dots, N, \quad h = 1, \dots, H, \\
& \sum_{k=1}^{K} P_k^n \psi_h^n \geq \frac{E^n}{T^s} - \varepsilon \quad n = 1, \dots, N, \\
& \sum_{k=1}^{K} P_k^n \psi_h^n \leq \frac{E}{T^s} + \varepsilon \quad n = 1, \dots, N,
\end{aligned}$$

$$\text{where, } \psi_h^n = \begin{cases} 1, & T_{\text{arr}}^n \leq h \leq T_{\text{dep}}^n. \\ 0, & \text{otherwise} \end{cases}$$

The objective is to minimize the total cost, which is the product of the day-ahead price and the energy consumed in that timeslot. The constraints include non-negativity and an upper bounds on the charging power, and the requirement that the total energy charged by each EV should match its required energy demand within a certain tolerance.

Inputs	
N	Number of EVs
H	Number of Imbalance Settlement Periods (ISPs)
ε	Small number that acts as as tolerance on energy constraint
T^s	Sampling time
U	Mains voltage
λ_k	Day ahead energy price at time k
E^n	The energy demand of EV n
$P^{\max}$	Upper bound on power
P^{lb}	Lower bound on power
T_{Arr}^n	Arrival time h of EV n
T_{Dep}^n	Departure time h of EV n
$\psi_{j,k}$	Auxiliary binary variable, whether an EV is connected at time k
Decision Variables	
P_k^n	Power consumption by EV n at time h

Table 3-4: Inputs and decision variables for the optimization model.

The optimization problem involves a linear objective function and linear constraints with continuous decision variables. The presence of binary indicator variables in the objective function and constraints makes it a is a mixed-integer linear program that. We use the Gurobi solver, a popular optimization software that can efficiently solve these type of problems [47].

3-3 Validation of Simulation Environment

In order to accurately represent real-world charging patterns and user behavior, it is important to validate the simulation environment used in this study. This section focuses on the validation of two key aspects of the simulation environment: user behavior and charge characteristics.

Validation of user behavior The probabilistic approach used to generate the arrival times for the charging sessions was based on the GreenFlux database and its CDR table.

The validation was done by comparing arrival time distributions of the original data with a sampled set of sessions. A plot comparing the arrival time distributions is shown in Figure 3-5, which validates that the distributions are similar.

In addition to this, a heat map of the correlation between the arrival time and duration, as well as the arrival time and volume charged, was created to further validate the approach. The resulting heat maps in Figure 3-5 demonstrate the clear relationship between these variables in the original data and that the correlations have been successfully preserved in the simulation.

The high degree of similarity suggests that the probabilistic approach has accurately captured real-life patterns and relationships present in the data and provides confidence that the simulation accurately reflects user behavior and charging patterns.

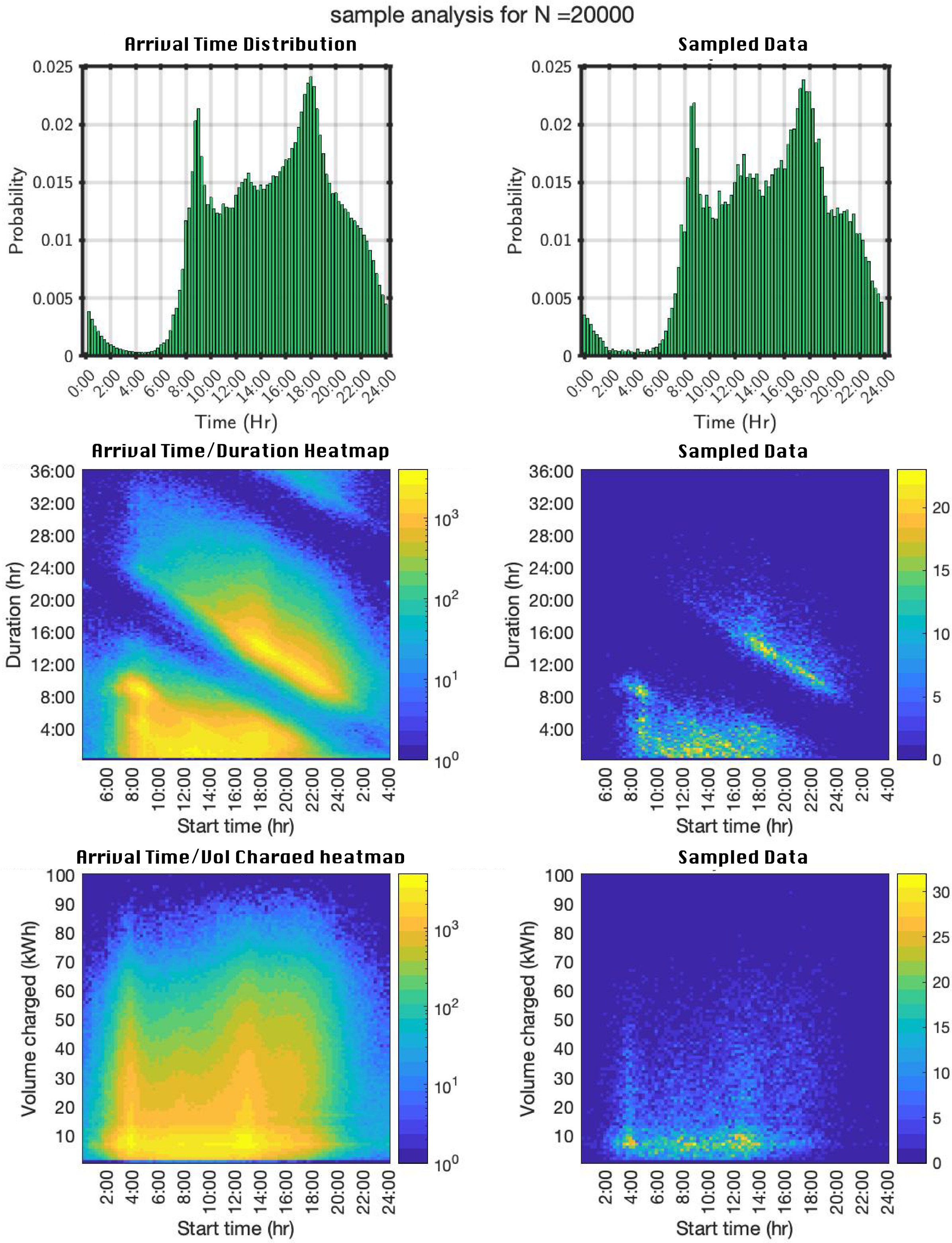


Figure 3-5: Sample analysis results showing the distribution of EV charging patterns over a 24-hour period.

Chapter 4

Smart Charging Controller Design

This chapter explores the technical aspects of the smart charging controller design, with a particular focus on the setpoint-tracking controller. The controllerontroller is intended to balance the charging demands of individual electric vehicles and the grid, while ensuring fair allocation of charging resources and minimizing data consumption. The co-regulation component is presented, as a separate optimization problem, which is essential to the overall efficiency of the system. The chapter provides a comprehensive overview of the mathematical models and methodology used to design the smart charging controller.

In the approach proposed in this research, a central controller (also referred to as the Charging Management System (CMS)), with system-wide information, determines the optimal course of action for the aggregator. The aggregator's goal is to maximize its flexibility potential by offering balancing services to TenneT, which will result in lower overall charging costs for the customers. To maximize the aggregator's profit, this research focuses on three key topics: generate revenue, reducing data costs, and preserving customer satisfaction. However, there will be several challenges to overcome in all three areas, which will be discussed in the following sections.

Generate revenue Effective energy management requires minimizing energy costs, which can be achieved through the implementation of co-regulation and power setpoint-tracking. While power setpoint-tracking alone may reduce the risk of incurring significant imbalance settlement prices, it is not a guarantee of cost savings. The imbalance settlement price is determined by a complex set of factors, including the difference between actual consumption and contracted power setpoint, market energy prices, energy production costs, market volatility, weather conditions, and technical issues. Therefore, to minimize energy costs, it is crucial to implement co-regulation, which involves determining the optimal power setpoint to minimize the aggregator's costs, while considering future regulation states and prices. Once the optimal power setpoint is identified, power setpoint-tracking can be employed to ensure that actual electricity consumption matches the optimal power setpoint. By implementing co-regulation and power setpoint-tracking, the aim is to create a planned imbalance between the contracted and actual consumption, based on market conditions, to receive the imbalance settlement price, which can be viewed as balancing revenue.

Reducing Data Costs The Electric Vehicle (EV) fleet presents an opportunity for power distribution flexibility. To exploit this potential, the CMS must receive information about charging sessions and send control commands. However, this data transmission incurs costs. One way to reduce these costs is by minimizing the frequency of updates.

Maintain customer satisfaction Maintaining customer satisfaction is crucial for the success of an aggregator's service, even though it cannot be directly quantified in financial terms. To ensure customer satisfaction, it is necessary to distribute available energy fairly among connected EVs when demand exceeds capacity. Several studies propose charging schemes that consider power allocation fairness among EVs [48, 49, 50]. However, since future arrival and departure times, energy demand, and charging time for individual EVs are unknown, creating a deterministic charging schedule does not always align with real-world scenarios [40]. For example, EVs may unplug earlier than expected, leading to a lower state of charge than desired when unplugging. To mitigate this inconvenience, a priority metric can be included in the charging schedule, which would distribute available power fairly in real-time, even without knowledge of future plans.

In summary, the primary goals of the proposed method are:

1. Generate aggregator's revenue by determining the optimal power setpoint.
2. Ensure precise tracking of the power setpoint.
3. Minimize data transmission costs by reducing the frequency of changes to the allocation profile.
4. Ensure fair real-time allocation of power to maintain customer satisfaction, despite limited information about future travel plans.

4-1 Problem Formulation

This section presents an overview of the notation and terminology used in this chapter, as well as the system architecture, including data partitioning, time granularity, and decision variables. The aim is to ensure clarity and consistency in the mathematical expressions and understanding of the problem at hand. This information is important for the reader to comprehend subsequent sections, where the optimization problem is formulated.

We consider a Virtual Power Plant (VPP) consisting of N Charge Points (CPs), where each CP can host one EV. Time is discretized into constant intervals, indexed by k. The CP keeps track of the number of connected EVs at each time step k. Information about future arrivals, expected departures, and future demands is unknown. The Control Station (CS) has access to the measured current $\tilde{I}(k)$ of EV i at every time k. The CP is able to control the charging current of an EV by sending the upper bound $I_i(k)$ to EV i at time k. The CMS receives an aggregated setpoint $P^{\text{setpoint}}(k)$ from the grid controller, and in return sends its updated status.

Our contributions to the field are as follows:

1. We consider a control scheme that has no internal knowledge of battery charging parameters or actual departure times of EVs, which is a more realistic scenario as modern charging stations lack this information.
2. We model the battery charging power in a realistic manner, where an EV can either be switched OFF with a charging power of 0 W, or be switched ON with a charging power within nonzero bounds.
3. We introduce a fair allocation metric to ensure customer satisfaction and retention.
4. We present a novel co-regulating controller for balancing the energy consumption of EVs.

4-1-1 Nomenclature and Terminology Overview

"x, y and z" are used as placeholder examples in the following descriptions.

Notation

- Sets are indicated by calligraphic letters $\mathcal{X}$
- Indices are denoted as Roman subscripts x_y
- Dimensions are indicated by Roman subscript indices in square brackets $x_{[x,y]}$
- Extended variable names are noted in Roman superscripts x^{xyz}
- Measured data is indicated with a hat symbol $\hat{x}$
- Estimated values are denoted by a tilde $\tilde{x}$

Mathematical Operations

- The cardinality operator is represented by $|x|$
- The rounding operator is indicated by $\lceil x \rfloor$ and rounds a value to the closest integer

4-1-2 System Architecture

This section provides an overview of the system architecture and the data partitioning of the CPs.

Decision Variables The current assigned to each electric vehicle EV, represented by I_j, is the decision variable in this problem. Previous research has often assumed that the charging power of an EV is a continuous value between 0 and the maximum charging power [50, 51, 52]. However, this is not always the case in reality as an EV can be turned off and not consume any power or can charge at a power that falls between non-zero bounds, with the minimum charging power being limited. While Zheng et al. [53] developed a control scheme that supports the ON-OFF states, it is limited to a constant power when the EV is turned ON.

To address this, we introduced a second decision variable, ω_j, as the on/off decision for the CPs. Specifically, $\omega_j$is equal to 1 when the CP is on and 0 when it is off. The charging current

$I_j$is constrained by the minimum and maximum charging rates, $I^{lb}$and I^{ub}. This approach considers both the ON-OFF possibilities and continuous charging power, which falls between an upper and lower bound when the EV is turned on. This results in the decision variables being represented as:

$$I_j \omega_j \in 0 \cup [I^{lb}, I^{ub}].$$

The presence of the binary variable $\omega_j$makes this a mixed-integer optimization problem. Furthermore, the multiplication between the two decision variables results in a bilinearty between them, making this a non-linear mixed-integer optimization problem.

Time Granularity EVs arrive and depart at continuous times, represented by the variable t_j^{ts}. However, the optimization problem is solved by the CMS at regular intervals, represented by the sampling interval T^s. To map the continuous information about EVs to a discrete time step, each day (D=24 hours) is divided into a set of discrete time steps, $\mathcal{K} = 1, 2, \ldots, k, \ldots, K$, where $K = D/T^s$. For example, if an EV connects to a CP at time t_j^{ts}, its arrival time will be calculated by rounding $t_j^{ts}$to the nearest time step, $t_j^{arr} = \lceil t_j^{ts}/T_s \rceil$. In addition, imbalances in the energy market are settled per Imbalance Settlement Period (ISP). Each day is therefore divided into a set of equal-length intervals, $\mathcal{H} = 1, 2, \ldots, h, \ldots, H$, each with duration Δh= 15 min. For one day, $H = 96$.

Data Partitioning The system considers a group of CPs that is controlled by an aggregator that aggregates the energy consumption of the entire fleet as one entity in the real-time energy market. The CP in the system are divided into four subsets based on the state.

- $\mathcal{E}$ collects all CPs without an EV plugged in.
- $\mathcal{L}$ is the collection of EVs whose charging rate is temporarily locked.
- $\mathcal{C}$ collects all the controllable EVs.
- $\mathcal{F}$ is the collection of fully charged EVs.

The CMS controls a network of CPs, indexed by (j).

Inputs

1. **Charging Limits**:
   This refers to the initial upper bound, I^{ub}, which is determined by $^{ub} = \min(I_{EV}^{ub}, I_{CS}^{ub})$.
   Note: In a practical scenario, the upper limit on the charging current cannot be directly communicated to the CP. To address this issue, the information must be collected. One approach is to assign the maximum capacity to the CP of newly arrived vehicles. The actual charging current is then determined by $I^{ub} = \min(I^{max}, \hat{I}_j)$, where $\hat{I}_j$ is the measured current drawn by the EV.
2. **Energy market data**:
   This includes the information about the energy market, including the wholesale energy price, the regulation state and the regulation price.
3. **Time horizon**:
   This includes the time horizon over which the optimization problem, in this case a day.
4. **Optimization parameters**:
   This includes the parameters required for the optimization algorithms.

With these inputs, the optimization problem can be formulated and solved to determine the optimal charging schedule for the fleet of EVs, while balancing the energy market and ensuring customer satisfaction.

Constraints

Given the context of the charging management system and its objectives, the optimization problem is subject to a number of constraints that must be satisfied. These constraints ensure that the charging system operates within the bounds of feasibility and optimizes the objectives defined in the problem:

1. **Maximum charging power constraint:**
   Ensures that the charging power of each EV does not exceed its maximum charging capability.

   The upper bound, I^{ub}, is continuously updated whenever new session information is received, $\tilde{I}$. The process of updating the upper bound is outlined in Algorithm 1

Algorithm 1 Update upper bound; I^{ub}

1: **if** $\hat{I}_j < I_j\omega_j$ **and** $I_j\omega_j = I^{ub}$ **then**
2: $\quad I^{ub} = \hat{I}_j$
3: **end if**

   The algorithm first checks if $\hat{I}_j$ is less than $I_j\omega_j$ and $I_j\omega_j$ is less than the current value of I^{ub}. If this condition is true, then the value of I^{ub} is updated to be equal to $\hat{I}_j$. This update ensures that the value of I^{ub} is always less than or equal to $I_j\omega_j$, which is a necessary condition for the optimization algorithm to converge.

2. **Minimum charging power constraint:**
   Ensures that the charging power of each EV does not fall below a certain threshold. The Renault Zoe car got the lowest threshold and goes into safety mode if the charging power falls below 13 A. Since the type of EV connected to the CS is unknown, we can only avoid this by setting 13 A as the lower bound for all EVs.

3. **Temporal constraint:**
   Ensure that EVs can only charge between their arrival and departure times, this is handled by moving the CSs to different sets. Only set $\mathcal{C}$ is included in the algorithm.

4. **Power allocation constraints:**
   These constraints ensure that the total energy charged by all connected EVs does not fall below a certain minimum threshold of the available energy potential. This helps to maintain a certain level of energy utilization efficiency in the system. It is for the objective of customer satisfaction.

These constraints must be satisfied in order for the optimization problem to be feasible and to achieve the desired objectives. The optimization problem will result in a solution that balances the trade-off between these constraints and the objectives of the system.

4-2 Optimization Problem

The CMS optimizes the resource allocation for all EVs in $\mathcal{C}$, at time k. The different objectives are incorporated with the different terms in the objective function. The weights, c_1 and c_2, are added in front of the objective function terms to reflect the relative importance of each term. The objective function is a linear combination of the two terms, where each term represents a different objective to be optimized. The weights control the trade-off between the two objectives, and can be used to adjust the balance between them.

$$\underset{I,\omega}{\text{minimize}} \quad \underbrace{c_1 f_1\left(I,\omega,\psi\right)}_{\text{Power setpoint-tracking}} + \underbrace{c_2 f_2\left(I,\omega,\psi\right)}_{\text{Fair allocation}} \tag{4-1a}$$

$$\text{subject to} \quad I^{lb} \leq I_j \leq I^{ub}, \forall j \in \mathcal{C}, \tag{4-1b}$$

$$\omega_j \in \{0,1\}, \forall j \in \mathcal{C}, \tag{4-1c}$$

$$\omega_j = 0, \forall j \in \mathcal{F}, \tag{4-1d}$$

$$\omega_j = 0, \forall j \in \mathcal{E}, \tag{4-1e}$$

$$\omega_j[k] = \omega_j[k-1], \quad \forall j \in \mathcal{L}, \tag{4-1f}$$

$$I_j[k] = I_j[k-1], \quad \forall j \in \mathcal{L}, \tag{4-1g}$$

$$I \in \mathbb{R}^N, \omega \in \mathbb{Z}^N, \tag{4-1h}$$

where:

- Equation 4-1a is the objective function to be minimized over the $2 \times N$ decision variable vector $[\mathrm{I}[1,N], \omega[1,N]]^\top$, which consists of both real-valued and integer-valued decision variables.
- The vector of parameters, ψ, acts as inputs to the controller.
- Due to Constraints 4-1b and 4-1c, the possible range of the joint contribution of the decision variables is given by
$$I_j\omega_j \in 0 \cup [I^{lb}, I^{ub}].$$
- Constraints 4-1d, 4-1e, 4-1f and 4-1g ensure that the decision variables for sets $\mathcal{F}$, $\mathcal{E}$and $\mathcal{L}$ are set to the correct values, respectively.
- Constraint 4-1h limits the extent to which the controller's decisions can negatively affect the ratio between the actual charged energy and the potential charged energy, by establishing a minimum threshold of ζ^{lb}.

4-2-1 Power setpoint-tracking

The first term in Equation 4-6 is responsible for tracking the aggregated power setpoint, $P^{\text{req}}[k]$. The locked EVs must be removed from the calculation of the aggregated setpoint because the power consumption is equal to the previous time step and thus known. For practical reasons, newly connected EVs will be charged at maximum power for one time step, these practical reasons are not included in this research. However, as this is a common practice in real-life situations, it is still used in this study to ensure a more realistic representation of the system.

$$f_1(I,\omega) = \left(P^{req} + P^{Co\_reg}[k] + P^{Comp}[k] - \sum_{j\in\mathcal{L}[k]} P_j[k-1] - \sum_{j\in\mathcal{N}[k]} P_j[k] - \sum_{j\in\mathcal{C}[k]} UI_j\omega_j\phi_j\right)^2$$

The number of phases that the j^{th} EV can charge with is represented by the parameter ϕ_j. The mains voltage, which is assumed to be constant at 230 V in this research, is represented by the parameter U [1].

If the energy consumption deviates from the contracted volume, the remaining charging time in the ISP can be used to compensate for this error. The calculation of the compensation power, P^{Comp}, is presented in Equation 4-2. This is calculated at each time step as the difference between the sum of the scheduled power, P^{req}, and the regulation power, P^{Co_reg}, and a term accounting for the deviation, $E_h^{RT}[k]$.

$$P^{Comp} = P^{req}[k] + P^{Co\_reg}[k] - \frac{\left(P^{req} + P^{Co\_reg}\right)\cdot x^{isp}[k] - E_h^{RT}[k]}{k} \tag{4-2}$$

The variable $x^{isp}[k]$ in Equation 4-2 serves to track the progression through one ISP, with the number of time steps in an ISP given by $T = \frac{\Delta h}{T_s}$. $x^{isp}[k]$ cycles through the values $1, 2, \cdots, T-1$ and then back to 0 every T time steps, with the time index k and the congruence operator $\equiv$.

$$x^{isp}[k] = \begin{cases} 1 & \text{if } k \equiv 1 \pmod{T} \\ 2 & \text{if } k \equiv 2 \pmod{T} \\ \vdots & \\ T-1 & \text{if } k \equiv T-1 \pmod{T} \\ 0 & \text{if } k \equiv 0 \pmod{T} \end{cases} \tag{4-3}$$

Furthermore, we have

$$E_h^{RT} = \left(E_h^{RT}[k-1] + \sum_j^N P_j(k)\right) \tag{4-4}$$

and $E_h^{RT}[k] = 0$ for $k \equiv 0 \pmod{T}$. In other words, the energy consumed in real-time, E_h^{RT}, is calculated as the sum of the previous energy consumed, $E_h^{RT}[k-1]$, and the power consumed at each time step, $P_j[k]$. At the end of each ISP, when $k \equiv 0 \pmod{T}$, the energy consumed in real-time, E_h^{RT}, is reset to zero.

[1] Even though the permitted deviation from mains voltage is large, ($U = 230\,\text{V} \pm 10\%$) [54], it is assumed to be constant for this research.

4-2-2 Fair allocation

The fair allocation of smart charging resources is an important aspect for the implementation of smart charging systems. Ensuring fair allocation of power in smart charging systems is crucial when the contracted power is insufficient to meet the demand of all electric vehicles EVs. There are two main approaches to fair allocation in smart charging: market-based mechanisms and priority-based mechanisms. Market-based mechanisms allow EV owners to bid for charging resources based on their needs and preferences, leading to a more efficient allocation of resources. However, this approach requires active customer involvement, which can be a challenge to implement. In order to participate in a market-based mechanism, customers must be educated and motivated to engage, which can be difficult to achieve. Priority-based mechanisms, on the other hand, allocate charging resources based on priority levels such as time of day or location. This approach helps ensure that charging resources are allocated to those who need them most. Besides, it is more passive and broadly implementable, as it does not require customer involvement.

In real-time charging allocation, it is also important to strive for fairness [40, 48, 49, 50, 55, 56, 57]. A fair allocation of resources strives to satisfy the charging needs of each EV to the best possible extent. However, simply providing each EV with the same amount of energy may not result in a fair distribution of charging resources. It is important to consider factors such as each EV's State of Charge (SoC), battery capacity, and departure time. These factors can impact the satisfaction of the EV owners. However, this information is often unknown and can vary greatly between EV owners. As a result, finding a way to ensure fair allocation of charging resources without knowing these factors can be challenging.

The objective function, f_2 [Equation (4-6)], aims to ensure fairness in the allocation of charging resources among the EVs. It does so by incorporating the priority metric, ζ_j, into the calculation. The priority metric incorporated the non-satisfied energy demand of individual charge sessions. So it measures the degree to which the charging demand of the EVs is met. This ratio penalized the difference between the maximum charging rate of the j^{th} EV, I_j^{ub}, and the current assigned to it by the controller, $I_j\omega_j$. The priority metric captures the extent to which the j^{th} EV was undercharged relative to its maximum charging capacity. If ζ_j is close to 1, this indicates that the j^{th} EV was charged close to its maximum charging rate, and therefore, has a lower priority for further charging. Conversely, if ζ_j is higher than 1, this indicates that the j^{th} EV was undercharged and has a higher priority for further charging.

Without steering, an EV plugged to an CP charges with its maximum charging rate until the battery is full. This charging profile ($E_j^{unsteered}$) is used as a reference value in the priority metric, denoted as ζ_j. It captures the missed charging capacity due to the CMS's decisions. The function f_2 incorporates this metric as follows:

$$f_2(\mathcal{I}, \mathcal{Z}) = \sum_{i \in \mathcal{C}} \left(I_j^{ub} - I_j\omega_j \right) \zeta_j^2,$$

$$\text{with,} \quad \zeta_j = \frac{E_j^{unsteered}}{E_j^{actual}} = \frac{U \cdot I^{ub}\omega_j + \phi_j \cdot k_j^{ct}}{\hat{E}_j + \sum_{k^{t+n}}^{k} P_j[k] \cdot T^s}. \tag{4-5}$$

The approach could benefit customer satisfaction and reduced likelihood of complaints and negative impact on the reputation of the charging services.

4-2-3 Limited data

The allocation profile must be updated regularly to distribute the available power properly. This requires the CMS to receive information about charging sessions and send control commands. This data transmission involves a cost. Limiting the number of messages is a practical issue that has not been widely considered as a constraint in current research on smart charging and ancillary services. Equation (4-1f) and (4-1 g)include a locker period of one timestep, essentially limiting how frequent a new allocation can be sent to a CP.

4-2-4 Co-regulation

Predicting the regulation state and price is a complex task as it is influenced by various factors such as energy demand, availability, weather conditions, fuel prices, and market trends. The interactions between these factors make the prediction of the regulation state and price a challenging task, however, these predictions are the inputs to the co-regulation optimization. The CEO of Dexter Energy Services, Luuk Veen, states that over 150 exogenous parameters are required for a complex machine learning model to predict the regulation state and price in the energy market.

Since predicting the regulation state and regulation price is a complex task, we assume that the predictions are supplied by a third party (e.g., Dexter Energy Services). However, it is unclear how accurate these predictions are. As a result, we assume perfect predictions for now so that we can use the known regulation state and price from TenneT's historical data, as it allows for the evaluation of the optimization method without the added complexity of uncertainty in the input data.

The objective of the optimization problem is to minimize the energy price per MWh. This is achieved by optimizing the combination of day-ahead price and the imbalance settlement price. The optimization problem is formulated as follows:

$$\underset{P^{Co-Reg}}{\text{minimize}} \qquad \frac{\sum_{k=1}^{K}\left(P^{DA}k\lambda^{DA}T_s\right)+\left(P^{Co-Reg}kT_s\right)\times w_k}{\left(P^{DA}+P^{Co-Reg}\right)T_s} \tag{4-6a}$$

$$\text{subject to} \quad -a_1 P_k^{\text{PDA}} \leq P_k^{Co-Reg} \leq a_2 P_k^{PDA}, \quad k=1,\ldots,K, \tag{4-6b}$$

$$b_1 \sum_{k=1}^{K}\left(P_k^{DA}\right) \leq \sum_{k=1}^{K}\left(P_k^{Co-Reg}\right) \leq b_2 \sum_{k=1}^{K}\left(P_k^{DA}\right), \tag{4-6c}$$

$$\sum_{k=1}^{K}\left|P_k^{coReg}\right| \leq d_1 \sum_{k=1}^{K}\left(P_k^{DA}\right), \tag{4-6d}$$

$$\text{where} \quad w_k = \begin{cases} Reg^{PriceTake}[k] & \text{if } P^{DA}[k]-\left(P^{PDA}[k]+P^{Co-Reg}[k]\right)<0 \\ Reg^{PriceFeed}[k] & \text{if } P^{DA}[k]-\left(P^{PDA}[k]+P^{Co-Reg}[k]\right)\geq 0 \end{cases}$$

Constraint (4-6b) limits the co-regulation power at each time step between certain bounds, with a_1 and a_2 determining these bounds as a percentage of $P^{DA}[k]$. Constraint (4-6c) limits the total co-regulation that is allowed during the day. Constraint (4-6d) limits the allowable deviation in the total energy consumption between the case with only the day ahead power setpoint and the case with the day ahead power setpoint and the co-regulation added, ensuring that the total energy needs of the end user are still satisfied.

It is important to note that the $Reg_k^{pricetake}$ and $Reg_k^{pricefeed}$ are already the result of the combination of the regulation price and regulation state.

Chapter 5

Results

In this chapter, we present the results of our simulation experiments for the different controllers. The simulations were run multiple times with different parameters for various controller designs to evaluate their performance. To assess the effectiveness of each controller, we used several performance metrics, which mainly capture the penalties, revenue, and user discomfort.

This chapter is organized into several sections. Section 5-1 provides an overview of the performance metrics used in our evaluation. In Section 5-2, we provide details on how we determined the simulation parameters. The subsequent sections focus on specific aspects of our simulation results, with Section 5-3 discussing the impact of clustering, Section 5-4 covering the optimization of contracted power setpoints, and Section 5-5 exploring the revenue from co-regulation.

5-1 Performance Metrics

In order to evaluate the performance of the charging control system, the following metrics have been used:

- **Non-Satisfied Energy Demand ($\mathbf{E}^{nsd}$)**:
  Non-satisfied Energy Demand, also referred to as 'charge loss' in some cases, is a metric that measures the degree to which the charging demand of the Electric Vehicles (EVs) is met. It is calculated as the ratio of the energy that was actually charged, E^C, to the energy that would have been charged without the controller's decisions, E^U.

  $$E^{nsd} = 1 - \frac{E^C}{E^U}$$

  If E^{nsd} is 1, then every EV was fully charged. E^{nsd} is basically a metric for total charge loss (energy not charged in the whole system). Moreover we use similar metrics for cluster satisfaction and client satisfaction:

- $\sigma_A(E^{nsd})$ and $\sigma_B(E^{nsd})$; The standard deviation provides information on how evenly the energy is distributed among the EVs, with smaller values indicating a more even and fair distribution.
- $\mu_A(E^{nsd})$ and $\mu_B(E^{nsd})$ for cluster groups A and B are metrics that track cluster satisfaction. Cluster group A includes the short stay sessions and cluster group B include the daytime and overnight sessions.

- **Tracking Performance (ε^{Tr}):**
This metric is calculated as the absolute power deviation from the setpoint. Perfect tracking is represented by a value of 1, while a value of 0.9 indicates that 10% of the total power consumption for that day was in an imbalance position. However, in cases where the contracted power setpoint exceeds the maximum charging capacity of the whole population, tracking becomes impossible and other factors are to blame. To address this issue, we introduce a new variable called P^{pot}, which represents the maximum charging potential of the whole population. The tracking performance is then calculated as follows:

$$\varepsilon^{Tr} = 1 - \left|\min\left(P^{Pot}, P^{setpoint}\right) - P^{C}\right|,$$

where P^C is the power consumption of the whole population. In other words, if the contracted power setpoint is higher than P_pot, the controller is expected to limit the charging power to P_pot, and any deviation from this limit is considered a tracking error.

  - **Penalty Reduction (PR):**
  This metric measures how well the controller's decisions reduce the penalty cost compared to the uncontrolled case. Mathematically, we can represent this as:

$$PR = 1 - \frac{\lambda_{Tr}^{pen}}{\lambda_{U}^{pen}},$$

  where λ_C^{pen} is the penalty cost incurred with the controller's decisions and λ_U^{pen} is the penalty cost that would have been incurred without the controller's decisions. A value of $PR = 1$ means that the penalty cost was completely eliminated by the controller, while a value of $PR = 0$ means that the penalty cost was not reduced at all.

  It is worth noting that PR can be greater than 1, meaning that there was an imbalance that coincidentally aligned with the market needs and therefore the imbalance price was paid out. In general, we want PR to be as close to 1 as possible, as this indicates that the controller is effectively reducing the penalty cost associated with any imbalances in the power consumption.

- **Cost Reduction Ratio (CRR):**
This is a performance metric that measures the percentage reduction in the energy cost per MWh achieved by the controller's decisions compared to the cost without the controller's interventions. It is calculated as:

$$CRR = \frac{\lambda^{Un} - \lambda^{Ac}}{\lambda^{Un}} \times 100\%,$$

where λ^{Un} is the energy cost per MWh without the controller's decisions, and λ^{Ac} is the energy cost per MWh after the controller's decisions. A higher value of CRR indicates a greater reduction in energy cost. It is important to note that this metric does not take into account any costs associated with the controller's operation, such as the computational cost of running the optimization algorithm.

It should also be noted that the actual cost reduction resulting from the controller's decisions involves not only the co-regulation based cost reduction but also the imbalance fines, which can be positive or negative on a random basis. To accurately measure the co-regulation performance, we have isolated the co-regulation based cost reduction and tracked only the cost reduction ratio resulting from co-regulation. So the resulting CRR value tracks the co-regulation performance.

In order to facilitate comparison and interpretation of the simulation results, each metric is scaled such that a value of 1 represents perfect performance, and smaller values represent worse performance. This scaling approach was chosen to allow for easy comparison of results across different simulations and scenarios.

In our analysis, we also scaled the standard deviation metric, denoted as $\sigma(E^{nsd})$. This scaling was performed by taking the reciprocal of the original value ($\sigma(E^{nsd}) = 1/\sigma(E^{nsd})$), such that a larger value now represents better performance. The reason for this modification was to provide a more intuitive interpretation of the metric and enable better comparison between the different scenarios.

Initially, we were hesitant to perform this scaling because the standard deviation is already in the same units as the original quantity being measured. However, we found that the modified metric was more effective in identifying improvements in performance and enhancing the clarity of our analysis.

5-2 Simulation Parameters

In this section, we describe the selection process of the simulation parameters and the rationale behind our final choices. We discuss N and x, which respectively determine the total sample size and sampling time used in the simulations.

To determine the optimal sample size for the simulations, we aimed to select a sample size that was large enough to mitigate the effects of randomness and stochasticity and capture the full range of charging behaviors, while still being computationally feasible to run multiple times for each performance analysis. Running multiple simulations is necessary because the simulation environment involves a significant degree of stochasticity, meaning that individual simulations may yield results that are not representative of the controller's performance. By running multiple simulations, we aimed to increase the reliability of the results. Randomness refers to the fact that individual charging sessions may exhibit behavior that is difficult to predict or model with high accuracy. Because we sampled from the real database, this randomness is still in the simulation to some degree.

We selected N = 3000 as the optimal sample size since it struck a balance between mitigating the effects of stochasticity and keeping computational costs and time required to run multiple simulations within feasible time limits. Additionally, we conducted a performance analysis for N = 20000 to ensure that the controller could handle large-scale problems while still maintaining a similar level of performance. As shown in Table 5-1, the performance metrics remain fairly consistent across these sample sizes.

Performance Metric	N=3000	N=5000	N=20000
E^{nsd}	0.92371	0.93818	0.93537
$\mu_A(E^{nsd})$, $\mu_B(E^{nsd})$	0.97212, 0.98395	1.00007, 0.98055	1.00004, 0.97857
$\sigma_A(E^{nsd})$, $\sigma_B(E^{nsd})$	0.06412, 0.04812	0.00281, 0.05754	00390, 0.06421
TP	0.98783	0.98165	0.98160
PR	0.05746	0.04141	0.04161
CRR	0.08089	0.08089	0.08224

Table 5-1: Performance metrics for the controller for different sample sizes. The table compares the performance metrics of the controller for sample sizes of N = 3000, N = 5000, and N = 20000.

The sampling time was determined to limit the number of new allocation profiles that must be sent to the controller. Rather than introducing a locking period, we analyzed the controller's performance for different sampling times. Because the imbalance is calculated over a 15-minute period, a small sampling time and including a locker period would complicate the process unnecessarily.

In order to select an appropriate sampling time for our study, we conducted a series of experiments using different sampling times. While the results for various sampling times were obtained, we found that the differences between them were negligible and hence, it was not necessary to include all of them in our report. Because one ISP is 900 seconds, and it is possible to offset ISP imbalnces in that same ISP, a must was to choose x smaller than 900. However, we also considered the fact that a very small sampling time could make the problem computationally complex without yielding significant benefits. Additionally, a smaller sampling time would require more allocation signals, which would involve extra data cost.

Therefore, a sampling time of 300 seconds was selected. This duration was deemed appropriate because it is large enough to avoid excessive computation, while also providing a sufficient number of time steps to compensate for any imbalances during the ISP. We concluded that three time steps within an ISP were the minimum required to achieve accurate results in our study.

5-3 Clustering

A clustering analysis was applied to the EV charging data in the Charge Detail Record (CDR) database to identify various charging session types, with the aim of using these clusters to estimate charging demand. To determine the optimal number of clusters, we used Gaussian Mixture Model (GMM) clustering algorithm. Different GMM models were fitted with varying

Parameter	Value
Sample size (N)	3000
Sampling time (k)	1000
Charge Point (CP) clustering threshold ϑ_{clus}	80%
Repeats per performance analysis	7
Locking period	-

Table 5-2: Simulation parameters used in the final simulations.

numbers of components, and the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) were utilized to identify the optimal number of clusters.

The AIC/BIC values were plotted against the number of clusters in Figure 5-1. The plot indicated that, as the number of clusters increased, the AIC/BIC values decreased; however, the decrease slowed down at a certain point, and the AIC/BIC values plateaued. This suggested that adding more clusters did not result in significant improvements in clustering quality and that a lower number of clusters might be optimal. Although this approach was appropriate for clustering individual charging sessions, our primary objective was to cluster charge points. Therefore, we also plotted the percentage of CPs assigned to a cluster for different numbers of clusters, and we found that assigning CPs to specific clusters became increasingly difficult as the number of clusters increased.

Our analysis of the clustering of CPs revealed that using a larger number of clusters enabled us to obtain more accurately defined clusters that better captured the underlying patterns in charging behavior. When we used only three clusters for the GMM analysis, the resulting clusters were poorly defined, with many CPs sharing their charge sessions between clusters. To address this issue, we increased the number of clusters to eight and grouped similar clusters to obtain three final clusters, as shown in Figure 5-2. The use of this method resulted in a significant 26% increase in the CPs assigned to a cluster. This demonstrates the importance of using a suitable number of clusters to accurately represent the variability of charging behavior in CPs.

Subsequently, we determined which CPs to assign to a certain cluster. To increase the probability of identifying a pattern in the charging behavior, we applied a filtering step and excluded all CPs with fewer than 100 recorded sessions. Such CPs are more likely to exhibit random charging behavior instead of having an underlying pattern, or more accurately said, the underlying pattern cannot be found. We established a threshold ϑ_{clus} such that if more than a specific percentage of a CP's sessions were associated with one cluster, we assigned that CP to that cluster. After analyzing different thresholds, we found that $\vartheta_{clus} = 0.8$ achieved a satisfactory balance between having clear charging patterns in the CPs and having enough CPs available for analysis. The distribution of charge sessions and CPs in the database for each type of cluster can be seen in Table 5-3.

The clustering analysis assigned CPs to three distinct clusters: Short Stay, Daytime and Overnight charging. None of the recorded charge sessions were assigned to the Undefined cluster, which was comprised entirely of CPs that did not fit the charging behavior patterns of one of the clusters. The undefined category consisted of a large share as 78% of all CPs were assigned to it.

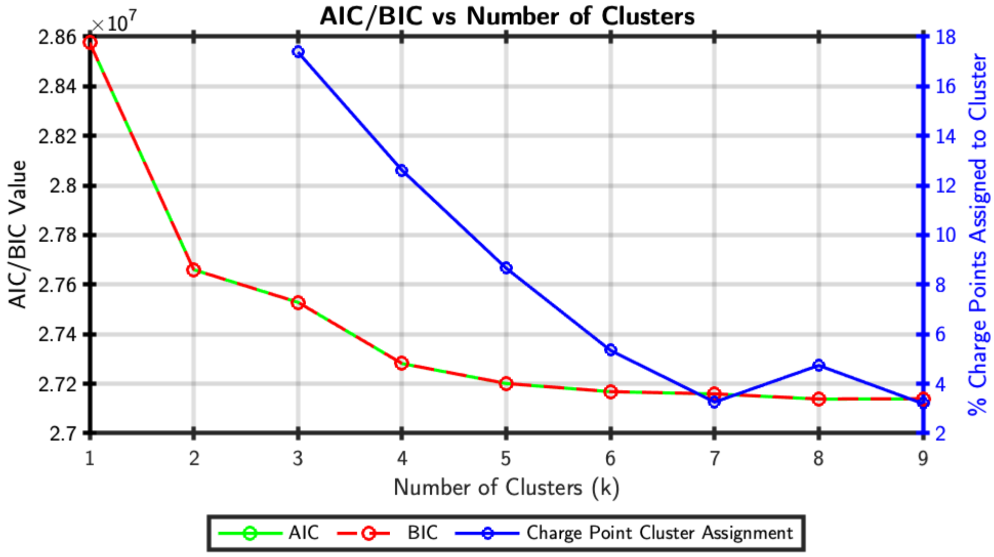


Figure 5-1: AIC/BIC for GMM clustering with varying numbers of clusters, including the percentage of CPs assigned to a cluster as a secondary axis, and a line showing the number of CPs assigned to a cluster.

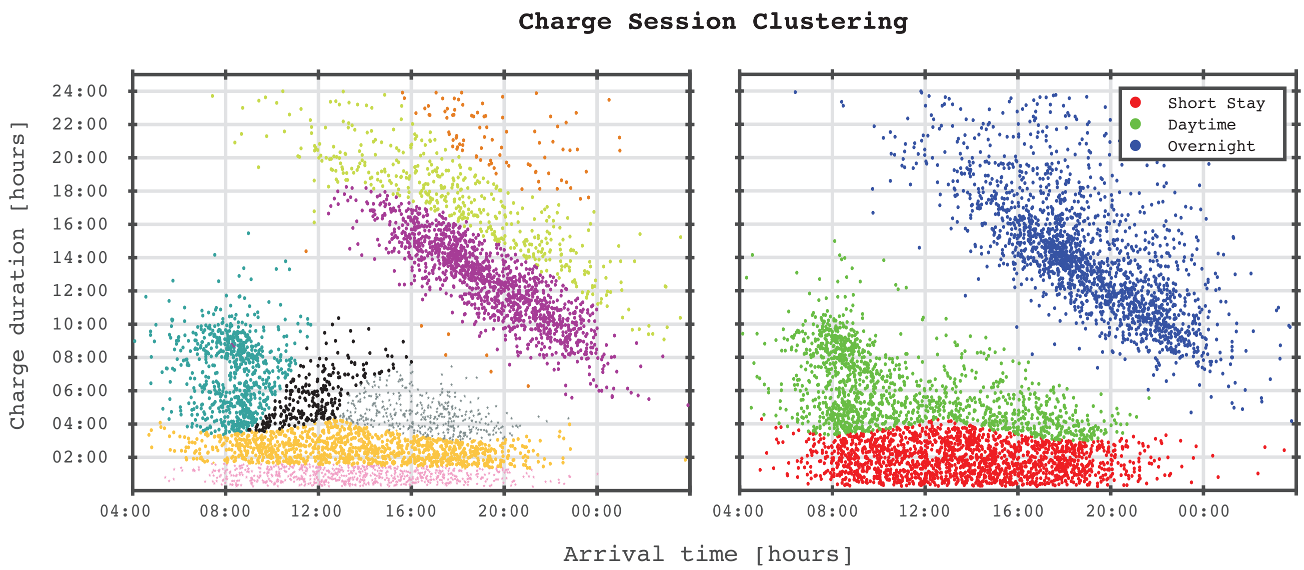


Figure 5-2: Two scatterplots of the same dataset with different clustering results. The left plot shows 8 clusters, while the right plot shows 3 clusters. Note that some clusters in the left plot have been grouped together, as indicated by the similar colors in the right plot.

Cluster	CDR's	Charge Points
Short Stay	37.72%	3.7%
Business	25.74%	12.8%
Overnight	36.54%	4.6%
Undefined	0%	78,9%

Table 5-3: Results of the clustering analysis showing the proportion of charge sessions and CPs assigned to each cluster.

Finally, we analyzed the average charge duration for each cluster and found that vehicles in the short stay cluster had a lower charge duration than those in the other two clusters. This suggests that these vehicles have less idle time, which could potentially lead to them departing with insufficient battery capacity. To address this issue, we assigned a higher priority to these EVs in the charging controller to ensure that they receive adequate charge before departure.

We also performed clustering on weekend data, but found it difficult to distinguish distinct clusters due to the smaller number of sessions recorded on weekends and less clear patterns. As a result, we chose to focus only on weekdays for our controller.

Overall, our clustering analysis provides insight into the usage patterns of charging sessions on weekdays and weekends, as well as the distribution of CPs among different categories. The results suggest that there are significant differences in charging behavior and usage patterns between weekdays and weekends, and that these differences should be taken into account for designing a controller.

5-4 Contracted Power Setpoint

In the following sections we use a consistent color scheme throughout the figures and the text. Each color will be explained before it is used. The blue color represents the day-ahead power setpoint (blue line), which is computed and optimized based on historical charge sessions data. The day-ahead power optimization algorithm [see: Section 3-2-6] optimizes the energy profile such that it meets the needs of each charge session at the lowest possible cost. It is not possible to make predictions on a session level, such as the arrival and departure times of each individual charging session. However, since the day ahead power setpoint optimization is for the whole Virtual Power Plant (VPP), we assumed it would be possible to incorporate some Time Of Use optimization. In the optimization it is assumed that charge sessions with shorter idle times charge first, as they need to be charged earlier to receive their energy demand. And sessions with longer idle times are charged later, when the energy is cheaper, because the arrival and departure times are unknown, the power was allocated based on the proposed fair allocation strategy. The priority metric distributes the "charge loss" fairly among the charging population.

Figure 5-3 shows the result of a simulation comparing the planned (blue line) and actual (red line) power consumption. The green line shows the unsteered profile, which is the consumption without controller intervention. The yellow line represents the potential charging capacity (P^{pot}), which is the maximum power capacity if all EVs were charging simultaneously (updated in real time based on past charging behavior). The red line represents the controlled

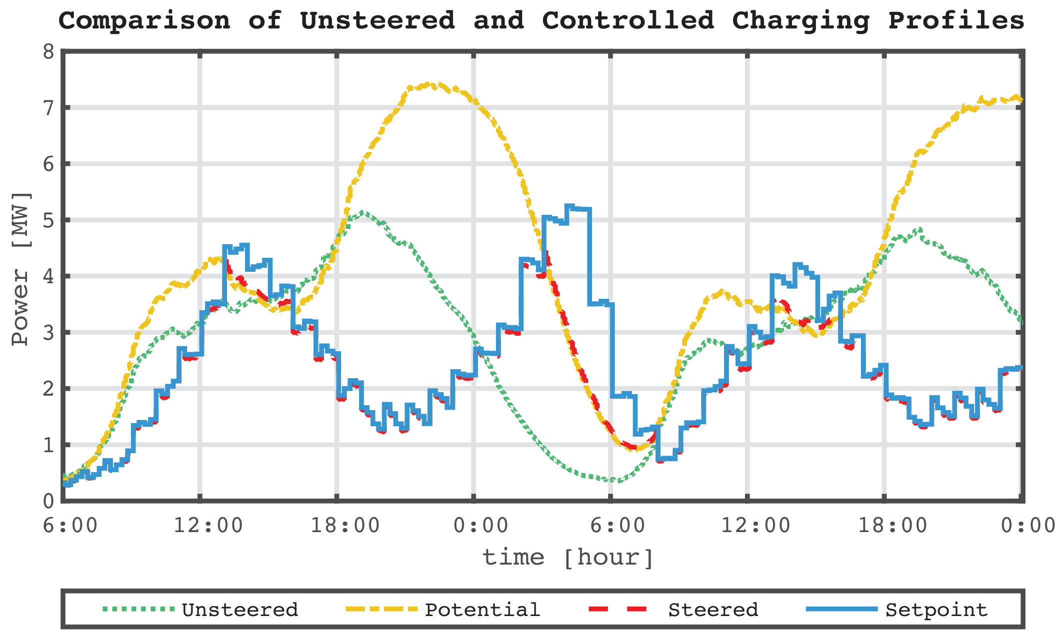


Figure 5-3: Day-Ahead Price Optimization for Energy Management System.

consumption, which is the actual consumption with the controller's decisions. And the blue line represents the desired consumption based on the contracted power setpoint.

It is immediately evident that the setpoint (blue line) cannot be followed during the nighttime hours. That is because the maximum charging capacity (yellow line) starts to roll over which means that sessions are either already fully charged or EVs leave a charge point. Since it happens around midnight and the potential capacity crosses the power setpoint in the nighttime hours, we can conclude that the former is the case.

This reason the power setpoint can't be reached is because charge sessions with high flexibility are charged together with sessions with lower flexibility based on the priority metric as whether a session has high or low flexibility is unknown in real time. This has two consequences:

1. Charge session with short idle times are allocated less power and therefore have a higher probability of departing with a higher "Charge Loss".

2. Sessions with long idle times that should be charged during the lower nightly rates are already fully charged causing the tracking error in the night.

This illustrates the challenges of implementing price optimization methods for charging EVs in real-life scenarios, where individual charging profiles and departure times are unknown.

To address these challenges we incorporated clustering information to prioritize short stay sessions as this could solve both the unwanted consequences above. The performance metrics for the controller performance with clustering with $\vartheta_c lus$ = 0.7 and $\vartheta_c lus$ = 0.9 are presented in Table 5-6 and the tracking performance for $\vartheta_c lus$ = 0.9 is shown in Figure 5-4. The inclusion of clustering information led to a big improvement in E^{nsd}, and significantly increased client satisfaction in the short stay cluster. However, this improvement in performance came at

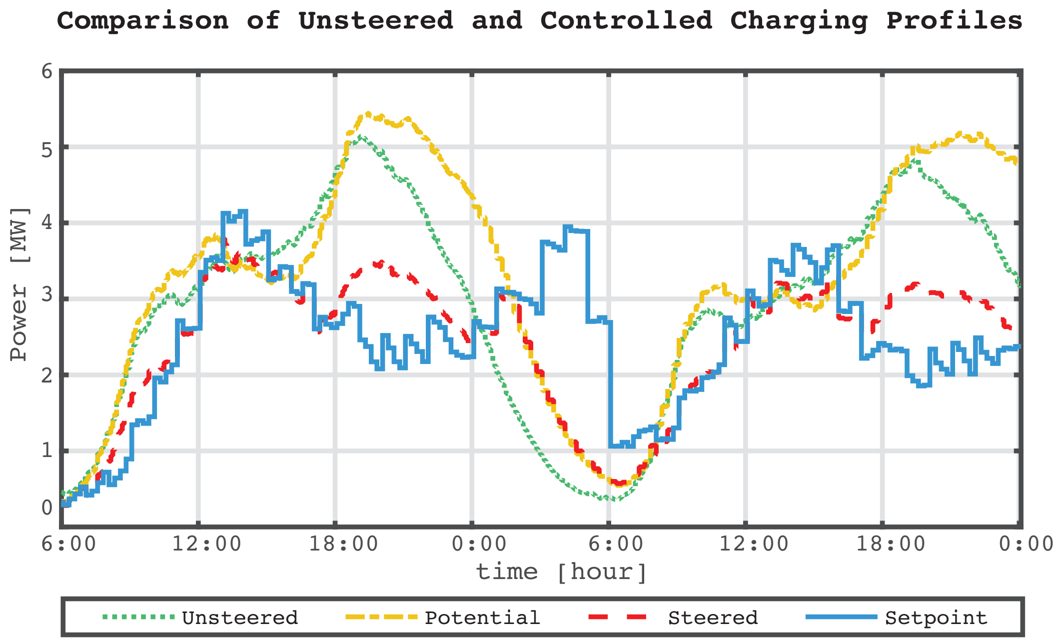


Figure 5-4: Controller performance for Day-Ahead Price Optimization without clustering.

a cost, as client satisfaction in other clusters decreased. Additionally, a decrease in the PR metric was observed, which is a welcome trade-off as a cost reduction of 17% is still significant. We also identified that the slightly worse tracking performance (P^{error} metric) was partly responsible for the lower PR value as imbalance fines were incurred. In order to further improve the performance, it may be necessary to optimize the power setpoint (blue line). However, the power setpoint optimization is part of the simulation environment and is not an accurate representation of how a real-world power setpoint would be calculated. Optimizing this simulated profile may artificially increase the performance metrics without reflecting actual improvements in the controller. Thus, any updates will only be considered based on their potential to benefit the analysis rather than their capacity to improve overall performance. This approach ensures that the research outcomes are realistic and relevant to actual implementation scenarios.

Performance Metric	Without clustering	Clustering, $\vartheta = 0.7$	Clustering, $\vartheta = 0.9$
E^{nsd}	0.75	0.77	0.84
$\mu_A(E^{nsd})$, $\mu_B(E^{nsd})$	0.82, 0.76	0.99, 0.59	0.97, 0.52
$\sigma_A(E^{nsd})$, $\sigma_B(E^{nsd})$	0.25, 0.36	0.05, 0.41	0.07, 0.43
P^{error}	0.97	0.94	0.89
PR	0.22	0.21	0.17
CRR	0.22	0.21	0.17

Table 5-4: Performance Metrics Comparison Across Controllers Run in a Simulation with Day Ahead Profile Optimized for Time of Use. The Controllers Prioritize Short Stay Sessions and Utilize a Fair Allocation Strategy, Resulting in Slightly Improved Client Satisfaction.

After analyzing the behavior of individual charge sessions and adjusting the parameters and day ahead profile, we found that Time of Use (ToU) optimization, without knowledge of arrival and departure times, resulted in a very high cost of Non Satisfied Energy Demand E^{nsd}. Furthermore, $\mu_A(E^{nsd})$, $\mu_B(E^{nsd})$, $\sigma_A(E^{nsd})$, and $\sigma_B(E^{nsd})$ metrics would always fluctuate around the base scenario E^{nsd}, which suggests a performance trade-off between clusters. Since client satisfaction is one of our main goals, we concluded that day-ahead power setpoint optimization is challenging without individual session information.

Table 5-5 provides more detailed information on the decrease in CRR and increase in E^{nsd} for each cluster and the client satisfaction, which is measured in the standard deviation.

Controller	**Change in** CRR	**Change in** E^{nsd}	**Change in Client Satisfaction**
Short Stay	-23%	+14%	+21%
Business and Overnight	-23%	-50%	-20%
Whole Population	-23%	+14%	-

Table 5-5: Impact of clustering on CRR, E^{nsd} and $\sigma(E^{nsd})$ for each cluster

As a result, we decided to focus on co-regulation, a more promising approach where knowledge on travel characteristics is not essential. This was supported by our findings from a simulation without contracted power setpoint optimization, which highlighted the effectiveness of co-regulation in meeting our goals. It is worth noting that the Time of Use optimization method, which operates on a longer time frame of typically a day or multiple hours, may be difficult to implement without session information. In contrast, co-regulation, operating on a shorter time frame, appears to be a more applicable approach for controllers with limited knowledge.

5-5 Co-regulation Controller

In this analysis, the performance of a co-regulation controller that balances financial benefits with EV customer needs was evaluated. The use of a reduction factor, α, was found to allow for co-regulation while the other parameters can mitigate the downsides of this reduction factor. The sensitivity analysis revealed that the total charge loss metric E^{nsd}, and the fair allocation metrics $\sigma_A(E^{nsd})$ and $\sigma_B(E^{nsd})$ all have an inverse relationship to the $a2$ parameter, where a smaller $a2$ improves performance. Additionally, scenario 4 and 5, which included a negative $b1$ parameter, showed improvements in performance compared to scenario 2. The analysis identified scenario 4 as the best balance between financial benefits and customer satisfaction. These results demonstrate the effectiveness of the co-regulation controller in optimizing EV charging while balancing the needs of customers and the financial benefits.

To determine the optimal settings for the co-regulation controller, a sensitivity analysis was conducted by adjusting the weight parameters in the optimization problem. The parameters used in the co-regulation controller, along with their symbols and descriptions, are detailed in Table 5-7.

The performance of different weight combinations was evaluated, as shown in Figure 5-6. Each individual axis in the polar plot was scaled to ensure that the relative difference in the metrics between simulations could be easily discerned, facilitating the identification of improvements between simulations. A plot that distorts reality was not desired, but since the metrics relative to each other do not provide direct insight into the controller performance, the scaling of the axis does not give a distorted view.

As concluded in Section 5-4, the power setpoint is not influenced by the energy price, and therefore the unsteered demand (green line) is used as a reference for the new setpoint (blue line). However, this operating point places the system at the maximum capacity (yellow line) of the VPP, making it impossible to increase the consumption beyond this point. Since co-regulation fluctuates around the setpoint to capitalize on imbalances, it is necessary to overcome these limits. The power setpoint was scaled down by multiplying it with a reduction factor α. This scaling allowed for increased power consumption while ensuring that the system stays within the VPP's capacity limit. The role of the alpha factor is to ensure that the system does not operate on the boundary condition, which would limit its ability to increase consumption (and thus to co-regulate). It is not related to grid constraints, but rather to the limitations of the VPP.

To illustrate the effect of the alpha factor, the base case is presented in Figure 5-5, with the corresponding metrics shown in Table 5-6. The colored lines still represent the same, but the co-regulation setpoint (black line) is added. This co-regulation setpoint fluctuates around the power setpoint (blue line) to benefit from imbalanced prices. While the co-regulation controller with $\alpha = 0.8$ maximizes profit, it may not meet the needs of EV customers.

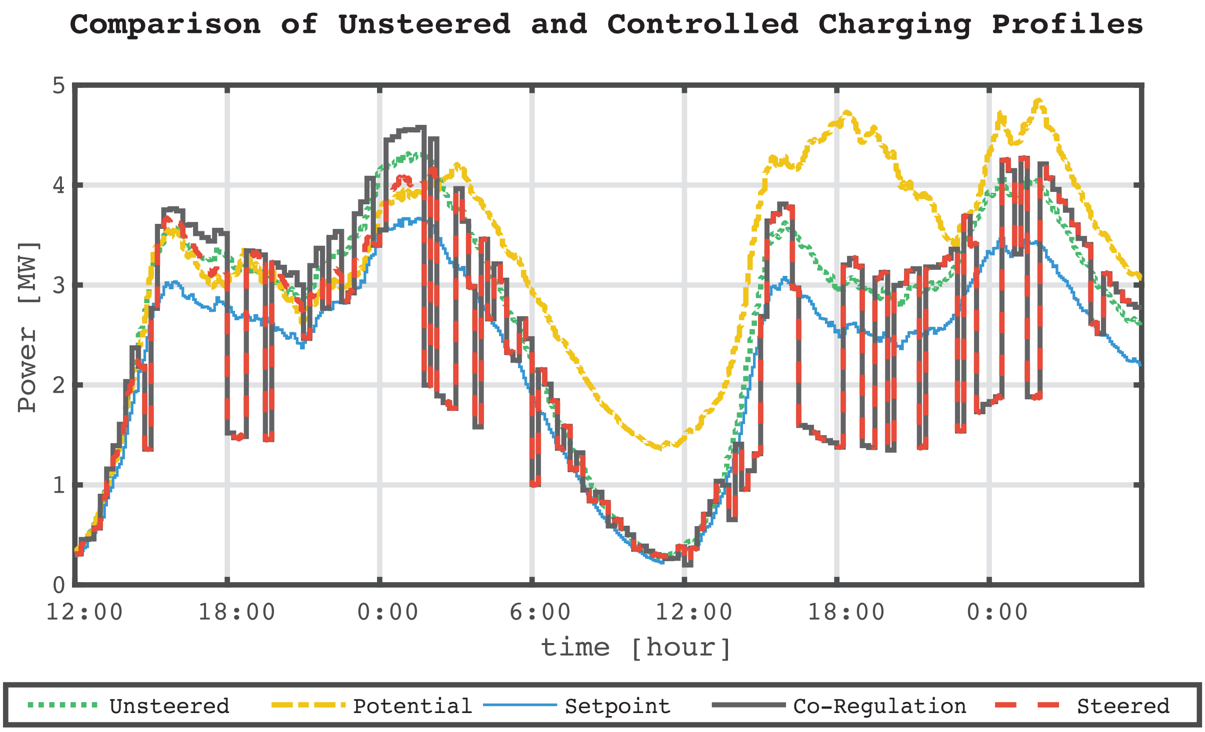


Figure 5-5: Co-regulation controller with the following parameter values: alpha = 0.85, a1 = 0.45, a2 = 0.25, b1 = -0.05, b2 = 0.10, and d1 = 0.50. The black line represents the co-regulation setpoint, which fluctuates around the power setpoint (blue line) to benefit from imbalanced prices.

Overall, the results demonstrate the effectiveness of the co-regulation controller in balancing financial benefits with EV customer needs. The use of the reduction factor, α, allows for

Performance Metric	Base case
E^{nsd}	0.86
$\mu_A(E^{nsd})$, $\mu_B(E^{nsd})$	0.89, 0.93
$\sigma_A(E^{nsd})$, $\sigma_B(E^{nsd})$	0.15, 0.12
P^{error}	1.00
PR	0.18
CRR	0.45

Table 5-6: Performance Metrics for Base Case With Sole Focus On Financial Benefits.

Parameter	**Description**	**Influence on the Co-Regulation Controller**
a_1 (a_2)	Lower (upper) bound co-regulation power	Limits the amount of power that can be used for co-regulation per time step.
b_1 (b_2)	Lower (upper) limit total energy deviation	Limits the amount of co-regulation that can be used in total for the day
d_1	Max deviation	Limits the amount of co-regulation that can be used in total for the day.
α	Scaling factor for the power setpoint	Scales the setpoint to ensure it does not operate on the boundary condition, allowing increased consumption.

Table 5-7: Description of Co-Regulation Controller Parameters.

co-regulation while the other parameters can mitigate the downsides of this reduction factor. As the energy market can vary greatly from day to day, each scenario was tested on 5 different days to gain a better understanding of the actual performance, and the average of these days is plotted in Figure 5-6.

In scenario 1, the base case for this analysis, moderate $a1$ and $a2$ parameters were used, which allowed for the same upward regulation as α since the consumption level could be met. However, in the other scenarios 2 and 3, different values were tested for $a1$ and $a2$, allowing for more downside regulation, potentially increasing CRR, but the results were negligible. The analysis showed that the total charge loss metric E^{nsd}, and the fair allocation metrics $\sigma_A(E^{nsd})$ and $\sigma_B(E^{nsd})$ all have an inverse relationship to $a2$, where a smaller $a2$ improves performance.

The analysis indicates that scenario 4, which included a negative $b1$ parameter that sets the total power deviation between +2% and +2.5%, achieved the best balance between financial benefits and customer satisfaction. This finding is significant as it demonstrates the trade-off between profit and customer needs. Although scenario 3 had the highest financial reward in terms of CRR, it showed a significant decrease in customer satisfaction metrics. Conversely, the base case, which focused solely on CRR, did not produce satisfactory results. Scenario 4 achieved a CRR of 15.2% while maintaining high levels of customer satisfaction. This finding highlights the importance of considering both financial and customer satisfaction metrics in the design of co-regulation controllers for EV charging. It also suggests that a negative $b1$

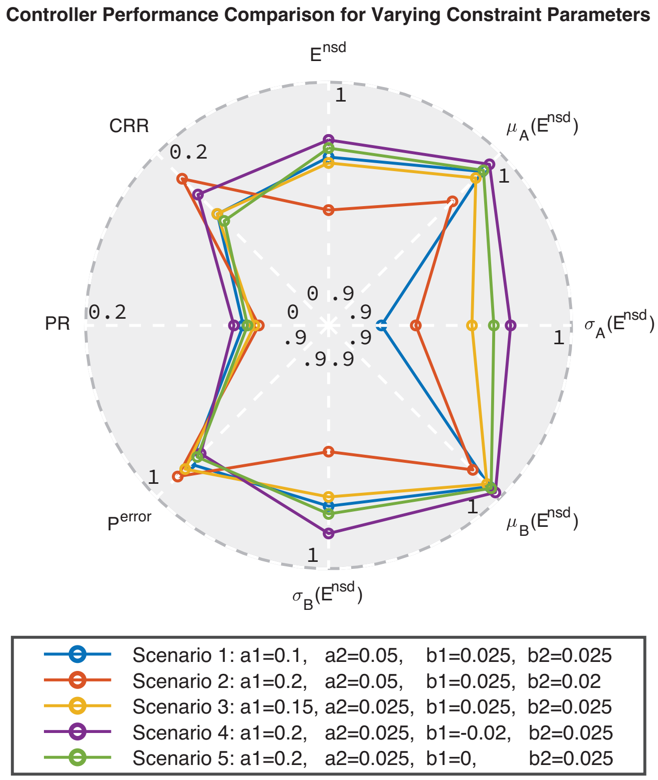


Figure 5-6: Performance metrics for different values of a1, a2, b1 and b2. ($\alpha = 0.95$, d1=0.5)

parameter can be an effective tool for balancing financial benefits and customer needs in a co-regulation setting.

Moreover, scenario 4 and 5, which included a negative $b1$ parameter that sets the total power deviation between $+2\%$ and $+2.5\%$, showed improvements in performance compared to scenario 2. Specifically, scenario 4, while it does not have the highest financial reward (scenario 3 has the highest CRR), showed the best balance between financial benefits and customer satisfaction.

Chapter 6

Discussions

The increasing adoption of Electric Vehicles (EVs) poses significant challenges for the power grid and the electricity market. To address these challenges, various control methods have been proposed for managing the charging of EVs in a way that balances the needs of EV drivers and the economic incentives of the electricity market. In this study, a simulation environment based on real-world data to evaluate the performance of different control methods for managing the charging of EVs has been used. Our performance metrics included non-satisfied energy demand, tracking performance, penalty reduction, and cost reduction ratio. The results of this study provide insights into the effectiveness of different control methods in achieving the research objectives. The purpose of this discussion section is to interpret and evaluate the results in the context of the research questions and prior literature. Specifically, we will discuss the impact of clustering, the optimization of contracted power setpoints, and the performance of co-regulation controllers in achieving a balance between financial benefits and customer satisfaction.

6-1 Analysis of Results

6-1-1 Clustering impact

The optimal number of clusters was determined using the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC), which provided an objective way to select the number of clusters that best captured the underlying patterns in charging behavior. As discussed earlier, the clustering analysis in our study revealed three distinct charging behavior patterns on weekdays, and using a larger number of clusters enabled us to obtain more accurately defined clusters that better captured the underlying patterns in charging behavior. While many studies in the literature assume only three clusters [44, 45], recent research has shown that using a larger number of clusters can result in a more accurate representation of charging behavior patterns. For example, Zhang et al. [58] used a Gaussian Mixture Model (GMM) clustering algorithm to cluster EV charging behaviors and found that using six clusters resulted in a more accurate representation of charging behavior patterns than using three clusters. Similarly, Zhang et al. [59] used a hierarchical clustering algorithm to cluster EV charging sessions and found that using four clusters resulted in a more accurate representation of charging behavior patterns than using three clusters.

Our study contributes to this literature by showing that careful consideration of clustering parameters is important for accurately identifying charging behavior patterns, and that using a suitable number of clusters can result in more accurately defined clusters that better capture the underlying patterns in charging behavior. Our analysis resulted in 26% more Charge Points (CPs) being assigned to clusters, highlighting the importance of selecting an appropriate number of clusters to accurately represent the variability of charging behavior in CPs. These results have important implications for the design of controllers that prioritize charging for vehicles with specific charging behavior patterns.

The results also suggested that there are significant differences in charging behavior and usage patterns between weekdays and weekends. When including weekends, 96% of CPs were undefined for $\vartheta_c lus = 0.8$, while only 78.9% was undefined when excluding weekends in the analysis. Our results showed that, by setting ϑ_{clus} at a relatively high value, we could strike a good balance between estimation accuracy and charge point availability.

These findings are important for informing the design of the controller. By understanding the charging behavior patterns of CPs, the controller can make more informed decisions that result in better performance metrics, such as higher client satisfaction and a more even distribution of energy among the EV. Clustering was particularly important in this research because our key objectives was to perform smart charging without knowing travel and charging characteristics that are not widely available.

In summary, the clustering analysis provides valuable information for designing a controller that prioritizes charging for vehicles in the Short Stay cluster, who have a lower charge duration and potentially depart with insufficient battery capacity. Prioritizing the Short Stay cluster did also improve the client satisfaction. It also highlights the importance of careful consideration of clustering parameters in accurately identifying charging behavior patterns.

6-2 Contracted power setpoint optimization

In this section, we analyze the performance of the controller using the contracted power setpoint optimization method and the impact of clustering information on the controller's performance.

Firstly, the contracted power setpoint optimization method has been evaluated. The day-ahead power setpoint optimization method is challenging without individual session information, moreover the simulations showed that it could not be followed during nighttime hours due to the maximum charging capacity being reached. Despite analyzing the behavior of individual charge sessions and adjusting the parameters and day ahead profile, we found that the Time of Use (ToU) optimization method resulted in a very high cost of Non Satisfied Energy Demand E^{nsd}. In addition, the $\mu_A(E^{nsd})$, $\mu_B(E^{nsd})$, $\sigma_A(E^{nsd})$, and $\sigma_B(E^{nsd})$ metrics were found to fluctuate around the base scenario E^{nsd}, which suggests a continuous performance trade-off between clusters. Based on these findings, we concluded that day-ahead power setpoint optimization is challenging without individual session information, and alternative approaches, such as co-regulation, may be more promising for controllers with limited knowledge. Although clustering improved the performance, the client satisfaction remained unacceptably low, making it impractical to implement in real life as we anticipate noticeable drawbacks for the end user.

After evaluating the performance of the contracted power setpoint optimization method, the impact of clustering information on this controller was analyzed. The results showed that clustering information improved the performance of the controller. Specifically, the Non Satisfied Energy Demand (E^{nsd}) metric increased from 0.75 to 0.84, which translates to a 25% charge loss without clustering and a 16% charge loss with clustering. This represents a 36% decrease in non-satisfied energy demand between the two scenarios, which in a positive outcome. However, this improvement in performance came at a cost, as the client satisfaction spread between different clusters increased significantly. In addition, a decrease in the PR metric was observed, suggesting a trade-off between performance metrics and client satisfaction in different clusters. These findings underscore the importance of carefully balancing performance metrics and client satisfaction in the design of controllers that optimize EV charging.

From the clustering impact, presented in Table 5-5, it is clear that Short Stay Cluster benefits from clustering, with a significant increase in client satisfaction and a decrease in non-satisfied energy demand. On the other hand, the other clusters experience a decrease in client satisfaction and an increase in non-satisfied energy demand. These results indicate that the clustering information should be carefully considered when designing a controller to optimize EV charging. Also CRR has drop 23%, which negatively impacts all clusters.

Finally, we discuss the trade-offs between performance metrics and client satisfaction in different clusters. The clustering information was used to assign CPs to certain clusters, resulting in a satisfactory balance between having clear charging patterns in the CPs and having enough CPs available for analysis. The trade-offs between performance metrics and client satisfaction in different clusters are important considerations for designing an effective controller. The results suggest that prioritizing charging for vehicles in the Short Stay cluster, who have a lower charge duration and potentially depart with insufficient battery capacity, which can significantly lower client satisfaction. However, this approach may come at the cost of decreasing client satisfaction in other clusters. The findings highlight the importance of carefully considering the impact of clustering information on the performance of the controller and the trade-offs between performance metrics and client satisfaction in different clusters.

6-3 Co-Regulation

In this section, we evaluate the performance of the co-regulation controller, which balances financial benefits and customer satisfaction. The methodology involves tuning the weight parameters, a_1, a_2, b_1, and b_2, to find the optimal balance between financial benefits and customer satisfaction. We conducted a sensitivity analysis on the weight parameters to assess the impact of their variations on the performance metrics of the co-regulation controller.

The analysis highlighted that the co-regulation controller's performance is significantly influenced by the weight parameters, which are crucial to achieving a balance between customer satisfaction and financial benefits. The flexibility of the system was found to be less intuitive than expected and challenging to grasp over time, which emphasizes the importance of performing a flexibility analysis before tuning the weight parameters. Our findings suggest that the co-regulation controller can effectively balance financial benefits and customer satisfaction with appropriate weight parameters.

Moreover, the impact of the reduction factor, α, on the performance of the co-regulation controller was analyzed. The reduction factor determines the degree to which the co-regulation controller reduces the charging power setpoints of the charge points. The results show that increasing the reduction factor enhances the financial benefits because more upside flexibility is added. However, the customer satisfaction decreases with an increase in the reduction factor. Therefore, the reduction factor should be carefully optimized to strike a balance between financial benefits and customer satisfaction.

Overall, the co-regulation controller demonstrates promising results in achieving a balance between financial benefits and customer satisfaction in the smart charging of EVs. The weight parameters and reduction factor have a significant impact on the performance of the controller, and their optimization is essential to achieve the desired balance. The co-regulation controller's success in balancing financial benefits and customer satisfaction highlights its potential as a practical and scalable solution for managing the charging demand of EVs in a cost-effective and sustainable way.

6-4 Comparing with Related Work

Our study estimated a yearly profit of €266.45 per EV, which is consistent with other studies in the literature. For example, research in France estimated potential profits between €193 and €593 per year per EV [15], and a study in the United States predicted annual profits between $161 and 635$ per EV when providing ancillary services [14]. In the United Kingdom, research found that using EVs to balance the energy system can lead to cost savings for the entire system [23]. However, it's important to note that direct comparisons across studies can be challenging due to variations in factors such as location, scale, pricing structure, and specific smart charging strategies. Our results are consistent with previous findings and provide valuable insight for the development of smart charging strategies that balance the needs of the EV driver, the grid, and other stakeholders.

6-5 Simulation Environment

The simulation environment used in this study was a crucial tool for modeling the interaction of EVs with the charging infrastructure and the Charging Management System (CMS). The process of pre-processing and filtering the data was complex and required significant effort, but was essential to ensure the accuracy of the simulation results. The resulting simulation environment was able to accurately model user behavior, charge characteristics, unsteered power and energy profiles, contracted power setpoints, and energy market information. By using a simulation environment, we were able to test and refine the co-regulation controller in a controlled and repeatable setting, and to identify areas for improvement.

Overall, the development of the simulation environment was a critical component of this research, and highlights the importance of utilizing appropriate tools and techniques to ensure the accuracy and validity of simulation results. The insights gained from the simulation environment provide valuable information for future research in this area, and can inform the development of new and improved solutions for managing the charging demand of electric vehicles.

6-6 Recommendations

In terms of future recommendations, we suggest that clustering based on arrival time and charge duration of individual sessions alone might not be sufficient for capturing the complexity of the charging behavior. Instead, we propose using clustering methods that incorporate additional features such as energy demand, duration since the last session, and time of day to obtain more meaningful and robust clusters that accurately represent the charging behavior of individual charge points. This could potentially improve the performance of the setpoint-tracking controller and enhance the overall user experience.

Furthermore, a potential recommendation for future work is to offer end-users the option to select slow charging, which allows for the session to be charged at a lower rate without risk of client dissatisfaction. This recommendation has the potential to benefit both the end-users and the grid operators in terms of cost savings and energy efficiency. By choosing slow charging, end-users can avoid peak charging periods, and the system can be better optimized to balance the energy supply and demand while reducing costs. Another potential direction for future research is to create a separate algorithm for each cluster and run them separately. This could be beneficial, especially when dealing with a large number of charge points in the Virtual Power Plant (VPP).

Chapter 7

Conclusions

The increasing adoption of Electric Vehicles (EVs) presents significant challenges for the power grid and the electricity market. In this study, we investigated the feasibility of developing a large-scale setpoint-tracking controller to regulate EV charge points and coordinate charging with energy market dynamics through co-regulation.

We addressed the following sub-questions to answer the research question:

1. How can smart charging be effectively implemented within the context of the energy market?
2. How can a simulation environment be developed to test the performance of a controller using real-world electric vehicle charging session data?
3. How can a feedback controller be designed to track a power setpoint in real-time while accounting for the potential impact of flexible charging schedules on future events, without relying on assumptions about travel patterns or charging characteristics?
4. What are the challenges and limitations of the proposed solution, and what recommendations can be made for future research in this area?

Through our simulations, we have evaluated the performance of the proposed controller and its impact on the charging cost, while taking into account various factors such as client satisfaction, penalty reduction, and cost reduction ratio. Our investigation revealed that co-regulation is a promising solution for managing the charging demand of EVs in a cost-effective and sustainable way. By utilizing a simulation environment based on real-world data collected from GreenFlux and TenneT, we evaluated the performance of the proposed controller and its impact on the charging cost. The performance metrics included non-satisfied energy demand, client satisfaction, tracking performance, penalty reduction, and cost reduction ratio. Our findings highlight the importance of considering both upside flexibility and optimization parameters while implementing the controller.

We performed clustering on both weekends and weekdays, but found it difficult to distinguish clusters on weekends. Therefore, we focused only on weekdays to accurately represent the charging behavior of individual charge points. The results demonstrated the effectiveness of the co-regulation controller in achieving the research objectives of client satisfaction and cost-effectiveness. Our findings highlight the significance of considering both upside flexibility and optimization parameters while implementing the controller. By incorporating additional features such as energy demand and duration since the last session into the clustering analysis, we expect that clusters will more accurately represent the charging behavior of individual charge points.

We also estimated a yearly profit of €266.45 per EV user, which is equivalent to 13.2% reduction in cost. This demonstrates the potential financial benefits of co-regulation and suggests that it could be a practical and scalable solution for managing the charging demand of EVs in the future.

In conclusion, our research has demonstrated the feasibility and effectiveness of using co-regulation to manage the charging demand of electric vehicles in a cost-effective and sustainable way. Our findings have important implications for the development of smart charging strategies and provide a practical and scalable solution for a rapidly growing problem.

Appendix A

Examples of Wholesale Electricity Market Operations

Day-ahead Market
Imagine that it's Monday and the day-ahead market is used to secure the necessary amount of electricity for Tuesday. Market participants, including producers and consumers, submit their offers and bids respectively, based on their expected production and consumption. The auction results in a single day-ahead price for the next day, and after market closing, market participants have to send their contracted power schedule to the Transmission System Operator (TSO) themselves or through a chosen Balance Responsible Party (BRP). The BRP is then responsible for abiding by their contracted volume. For example, a producer might offer to sell 10 MW of electricity at a price of €50 per MWh, while a consumer might bid to buy 5 MW of electricity at a price of €60 per MWh. The auction would then determine the clearing price, which might be €55 per MWh, and each participant would be required to abide by their contracted volume.

Intraday Market
Imagine that it's Tuesday and the intraday market is being used to balance supply and demand in real-time. Throughout the day, market participants such as generators and retailers adjust their positions in the market by buying or selling electricity to align their schedules with their expected production and consumption. For example, a generator might have expected to produce 5 MW of electricity at a certain time, but due to unexpected circumstances, they are only able to produce 4 MW. To correct this imbalance, the generator would need to purchase 1 MW of electricity from the intraday market. Similarly, a retailer might have expected to consume 3 MW of electricity at a certain time, but due to unexpected circumstances, they are only able to consume 2 MW. To correct this imbalance, the retailer would need to sell 1 MW of electricity on the intraday market.

Case study of energy scheduling and optimization:
To illustrate the concept of energy scheduling and optimization, a case study could be used to demonstrate how a company might optimize their energy consumption to reduce costs. For example, a manufacturing plant might use a predictive analytics tool to forecast their energy consumption over the next day, and then use this information to schedule their production processes in the most energy-efficient way possible. By optimizing their production processes, they could reduce their energy consumption and lower their energy costs. The company might also use an energy management system to monitor their energy consumption in real-time and make adjustments as necessary. These tools could help the company to participate more effectively in the day-ahead and intraday markets by allowing them to better predict and control their energy consumption.

Appendix B

Balancing markets

FCR

Primary reserve: Restore frequency for the synchronous grid of continental Europe

Step 1 — **BSP must qualify. If accepted, TenneT will authorize the BSP to submit FCR bids**

The BSP must invest in infrastructure that can accurately measure the frequency deviation and communicate with TenneT's infrastructure to automatically deliver the correct amount of reserve power.

Step 2 — **TenneT procures FCR with BSPs on a contractual basis to cover their share in the IGCC**

Step 3 — **BSPs bid on the FCR auction**

Place bids in contracts of 4 hours on the day before delivery.

Symmetrical bids of at least 1 MW.

Step 4 — **FCR activation**

The BSP must monitor the frequency on the grid at least every 4 sec and automatically react to deviations. The actual volume of delivery depends on the extent of the deviation.

Availability
Full capacity must be available over the entire contract period.

Activation

Deviation > 200 mHz	The full contracted capacity is activated.
Deviation < 200 mHz	Activation is proportional to the deviation.
Deviation < 10 mHz	Dead-band, no activation.

Reaction time

< 30 sec	The BSP must be able to deliver the full contracted power.
< 15 sec	The BSP must have delivered half of the full contracted power.

Special requirements for limited energy reservoirs (e.g., EV batteries)

< 15 min	The BSP is required to provide full power uninterrupted (or proportionally longer for imbalances smaller than 200 mHz).
< 2 hours	After delivery, the BSPs have 2 hours to make themselves available again for delivery.

Step 5 — **Remuneration**

BSPs receive both the capacity price for availability and energy price for activated energy. If the BSP cannot supply the contracted capacity of FCR Tennet fines the BSP.

Extra — **Contract termination**

If the BSP is unable to deliver the contracted quantity of FCR on multiple occasions.	⟶ TenneT and BSP discuss how the reliability can be improved.
If the BSP cannot improve reliability.	⟶ TenneT can revoke the prequalification status of the BSP, excluded them from future FCR auctions.

Figure B-1: FCR market

aFRR

Secondary reserve: Restore long lasting imbalances, gradually replaces the FCR

Step 1 — **BSP must qualify by doing an activation test**

Step 2 — **TenneT calculates the amount of aFRR reserve needed every 6 months**

This amount is procured with BSPs, meaning they must always place bids for at least the contracted capacity. In this way, TenneT is always assured of enough aFRR.

Step 3 — **BSPs bid on the aFRR auction**

Possible on a contractual and voluntary basis. Contracted aFRR has no priority over voluntary bids; the merit order list is determined based on the bid price, ensuring a competitive market environment. BSPs can submit up to three bids (aFRR and mFRRsa combined), smaller than 4 MW, per ISP.

BSPs can offer upward and/or downward regulation. Bids of at least 1 MW.

Contractual bids
Bids must be placed on the day before delivery.
Must be available 24 hours.

Voluntary bids
Bids can be placed up until 60 min before delivery.
For a minimum of one ISP.

Step 4 — **aFRR activation**

Availability
Full capacity must be available over the entire contract period. Or per ISP for voluntary bids.

Activation
TenneT sends activation request. Full activatoin within 15 min (5 min as of 1-7-2022).

Reaction time
Minimum ramp rate of 7% (minimum 20% as of 1-7-2022) of the bid size per minute.

Step 5 — **Remuneration**

	Contractual	**Voluntary**
BSP can supply the contracted quantity.	Capacity price Energy price	- Energy price
BSP cannot supply the contracted quantity.	Tennet fines BSP	No sanctions

Extra — **Contract termination**

TenneT can withdraw BSP approval if activation structurally not followed.

Figure B-2: aFRR market

mFRRsa

Tertiary reserve: For extensive and/or prolonged imbalance situations

Step 1 **BSP must qualify by signing a declaration that it meets the requirements**

Step 2 **TenneT does not procure any mFRRsa in advance**

Unlike FCR and aFRR, there is no deadline for mFRRsa bids and all bids are voluntary, meaning there is no bid-obligation and no requirements for capacity availability.

Step 3 **BSPs bid on the mFRRsa auction**

When a BSP decides to place an offers they do enter into a capacity contract. BSPs can submit up to three bids (aFRR and mFRRsa combined), smaller than 4 MW, per ISP.

Symmetrical bids of at least 1 MW and a maximum of 999 MW.

Step 4 **mFRRsa activation**

Availability
Full capacity must be available over the entire contract period.

Activation
Via a manual procedure, TenneT can activate mFRRsa until sufficient aFRR becomes available or the balance is sufficiently restored. TenneT can activate them up to the beginning of the last ISP before the respective ISP. Activation order is based on the bid prices of offered mFRRsa bids.

Reaction time
It is scheduled, so the power must be available for the scheduled ISP. Actual reaction time is not specified.

Step 5 **Remuneration**

Only an energy price for activated energy.

Extra **Contract termination**

TenneT may, after a documented warning, reject mFRRsa bids of a BSP indefinitely.

Figure B-3: mFRRsa market

mFRRda

Tertiary reserve: Incident reserve, when all aFRR and mFRRsa have been depleted

Step 1 **BSP must qualify by doing an activation test**

Step 2 **TenneT organizes auctions on a quarterly and monthly basis**

Step 3 **BSPs bid on the mFRRda auction**

An individual Installation can have an mFRRda contract in one direction. Minimum bid size is 20 MW.

Step 4 **mFRRda activation**

Availability
Full capacity must be available over the entire contract period.

Activation
TenneT manually activates mFRRda in event of incidents or prolonged power deviations. The guaranteed period that the offered power can be fully activated is 60 minutes. With a maximum of 6 hours between deployments.

Reaction time
As short as possible with a maximum of 15 minutes for upward regulation and a maximum of 10 minutes for downward regulation.

Step 5 **Remuneration**

mFRRda is compensated on the basis of five-minute-periods.

The compensation for upward regulation equals the highest of the two options listed below.
1. Deployment price in downward direction plus 10%.
2. EPEX-price (day-ahead price) plus €200 per MWh.

The price for downward regulation equals the lowest of the two options.
1. Deployment price in upward direction minus €100 per MWh.
2. EPEX-price (day-ahead price) minus €250 per MWh.

If for one or more five-minute-periods the agreed quantity is not delivered in full or not delivered for the agreed activation time, the BSP will pay a penalty to TenneT.

Extra **Contract termination**

If 'non-availability' periods are communicated, lack of delivery will not be penalized. But if the “non-availability” exceeds 1%, TenneT may suspend prequalification in whole or in part.

Figure B-4: mFRRda market

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Glossary

List of Acronyms

EV	Electric Vehicle
V2G	Vehicle to grid
CDR	Charge Detail Record
CCCV	Constant Current Constant Voltage
CMS	Charging Management System
CS	Control Station
CP	Charge Point
SoC	State of Charge
ToU	Time of Use
GMM	Gaussian Mixture Model
OSCP	Open Smart Charging Protocol
OCPP	Open Charge Point Protocol
IEC	International Electrotechnical Commission
DAM	Day Ahead Market
CPO	Charge Point Operator
TSO	Transmission System Operator
BRP	Balance Responsible Party
BSP	Balancing Service Provider
FCR	Frequency Containment Reserve
aFRR	automatic Frequency Restoration Reserve
mFRRsa	manual Frequency Restoration Reserve scheduled activated
mFRRda	manual Frequency Restoration Reserve direct activated
ISP	Imbalance Settlement Period
ToU	Time of Use

VPP	Virtual Power Plant
AIC	Akaike Information Criterion
BIC	Bayesian Information Criterion

j	Index of Control Station (CS)	
$\mathcal{E}$	Set of empty EVSE	
$\mathcal{L}$	Set of locked EVSE	
$\mathcal{C}$	Set of controllable EVSE	
$\mathcal{F}$	Set of fully charged EVSE	
k	Index of time step	
h	Index of Imbalance Settlement Period (ISP)	
Contact geometry		
T^s	Sampling interval	[TBD]s
Δh	Duration of one ISP	900 s
U	Mains voltage	230 V
I^{ub}	Upper bound charging current	W
P^{Co_reg}	Regulation power	W
P^{Comp}	Compensation power	W
t_j^{arr}	Arrival time	-
E_j^{actual}	Actual charged energy	W h
$\mathrm{E}_j^{unsteered}$	Uncontrolled charging rate	W h
E_h^{RT}	Energy consumed in real-time	MW h