Making Smart Charging More Intelligent

"Dynamic optimization strategy for EV charging speeds based on imbalance settlement prices"

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Abstract

This research develops a strategy to optimize electric vehicle (EV) charging speeds based on imbalance settlement prices, enhancing profitability for charge point operators (CPOs) while minimizing costs. The growing integration of renewable energy sources (RES) introduces significant volatility in electricity markets, creating challenges for grid stability and CPO operations due to mismatches between energy generation and consumption patterns.

Employing a mixed-methods approach—including comprehensive literature review, data analysis, and econometric modeling—the research identifies key parameters influencing EV charging behavioUr and grid imbalance dynamics. It proposes a dynamic strategy that adjusts charging speeds in response to real-time imbalance settlement prices, incorporating flexible adjustments both upwards and downwards (steering up and down). Central to this strategy is a dynamic strike price mechanism optimizing the timing of charging speed adjustments based on factors like the rebound effect and remaining steering periods. Cost management is enhanced through expected cost calculations, accounting for potential lost revenues from unfinished charging sessions and the impact of deferred loads returning later.

The strategy integrates participation in the Day-Ahead Market (DAM) and the Intraday Market (IDM), to align charging schedules with periods of lower energy costs and allowing real-time energy procurement or sales to manage deviations from forecasts. The most advanced model improved rewards over the tested period with 32% compared to the simplest model, mostly coming from improved timing of steering actions and cost mitigation through optimized energy procurement. Yet, the simplest model already protects against peak imbalance prices, making the actual improvement on standard charging strategies likely to be above this percentage. Hence, it can be stated that this model effectively transformed the undesired balancing costs into a an additional source of income, while contributing to grid stability.

The findings offer practical insights for energy companies and policymakers, advancing the understanding of smart grid technologies and providing a framework for scaling these strategies across different markets. By showcasing how intelligent EV charging strategies could contribute to grid balancing and enhance the integration of RES into the grid, the study contributed to sustainable energy management and opens avenues for future research and implementation.

Keywords: *electric vehicles, smart charging, imbalance settlement prices, charging speed optimization, grid stability, dynamic strike price, energy markets, sustainable energy management.*

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List of Abbreviations

BESS	Battery Energy Storage System
BRP	Balancing Responsible Party
BSP	Balance Service Provider
CP	Charging Point
CPO	Charge Point Operator
DAM	Day-Ahead Market
EV	Electric Vehicle
GHG	Green House Gas
IDM	Intraday Market
KPI	Key Performance Indicator
ML	Machine Learning
MDP	Markov Decision Process
PTU	Program Time Unit
PV	Photovoltaic
Reg. Down	To Regulate Down
Reg. Up	To regulate Up
RES	Renewable Energy Sources
RL	Reinforcement Learning
SoC	State of Charge
TSO	Transmission System Operator

Table 1: List of Abbreviations

Chapter 1

Introduction

This first chapter introduces the aim of the thesis by covering the problem context and motivation behind the energy transition, the need for grid balancing, and the integration of EVs and their charging infrastructure into the energy system. It discusses the core problem derived from the current situation and presents the problem-solving approach. The chapter highlights the literature gap to emphasize the importance of this thesis. Finally, it presents the research questions and scope, providing an outline of the thesis structure to ensure clarity on the objectives and a systematic approach to address the core problem.

1.1 Relevance

Transitioning from polluting fossil fuels to more environmentally friendly options is a global imperative. Globally accepted climate targets were established in (UN, 2015) to guide the shift towards a more sustainable global economy. In response to these challenges, electrification is a pivotal method for decarbonizing the economy. By integrating RES such as wind and solar, electrification offers a way to contribute to the climate targets (Steinberg, 2017). This has been confirmed by many long-term energy scenarios (Tsiropoulos, 2020), which predict that the ongoing adoption of EVs is crucial for environmental sustainability but increases pressure on the stability of the electricity grid (Prettico et al., 2022) and introduces volatility and unpredictability into energy markets (Pen, 2023b); as electricity production from RES like wind and solar power is volatile and cannot be planned (Kempton et al., 2008; Milligan et al., 2011).

Volatility in production can create an imbalance between supply and demand, which might cause changes in the frequency or voltages of the grid and possibly cause outages. Hence, to maintain proper grid functionality, electricity supply and demand must always be balanced. Addressing these challenges requires innovative solutions to maintain grid stability and balance supply and demand efficiently.

An innovative approach that significantly contributes to maintaining grid stability is the use of imbalance settlements (Greunsven & Derks, 2018). Imbalance occurs when market participants deviate from their scheduled production or consumption levels. However, as illustrated in Figure 1.1, when such deviations help to mitigate overall grid imbalance, market participants are often rewarded accordingly (ENTSO-E, 2020). Depending on the grid's current needs, imbalances can be addressed by either increasing electricity supply to the grid or reducing demand. Increasing supply or reducing consumption is referred to as "regulating up", while decreasing production or increasing consumption is termed "regulating down." The extent to which consumption or production can be adjusted in the desired direction is traded on imbalance markets (IEA, 2011). This adjustment is monetized through mechanisms such as imbalance settlements (Greunsven & Derks, 2018), and has demonstrated potential for financial gain (Eicke et al., 2021; Lisi & Edoli, 2018).

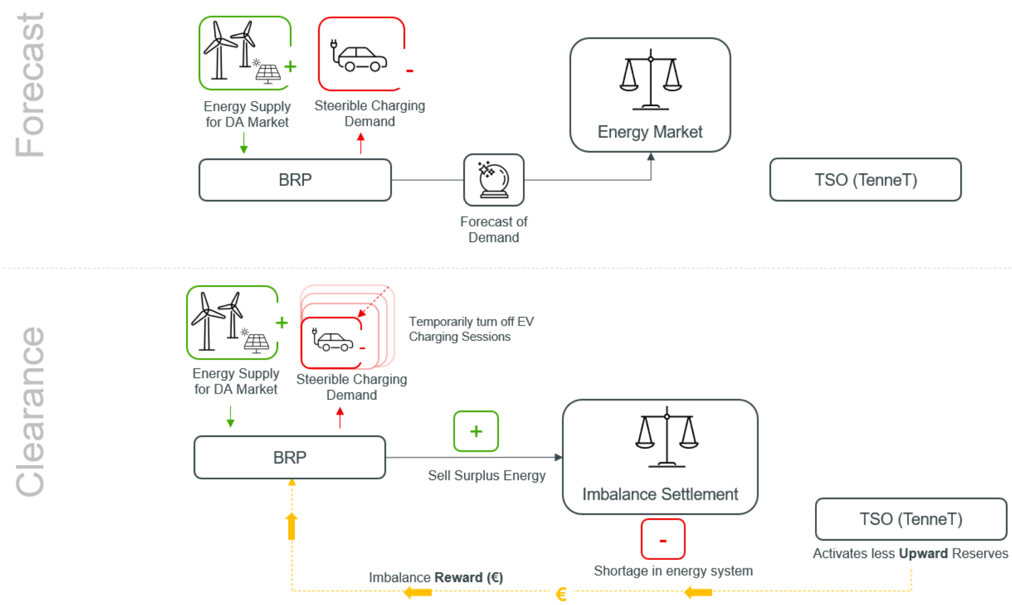


Figure 1.1: Process of Steering EV Charging Sessions.

Road transport accounts for a significant part of global emissions (IEA, 2020). The switch to EVs is a crucial component for reducing these emissions and is gaining popularity (McKinsey, 2023). However, the energy demand of EVs is significant; the average EV charging session consumes the same amount of energy (Database, n.d.) as one Dutch household in ten days (CBS, 2023). Hence, it can be concluded that smart EV charging on a large scale is a hard requirement (Monteban & Geerts, 2023), recognizing EVs not only as large-scale electricity consumers but also as a flexible resource capable of supporting grid stability (M. A. Amin et al., 2022; McKerracher & Soulopoulos, 2021; Nelder et al., 2019). This thesis explores the potential of EV charging as a strategic asset in Dutch imbalance settlements on behalf of TotalEnergies, where the objective is to develop a strategy that leverages the flexibility capabilities of EVs to address and monetize grid imbalances and optimize the timing of energy consumption.

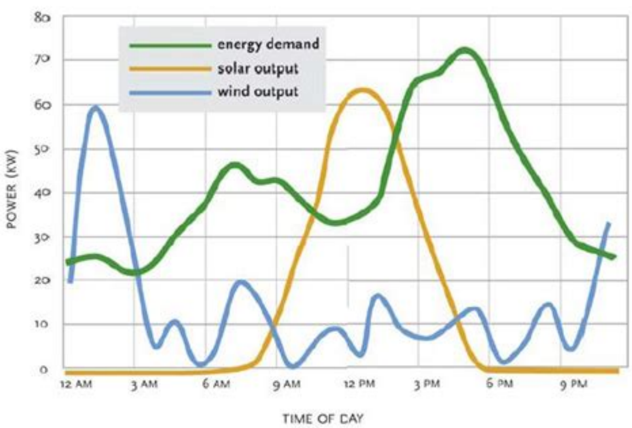
1.2 Company Description

TotalEnergies SE is considered one of the major energy companies worldwide. It finds its business through the whole value chain of the energy sector, with a growing focus on RES. This can be seen through the expansion of its charging infrastructure in the Netherlands and other European countries. With more than 17,500 charging points (CPs) in the Netherlands at the time of writing, with an installed capacity exceeding 200 MW, its EV charging solutions are becoming a significant part of the business. An increasing number of CPs are using smart charging technologies to optimize the charging process on, among others, electricity costs in different markets and the timing of energy usage.

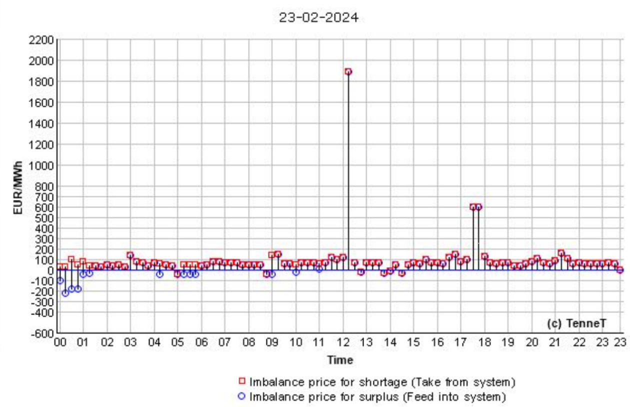
1.3 Problem Context

Increasing renewable energy generation is a good start, but as illustrated in Figure 1.2a, it often does not align with consumption at that time (IEA, 2021). The figure shows that production from RES is volatile and cannot be controlled as precisely as conventional generation methods (Shazon et al., 2022) and increases the frequency and severity of imbalance on the grid.

Consequently, CPOs face rising balancing costs (Pfenninger et al., 2014) and decreasing operating margins. This situation underscores the urgent need for strategies that mitigate balancing costs by adjusting EV charging speeds to a stated level (henceforth, steering) (Pen, 2023c). Steering aims to synchronize electricity demand with energy availability within specific periods, thereby enhancing grid stability and optimizing financial performance for CPOs.



(a) Average Daily Energy Supply & Demand Loads (Edrisian et al., 2013).



(b) Imbalance prices in NL on Arbitrary Day (Tennet, 2024).

Figure 1.2: Daily Energy Loads and Prices for Resulting Imbalance.

According to research by Dexter Energy, balancing costs in the EU have surged by 40% year-on-year, reaching over €20 billion in 2022 Pen (2023b, 2023c). This surge is driven by increased usage of the grid capacity and fluctuating RES energy flows, making grid balancing more challenging (Shazon et al., 2022). Figure 1.2b depicts a representative imbalance price pattern, illustrating how these prices can peak throughout the day — a trend expected to intensify in the future (de Boer, 2024). However, the actual imbalance prices for the next price-time unit (PTU), a 15-minute period, remain unknown until two weeks after the PTU (TenneT, 2019a). Therefore, this research utilizes forecasted imbalance prices for the current and next PTU, sourced from an external party.

Figure 1.3 presents a flowchart that covers the problem context for CPOs and helps to identify the core problem for TotalEnergies in Section 1.5. This flowchart helps to understand why balancing costs are rising due to increased grid imbalances and volatile prices. The volatility in imbalance prices is primarily driven by the growing share of RES and their unpredictable energy generation, necessitating greater flexibility to manage these fluctuations. Given that flexibility is both costly and limited, the integration of more RES alongside rising electricity consumption makes grid balancing increasingly challenging and costly (Shazon et al., 2022), thereby shrinking operating margins for CPOs (Pen, 2023c). The resulting grid imbalances and subsequent price volatility not only present profit opportunities when leveraging this volatility but also highlight the critical need for effective steering strategies. Without such strategies, the viability of operating charging infrastructures could be severely undermined. Conversely, with robust steering mechanisms, rising balancing costs can be mitigated, and imbalance settlements can be transformed into additional revenue streams, as depicted in Figure 1.3.

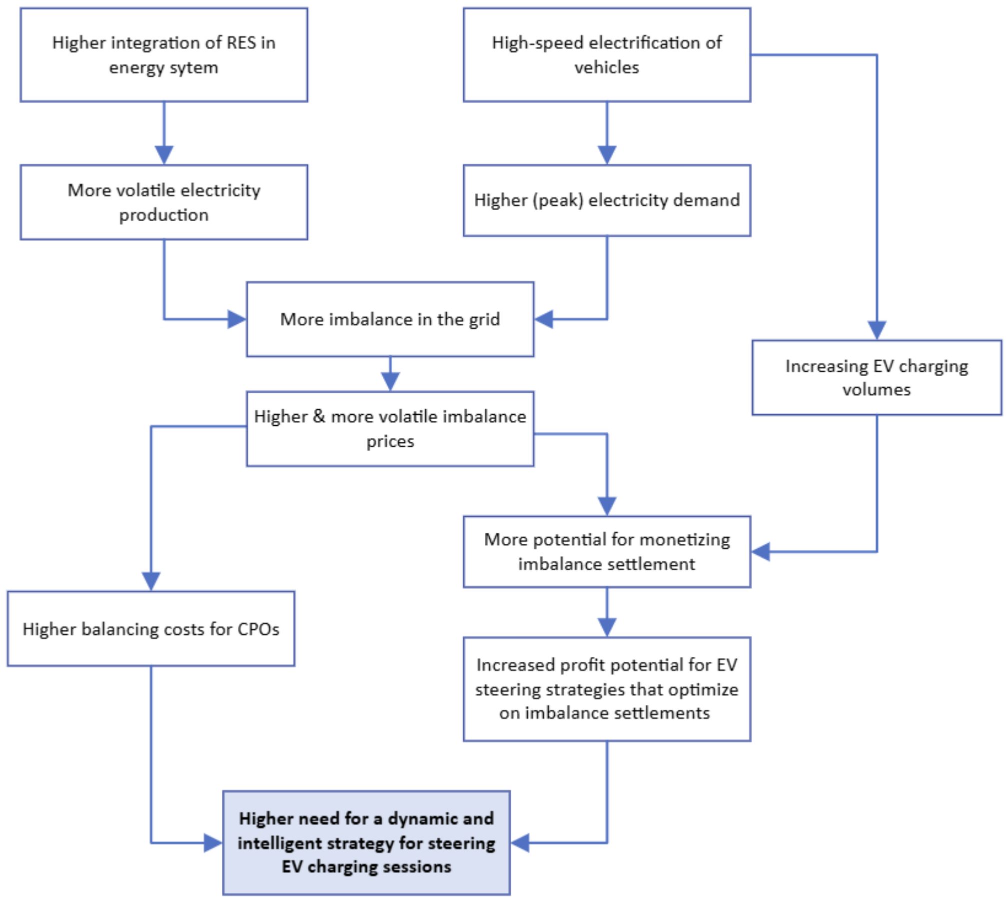


Figure 1.3: Problem Context.

Furthermore, cars are electrified at high speed. EVs in the Netherlands increased by 35% in 2022 and are on track to reach 10 million by 2050 Marktontwikkeling (2024). The increasing number of EVs on the road directly correlates with an increasing demand for charging sessions (IEA, 2023a) and higher (peak) electricity demand. This increased usability provides more potential for steering strategies and an increased profit potential for CPOs. Moreover, EV batteries have a faster response than energy sources from fossil fuels, making the adjustment of EV charging speeds a practical option for grid balancing (Nour & Chaves-Avila, 2020).

Traditionally, managing grid imbalances was handled by large centralized electricity producers, such as gas turbines, that could adjust their generation capacity to cover grid imbalances. Nowadays, a wider range of producers and consumers are engaged in balancing services. Financial rewards can be earned when contributing to balancing the grid. One potential method to contribute to the balance is smart charging of EVs (Nour & Chaves-Avila, 2020), where charging could be slowed or completely stopped during grid shortages (negative imbalance). In contrast, charging could be accelerated during surpluses (positive imbalance).

1.3.1 Current Situation

TotalEnergies procures energy for its EV charging operations based on the forecasted energy consumption for the next day (hereafter referred to as 'the forecast'), utilizing future contracts and the energy bought on the DAM as shown in Figure 2.2. The acquired energy is distributed through charging sessions in the CPs, which can regulate (steer) the charged loads per PTU by temporarily stopping the charging sessions. The imbalance settlement graph in Figure 2.2 shows how pausing the charging session results in a deviation from the forecast and leads to an imbalance settlement.

As a Balance Responsible Party (BRP), TotalEnergies is penalized or rewarded based on deviations from its forecasted energy consumption in a PTU. If the forecasted imbalance settlement price (hereafter, "imbalance price") indicates a high value for reducing consumption, EV charging sessions can be paused (steered down) in exchange for compensation. This reduction in consumption lowers the need for the Transmission System Operator (TSO) to provide reserve energy, thereby decreasing balancing costs. These reduced balancing costs translate into financial rewards for the BRP, calculated based on the imbalance price per offered MWh. Therefore, by reducing consumption, the BRP can monetize imbalance prices and create an opportunity to be rewarded for deviations from the forecast. The energy offered through such deviations is called an imbalance settlement and forms the main concept of this thesis. In this thesis, it is assumed that TotalEnergies' steering actions do not influence imbalance prices.

Steering down is permitted only within the steering window (17:00 - 08:00) to minimize the effect on the amount of charged loads within a charging session. However, uncertainty lies in the exact departure time and the desired amount of energy needed within the charging session. This means the precise amount of flexibility, indicating to what extent a charging session can be interrupted without revenue loss, is still unknown. Moreover, the imbalance (settlement) price for only 15 minutes ahead is forecasted with high enough accuracy. Hence, many uncertainties should be considered when creating a strategy for adjusting (steering) EV charging sessions, as visualized in Figure 1.4.

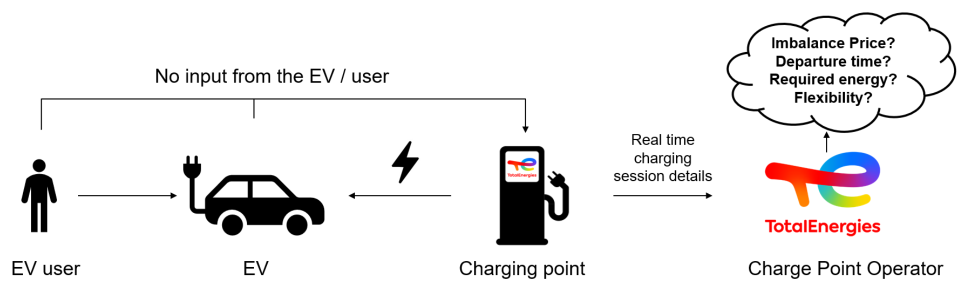


Figure 1.4: Uncertainties within EV Charging Sessions in this Research.

As mentioned, the charged load in a PTU could be set to zero (steer down) when the forecasted imbalance price (in €/MWh) rises above the strike price. This strike price (in €/MWh) can be set manually, but in this research is equivalent to the selling price (in €/MWh) at that time. To overcome inefficiencies in energy transmission, it is chosen that the charging speed cannot be above 0 kW while steering down. While the DAM optimization (explained in Section 3.2.3) charges at a reduced rate of 8 kW, steering down would be most effective below that rate. At lower rates, a larger proportion of energy is lost due to resistance and other inefficiencies. Fixed losses in the charger and cables, such as standby power consumption and heat generation, become more significant compared to the energy delivered to the battery (Apostolaki-Iosifidou et al., 2017). This would lead to lower charging efficiencies and higher total energy consumption per kWh charged, making a complete pause more convenient.

It is stated in agreements with municipalities that steering down actions are allowed for a maximum of three (non-subsequent) times per day for up to 15 minutes. In this way, when the imbalance prices are forecasted to be high, a reward can be received for contributions to balance the grid. This method is expected to decrease TotalEnergies' total balancing costs or add another source of profit. Theoretically, this steering method is rather effective, as only a small part of PTUs significantly affect total balancing costs for energy companies. The research of (Pen, 2023a) states that a strong steering strategy can increase revenues by 19 percentage points and could offset balancing cost (Penn & Gastel, 2024). However, the result of its application on EV charging sessions remains to be seen.

1.3.2 Core Problem

In Section 1.3, it was explained how increasing balancing costs for CPOs present an urgent need for an intelligent and dynamic steering strategy for EV charging sessions. The core problem builds upon the sector-specific problem context outlined in 1.3 and shall be based on discrepancies between norm and reality specifically for TotalEnergies.

Steering EV charging sessions based on forecasted imbalance prices cannot be done without considering its effects on subsequent charging behaviour. Since EVs are charged until a full state of charge (SoC) and the loads that are not charged during the PTUs of steering are charged in later PTUs, it can cause an undesired rebound. This is the steered load that returns later, as visualized in Figure A1. The forecast, and therefore the purchased amount of energy during these PTUs, did not anticipate on the extra loads during rebound periods. This makes the actual consumption deviate from the forecast and creates a positive imbalance during the later periods. A rebound could lead to costs that are higher than the revenue from steering and, therefore, forms a notable cost when steering.

Currently, steering is done on a small part of the CPs when the forecasted imbalance price rises above a fixed price level, being the strike price. As illustrated in Figure 1.5, this static policy does not consider current and future charging loads, nor its operating environment, and does not mitigate or quantify potential costs from steering actions. This leaves steering opportunities unfulfilled when the price peaks slightly below the strike price and does not peak again in a later PTU. However, lower strike prices might cause steering actions to be triggered during sub-optimal times. Since the number of steering actions within a steering window is limited, this might cause missing the opportunity of steering when it is the most advantageous. Additionally, the performance of the current steering actions is not adequately tracked or tested on a benchmark. Hence, the current steering strategy does not reach the desired level of performance, as it is entirely static and unable to mitigate eventual costs, leaving much of its profit potential unfulfilled.

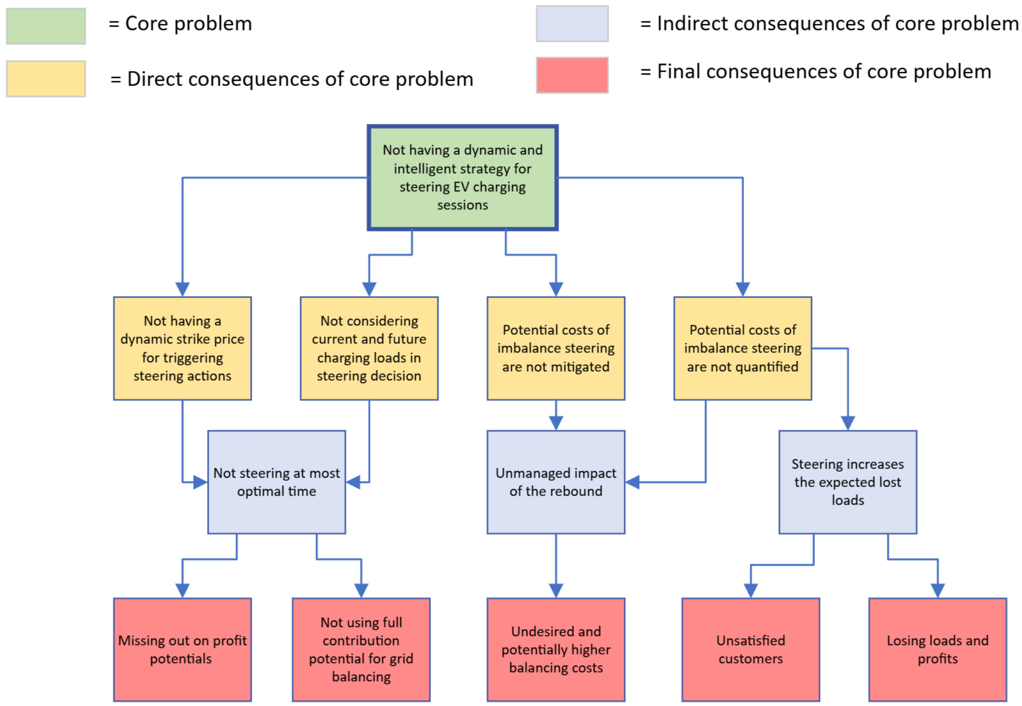


Figure 1.5: Problem Cluster.

The problem cluster illustrated in Figure1.5 starts with the core problem, which is the leading cause for the observed discrepancies between the norm and reality, as perceived by the problem owner (Heerkens & Winden, 2017). The core problem causes direct consequences (action problems) and describes the potential costs that arise with steering and the sub-optimal timing of steering. The method of Heerkens & Van Winden (Heerkens & Winden, 2017) is used to define the core problem of this research:

"Not having an intelligent and dynamic strategy for steering EV charging sessions."

This was concluded to be the core problem, as it can resolve all direct and indirect consequences. The direct and indirect consequences are elaborated on in Sections 1.1, 1.3, and 1.3.1, which provide a more elaborated analysis of these discrepancies.

1.4 Problem-Solving Approach

Addressing the challenge of price uncertainty in imbalance prices with an intelligent steering strategy for EV charging sessions requires an inductive multidisciplinary research approach (Streefkerk, 2019), combining knowledge of energy market dynamics with the financial implications of energy trading and cost management. Its complexity arises from, on the one hand, the need for a thorough understanding of energy market dynamics and the possibility EV charging offers to enter these markets, which is mainly discussed in literature and tested through data analysis. On the other hand, models and policies need to be developed and tested to test the performance of the steering actions. This approach is executed following the framework of Figure 1.6.

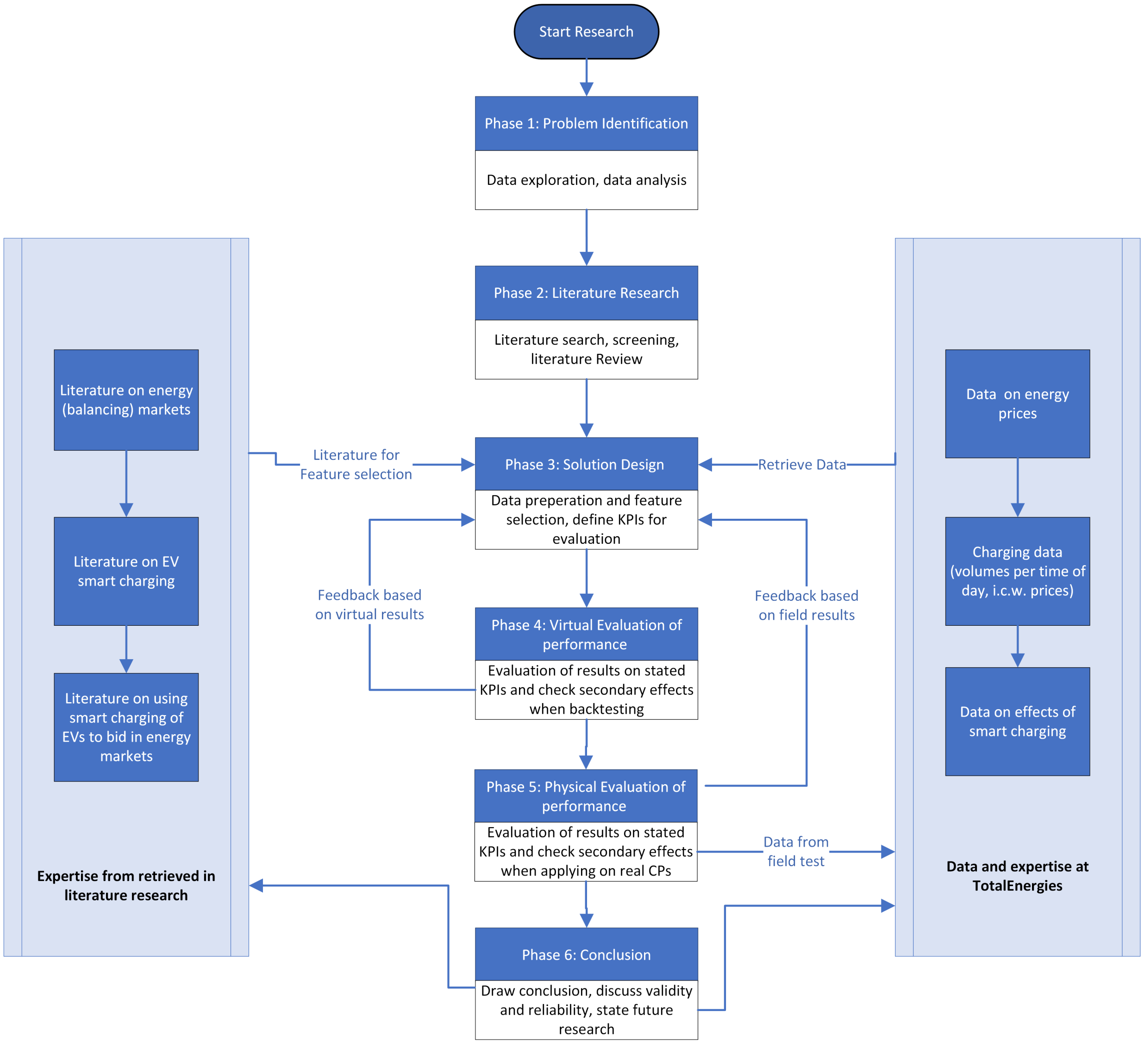


Figure 1.6: Research Framework.

Developing an optimal control (steering) strategy for EV charging sessions to monetize on imbalance settlements requires an understanding of parameters that influence the robustness of steering decisions. The strategy must consider EV users' behaviour to manage lost loads from steering actions, recognize existing constraints that limit the strategy, and account for the negative effect (impact) of the rebound effect — temporary load reductions affecting future consumption. Minimizing the rebound's impact involves optimizing its value and severity.

Figure 1.7 illustrates the main components of the development of the strategy. The figure shows that the imbalance price forecasts and flexibility analysis are the primary input data for this research. To start the modelling process (steering execution), a flexibility analysis was performed through which the expected lost loads per PTU were computed. This analysis considers instances where EVs disconnect before charging completes and cause revenue loss and potential customer dissatisfaction. Moreover, excessive lost loads harm TotalEnergies' reputation as a CPO, especially if due to steering actions. The figure shows that the strategy needs steerable CPs to monetize imbalance settlements.

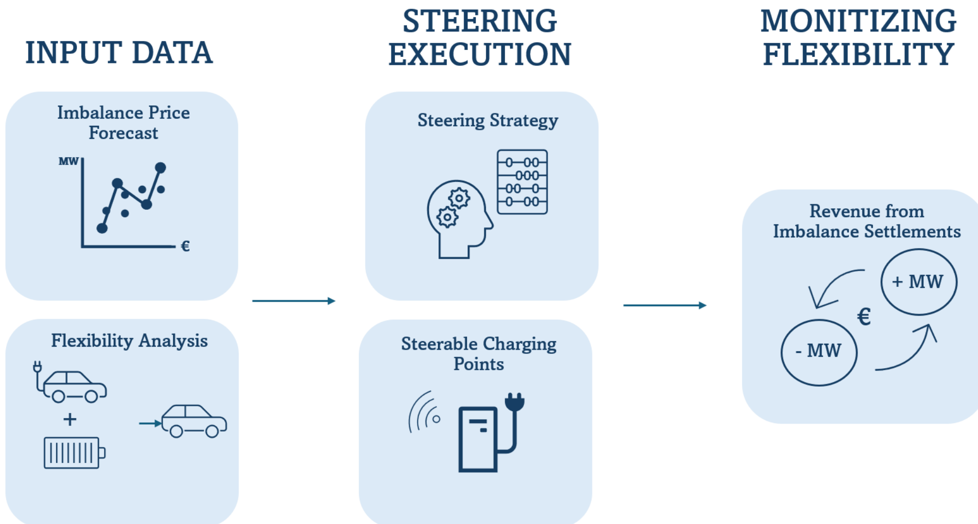


Figure 1.7: Illustration of the Steering Principle.

Since steering EV charging sessions might result in costs that are higher than the reward, it is crucial to measure and manage these costs. Measuring the cost from each steering action involves computing the expected costs from lost revenues and the rebound effect. This metric provides insights into costs from steering decisions and can illustrate the impact of cost management on the total reward. Since imbalance prices are known only up to 15 minutes before each PTU, determining the impact of rebound is feasible only for the next PTU.
The last modelling phase included developing a formula for the dynamic strike price for steering down. This evolving price limit triggers steering down when the imbalance price for regulating up exceeds the threshold. The strike price is based on current and future charging loads to optimize revenue potential while considering steering costs to ensure effective decisions.

Lastly, several choices are made during the development of the steering strategy. One is to select a modelling method that accurately represents EV charging dynamics, steering effects, and interactions with electricity markets while accounting for external factors like imbalance prices, rebound effects, and expected lost loads. Within the model, constraints are established by which the steering strategy needs to operate. The constraints might include technical limitations of the charging infrastructure, limitations on steering actions, and physical limitations of the grid.

1.4.1 Literature Gap

In recent years, substantial research has been conducted on the behaviour of market participants in energy-balancing markets and smart EV charging solutions. However, the potential of EVs to monetize imbalance settlements is relatively understudied in the academic literature. Traditionally, load steering has been extensively studied for applications such as heating (HVAC) systems (Lu, 2012) and Home Energy Management Systems (HEMS) (GridX, 2022), showing that load management techniques are established in specific domains but not fully explored in the context of EV charging.

In addition, extensive research has been conducted and is still ongoing on how EVs can help alleviate grid stress by contributing to peak shaving or reducing grid tension (Gu et al., 2023; Moncecchi et al., 2021; van der Klauw et al., 2014). While the studies of IEA (2020, 2023b), IRENA (2020), Refa et al.

(2024), and Zeromski et al. (2024) recognize the potential of EVs in addressing grid imbalances, they often conclude without providing a well-defined strategy or methodology for effectively deploying EV charging in this role. Moreover, current research mainly focuses on bidding strategies in the DAM (R. Bessa & Matos, 2014; Philipsen et al., 2019) and IDM (Koch, 2022; Vardanyan et al., 2018), or a combination of both (Löhndorf & Wozabal, 2023; Weerd et al., 2022). However, strategies specifically designed to optimize EV charging sessions in imbalance settlement bidding remain unexplored.

Moreover, the literature frequently addresses imbalances from the production side, particularly concerning RES such as photovoltaics (Lee & Won, 2021; Zakariazadeh et al., 2014) or wind farms (Foley et al., 2010; Jiang et al., 2018; Morales et al., 2010), potentially in conjunction with a battery energy storage system (Mohamed et al., 2014). These discussions reveal a literature gap in how EVs, as mobile energy storage systems, could be used for active participation in real-time energy (imbalance) markets.

1.5 Research Questions

As mentioned above, this research aims to develop a strategy that optimizes the steering decisions for EV charging sessions based on forecasted imbalance prices. During the development of this strategy, more knowledge is obtained about the concept of smart charging, as well as factors that influence the profitability of steering EV charging sessions and the potential costs that come with it. The research questions below contribute to obtaining the required knowledge to develop the steering strategy. The main research question is as follows:

"How can flexibility in EV charging be used to increase profits for CPOs through imbalance settlements while contributing to balance the Dutch electricity grid?"

We try to answer this question using sub-research questions that can be divided per stage of the research, as presented in the research framework in Figure 1.6.

Phase 1: Literature Research
What is smart charging, and in which situations is it desired? (Literature research & data analysis)
Through literature research, the concept of smart charging is concretized, as well as the forms of smart charging. However, in this research, the main focus lies on steering EV charging sessions, a form of smart charging. With data analysis, the potential effects of steering are examined. This research question brings more insights into the problem context and why smart charging is essential in managing EVs' energy demand and optimizing their integration into the electrical grid. Furthermore, identifying the scenarios in which steering EV charging sessions is most beneficial contributed to the development of the strategy, as understanding and recognizing the effects of external factors stimulates the learning process for the development of a strategy.

How can steering EV charging sessions be used to monetize imbalance settlement prices? (Literature research)
This research question helps to familiarize with imbalance markets and elucidates how fluctuations in imbalance prices can be used to monetize imbalance settlements. Literature research is done on existing energy trading strategies and models that monetize the flexibility in EV charging sessions.

What potential costs arise when steering EV charging sessions based on forecasted imbalance prices, and how can they be concretized? (Literature research & data analysis)
This research question requires identifying, concretizing, and quantifying the potential costs of steering EV charging sessions based on imbalance prices, which is critical for developing a profitable steering

strategy. Understanding these costs involves literature study and data analysis and helps formulate mitigating methods.

What modelling method can be used to model the research problem? (Literature research)
This research question delves into mathematical modelling methods and addresses why the current method has been chosen.

Phase 2: Problem Context Analysis
What are the effects of the current smart charging strategy of TotalEnergies on EV charging sessions, and what is the role of steering in imbalance settlements monetization? (Data analysis)
Examining TotalEnergies's current steering strategy can provide insight into its effectiveness, efficiency, drawbacks, and potential costs. Hence, it could be the benchmark for the developed strategy against which performances can be compared.

What do imbalance settlement bidding strategies look like, and what factors increase their effectiveness? (Literature research & data analysis)
Different strategies to monetize imbalance settlements are examined to answer this research question. In addition, approaches that enhance the effectiveness of strategies and features that increase profitability are identified while considering their applicability to EV charging. For this research question, different strategies are found through literature research. The strategies are not always applied to EV charging, but their frameworks and modelling methods could form an inspiration for modelling the steering strategy.

Phase 3: Solution Design
How can the steering policies be modelled? (Modelling)
This research question discovers how the chosen modelling method can be applied, what the modelling procedures are, and what constraints must be followed to ensure feasibility.

How do the steering up and steering down policies differ across the three MDP models, and what are their respective impacts on adaptability and performance? (Modelling)
This research question examines the variations in steering policies among the models, highlighting how each policy contributes to the models' adaptability to changing market conditions.

How can the costs associated with the steered loads (that return in later PTUs) be most efficiently mitigated? (Modelling)
This research question addresses how the strategy should handle the potential costs of steering EV charging sessions. Potential answers could come strategically, technically, or financially. A more strategic approach evaluates the timing of steering and investigates its effects on charging sessions. The technical method examines parameter tuning and the optimization of strike prices. Lastly, a financial approach covers mitigation methods through more intelligent energy procurement, using different energy markets or deviations from the current energy purchasing strategy.

How can the strike price for steering down be made dynamic, and what parameters should have an influence? (Modelling)
The third and most sophisticated policy contains a dynamic strike price for steering down. This research question covers the development method for this dynamic strike price and examines what parameters are convenient to consider.

Phase 4: Evaluation of Performance
What are the results of the proposed steering strategy for TotalEnergies? (Modelling)
This question evaluates the effectiveness of the proposed steering strategy on different topics. It examines the effects of the strategy on the charging behaviour during the field tests and visualizes the outcomes.

How do the inclusion of the DAM optimization and IDM trading influence the performance of the steering policies? (Modelling)
This question investigates the benefits of integrating DAM and IDM into the steering policies, assessing how market participation and the resulting increase in flexibility affect the models' ability to handle the rebound, behaviour towards lost loads, and total expected reward.

In what ways does the dynamic strike price mechanism enhance the flexibility and profitability of the steering strategy? (Modelling)
This question delves into the integration of the dynamic strike price within the MDP models by exploring its functionality and analyzing its role in optimizing charging speeds. It aims to improve the timing of steering to improve the probability of steering during the optimal PTUs and better utilize the full steering potential.

1.6 Research Scope

The research aims to develop a strategy for intelligently steering EV charging sessions to monetize imbalance settlements and maximize profit while contributing to balancing the Dutch electricity grid. A core objective of this undertaking is mitigating undesired balancing costs. The most sophisticated strategy contains, among others, a variable strike price for every PTU within the steering window. This strike price directly influences the strategy's actions and performance and is pivotal for this research.

The research also addresses the management of uncertainties in imbalance settlement prices. This includes exploring various strategic, technical, and financial approaches to effectively handle these uncertainties, as multiple methods are likely feasible and beneficial. Lastly, the strategy must be compatible with the existing smart charging strategy, specifically integrating with the DAM optimization algorithms. The goal is to ensure that the steering strategy functions as an individual component and in combination with existing optimizations.

However, to maintain focus and manageability, certain topics are consciously excluded from the scope of this thesis. For example, speculation on future imbalance prices by holding positions different than the optimized or forecasted demand is outside the scope. The research aims to develop a practical strategy rather than a thorough prediction of market movements. Additionally, current models used for predicting imbalance prices are assumed to be optimal and improving their performance is outside the scope of this thesis. Hence, their predictions are taken as a perfect forecast of the actual imbalance price for that PTU.

Moreover, this research uses existing forecasting methods and algorithms that might include inaccuracies. As this research wants to examine the performance of the steering policies created in this research, the effects of inaccuracies in external forecasts are considered out of scope. This means that the policies in this research are not penalized for forecast errors for energy consumption or the imbalance price per PTU.

This research does not explore the calculation of flexibility within individual charging sessions (the extent to which it can be steered until demand is not fulfilled) or the optimization of load-shifting strategies based on DAM prices, as these are considered to be adequately optimized in historical studies and projects in the company. Furthermore, the potential use of bidirectional charging in the forms of Vehicle-to-Grid (V2G), Vehicle-to-Vehicle (V2V), and Vehicle-to-Load (V2L), which introduce an additional dimension of complexity to a charging strategy and bring regulatory difficulties, are not explored.

Furthermore, this thesis focuses on steering Dutch CPs to bid on the Dutch market for imbalance settlements. The developed strategy must adapt to the behaviour of EV drivers, which could deviate internationally. Moreover, extending the exploration to international imbalance settlement markets brings different market dynamics, as generation methods and market structures strongly deviate per country. Furthermore, it does not consider the financial impacts of energy taxes, distribution fees, or the specifics of delivery rights, as their economic impact is minimal but deviates per region within the Netherlands. Hence, these factors are assumed to not significantly influence the steering strategy's outcomes.

1.7 Conclusion

What is smart charging, and in which situations is it desired?

Smart charging refers to the intelligent management of EV charging sessions by using steering signals to deviate from the regular charging speed. In this research, smart charging aims to optimize the timing of energy usage based on electricity prices, grid conditions, and resulting imbalance prices. Smart charging allows EVs to unlock their flexibility potential towards the grid by dynamically adjusting their charging schedule. This can be based on the DAM prices, the expected flexibility, available renewable energy, grid conditions, and the resulting imbalance price forecasts. This means that during periods of shortages on the grid, smart charging algorithms can decide to temporarily stop charging, while during periods with low DAM prices or high renewable energy availability, charging speeds can be increased to the maximum available speed.

With the increasing integration of RES in the energy system, severe imbalances are observed more frequently and could lead to high costs when deviating from the forecast. Hence, smart charging is desired in situations of (severe) imbalances on the grid to protect CPOs from using more energy than forecasted in PTUs with peaking imbalance prices. This is particularly relevant during PTUs of high volatility in energy consumption and supply, often caused by the fluctuating nature of RES. By synchronizing EV charging speeds with the state of balance on the grid, smart charging helps reduce the need for fossil fuel power plants and minimize consumer electricity costs.

Chapter 2

Theoretical Framework

This chapter discusses how the literature search was conducted. It presents essential topics from the literature to improve understanding of the matter required to develop an effective steering strategy for EV charging sessions. The chosen topics enhance the knowledge of the operational environment, directly relate to the research area, and address the knowledge gap explained in the previous chapter. Examples include energy (imbalance) markets, settlement mechanisms, and integrating EVs on the grid.

2.1 Literature Study

This study follows the PRISMA framework illustrated in Figure 2.1, which structures the literature selection process and makes the systematic review transparent and traceable. This enhances the reliability of the research by ensuring repeatability. The PRISMA framework is widely used for literature studies and serves as a checklist to determine whether literature should be included in research. It provides a flow chart showing the number of studies identified and their inclusion status. This process illustrates the literature search and maintains the quality of the systematic review.

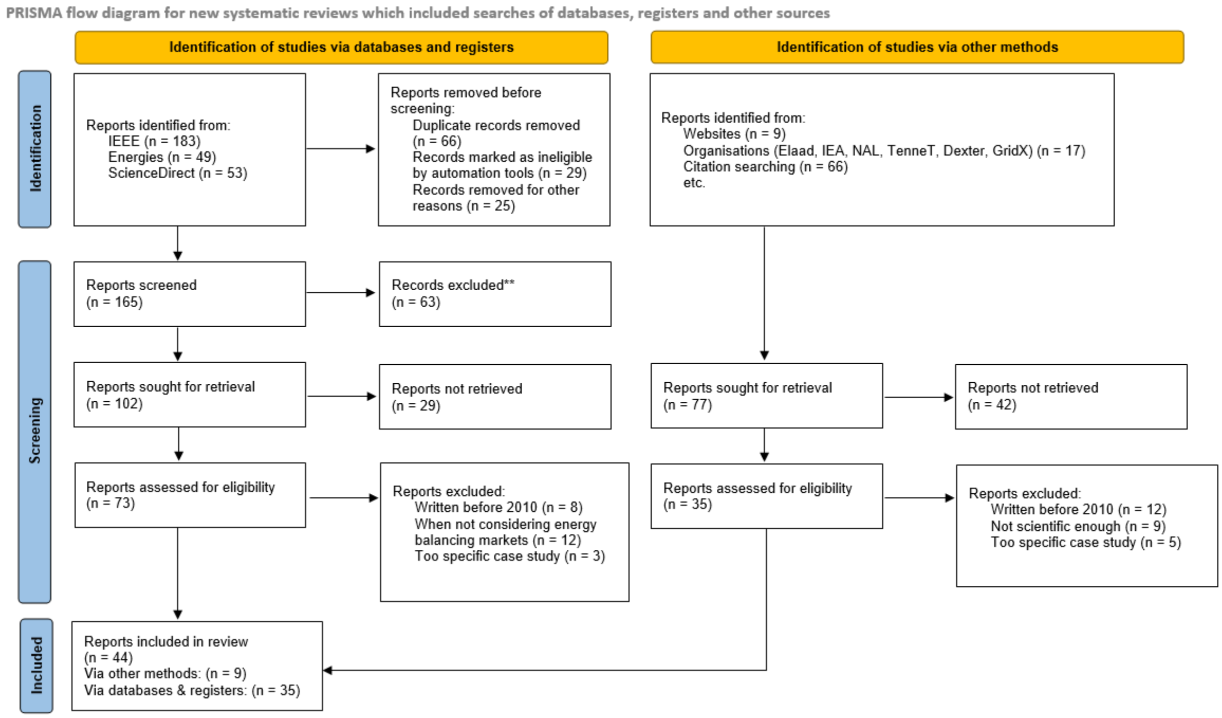


Figure 2.1: PRISMA Flow Diagram for New Systematic Reviews (Page, McKenzie, et al., 2021), Including Searches of Databases, Registers, and Other Sources.

The literature sources for this research are scientifically rigorous and focus on energy markets, preferably in combination with EV charging. The primary sources come from IEEE, which publishes numerous journals and conference papers accessible through IEEE Xplore. Relevant journals include IEEE Transactions, IEEE PES (on Smart Grid Technologies), and Energies, which provide the latest research on EV charging and smart grids. Additionally, Energy Economics is frequently used for its focus on finance in the energy sector. Non-IEEE journals were identified using search engines like Scopus, Google Scholar, and EBSCO.

Search Query Keywords

To search for relevant literature in the literature sources mentioned above, the following keywords have been used:

- (Imbalance Market OR Balancing Market OR Imbalance Settlement) AND (EV OR Electric Vehicle)
- (Imbalance Market OR Balancing Market OR Imbalance Settlement) AND (EV Charging OR Electric Vehicle Charging OR Mobility Charging)
- (Energy Trading OR Trading Algorithm) AND (EV OR Electric Vehicle)
- (Energy Trading OR Trading Algorithm) AND (Balancing OR Smart Charging)
- (Smart Charging OR Intelligent Charging) AND (EV OR Electric Vehicle)
- (Trading Algorithm) AND (Energy Markets OR Balancing Markets OR Imbalance Markets OR Imbalance Settlement)
- (Imbalance Settlement Trading Strategies)
- (Cost Management) AND (Imbalance OR Energy Markets)

Selection Criteria

A well-argumented literature selection process is crucial in securing the validity and reliability of the research. In addition, transparency of the process is required to ensure the integrity and repeatability of this research. This is done by stating the selection criteria in Table 2.1 that cover the reasons for excluding literature from the study.

To ensure the validity and reliability of this research, selection criteria have been established to address reasons for excluding literature from this research. The selection criteria are presented in Table 2.1 and caused the exclusion of 114 references.

Selection Criteria	**Reason**	**Papers Excluded**
Models Published before 2012	It is assumed that before this date, the effects of RES on Dutch energy markets could not yet be modelled accurately (Ball et al., 2022)	14
Written in English	Only English literature is included to ensure repeatability.	0
Considering balancing markets or EV charging	Lack of relevance making the literature inapplicable	31
Decentralized balancing markets	US balancing markets are centralized and, therefore, lack the market mechanism aspect.	6
Non-commercial perspective	The research needs to have the objective of developing a profitable solution instead of conserving the grid	53

Table 2.1: Literature Selection Criteria.

2.2 Literature Review

This chapter reviews the 45 literature studies to form a foundation for this research on steering EV charging sessions for imbalance settlement bidding. We start with an overview of the energy markets, focusing on the balance of supply and demand in DAM and IDM. Next, we examine the integration of EVs into the grid, discussing their potential to enhance grid stability by charging during energy surplus PTUs and contributing to balancing the grid. We then explore smart charging technologies, which optimize EV charging sessions using real-time data analytics to manage grid stress and reduce costs. We also review imbalance markets and settlement mechanisms, explaining how these markets balance scheduled and realized electricity consumption and provide financial incentives. Finally, we address cost management in energy trading, highlighting strategies to handle the potential costs from monetizing imbalance settlements, including using advanced models and decision-making strategies.

2.2.1 Electricity Markets and Settlement Mechanisms

Before physically acting on energy markets, it is crucial to understand the Dutch electricity markets and their relations and dynamics. After being deregulated, the dynamics of the Dutch electricity markets changed and have been studied, for example, in Tanriserver (2015). Similarly to other European markets, the Dutch market transitioned to a liberalized form following the 1998 Electricity Act, giving customers and suppliers greater autonomy in electricity transactions (Jong & Dieperink, 2019). This transition has resulted in a more resilient, sustainable, and efficient market structure, with the vertical supply chain now fragmented among various entities.

Figure 2.2 shows how electricity markets can be segmented into five distinct categories, each serving a specific purpose: forward and futures markets concentrate on long-term contracts to ensure price stability and hedge potential volatility (Kupiec, 2017). The DAM is most importantly used to fulfil the forecasted energy consumption, and the IDM helps to act upon foreseen changes in consumption. The DAM is still the most used market for electricity trading (EPEX, 2024a), as it allows electricity to be traded for each hour of the following day, allowing participants to interact on trends at relatively short notice (EPEX, 2024b). In addition, Figure 2.2 shows how balancing markets provide the energy to directly cover imbalances in the grid using reserve capacity, and imbalance settlements aim to stimulate balancing the grid by real-time steering on system imbalance and compensating or penalizing deviations from the purchased energy amount. However, as actual imbalance settlement prices are unknown and the results are processed afterwards, it is seen as a settlement mechanism instead of an energy market.

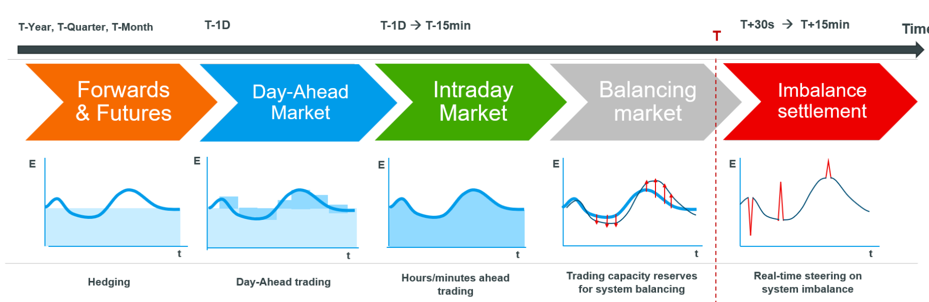


Figure 2.2: Dutch Electricity Markets on Chronological Dispatch (TCSNL Solutions Team, 2023).

Market parties submit their bids on the DAM for the following day before noon. Each bid specifies the offered or demanded energy volume during a certain hour and the price for that energy. A uniform market clearing price is determined at the price where supply and demand intersect. Figure 2.2 shows how TotalEnergies purchases the largest part (area under the curve) of their electricity on the futures market and buys the loads missing in their consumption profile on the DAM. This consumption profile is generated using the energy used in historic EV charging sessions, determining the volume per hour bought on the DAM. However, participation in the IDM is also examined in this research.

Even after the DAM closes, trading is still possible on the IDM, which means that the IDM allows for trading closer to the delivery time. This proximity to delivery time enables better responses to unexpected changes in energy consumption or supply, such as fluctuations in the production of RES or sudden spikes in consumption for EV charging. The IDM includes three market time windows, allowing bids to be placed on loads delivered during 1 hour, 30 minutes, and 15 minutes (EPEX, 2024c). As delivery times approach, the accuracy of forecasts improves. Higher accuracies allow BRPs to bid more aggressively, as the actual value of energy offered on the IDM can be calculated more robustly and be a potential method to cover forecasted short-term imbalances (Kiesel & Paraschiv, 2017). Weron et al. (2023) states that this flexibility leads to higher average prices than the DAM, as market participants may be willing to pay more to secure electricity at short notice. IDM prices combine imbalance settlement prices and DAM prices in wholesale electricity markets (Larrieu, 2016). On the contrary, the research of Wolff and Feuerriegel (2017) argues that nowadays, IDM prices are more affected by volatilities in production from RES, where the prices on the DAM are increasingly influenced by the forecasted generation from RES (Wei, Li, et al., 2021), but still are mainly correlated with the prices of natural gas (Elbourne et al., 2023).

However, if IDM trades do not adequately rectify imbalances in the consumption and production of the purchased energy on the DAM, the Transmission System Operator (TSO) intervenes through the imbalance market to restore equilibrium. Here, all market participants must settle for deviations from the forecasted levels, with prices determined based on the TSO's cost price to rectify the imbalance (Zheng & Wang, 2022).

The energy that is primarily used to cover imbalances on the grid is traded on balancing markets. Participation in balancing markets is comparable with submitting to the DAM, as market parties must submit their bids and specify the offered volume or capacity for extra consumption and the price for that energy in a PTU (Parliament, 2019). As illustrated in 2.3, the point of intersection of the supply and demand curves during a PTU determines the market clearing price per MWh (mid-price) and resulting volumes. This uniform clearing price is established through marginal pricing, where all market participants pay or receive the same clearing price per MWh.

Once the market results are determined, the market participants must convey their commercial trade schedule to the TSO directly or through a chosen BRP. A BRP is a market participant or its chosen representative responsible for its imbalances' (Union, 2017). This trade schedule outlines the planned selling or buying amounts and their feeding or consumption from the system for each time interval. The BRP is accountable for following its schedule after submitting it; any deviations from the position during a PTU result in an imbalance settlement.

2.2.2 Imbalance Markets

Imbalance markets are essential for adjusting the discrepancies between forecasted and actual electricity consumption and production. Wilson and Zhang (2018) provide a comprehensive look at how these markets operate to balance supply and demand in real-time. Thompson (2022) highlights that imbalance settlements incentivize market participants to follow their schedules or compensate for deviations.

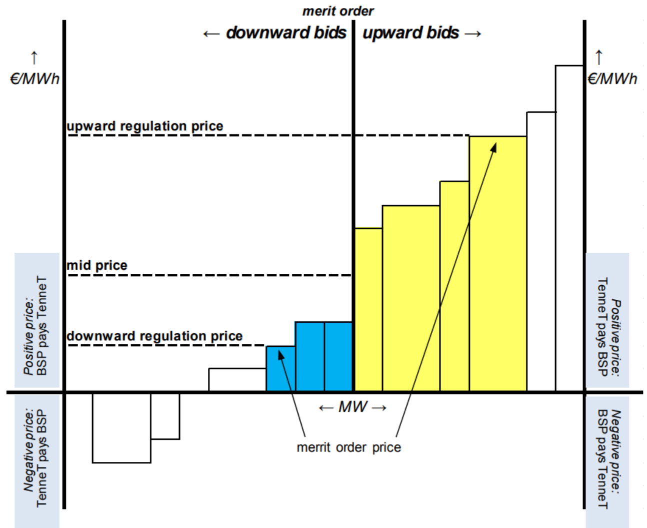


Figure 2.3: Bidding Ladder for Imbalance Regulation (Tennet, 2024).

Each PTU results in a balance delta, which indicates the direction the grid must be balanced by the Transmission System Operator (TSO) (TenneT, 2019a). This delta can be positive (regulating up) or negative (regulating down). The grid regulation states reflect these shifts: -1 (surplus), 1 (deficit), or 2 (direction change). In the Netherlands, imbalances in states -1 and 1 result in equal pricing per MWh (Zheng & Wang, 2022), while state 2 imposes balancing costs regardless of direction (TenneT, 2019b). The price for regulating up or down within a PTU (the imbalance price) is determined by the direct balancing costs incurred by the TSO. Figure 2.3 shows how balancing service providers (BSPs) bid their available energy, with the lowest bids selected to meet grid needs. The imbalance price is calculated from the energy used and the associated balancing costs. This ensures that only the most economically viable energy is utilized for grid balancing.

The price for regulating up or down during a PTU comes from the direct cost for TenneT that comes from grid balancing during a certain PTU, which determines the price for regulating up or down during a certain PTU. Figure 2.3 shows how this imbalance price is determined as balancing service providers (BSP) offer their available energy and receive compensation when the power is used. This bidding happens through a merit order, from which a bidding ladder is created, meaning that prices are sorted from high to low and per MWh demanded, the cheapest option is chosen. Logically, TenneT uses only the required energy during a PTU and calculates the balancing costs per PTU per MWh, which forms the imbalance price. This means that energy offered against a price above the upward regulation or below the downward regulation price will not be used, and the available energy stream of the BSP will not be monetized.

2.2.3 Imbalance Settlement Bidding Strategies

Over the years, many different bidding strategies have been developed for acting on imbalance markets using batteries (M. Bessa, 2012a; Lund et al., 2015; Sioshansi, 2012), hydro reservoirs (Lund et al., 2015; Wang et al., 2021), minimizing balancing costs for RES (Edwards & Li, 2021; Hou et al., 2021; Zhang & Fan, 2019), and even already using EVs (R. Bessa & Matos, 2014; Liu et al., 2013; Masuta & Yokoyama, 2012; Ota et al., 2012; Vagropoulos & Bakirtzis, 2013). However, even per the application method, the bidding strategies deviated from their approach and main objective. Where the strategies of Linda et al. (2022) and Bailey and Gupta (2021) prioritized avoiding exposure towards high imbalance prices, other strategies try to maximize profits by steering EV charging sessions based on only imbalance prices (R. Bessa & Matos, 2014; Rashidizadeh-Kermani et al., 2018; Vagropoulos & Bakirtzis, 2013), or arbitrages between different energy markets (Das et al., 2023; Rashidizadeh-Kermani et al., 2018; Tomašov et al., 2023). It is seen that in most studies, the price component is the leading parameter within steering decisions, and often a penalty is given for uninstructed deviations from the forecast Boomsma et al. (2014) and Koch (2022) or not finishing a charging session (Li et al., 2020; Vagropoulos & Bakirtzis, 2013; van der Klauw et al., 2014).

Moreover, for more simple bidding strategies, the energy of the forecast is bought on the DAM (Klæboe et al., 2022). In contrast, more advanced strategies prefer to buy their energy on the DAM than the IDM (Koch, 2022) or a combination of both (Boomsma et al., 2014). More straightforward strategies using EV charging sessions as underlying energy consumption often limit their focus on the behaviour of individual charging sessions (van der Klauw et al., 2014), whereas more advanced strategies focus on the dynamics of the aggregated energy consumption (M. Bessa, 2013; Shinde et al., 2022; Vagropoulos & Bakirtzis, 2013).

With the rise of reinforcement learning (RL) in the past years, predicting the value of uncertainties within the model using RL has become a more frequently covered topic (Li et al., 2020; Poplavskaya et al., 2020; Shahriar et al., 2020). Nevertheless, Shahriar et al. (2020) shows that studies using RL do not particularly achieve better results, as their focus lies more on prediction accuracy than on using the outcome. In these studies, the bidding strategy itself is rather limited and achieves poorer results than the conventional but advanced strategies mentioned above (Chifu et al., 2024). However, as the integration of RL applications shows potential to get more insight into uncertainties, it could further improve the performance of the more advanced strategies (Davis & Lee, 2023).

The literature review of Rashidizadeh-Kermani et al. (2018) concludes that trading strategies' performance is mainly affected by their flexibility to operate in different energy markets and the risk-aversion of the decision-maker. A case study showed that the ability to choose between buying on the IDM or DAM and both regulate up and down significantly increased profits while costs remained stable. Costs mainly influence the volatility in daily rewards, where strategies that steer more frequently and for longer periods show higher volatility and long-term average profits.

2.2.4 Electric Vehicles and Grid Integration

EVs are increasingly considered integral components of modern energy systems, contributing to environmental sustainability and energy security. Integrating EVs into the grid poses unique challenges and opportunities for grid management. Studies by Smith and Johnson (2020) highlight that EV charging can create significant peaks in electricity consumption, necessitating advanced grid management solutions. Conversely, much research has already been conducted on steering strategies that cover imbalances in the energy production of RES. The study of Jones et al. (2021) and Moncecchi et al. (2021) discusses the potential of EVs to decrease imbalances by charging EVs faster in times of surplus energy from RES, which discovers the potential to regulate down (consuming more than expected). In this case, EVs overcome the waste of this energy, known as curtailment, in times of oversupply.

In the research of M. Amin (2022), an optimization was done on costs and CO2 emissions by adjusting charging rates based on the availability of wind energy. Renewable integration strategies, as discussed by Patel and Kumar (2022), often involve improved energy storage solutions and improved forecasting techniques to mitigate the effects of fluctuations in energy generation.

Furthermore, the research papers of R. Bessa and Matos (2014), Das et al. (2023), and Rashidizadeh-Kermani et al. (2018) and Tomašov et al. (2023) examine the participation of CPOs in imbalance markets. They propose an optimization approach that allows parties to bid in both the DAM and imbalance markets, leveraging the flexibility of EV charging to provide energy in case of imbalances on the grid. This flexibility allows CPOs to contribute to the balance of the grid while optimizing their bidding strategies and reducing charging costs. However, all of these studies regulating down (consuming less than forecasted) is done with V2G technologies, which is outside the scope of this research. Nevertheless, their structures and modelling techniques are still beneficial for this research.

2.2.5 Smart Charging Technologies

As discussed by Hannah et al. (2023), steering strategies have evolved with the rise of smart charging technologies. The flexibility offered by EV charging can be used to respond to imbalances, reducing the need for conventional peak power plants, as described by Hughes and Roberts (2022).
Smart charging refers to the intelligent management of EV charging using steering signals to optimize energy consumption based on the balance on the grid and electricity prices (Alberts et al., 2023). This steering signal is sent when the EV is plugged in. The power with which the EV is charged is determined and communicated with the charging station based on the steering signal. The two most common steering signals are electricity prices and the forecasted consumption (Uiterkamp, 2016).

Brown et al. (2020) defines smart charging frameworks that create steering signals by incorporating real-time data analytics and price forecasts for IDM prices to adjust charging rates dynamically. This technology aims to decrease charging powers during high grid stress while minimizing electricity costs for consumers. Research by Edwards and Li (2021) has demonstrated how smart charging can effectively integrate with RES, ensuring that EVs charge primarily during periods of high renewable production.

The research papers of Liu et al. (2013), Masuta and Yokoyama (2012), and Ota et al. (2012) develop steering strategies for EV charging sessions based on balancing markets. In Figure 2.2, it is seen that this is the initial load that covers for imbalances. These balancing markets handle minute-to-minute random fluctuations, causing slight imbalances. In that regard, the models illustrate possible modelling methods for steering strategy. However, since the strategies cover minute-to-minute volatility, which has a less significant impact on charged loads, this research has not discussed the rebound effect. Moreover, the study of Davis and Lee (2023) introduces RL models that try to predict the charged load of EVs within a charging session and compute the resulting flexibility for steering actions to minimize lost loads. Hence, these models show the potential of RL in steering strategies.

2.2.6 Cost Management in Energy Trading

As energy markets are complex and constantly evolving, unforeseen costs may arise that can form a risk for market participants. Since, from a financial perspective, risks are by default unexpected, and this research computes the model's costs as expected costs, this research only involves cost management. Nevertheless, risk- and cost-management methods are rather similar in structure and, therefore, applicable to this research. The study of R. Weron (2014) the influence of unpredictable external factors, such as unsystematic deviations in weather conditions, on balancing costs in EV charging. Still, it does not consider costs from instructed deviations in charging behaviour. However, unpredictable external factors influence DAM and IDM prices, affecting profit margins. The research of Sorensen and Bolwig (2018) supports the argument that regulatory policies greatly influence energy prices on the DAM, emphasizing the influence of OPEC decisions on electricity prices as they are strongly correlated to oil prices.

However, for CPOs, the costs do not only come from energy price fluctuations affecting IDM and DAM prices. As highlighted in (Jong & Dieperink, 2019), the possible volatility in consumption creates another dimension of uncertainty. Unlike most financial products, energy products are physical products that must be bought or sold during a predetermined PTU.

Monetizing imbalance settlements involves inherent uncertainties, primarily due to future imbalance price uncertainty in PTUs where a rebound is seen. The research of Linda et al. (2022) examines cost management strategies handled by various energy portfolio holders, emphasizing the importance of accurate forecasting and hedging techniques. Additionally, the work by Bailey and Gupta (2021) focuses on applying advanced econometric models to predict imbalance prices and manage associated costs effectively. The research of Hou et al. (2021) created a decision-making strategy for energy companies with a portfolio of RES. The main objective of this strategy was to minimize the financial effects of imbalance, which are linearly penalized. However, in this research, penalties for imbalance are known beforehand and capped with a maximum fee per MWh, which is not the case in practice.

In practice, associated costs might come in the form of opportunity costs - from uncharged (lost) loads (M. Bessa, 2012b) - or deferred imbalance (rebound) costs (Shinde et al., 2022). Lost loads refer to the portion of electricity demand from EV charging sessions that remains unmet due to intentional pausing or slowing of charging. This occurs when the charging session does not reach its desired state of charge (SoC) because of steering actions (Jaruwatanachai et al., 2023). The study of Yi et al. (2019) discusses costs from lost loads and accounts by penalizing unfinished charging sessions. The rebound effect creates a new imbalance that must be settled, potentially incurring additional costs (Thwany et al., 2023).

Lastly, the paper of Shinde et al. (2022) introduces a modified progressive hedging strategy for trading away expected imbalances on the German IDM, with EV charging sessions as underlying consumption. This multistage stochastic programming problem aims to overcome uncertainties in energy demand and price fluctuations forecasted by Monte Carlo simulation.

2.3 Conclusion

The conclusion of this literature review reflects on the literature search process and clarifies the findings of the literature study. The study reviewed research papers and industry reports on smart charging, EV integration into the grid, imbalance settlement bidding, and cost management in energy trading. This section summarizes how the literature was identified, the type of literature reviewed, and the insights gained from these sources. Additionally, an answer is formulated on the research questions that could be handled through a literature study.

The literature for this review was systematically selected through the PRISMA framework in Figure 6.4 to guarantee thoroughness and transparency. During the search process, various databases and keywords relevant to the core topics of smart charging, imbalance markets, and EV grid integration were used. The sources included (peer-reviewed) journals, conference papers, industry reports, and institutional publications to ensure a diverse collection of research papers within the knowledge base for this research. They can be used to answer the first part of sub-research questions.

What do overall imbalance settlement bidding strategies look like, and what factors increase their performance? As stated in 2.2.3, overall imbalance settlement bidding strategies are diverse and can adapt to various applications. The main objectives of these strategies vary from minimizing balancing costs (Hou et al., 2021; Zhang & Fan, 2019) to maximizing profits through arbitrage between different energy markets (Das et al., 2023; Rashidizadeh-Kermani et al., 2018; Tomašov et al., 2023) or steering EV charging based solely on imbalance prices with known SoC and future imbalance prices (R. Bessa & Matos, 2014; Vagropoulos & Bakirtzis, 2013).

Most strategies have in common that price signals are often the leading factor in decision-making, with penalties for uninstructed deviations or incomplete charging sessions (Boomsma et al., 2014; Koch, 2022; Vagropoulos & Bakirtzis, 2013). More straightforward approaches purchase the forecasted consumption only on the DAM (Klæboe et al., 2022), while more advanced strategies may dynamically switch between buying on the DAM and the IDM, which maximizes flexibility (Boomsma et al., 2014; Koch, 2022). Advanced strategies also tend to consider the aggregated behaviour of multiple charging sessions rather than focusing on individual sessions (M. Bessa, 2013; Vagropoulos & Bakirtzis, 2013). The performance of bidding strategies is heavily influenced by the flexibility in energy market participation and the usage of energy assets. According to Rashidizadeh-Kermani et al. (2018), strategies that allow participation in the IDM and DAM while bidding on imbalance settlements yield higher profits with stable costs.

How can steering EV charging sessions be used to monetize imbalances settlement prices?
Figure 2.4 illustrates the amount of energy purchased on the DAM based on the forecasted energy consumption per hour (green line). This forecast serves as the basis for the steering strategy, as it is the fundament for charging revenues and determines the volume for potential steering actions. To monetize imbalance settlements through EV charging sessions, steering actions are triggered when the forecasted imbalance price reaches a predetermined strike price (blue line). When steering down, charging sessions are temporarily paused to reduce consumption in that period. This reduction is a strategic deviation from the forecast and generates an imbalance settlement bid to regulate up. Integrating the existing DAM optimization causes charging speeds to reduce in periods with higher DAM prices (red line). When charging at a reduced rate (caused by DAM price-optimized charging speeds) and steering up (blue line), all charging sessions charge at maximum speed. This causes the charging sessions to consume more energy in that PTU than forecasted and creates a bid for regulating down.

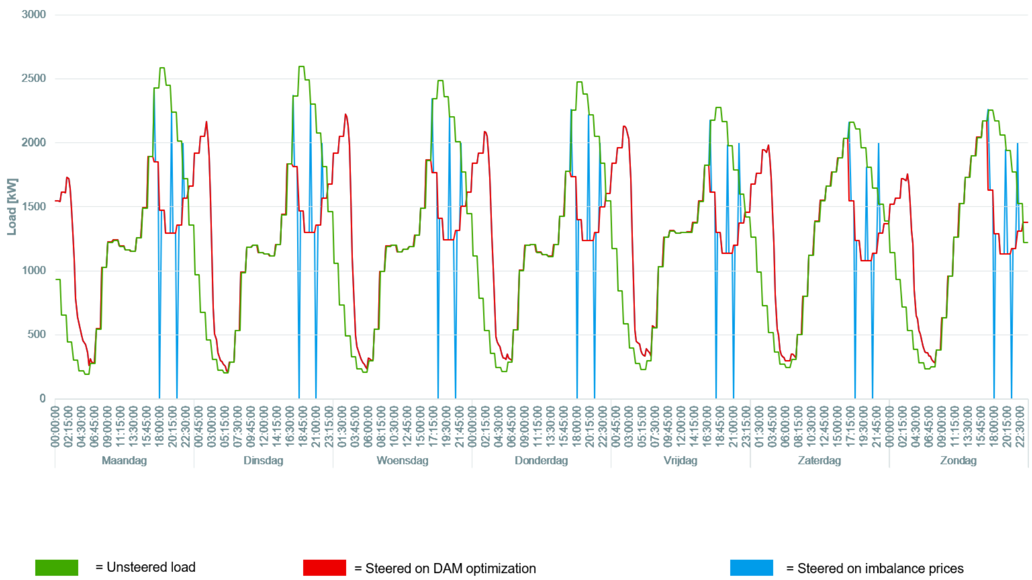


Figure 2.4: Standardized Energy Consumption in Different Charging Profiles

The steered load (in kWh) represents the deviation between the consumption and the forecast in a PTU. The imbalance price (in €/MWh) is the price for regulating up when steering down or for regulating down when steering up. The steering revenue (in €) is calculated based on the direction and size of the deviation from the forecast. It applies to steering up and down:

$$\text{Steering Revenue} = \text{Steered Load} \cdot \text{Imbalance price} \tag{2.1}$$

What potential costs arise when steering EV charging sessions based on forecasted imbalance prices, and how can they be concretized?
Steering EV charging sessions based on forecasted imbalance prices introduces potential costs that must be addressed to ensure an effective steering strategy. The two primary costs come from not fully charging the demanded load after having steered down and the impact of the rebound. The rebound represents the steered load that returns in later PTUs, making the realized consumption deviate from the forecast and creating an imbalance. Without managing this rebound, its impact is unforeseen, and it could lead to higher costs than the steering revenue.

Lost loads occur when EV charging sessions are stopped before they are completed due to the steering-down actions. This can lead to customer dissatisfaction and lost revenues because less energy is sold. The amount of lost loads is computed as an expectation and calculated by a long-term average for each PTU on that weekday in the historical data discussed in Chapter 4. Lost revenues can be calculated as the difference between the revenue from the forecasted consumption and the actual revenue received. More than the probability of hot unplug, the lost revenue directly concertizes the costs of unfinished charging sessions when steering down and is used in this thesis's continuance.

Steering down causes a positive imbalance in later PTUs, and steering up creates a negative imbalance. For later PTUs, imbalance prices cannot be forecasted yet and are still unknown. Hence, the impact of the rebound is only measurable for the next PTU by multiplying the rebound volume with the imbalance price (in €/MWh). A cost forms when imbalance prices to regulate up during later PTUs are higher than the regulate up prices during the steering action. The volume is represented by the deviation (positive or negative) between the forecast and the realized consumption in a PTU. Chapter 3 will continue upon this topic and discuss the developed models and steering policies.

2.3.1 Research Gap and Contribution

Despite the extensive research on imbalance settlement bidding strategies, smart charging technologies, and the integration of EVs into the grid, several topics remain unaddressed in literature. Existing studies focus on maximizing profitability through imbalance price arbitrage or minimizing balancing costs by regulating EV charging behaviours. However, there is a lack of comprehensive models that simultaneously optimize both steering up and steering down actions within the context of the Dutch imbalance settlement mechanisms. Furthermore, while advanced strategies consider aggregated energy consumption dynamics, they often overlook the intricate rebound effects and lost loads that arise from pausing EV charging sessions. These rebound effects, which create subsequent imbalances and incur additional costs, are inadequately quantified and managed in current models.

This research aims to bridge these gaps by developing a novel steering strategy that integrates both steering up and steering down decisions, effectively balancing the dual objectives of maximizing revenue and minimizing balancing costs. By incorporating a scalable and consistent approach to handling charging revenues—albeit using scaled fictional numbers due to confidentiality constraints—this study maintains the dynamic integrity of real-world scenarios. Additionally, it introduces a comprehensive cost management framework that accounts for both the immediate and deferred costs associated with rebound effects and lost loads. This dual optimization approach not only enhances the financial viability of CPOs but also contributes to grid stability and the efficient integration of RES.

Addressing these gaps, this research provides a more holistic and resilient framework for EV charging steering strategies, offering valuable insights for both academia and industry stakeholders seeking to optimize energy trading and grid balancing in increasingly electrified and renewable-driven energy markets.

Chapter 3

Modelling & Policies

This chapter focuses on the three developed models that form the basis of the proposed steering strategy. For each model, we specified a policy that contains decision-rules for steering up and steering down decisions. We begin by explaining the relevant sets and parameters, and follow with the transition formulas and constraints. Hereafter, the distinguishing features and their contribution is discussed for each model. Lastly, the developed methodology to quantify and optimally control costs is elaborated.

3.1 Steering Models

0To develop a steering strategy for EV charging sessions based on imbalance prices, we draw inspiration from the policies proposed in the works of M. Bessa (2012a), Shinde et al. (2022), and Vagropoulos and Bakirtzis (2013) and R. Bessa and Matos (2014), but are significantly adjusted to improve understandability and applicability to our use case. The models are formulated as a Markov Decision Process (MDP) since the outcomes are partly random, affected by uncontrollable factors influencing behaviour and rewards, while our actions control the other part, as is typical in MDPs (Spieksma, 2015). Moreover, the next state depends only on the current state and action, not on prior states or actions. Hence, we created three MDP variants, each containing a policy that states when to steer up and when to steer down. The objective is to optimize the expected cumulative reward by determining optimal actions for each state within the state space.

Formulating the model as an MDP requires defining several components. The MDP optimizes decision-making across 60 discrete stages (t) within the steering window ($\mathcal{T}$). Each stage corresponds to a PTU, and the steering window spans from 17:00 in the evening to 08:00 the following morning. The sets and parameters represent the factors that are not influenced by the actions taken. The state space ($\mathcal{S}_t$) represents all possible operating environments during a PTU using state variables. This includes endogenous state variables ($s_t \in \mathcal{S}_t$), which are directly influenced by the models' actions in a PTU. The model has no exogenous state space since the uncertainty factors follow a non-defined and independent probability distribution. The uncertainties in the model are represented by (some of the) parameters that are given for each PTU and represent the evolving but random uncertainties within the model.

The action space ($\mathcal{A}_t$) is the set of all possible actions in a PTU. For each PTU, one action ($a_t \in \mathcal{A}_t$) is chosen from the action space. The reward function (r_t) calculates the immediate reward per PTU by the state variables from the current en next PTUs and the actions taken in the current PTU.

The total reward (R) is the sum of all immediate rewards (r_t) within the steering window and follows directly from the accumulated reward from steering actions. From each MDP, we retrieve a policy that aims to maximize the total expected reward over time (elaborated on in 3.3).

Given the complexity introduced by fluctuating imbalance prices and extensive state spaces, establishing a unique optimal policy within the MDP framework is challenging. Multiple policies may yield similar cumulative rewards under varying market conditions, indicating that the optimal solution is not necessarily unique. Furthermore, the high dimensionality of the state space would make it computationally impossible, making traditional optimization methods impractical due to the curse of dimensionality. As a result, heuristic-based decision rules are used to overcome these complexities and offer a practical and scalable method to implement the steering policies. Additionally, to ensure that certain variables remain discrete, constraints are incorporated into the model to restrict these variables to integer values. For instance, binary decision variables such as δ_t^{up} and δ_t^{dwn} are constrained to take values in 0, 1, representing a steering action in that PTU. Integer variables like η_t are restricted to non-negative integers to count the number of PTUs steered down. These discrete constraints are crucial for the correctness of the model and ensure that the outcomes are feasible.

3.1.1 Model Notations

To elaborate on the features of each model, mathematical formulations and -notations are made using the following sets, parameters and variables. Note that not every variable is used in each model and this Section represents the sets and variables for Model 3. For all parameters and variables below, the parameters and variables related to regulating down are excluded in Model 1, and the variables related to the IDM are excluded in Model 1 and Model 2.

Sets & Parameters

The sets and parameters presented in 3.1 represent the values on which the policies respond, but on which they do not have an influence. In this research, energy prices are assumed to be entirely random, do not follow a probability distribution, and cannot be categorized as exogenous state variable.

$\mathcal{T}$	Set of PTUs within the daily steering window
$\mathcal{I}$	Set of EV charging sessions ι
SP	Selling price per MWh charged (in € /MWh)
δ^{max}	Maximum number of PTUs in which steering down is allowed
X_t^{dwn}	Strike price for regulating down in t (in € /MWh)
E_t^{fct}	Forecasted energy consumption in t (in MWh)
E_t^{max}	Maximum load that can be charged in t (in MWh)
P_t^{up}	Imbalance price for regulating up in t (in € /MWh)
P_t^{dwn}	Imbalance price for regulating down in t (in € /MWh)
P_t^{IDM}	Price of energy on IDM at time t (in € /MWh)

Table 3.1: Sets & Parameters.

State Space ($s_t \in \mathcal{S}_t$)

The state space consists of endogenous state variables presented in Table 3.2. The state space deviates per stage and is therefore time-dependent. The state space of Model 1 excludes E_t^{dwn} and δ_t^{dwn}.

E_t	Realized energy consumption in t (in MWh)
E_t^{up}	Steered load for regulating up in t (in MWh)
E_t^{dwn}	Steered load for regulating down in t (in MWh)
X_t^{up}	Strike price for regulating up in t (in €/MWh)
δ_t^{up}	Bin. var. indicating if steering down in t
δ_t^{dwn}	Bin. var. indicating if steering up in t
Δ_t	Volume of the rebound in t (in MWh)
η_t	PTUs steered down in steering window at start of t

Table 3.2: Endogenous State Variables.

Actions ($a_t \in \mathcal{A}_t$)**:**

The possible actions per PTU are shown in Table 3.3, representing the action space. However, the action space of Model 1 excludes steering up and IDM trading actions, while the action space of Model 2 excludes IDM trading actions.

Action	**Mathematical Representation**
Steer up	$E_t = E_t^{\max}$
Steer down	$E_t = 0$
Sell on IDM	$E_t^{\mathrm{IDM}^-} = E_t^{\mathrm{fct}} - E_t$
Buy on IDM	$E_t^{\mathrm{IDM}^+} = E_t - E_t^{\mathrm{fct}}$
Steer to forecast	$E_t = E_t^{\mathrm{fct}}$
Do not steer	$E_t = E_t^{\mathrm{fct}} + \Delta_t$

Table 3.3: Possible Actions per PTU.

For all given periods (of one PTU) and states $(t, s_t, w_t) \in \mathcal{T} \times \mathcal{S}_t \times \mathcal{W}_t$, one action is taken. The resulting policy is a collection of decision-rules that determine the action for every state, resulting in an immediate reward for the PTU and a transition to the next PTU.

Rewards ($r_t \in \mathcal{R}$)

The reward function of the model aims to maximize the total expected cumulative reward over the steering window. It achieves this by summing the expected immediate rewards for each PTU derived from the actions taken in each state. By improving upon the heuristics-based decision rules and selecting the optimal policy from the set of all possible policies, we aim to find the strategy that yields the highest expected cumulative reward. This relationship is mathematically represented as:

$$\max_{\pi \in \Pi} \mathbb{E}\left[\sum_{t \in \mathcal{T}} r_t\left(s_t^{\pi}, A_t^{\pi}(s_t^{\pi})\right) | (s_{t-1})\right] \tag{3.1}$$

The immediate reward in each PTU results directly from the action taken during that PTU. For all models, this reward is calculated in every PTU using the formula provided below. All components within the formula represent financial outcomes measured in euros.

$$\text{Immediate Reward}_t = (\text{Charging Revenue}_t) + (\text{Imbalance Result}_t) - (\text{Impact of Rebound}_t) \quad \forall t \in \mathcal{T} \tag{3.2}$$

Assuming that the forecasted energy consumption is perfect. The charging revenue is, therefore, derived from the forecasted energy consumption minus the lost loads caused by steering actions. This calculation leads to the realized consumption and the corresponding revenue, which is computed using the following formula:

$$\text{Charging Revenue}_t = (\text{SP} \cdot E_t) \quad \forall t \in \mathcal{T} \tag{3.3}$$

The imbalance result comes from instructed steering up or steering down actions and is calculated by the formula:

$$\text{Imbalance result}_t = \left(E_t^{up} \cdot P_t^{up} + E_t^{dwn} \cdot P_t^{dwn}\right) \quad \forall t \in \mathcal{T} \tag{3.4}$$

As discussed in Section 3.3, the value of the rebound ($\widetilde{P}_t^{\Delta}$), measured in €/MWh, is minimized using a comparison between the imbalance price and IDM price in the PTU:

$$\widetilde{P}_t^{\Delta} = \min\left(P_t^{IDM}, P_t^{up/dwn}\right) \tag{3.5}$$

Lastly, the minimized value of the rebound enables calculating the impact of the rebound through:

$$\text{Impact of Rebound}_t = \text{Value of Rebound} \cdot \text{Volume of Rebound}$$

$$\text{Impact of Rebound}_t = \widetilde{P}_t^{\Delta} \cdot \Delta_t \tag{3.6}$$

The value of the rebound when accepting the imbalance ($\Delta_t \cdot P_t^{up/dwn}$) depends on the regulation state in that PTU. If compensated for regulating up, the imbalance price corresponds to the price for regulating up; similarly, if compensated for regulating down, the imbalance price corresponds to the price for regulating down. Consequently, a positive rebound has an unfavourable (positive) value when compensated for regulating up, and a negative rebound carries an unfavourable value when compensated for regulating down. The rebound value is therefore calculated as follows:

$$P_t^{up/dwn} = \begin{cases} P_t^{up} & \text{if} \quad RS = 1 \quad \text{(reg. up)} \\ -P_t^{dwn} & \text{if} \quad RS = \text{-1} \quad \text{(reg. down)} \end{cases}$$

As discussed in Section 3.3, a positive rebound generally results in additional costs, so all minimization outcomes are treated as positive by default. However, because regulating down compensates for the rebound in the opposite direction, its value must be represented as the negative product of its price. Additionally, since IDM prices are negative only 3.7% of the time during the steering window, selling the negative rebound on the IDM yields extra profit 96.3% of the time.

Thus, the total reward ($\mathcal{R}$) is calculated as the sum of all immediate rewards (r_t) within the steering window ($\mathcal{T}$), as shown below:

$$\mathcal{R} = \sum_{t=1}^{\mathcal{T}} \left[(\text{SP} \cdot E_t) + (E_t^{up} \cdot P_t^{up} + E_t^{dwn} \cdot P_t^{dwn}) - (\Delta_t \cdot \widetilde{P}_t^{\Delta})\right] \tag{3.7}$$

Transition Formulas

Transition formulas are given for the endogenous state variables to capture the dynamics of the model and define the values or ranges of its state variables. Since the first model does not account for the ability to regulate down (steer up), equations 4, 6, and 7 do not apply, and equation 9 would be limited to the last two options.

1. Calculation of Aggregated Load:

$$E_t = \sum_{\iota \in \mathcal{I}} E_t^{\iota} \qquad \forall (\iota, t) \in I \times \mathcal{T} \tag{3.8}$$

The realized (aggregated) energy consumption in each PTU aggregates the energy used in each charging session (ι) during that PTU.

2. Measurement of Upward Regulation Volumes:

$$E_t^{up} = \begin{cases} E_t - E^{fct} & \text{if} \quad E^{fct} > E_t \\ 0 & \text{if} \quad E^{fct} \leq E_t \end{cases} \quad \forall t \in \mathcal{T} \tag{3.9}$$

As the energy for regulating up indicates to what extent a negative deviation from the forecasted energy consumption is seen, the energy used for up-regulating cannot exceed the forecasted consumption during each PTU.

3. Measurement of Downward Regulation Volumes:

$$E_t^{dwn} = \begin{cases} E_t^{max} - E_t^{fct} + \Delta_t & \text{if} \quad E^{fct} < E_t \\ 0 & \text{if} \quad E^{fct} \geq E_t \end{cases} \quad \forall t \in \mathcal{T} \tag{3.10}$$

The energy for regulating down indicates to what extent a positive deviation from the forecasted energy consumption is seen. The volume used for down-regulation cannot exceed the amount with which the charging speed can be increased compared to the forecasted consumption plus the rebound volume during each PTU.

4. Strike Price Constraint for Regulating Up Steering Actions

$$\delta_t^{up} = \begin{cases} 1 & \text{if} \quad (X_t^{up} \leq P_t^{up}) \wedge (\eta_t \leq \delta^{max}) \\ 0 & \text{otherwise} \end{cases} \quad \forall t \in \mathcal{T} \tag{3.11}$$

Indicates if regulating up would be allowed in that PTU since regulating up is allowed only if the price for regulating up exceeds the stated strike price for regulating up and the maximum frequency for steering down has yet to be reached.

5. Strike Price Constraint for Regulating Down Steering Actions

$$\delta_t^{dwn} = \begin{cases} 1 & \text{if} \quad X_t^{dwn} \geq P_t^{dwn} \\ 0 & \text{otherwise} \end{cases} \quad \forall t \in \mathcal{T} \tag{3.12}$$

Steering up is only allowed if the price for regulating down is above the stated strike price for regulating down.

6. Determination of the Dynamic Strike Price

$$X_t^{up} = \text{SP} \cdot \left(1 + \alpha \cdot \Delta_t + \beta \frac{t}{\mathcal{T}} + \gamma \frac{\delta_t}{\delta^{max}}\right) \tag{3.13}$$

In the third model, the strike price for regulating up is dynamic and aims to optimize the timing of steering decisions based on the size of the rebound in PTU t, the remaining PTUs in the steering window, and the number of remaining steering acitons. The more details regarding the formula for the dynamic strike price are discussed in Section 3.2.4.

7. Measurement of Total Upward Regulation Frequency

$$\eta_t = \eta_{t-1} + \delta_{t-1} \quad \forall t \in \mathcal{T} \tag{3.14}$$

The total number of steering times within the steering window time frame is measured with η_t*, whose value increases by 1 when steering in a PTU.*

8. Volumes of the Rebound

$$\Delta_t = \begin{cases} E_t^{IDM^+} & \text{if} \quad (P_t^{IDM} \leq P_t^{up}) \wedge (\Delta_t > 0) \\ -E_t^{IDM^-} & \text{if} \quad (P_t^{IDM} \geq P_t^{dwn}) \wedge (\Delta_t < 0) \\ E_t^{dwn} & \text{if} \quad (X_t^{dwn} \leq P_t^{dwn}) \wedge (\eta_t \leq \delta^{max}) \\ 0 & \text{if} \quad (\mathbb{E}[E_t^{fct} - E_t] \cdot \text{SP}) < \left(\Delta_t \cdot \widetilde{P}_t^{\Delta}\right) \\ \Delta_t & \text{otherwise} \end{cases} \qquad \forall t \in \mathcal{T} \tag{3.15}$$

Whenever IDM trading optimizes the impact of the rebound on the immediate reward in PTU t, the volume of the rebound (Δ_t) *is represented as the traded volume. As selling energy on the IDM creates a negative deviation, the variable becomes negative. When the imbalance price for regulating down is higher than the strike price, the volume of the rebound is used to regulate down. Moreover, when the expected value of the lost loads is less than the impact of the rebound, we steer to zero and make the rebound impactless in that PTU. Lastly, when it is advantageous to accept imbalance,* Δ_t *is maintained and represents the unintended imbalance.*

Model Constraints

1. Band Width of Charging Speeds per Charging Session

$$0 \leq E_t^{\iota} \leq E_t^{\iota,max} \qquad \forall (\iota, t) \in I \times \mathcal{T} \tag{3.16}$$

In the models in this research, charging speeds within each charging session (ι) *cannot become negative and are limited by the maximum charging speed the grid connection allows.*

2. Determination of Actual Consumption:

$$E_t = E_t^{fct} - E_t^{up} + E_t^{dwn} + E_t^{IDM} + \Delta_t \tag{3.17}$$

The realized energy consumption during a PTU can only be influenced by steered volumes, volumes from the IDM and the volume of the rebound.

3. Limitation of Volumes Traded on IDM

$$E^{IDM^{+/-}} \leq |\Delta_t| \tag{3.18}$$

As speculation on the direction of energy prices is out of scope for this research, the volume of bought and sold energy on the IDM cannot exceed the volume of the rebound.

4. Non-subsequent Steering

$$\delta_t^{up} \leq 1 - \delta_{t-1}^{up} \tag{3.19}$$

A steering action can only be made when the previous PTU was not steered down.

5. Limitation on Frequency of Regulating Up

$$\eta_{\mathcal{T}} \leq \delta^{max} \tag{3.20}$$

To avoid having too many charging sessions that do not reach completion and losing too much charging revenues, steering down is permitted only for a limited number of PTUs within the steering window. Therefore, the number of PTUs steered down during the steering window ($\eta_{\mathcal{T}}$) must be less than or equal to the maximum number of PTUs for which steering down is permitted (δ^{max}).

6. Integer Variables

$$\eta_t \quad \in \mathbb{Z}^+ \quad \forall t \in \mathcal{T} \tag{3.21}$$

$$\iota \quad \in \mathbb{Z}^+ \quad \forall \iota \in I \tag{3.22}$$

$$\delta_t^{max} \quad \in \mathbb{Z}^+ \quad \forall t \in \mathcal{T} \tag{3.23}$$

The number of steering decisions already taken at the start of a PTU (η_t), EV charging sessions (ι), and the maximum number of PTUs in which steering down is allowed (δ_t^{max}) can only have positive integer values.

3.1.2 Model 1 Equations

The first and simplest model represents and approximates the current situation, being the steering strategy of TotalEnergies at the start of the research. Figure A3 shows the mathematical representation of the policy, which can only steer down or steer to the forecast. When not steering, EVs charge at the maximum speed. The reward for this model is based solely on charged loads, steering-down actions, and the impact of the rebound. The imbalance result, which is calculated by the formula below, arises only from instructed steering down actions, which are calculated by the formula:

$$\text{Imbalance result}_t = \sum_{t=1}^{\mathcal{T}} (E_t^{up} \cdot P_t^{up}) \tag{3.24}$$

The volume of the rebound Δ_t can be made zero when steering to the forecast, making the rebound impactless. However, it cannot be traded away on the IDM, and is therefore calculated through:

$$\text{Impact of the Rebound}_t = \left(\Delta_t \cdot P_t^{up/dwn}\right) \tag{3.25}$$

Note that the total rebound will extend across multiple PTUs, but the equation above only addresses how this rebound is handled within the current PTU. The method of treating the rebound in later

PTUs cannot be determined since imbalance prices are still unknown for those PTUs.

When combining the equations above, we can calculate the immediate reward for Model 1:

$$r_t = \sum_{t=1}^{\mathcal{T}} \Big[(\mathrm{SP} \cdot E_t) + (E_t^{up} \cdot P_t^{up}) - (\Delta_t \cdot P_t^{up/dwn}) \Big] \tag{3.26}$$

In addition to the equations stated in 3.1.1, as the charging speed is set to the maximum charging speed by default, only Model 1 is subject to the following constraint related to regulating up:

$$E_t^{up} \leq E_t^{fct} + (1 - \delta_t^{up}) \quad \forall t \in \mathcal{T} \tag{3.27}$$

If the price for regulating up exceeds the strike price for regulating up, the consumed amount of energy cannot exceed the forecasted consumption.

3.1.3 Model 2 Equations

Building on the first model, the second model introduces additional parameters and variables related to steering up (regulating down). Its mathematical framework is illustrated in the Appendix, with Figure A4 showing steering down and Figure 3.5 depicting steering up. These include the strike price (X_t^{dwn}) (in €/MWh), the binary variable indicating steering up for regulation down ($\delta^{dwn}t$), and the steered load for regulating down ($E^{dwn}t$). Additionally, the action of steering up ($E_t = E_t^{max}$) is incorporated into the action space.

For the reward calculation, the charged loads and the impact of the rebound follow the same approach as the policy in Model 1. However, the imbalance result now also accounts for steering up (to regulate down), leading to the following imbalance result formula:

$$\text{Imbalance result} = \sum_{t=1}^{\mathcal{T}} \Big(E_t^{up} \cdot P_t^{up} + E_t^{dwn} \cdot P_t^{dwn} \Big) \tag{3.28}$$

The calculation of the reward per PTU:

$$r_t = \sum_{t=1}^{\mathcal{T}} \Big[(\mathrm{SP} \cdot E_t) + (E_t^{up} \cdot P_t^{up} + E_t^{dwn} \cdot P_t^{dwn}) - (\Delta_t \cdot P_t^{up/dwn}) \Big] \tag{3.29}$$

3.2 Model Intuition

It is illustrated in Figure 3.1 how each successive model shows increased feature capabilities, complexity and adaptability to market conditions. This progression enables the policies to better coordinate with uncertain external factors, manage costs more effectively, and enhance profit potential. After the detailed modelling, we discuss in 3.3 how to quantify the costs associated with steering actions. Lastly, the method for determining the dynamic strike price is discussed in Section 3.2.4 and how it adapts to changing market conditions.

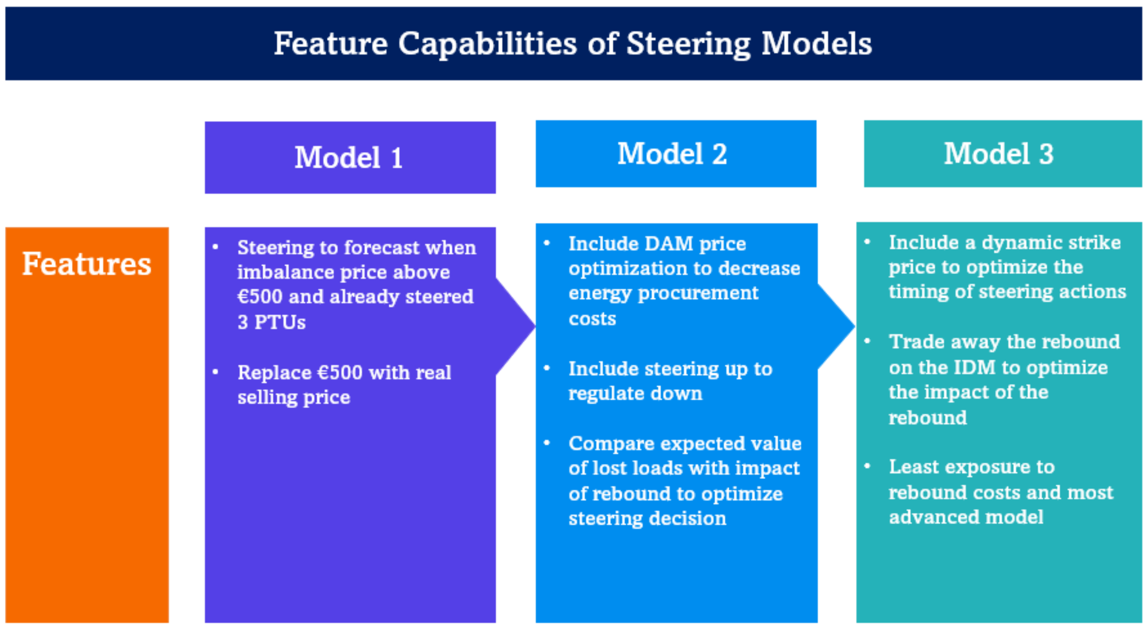


Figure 3.1: Overview of the Features of the Models.

3.2.1 Assumptions of the Models

Before introducing the models, several key assumptions are made to simplify the modelling process. Firstly, the model treats forecast inaccuracies in both imbalance prices and hourly consumption as out of scope, using a deterministic approach to optimize charging speeds based on imbalance prices, chargeable load in the upcoming PTU, and expected lost loads. Inefficiencies or delays in steering actions are also not considered; steering down is assumed to reduce the charged load in a PTU to 0 kWh.

Since SoC at arrival and the exact arrival and departure times are unknown in advance, we calculate the impact of steering actions on charged kWhs by back-testing on a large dataset of historical charging sessions. This data allows us to derive customer patterns, as most consumption follows daily or weekly trends (M. Bessa, 2013). Based on these patterns, the lost load and the probability of a hot unplug can be estimated (Ansari & Keypour, 2023). Finally, energy costs incurred to meet the forecast are considered sunk costs and do not influence the rewards from steering actions.

3.2.2 Model 1: Optimization on Imbalance Prices for Regulating Up

Model 1 represents the simplest improvement on the current situation and overcomes high balancing costs within the steering window. Model 1 provides a policy for only steering down, which is defined in 3.2, and aims to generate additional revenue and mitigate high balancing costs by steering down when regulate-up prices are high. This policy is limited to steering down during three non-consecutive

PTUs or steering to the forecast within the steering window and charges at maximum speed otherwise. Steering to the forecast happens when a valuable rebound is detected. A more extended explanation of the policy is given in 6.4, and the equations that specifically hold for Model 1 are given in 3.1.2. In this section it is given that the reward is calculated by accumulating charging revenues, results from steering down, and the impact of eventual rebounds.

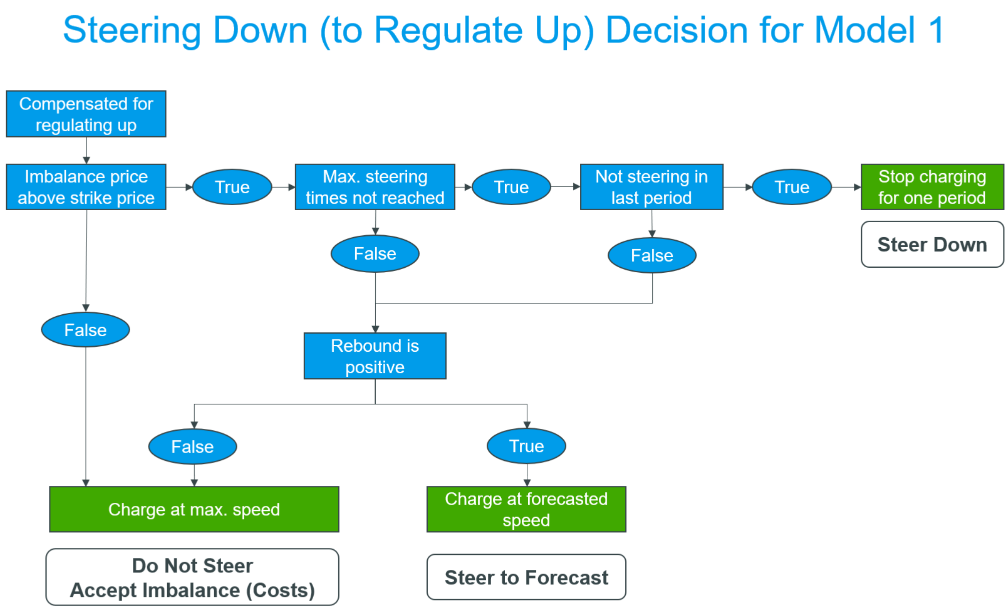


Figure 3.2: Steering Decisions for Model 1.

3.2.3 Model 2: Optimizing on Imbalance and Day-Ahead Market Prices

Building upon Model 1, Model 2 follows the decision-rules in Figure 3.4 for steering down and incorporates DAM prices to optimize charging schedules. DAM prices deviate per hour and are known beforehand. Therefore, energy costs from DAM prices can relatively easily be optimized by charging slower when prices are high and faster when prices are low. The exact charging speeds are determined using the framework of Van Dijk (2021) and shown in Figure 3.3, which illustrates how this delays part of the charged loads to later in the night. This optimization yields an optimized load curve (E_t^{opt}) as shown in Figure 3.3, which replaces the forecasted (unsteered) load curve (E_t^{fct}) in both this model and Model 3. Nevertheless, this optimization does not influence steering down decision-rules and operates independently from the policies developed in this research.

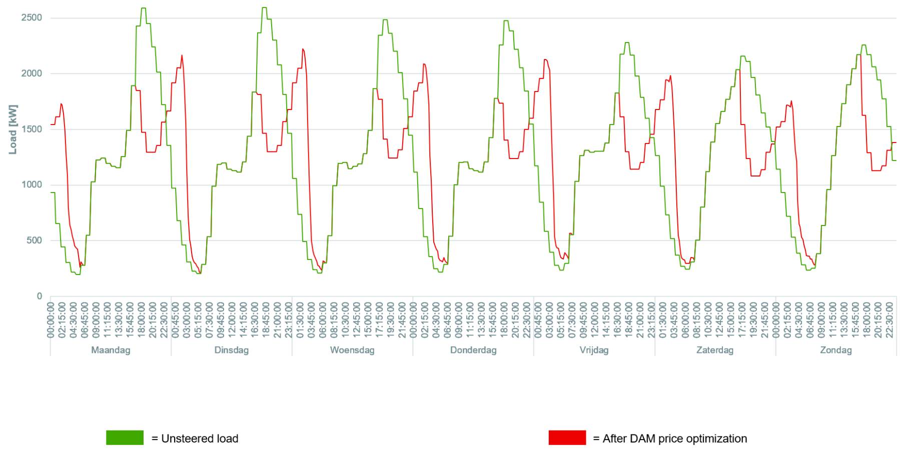


Figure 3.3: The DAM Optimized Load Curve.

Moreover, as the DAM optimization by default reduces charging speeds, the opportunity for steering up (charging faster) arises. For steering up, Model 2 follows the decision-rules of Figure 3.5 to determine its actions. Charging faster further increases the imbalance result when compensated for regulating down. Additionally, since charging faster reduces the time required for the vehicles to reach full SoC, the likelihood of loads remaining uncharged decreases. Hence, expected lost loads and eventual rebounds decrease, charging revenues increase, and customer satisfaction increases. Furthermore, when EVs charge faster in earlier PTUs, less energy is used in later PTUs. This creates a negative deviation from the scheduled (optimized) consumption, which can be beneficial when compensated for regulating up but introduces costs when compensated for regulating down.

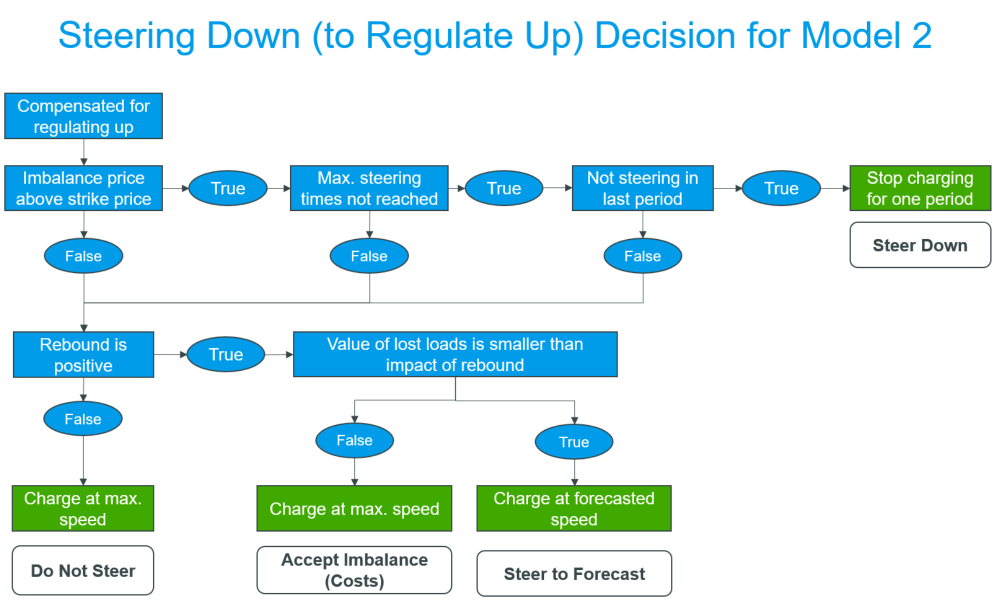


Figure 3.4: Steering Down Decision for Model 2.

The primary goals of Model 2 are: (1) to increase profitability by aligning charging speeds with low DAM prices, thus reducing energy procurement costs; (2) to monetize imbalance prices by both steering down (regulating up) and steering up (regulating down) when advantageous; and (3) to reduce expected lost loads and increase customer satisfaction by charging faster than the optimized load curve when appropriate. Since charging at reduced speeds increases the expected lost loads, Model 2 could show higher potential costs than Model 1 when not mitigated. However, Model 2 introduces steering up to (partially) manage the rebound effect and reduce the expected lost loads. The reward for Model 2 considers the imbalance results from both steering down and steering up actions, as well as the impact of the rebound.

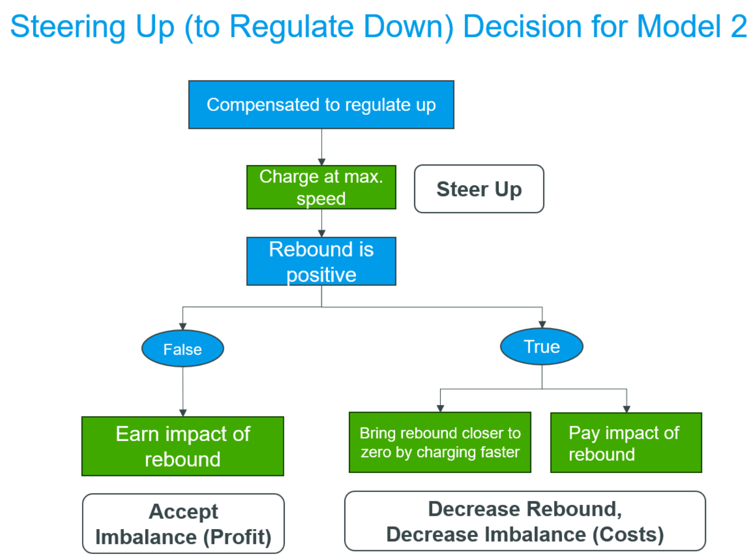


Figure 3.5: Steering Up Decision for Model 2.

3.2.4 Model 3: Optimizing on Imbalance and Day-Ahead Market Prices Using the Intraday Market

Model 3 builds upon the policy introduced in 3.2.3. It enhances procurement decisions and the timing of steering by utilizing the IDM for handling rebounds and incorporating a dynamic strike price. Via this method, the policy uses a finite timeframe by considering the number of PTUs until the end of the steering window. Other policies lack this consideration of time-based decisions, resulting in sub-optimal steering decisions. Hence, this model offers the most advanced policy for both upward and downward steering and represents the proposed steering strategy that results from this research.

For steering up, Model 3 follows the decision-rules outlined in Figure 3.6. As discussed in Section 2.2.1, the IDM permits trading until five minutes before the start of the PTU. This allows for better management of costs associated with negative rebounds when compensated for regulating down. In such cases, the excess energy (negative rebound) can be sold on the IDM and provides an additional source of profit. When compensating for regulating up, this excess energy can either be sold on the IDM or used for upward regulation. The decision between these options is determined by the respective prices. IDM prices tend to be less volatile and are not based on forecasts, making selling on the IDM the preferred action when prices are comparable.

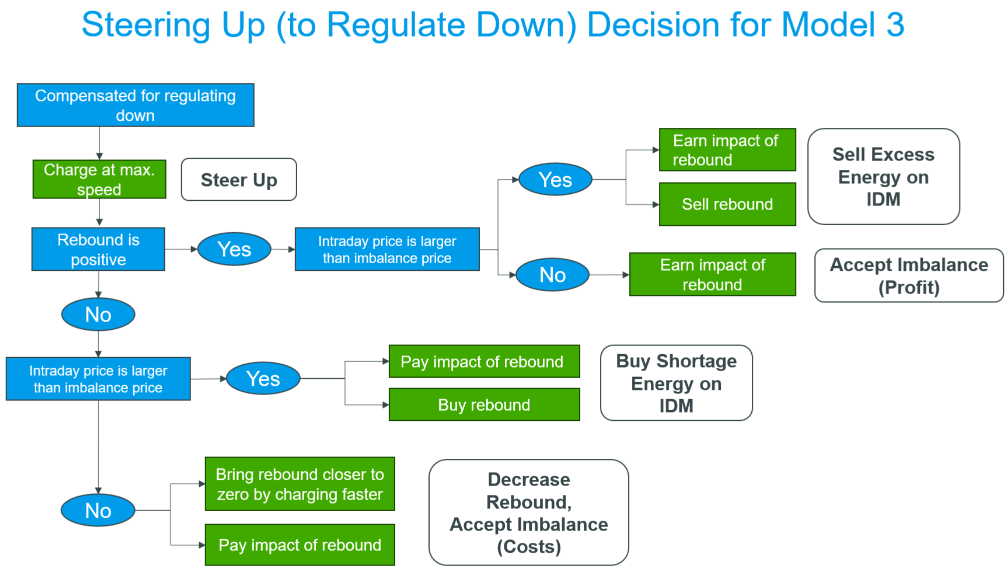


Figure 3.6: Steering Up Decision for Model 3.

Additionally, when deciding on steering down, Model 3 follows the decision-rules presented in Figure 3.6. The figure illustrates that the IDM can also be used to purchase energy when there is a positive rebound (deficit) and when prices for regulating up are higher than the IDM price. By default, the policy would limit the charged load in that PTU to the optimized consumption, accepting the possibility of lost loads and incomplete charging sessions. However, this issue can be mitigated by purchasing additional energy on the IDM equal to the volume of the rebound, thereby ensuring charging sessions are completed.

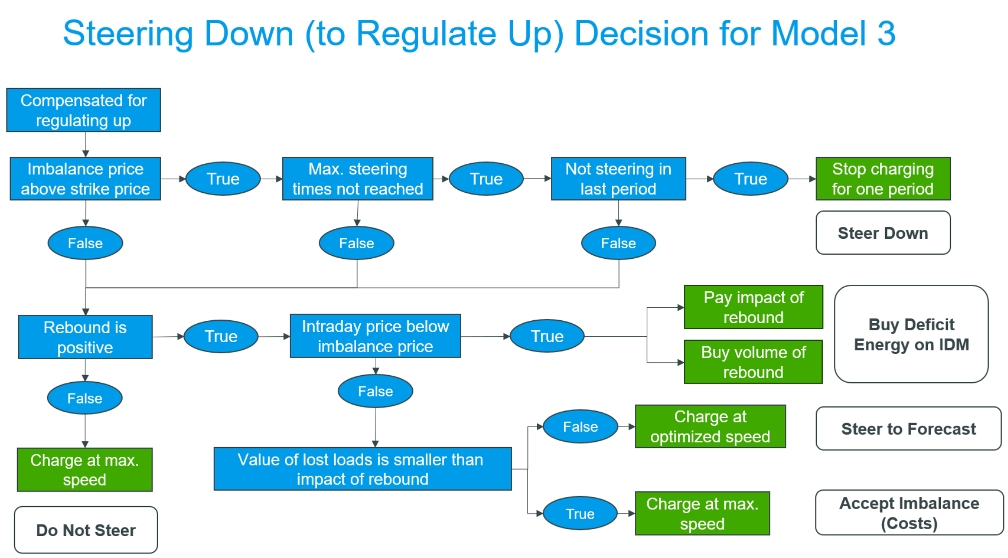


Figure 3.7: Steering Down Decision for Model 3.

Integrating IDM trading aims to optimize the value of the rebound by selecting the best option among accepting the imbalance, trading on the IDM, or adjusting charging speeds. This adaptability is expected to further enhance profit opportunities and improve cost management. Since IDM prices are less volatile and have lower price peaks than imbalance prices for regulating up, trading on the

IDM provides a more constant alternative for the value of the rebound. In addition to the actions possible in Model 2, Model 3 includes buying and selling on the IDM. The ability to trade on the IDM improves the model's cost management capabilities, as the rebound effect can be actively managed. Negative rebounds (excess energy) can be sold on the IDM. Optimizing the impact of the rebound (by comparing imbalance and IDM prices) is expected to make the policy from Model 3 achieve higher rewards than the previous policies due to its enhanced flexibility and optimization strategies.

Dynamic Strike Price

Another critical aspect of the intelligent steering strategy is the dynamic strike price for steering down. This mechanism adapts to fluctuating conditions throughout the day by adjusting the imbalance price at which a steering action is triggered, balancing profit and cost potentials. In this calculation, the coefficients α, β, and γ are optimized to account for the impact of changes in the rebound volume, the number of expired PTUs within the steering window, and the number of PTUs already steered down. Under comparable circumstances, a higher strike price may lead to less frequent steering-down actions. Lower strike prices might lead to more frequent steering down actions and increased reward potential. On the other hand, when steering more frequently, the constraints regarding steering in subsequent PTUs and the maximum steering-down frequency might increase the chance of missing out on the most optimal steering times.

The formula for the dynamic strike price for steering down (X_t^{up}) is defined as:

$$X_t^{up} = \text{SP} \cdot \left(1 + \alpha \cdot \Delta_t + \beta \frac{t}{\mathcal{T}} + \gamma \frac{\delta_t}{\delta^{max}}\right) \tag{3.30}$$

Where the current PTU t (for $t = 1, 2, ..., 60$) represents the t^{th} PTU in the steering window $\mathcal{T}$. Additionally, δ^{max} represents the maximum number of PTUs allowing steering down within the steering window. In Equation 3.30, α determines the sensitivity of the strike price to the volume of the rebound, where a higher α may indicate a higher strike price, potentially decreasing the number of times steering down. β increases the strike price as time progresses to avoid missing the optimal period and γ discourages using steering options before the optimal time. The resulting strike price is used to maximize Equation 3.7, calculating the total reward.

This optimization of the values of α, β, and γ, is done through a grid search using historical data to test the simulated performance of every combination of coefficients. Even though grid searches are computationally extensive, this method is the most fitting as the optimization needs infrequent repeating and guarantees the optimal combination of values. The resulting values for α, β, and γ remain fixed until a trend deviation is seen for one of the variables in the formula. Meanwhile, the strike price for regulating down is much easier, as for every $P_t^{dwn} > 0$, it is beneficial to charge faster than expected.

3.3 Cost Management

Before creating a steering strategy for EV charging sessions to monetize imbalance settlements, it is crucial to be aware of the costs that come with it. Yet, managing costs is only possible when they are measured and preferably appropriately quantified. In this model, this is challenging due to their dependence on the value of the rebound and the lost revenue (from uncharged kWhs of unfinished sessions). The value of the rebound (€/MWh) depends on its direction (positive or negative) and can change per PTU as affected by imbalance prices. On the other hand, lost revenues are purely based on an expectation. Moreover, both uncertainties develop over time, which adds another dimension of complexity. This chapter elaborates on the methods used to measure and manage costs from the expected lost revenue and the impact of the rebound.

If revenues from selling energy decrease, as charging sessions become unfinished and less energy is sold, steering down actions can lead to lost revenue. When the revenue from steering down cannot cover the lost revenue, this could form a cost. Additionally, for both up- and down-steering, the rebound might affect the immediate reward from steering actions when not being acted upon. In all policies, the volume of the rebound is limited when its value per MWh reaches above the strike price for steering down. In the policies of Model 2 and Model 3, this is done by comparing the impact of the rebound with the expected lost loads. The policies could act upon this cost by steering to the forecast, making the volume of the rebound unable to become positive in that PTU. This is triggered when the imbalance price for regulating up exceeds the strike price, creating the following constraint:

$$\Delta_{t+1} \begin{cases} > 0 & \text{if} \quad P_t^{up} \leq X_t^{up} \\ = 0 & \text{if} \quad P_t^{up} > X_t^{up} \end{cases} \tag{3.31}$$

Furthermore, in the policy of Model 3, the impact of the rebound is limited by buying energy on the IDM when the rebound becomes more valuable than the energy price on the IDM. Hence, Model 3 minimizes the negative impact of the rebound by either steering to the optimized load curve or buying the volume of the rebound on the IDM.

The sum of the expected lost revenues and the impact of the rebound in a PTU is represented as the expected costs from steering actions per PTU ($\mathbb{E}[C_t]$). The calculation of expected costs is compared with expected revenue. If the expected costs exceed the expected revenue, the steering action will not proceed. The formula for calculating the expected revenue is provided in 3.4, but differs in Model 1 since steering up is not yet incorporated.

Moreover, the above-mentioned strategies aim to minimize the expected costs from steering actions for every PTU within the steering widow. This minimization is independent per PTU, as the latter costs depend on imbalance and IDM prices that are still unknown or fluctuating. Generally, the formula for calculating these costs is as follows:

$$\mathbb{E}[\mathrm{C}_t] = \Big([\text{Impact of Rebound}_t] + \mathbb{E}[\text{Lost Revenue}_t]\Big) \tag{3.32}$$

Which can be broken down into:

$$\mathbb{E}[\mathrm{C}_t] = \Big([\text{Volume of Rebound}_t] \cdot [\text{Value of Rebound}_t] + \mathbb{E}[\text{Lost Loads}_t] \cdot [\text{Selling Price}]\Big) \tag{3.33}$$

The actual cost in a given PTU cannot precisely be determined because it relies on an expected value rather than an actual measure. Hence, expected lost loads represent an estimate of how a steering action in the current PTU could affect the charged volumes for the remainder of the steering window. This estimation comes from the long-term average of negative deviations from the forecasted volume, based on a simulated steering action in each PTU within the 1,186 steering windows. We hereby assume that if charging was ongoing in the last PTU, all the steered loads are considered lost loads. Since this average serves as an estimate for future volumes, it is expressed as an expectation. This allows for the calculation of lost revenue by multiplying the lost loads by the selling price, resulting in the following formula:

$$\mathbb{E}[\text{Lost Revenue}_t] = \Big(\mathbb{E}\left[E_t^{fct} - E_t\right] \cdot \mathrm{SP}\Big) \tag{3.34}$$

The second factor that influences expected costs is the impact of the rebound. $\widetilde{P}_t^{\Delta}$ (in €/MWh) is introduced as the variable that represents the minimized value of the rebound per PTU. The total (optimized) impact of the rebound (in €) can be calculated by multiplying the value of the rebound in a PTU by the volume of the rebound in that PTU (in MWh). This gives the equation:

$$\text{Impact of Rebound}_t = \left(\Delta_t \cdot \widetilde{P}_t^{\Delta}\right) \tag{3.35}$$

The value of the rebound comes from the price of imbalance, or in Model 3, from the minimization between the imbalance and the IDM price. Hence, for Model 3, having the opportunity to trade away the rebound on the IDM, the equation becomes:

$$\widetilde{P}_t^{\Delta} = \min\left(P_t^{IDM}, P_t^{up/dwn}\right), \tag{3.36}$$

Where the imbalance price is dependent on the direction of the rebound.

$$P_t^{up/dwn} = \begin{cases} P_t^{up} & \text{if} \quad \Delta_t > 0 \\ P_t^{dwn} & \text{if} \quad \Delta_t < 0 \end{cases}$$

Combining the above equations, we can calculate the expected costs per PTU and the total expected costs over the steering window. The latter is a simple aggregation of the costs per PTU, giving the equation:

$$\mathbb{E}[C_t] = \left[\Delta_t \cdot \widetilde{P}_t^{\Delta} + \mathbb{E}[E_t^{fct} - E_t] \cdot \text{SP}\right] \tag{3.37}$$

As mentioned, imbalance prices for regulating up or down are time-dependent and highly volatile. Prices on the IDM are less volatile but still fluctuate up to five minutes before the start of the PTU. This makes it impossible to estimate the value of the rebound beyond the next PTU and obtain a valid expectation of the total costs in the steering window. Fortunately, expected costs over the entire steering window will never exceed total revenue when following the steering policy of Model 3. Within this policy, the impact of the rebound cannot exceed the expected revenue from a steering action, as we steer to the optimized load curve when the rebound becomes too valuable. This means that the charged loads in a PTU are limited to a set amount to avoid the rebound. Moreover, since most charging sessions contain flexibility, only a part of the steered load remains uncharged. When steering back to the optimized load to avoid imbalance, more loads will likely remain uncharged, and some revenue will be missed. However, expected costs will still decline as the impact of the rebound decreases more significantly.

Charging faster can help manage the cost from the positive rebound and cause the expected lost revenue to decline or even approach zero. While this model acknowledges that the financial outcome from steering down (regulating up) is moderated by the energy costs on the IDM, it limits the deviation between expected costs and actual costs. As a result, the probability that the actual costs per PTU will surpass the actual revenue is minimized.

3.4 Conclusion

How can the costs of steering actions be managed?
As mentioned in Section 2.3, steering actions introduce various types of cost. Among them are not fully charging the demanded load (causing lost revenues) and the impact of the rebound, where deferred loads return later and cause imbalances with unforeseeable costs. These costs must be managed to ensure an effective steering strategy.

Within the models in this research, several methods are proposed to decrease costs. These methods include steering to the forecasted (policy of Model 1) or DAM-optimized consumption (policy of Model 2 and Model 3), implementing a dynamic strike price, comparing expected revenues with expected costs, steering up, and trading away the rebound on the IDM (policy of Model 3). Each method helps manage and mitigate at least one type of cost, leading to a more intelligent and profitable strategy.

The simplest method is steering to a forecasted or optimized load curve, which involves aligning the realized energy consumption with the predetermined consumption to avoid imbalance. This solution helps stabilize the load profile and overcome balancing costs for that period, but will likely increase the lost revenue. The method is most helpful when an impactful rebound occurs, but the maximum number of PTUs for steering down has already been reached. Calculating the expected costs (from a steering action in PTU t) helps to stay aware of the potential costs of the steering action and helps to keep track of the strategy's performance. This calculation is done through the formula found in 3.3 and involves the impact of the rebound and the lost revenues from unfinished charging sessions. More informed decisions about a steering action can be made by comparing the expected costs with expected revenues.

Steering up is beneficial in all scenarios where one is compensated for regulating down. Without additional energy costs, EVs are charged faster than initially planned, which reduces the expected lost loads. Moreover, the volume of a positive rebound decreases by steering up. When not having a positive rebound, steering up might cause a negative rebound. This negative rebound allows anticipating the rebound from future steering actions, but on the other hand, might introduce a cost when compensated to regulate down.

Implementing a dynamic strike price is another effective strategy. This method aims to optimize the strike price for steering down by considering the volume of the rebound, the remaining PTUs and steering actions. As a larger rebound brings higher cost, the strike price for steering down increases in case of a larger positive rebound to decrease the likelihood of steering down and further expanding this rebound. In addition, increasing the strike price when reaching the maximum number of PTUs in which steering down is allowed overcomes reaching this limit prematurely and missing out on optimal steering opportunities. The extent to which this is considered is scaled by optimization coefficients α, β, and γ, which are optimized through a grid search on historical returns.

The last mitigation method is trading away the rebound on the IDM. IDM trading provides a real-time opportunity to adjust the forecasted or optimized consumption by procuring (deficit) or selling (excess) energy. This method increases the model's performance by reducing the value of the rebound or allowing it to sell against the most favourable price. When a negative rebound occurs (excess energy), it can be sold; when a positive rebound occurs (energy deficit), additional energy can be purchased.

In conclusion, this research introduces a comprehensive set of techniques to manage the costs associated with steering EV charging sessions. By integrating multiple methods, the policies from the models establish a robust, multilayered cost management framework that addresses and mitigates each type of cost.

Chapter 4

Data

This chapter provides an overview of the data sets used, exploring the operating environment of the models from the previous chapter and emphasizing their relevance. The data is crucial to understanding market dynamics and charging behaviour, which helps to ensure model effectiveness. Data collection and processing methods are described to ensure the research's transparency, reproducibility, and validity.

An in-depth evaluation of the data sets follows, analyzing imbalance prices and regulation states from January 1, 2021, to April 1, 2024. It must be noted that this period includes price volatility driven by the war in Ukraine, with geopolitical uncertainty causing energy prices to peak and potentially bias the data. However, since the adoption of RES greatly influences imbalance price dynamics, this timeframe is still the most representative of current imbalance prices.

4.1 Data Collection Methods

The collected data mainly refers to charging times, energy positions and energy prices. The data collection process involved different methods for retrieving the required data. The first method contained an API integration of forecasted imbalance prices for the next PTU, being the most critical data for this research. This API was activated in the cloud environment of TotalEnergies and provides real-time and historical price data, used for modelling and retrieving the values of different parameters within the model. Data on DAM and IDM prices, as well as historic imbalance prices, is publicly accessible through the website of Tennet (2024).

Additionally, charging session data was sourced from TotalEnergies' data lake, which houses all data from the Dutch EV charging division. This data is used to compute the charged loads per period, the flexibility analysis, and analyse overall charging behaviour. However, the third and most representative data collection method is the pilot field test on real-world CPs. The three different models were practically tested on 200 CPs that were selected based on their representativeness for the general charging behaviour of the 17,500 charging points across the Netherlands. The pilot provided valuable real-world information on the models' performances and highlighted its profit opportunities and potential complications.

4.2 Data Processing Procedures

The collected data required processing before use in this research. Processing involved cleaning raw data from the data lake, including removing null values, unnecessary columns, and inaccurate measurements. The data was then aggregated by rounding charged loads and aligning arrival and departure times per PTU, reducing computation time and simplifying load profile analysis.

Imbalance prices were separated for regulating up and down to ensure the steering strategy works for regulation state 2. In regulation state 2, one is fined for all directions of imbalance, but with a different severity. Although this research does not focus on regulation state 2, this separation makes it applicable for such scenarios.

The pilot test period was deemed too short to give valid results for lost loads, and unfinished sessions made it impossible to determine how much load was actually lost. As an alternative, the effects of steering down across 1,186 PTUs from January 1, 2021, to April 1, 2024, were back-tested, a period considered sufficient to provide meaningful averages on lost loads.

Imbalance Price Data

The data set in Table 4.1 includes up- and down-regulation prices and IDM prices per PTU. This data is essential for analyzing imbalance price dynamics, identifying profitable PTUs for steering actions, and assessing the expected costs of each action, as both prices (in Model 3) influence potential revenues and costs.

Variable	**Description**
Date	Date of the period
Period from	Starting time of t
Period until	End time of t
Regulation State	Balancing state of the grid (1 = reg. up, -1 = reg. down)
To regulate up ($P_t^{imb^+}$)	Imbalance price for regulating up in t (in € /MWh)
To regulate down ($P_t^{imb^-}$)	Imbalance price for regulating up in t (in € /MWh)
Intraday (P_t^{IDM})	Intraday price in t (in € /MWh)

Table 4.1: Data Set for Imbalance and Intraday Prices (Tennet, 2024).

Charging Session data set

The charging session data set, presented in Table 4.2 contains in-session meter readings of charging speeds and steering actions, providing insight into current charging behaviour. Allowing computations of the aggregated charged load per PTU and estimating the expected lost loads when steering in a PTU.

Variable	**Description**
Event DateTime (t)	Date and start time of the charging session
Session ID (ι)	Unique identification for each charging session
Observed kWh (E_t)	Realized energy consumption (load) in t (in kWh)
Unsteered kWh (E_t^{fct})	Charged load in t if not steered or DAM optimized (in kWh)
Is steering	Binary variable indicating if the session is steered in t

Table 4.2: Charging Session Data Set (TotalEnergies, 2024).

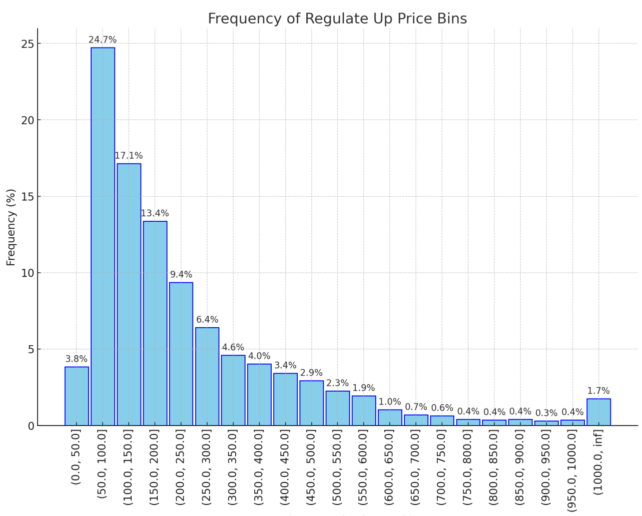
4.3 Data Set Evaluation

Data analysis was conducted on up- and down-regulation prices over the 1,186-day period to gain deeper insight into price dynamics, while regulation states were examined to understand the model's operating environment.

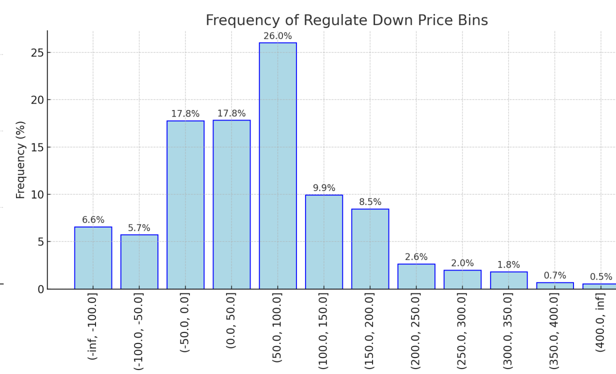
4.3.1 Imbalance Prices

The two figures in Figure 4.1 display the frequency distribution of price bins for regulating up and down prices during the steering window. Figure 4.1a shows a significant skewness to the left, indicating that most regulating up prices are concentrated in lower bins. When compensated for regulating up, 59.0% of occurrences are within €0 and €200 per MWh. Remarkably, prices above €450 still occur in 13.0% of those PTUs, indicating that a steering-down action would be triggered for 13.0% of those PTUs when handling the strike price of €447.50/MWh, which is used in all policies. Moreover, since Figure 4.2b illustrates how regulation state 1 occurs 39.3% of the time, steering down happens on average 2.12 times per steering window.

In contrast, Figure 4.1b shows that regulate-down prices are more concentrated around €0/MWh, are less volatile and rarely peak above €400. Prices above €0 occur in 69.8% of the PTUs that compensate for down-regulation. Regulate-down compensation happens in 41.2% of PTUs, meaning that steering up happens on average 17.3 times per steering window.



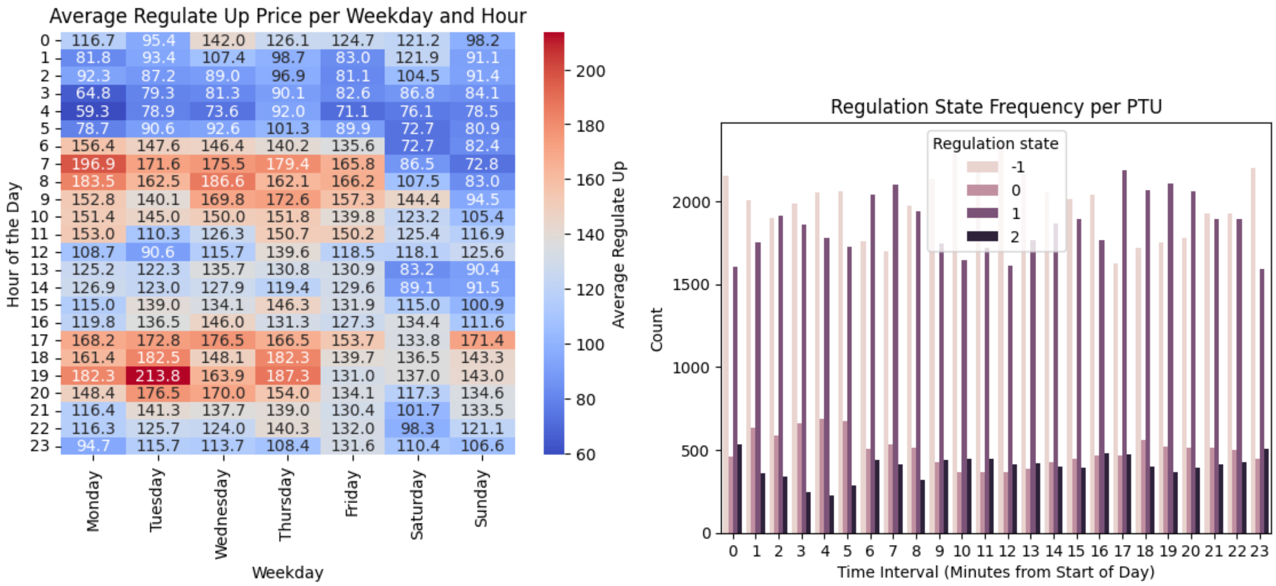
(a) Price Bins for regulate up prices (P^{imb^+}).



(b) Price Bins for regulate down prices (P^{imb^-}).

Figure 4.1: Distribution of imbalance prices.

Figure 4.2a displays the average P^{imb^+} per hour of the day per weekday. The heatmap shows that prices are relatively high during the evening, with a noticeable drop in prices at weekends and around mid-day. Figure 4.2b (right) shows the regulation state frequencies per hour of the day, showing higher frequencies for regulating up (reg. state 1) between 17:00 and 20:00. Figure A9 in the Appendix substantiates the statement that apart from a slightly more frequent occurrence during these hours, regulation states are entirely random.



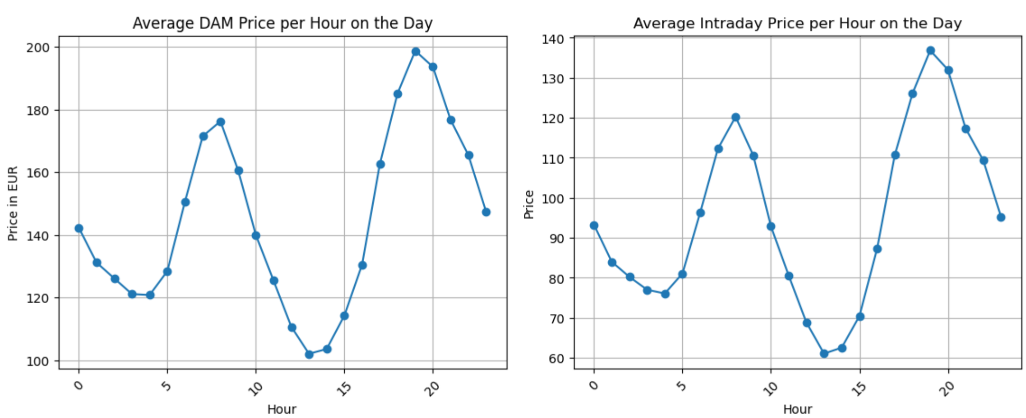
(a) Heatmap of Average Regulate Up Prices.

(b) Regulation States per PTU.

Figure 4.2: Analysis of Regulate Up Potentials.

4.3.2 DAM & Intraday Prices

Figure 4.3 shows the average DAM and IDM (P_t^{IDM}) prices (in EUR/MWh) per hour of the day. Both prices follow a clear trend, peaking in the morning and evening, with the highest in the evening and a sharp drop overnight. This recurring trend is used in Models 2 and 3 to optimize the load curve with DAM optimization. Even during peak hours, P_t^{IDM} remains lower than P_t^{imb+} but higher than P_t^{imb-}. The only scenario in which Model 3 will always return a loss for the period arises with negative IDM prices when regulating down while wanting to sell the negative rebound on IDM. From 01-01-2021 to 01-04-2024, this occurred in 3.7% of the PTUs when compensated for regulating down between 17:00 and 08:00 (and 1.5% of all PTUs), mainly due to DAM prices.



(a) Average DAM Prices per Hour.

(b) Average IDM Prices per Hour.

Figure 4.3: Average DAM & IDM Prices per Hour on the Day.

Chapter 5

Results

This chapter presents the performance of the three models' policies developed in Chapter 4. It conducts a comparative review between the policies of Model 1 (only steering down), Model 2 (steering both up and down, using DAM optimization), and Model 3 (steering up and down with DAM optimization and IDM integration). The policies' performance is illustrated through the reward metric, which captures all factors that the policies directly influence but does not directly represent the total profit or revenue. The reward does, among others, not consider the costs of energy or the depreciation and maintenance costs for the CPs. On the contrary, it provides a clear view of the effects of the policies' actions. Hereby note that since this thesis assumes demand forecasts to be perfect, no realistic comparison can be made with the current situation that faces balancing costs.

More detailed explanations of the results of the individual KPIs are given in later sections of this chapter. More thorough explanations and informative visualizations are given to understand and express the dynamics of the model and the specific contribution of each feature.

5.1 Total Rewards

Due to publicity restrictions imposed by TotalEnergies, the actual charging revenue figures cannot be disclosed within this research. Hence, Table 5.1 presents fictional charging revenues, being a random but consistent multiplication of the original values. By ensuring that the presented relationships and dynamics of the model remain inherent to the original data, the consistent scaling multiplier preserves the integrity, validity, and representativeness of the model. Therefore, it must be noted that while the presented values are fictional, the proportional adjustments guarantee that the outcomes and insights derived from the model remain valid and applicable to the research.

The performance of the models' policies in the field test is detailed in Table 5.1, showing the daily average results across various key performance indicators (KPIs) based on 200 CPs. Although these results provide useful comparative insight, they are only a fraction of TotalEnergies' charging network and do not represent the full reward potential. Their individual effects are separately detailed for KPIs influenced by upward (U) and downward (D) steering. This is meant to show the effectiveness of the policies from each model but is not guaranteed to properly represent the actual robustness. Nonetheless, it is crucial to note that the performances only show a comparison with earlier situations and are not compared to a benchmark. Hence, it remains unknown how well the policies perform. Since the models imply heuristic-based decision rules for practical ease, it remains possible that even slight adjustments significantly improve the models' performance.

	Model 1	**Model 2**	**Model 3**
Charging Revenue (€)	1663.11	1889.38	1896.09
Number of Steering Actions	1.7	7.3 (2.3D, 5.0U)	6.7 (1.7D, 5.0U)
Steered Load (kWh)	40.2	146.8 (117.7U, 29.1D)	140.5 (117.7U, 22.8D)
Imbalance Result (€)	46.42	146.56 (81.08 U, 65.48D)	427.58 (81.08U, 346.50D)
DAM Result (€)	0	19.94	19.94
Expected Value of Lost Loads (€)	24.13	31.64	22.88
Impact of Rebound (€)	14.79	27.95	-9.03
Expected Costs (€)	38.92	59.59	13.85
Total Reward (€)	1694.737692	2007.994615	2332.702308

Table 5.1: Daily Average Results for KPIs.

Table 5.2 extends upon the fictional daily average results to estimate the potential profit when applying the models across the entire network of 17,500 chargers. This projection assumes a consistent reward per CP and per day based on the results of the 200 CP sample. This allows for a more insightful view of the economic impact of each model when applied on a larger scale.

	Model 1	Model 2	Model 3
Daily Avg. Total Reward / CP (€)	10.97	12.87	14.51
Yearly Total Reward / CP (€)	4,003.45	4,699.03	5,295.29
Yearly Total Reward 17,500 CPs (€)	70,060,335.63	82,232,994.38	92,667,614.38

Table 5.2: Total Rewards.

In Table 5.2, it is seen that Model 3 notably outperforms other models, yielding a 32% higher reward than Model 1 and a 13% increase over Model 2. In addition, the extrapolated total annual rewards for 17,500 chargers illustrate the significant revenue potential, with Model 3 increasing its reward with €22,607,278.75 compared to Model 1 and €10,434,620 compared to Model 2.

5.2 Load Profiles

Model 1 is tested during the steering windows from July 10th until August 6th 2024, and is limited to steering down or steering to the forecast. Figure 5.1 illustrates the effects of steering-down actions and the subsequent rebound.

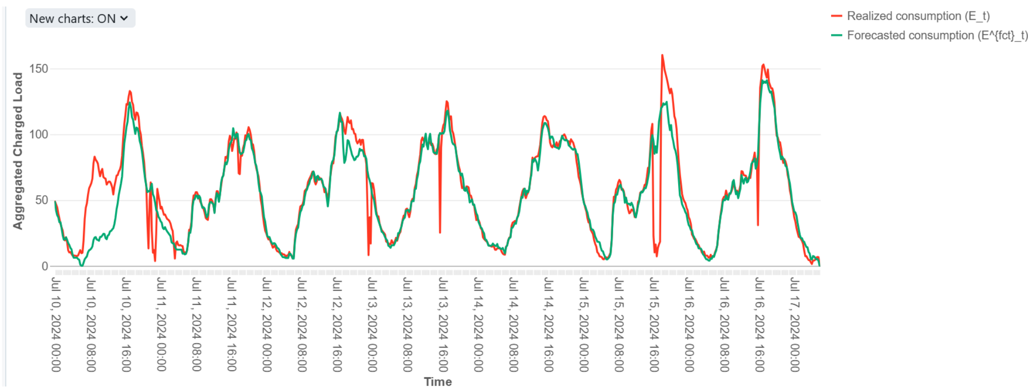


Figure 5.1: Aggregated Loads During a Week for Forecasted Consumption and Steering Down.

Model 2 is tested from August 6th until September 17th 2024, resulting in the load profile shown in Figure 5.2. Model 2 can steer up and down, resulting in a more dynamic load profile with higher deviations from the forecasted load in the steered and subsequent PTUs. Steering up occurs more frequently but tends to cause less noticeable deviations from the forecast compared to steering down.

Figure 5.2: Load Profile of Models 2 & 3.

Model 3 extends Model 2 by incorporating IDM trading. However, due to limitations related to market access and the scale of traded loads, the policy of Model 3 has been tested only in a virtual environment. Importantly, Model 3 focuses solely on optimizing energy procurement without altering the steering decisions of Model 2. As a result, the load profiles for both models remain similar, enabling virtual testing of the policy of Model 3 during the same period used for testing the policy of Model 2.

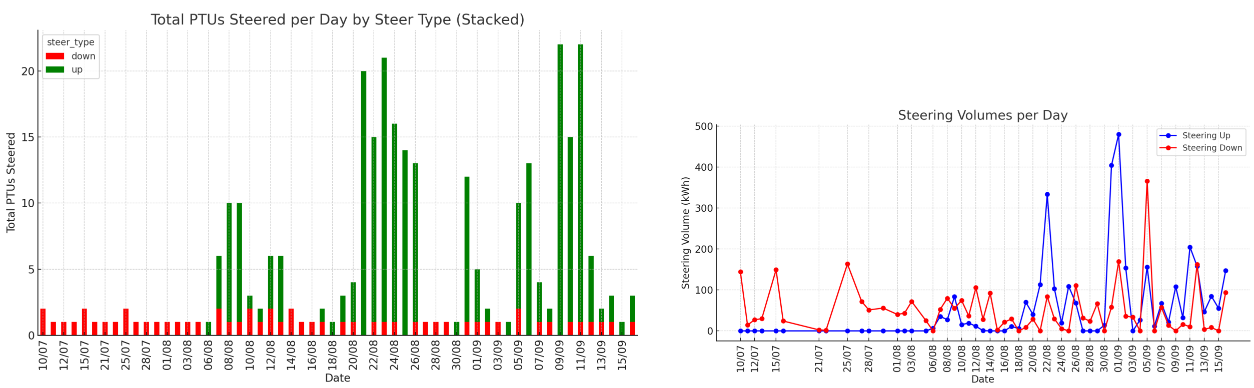
5.3 Steering Actions

As depicted in Figure 5.3a, the number of steering-down actions is often limited to the maximum number of steered-down PTUs. Based on imbalance prices between 2021 and 2024, there were 269 steering windows in which a steering down action could have been triggered more than three times, representing approximately 22.7% of the total steering windows.

From the 1,200 PTUs in which the policy of Model 1 is tested, steering down occurred in 33 PTUs (2.8%), averaging 1.7 PTUs per day. In the 2,520 PTUs that tested the policies of Models 2 and 3, steering down occurred in 96 PTUs (3.8%) for Model 2 and in 70 PTUs for Model 3. This deviation is caused by the dynamic strike price used in Model 3, which mostly causes an increased strike price. For both models, 210 PTUs (8.3%) are steered up, averaging 5.00 PTUs up and 2.29 and 1.7 PTUs down per day for Models 2 and 3, respectively.

Steering volumes heavily depend on the amount of ongoing charging sessions in that period, and their current charging speed. Steering-down volumes are limited to the forecasted load for that PTU, while steering-up volumes involve the difference between the realized charged load and the maximum possible charged load in a PTU. As shown in 5.2, the forecasted load fluctuates during the day and ranges from 1 kWh to 117 kWh per PTU.

Figure 5.3b illustrates the daily steering volumes. Since steering-up was introduced on August 7th, no steering-up volumes have been recorded prior to that date. Steering down averaged 40.2 kWh per day in Model 1, 29.1 kWh for Model 2, and 22.8 kWh for Model 3. For steering up, 117.7 kWh was the average load per day in Models 2 & 3, with 23.5 kWh per action. Over the entire period, 2,028 kWh was steered down, and 4,931 kWh was steered up.



(a) Number of Steered PTUs.

(b) Steering Volumes per Day.

Figure 5.3: Steering Frequency and Volumes over Time.

5.4 Imbalance Results

Imbalance results refer to the direct revenue from steering actions and do not consider the impact of the rebound. They are calculated through the steered volume and the imbalance prices in the PTU and heavily rely on the forecasted load that determines the steerable volume. As shown in Figure 5.4, the imbalance results per steering action ranged between €1.39 and €64.89 when steering down and €0 and €98.93 for steering up.

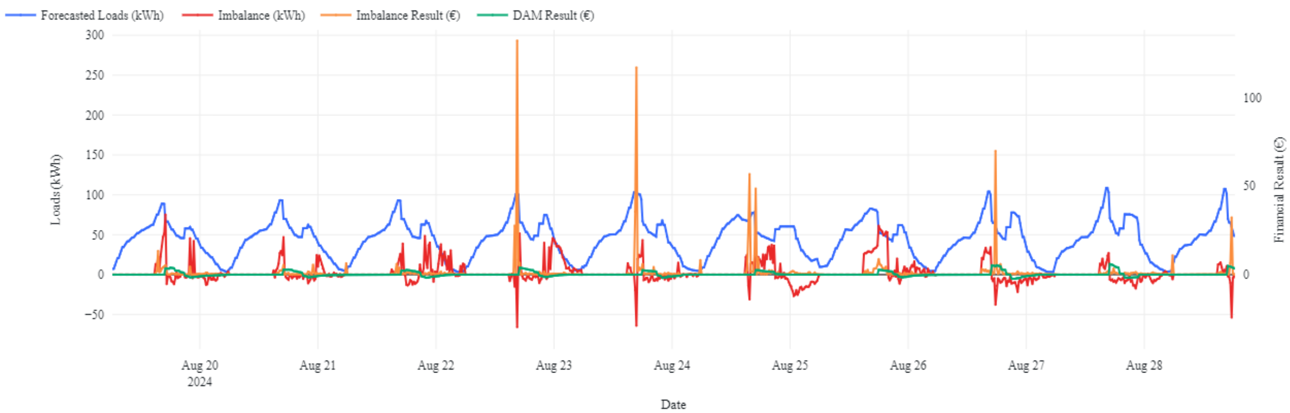


Figure 5.4: Imbalance & DAM Results.

The total imbalance result for Model 1 amounted to € 928.49, or €46.42 on average per day. Model 2 resulted in €6,155.56 (€146.56 per day), which came from €2,750.31 (€65.48) from steering down and €3,405.25 (€81.08) from steering up. Yet, the dynamic strike price caused an increased reward for Model 3 of €17,958.36, stimulated by increased steering down result of €14.553 (€346.50 per day). Figure 5.5 shows the daily aggregated imbalance result when not considering the dynamic strike price, differentiated on steering up and steering down.

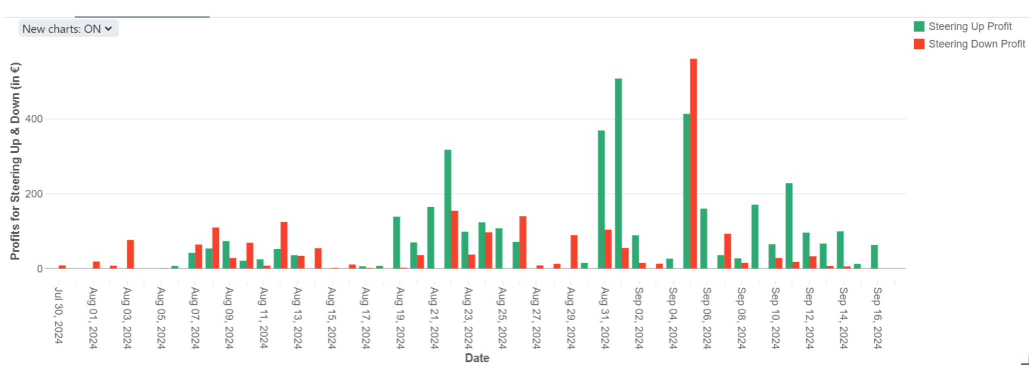


Figure 5.5: Daily Profits for Steering Up & Steering Down.

As mentioned at the beginning of the chapter, no clear comparison can be made between the historic balancing costs and current balancing costs since demand is assumed to be perfectly forecasted. Nevertheless, it should be mentioned that average balancing costs per day for the 200 CPs before testing Model 1 have been €294.68, or €107,557.16 per year. Assuming that balancing costs are consistent per CP, this would indicate total balancing costs of nearly €9.5 million for the entire charging network.

5.4.1 Dynamic Strike Price

The dynamic strike price mechanism contributes to optimizing the timing of steering actions, enhancing responsiveness to changing operating environments, and maximizing total profits. Equation 3.2.4 is used to compute the dynamic strike price for steering down, incorporating steering opportunities, rebound volume and the remaining duration of the steering window.

Figure 5.6 illustrates the development of the dynamic strike price and its interaction with the imbalance price and steering decisions (indicated by the red dots). The optimized coefficients resulted to be $\alpha = 0.157, \beta = -0.005, \gamma = 0.048$, with a base strike price (X_0^{up}) of €447.50. The figure shows that the strike price remains relatively stable in most cases but shows peaks within a range between €10.67 and €860.35.

Out of the 2560 influenced decisions, 33 sub-optimal steering actions have not been taken based on the dynamic strike price but would have been taken with the base strike price. There were seven cases where a steering action was taken with the dynamic strike price that would not have been taken with the base strike price. This optimization further increased the total reward for Model 3 with €1,803.60 (or 281.02 per day), mainly caused by steering down at peak imbalance prices instead of sub-optimal prices.

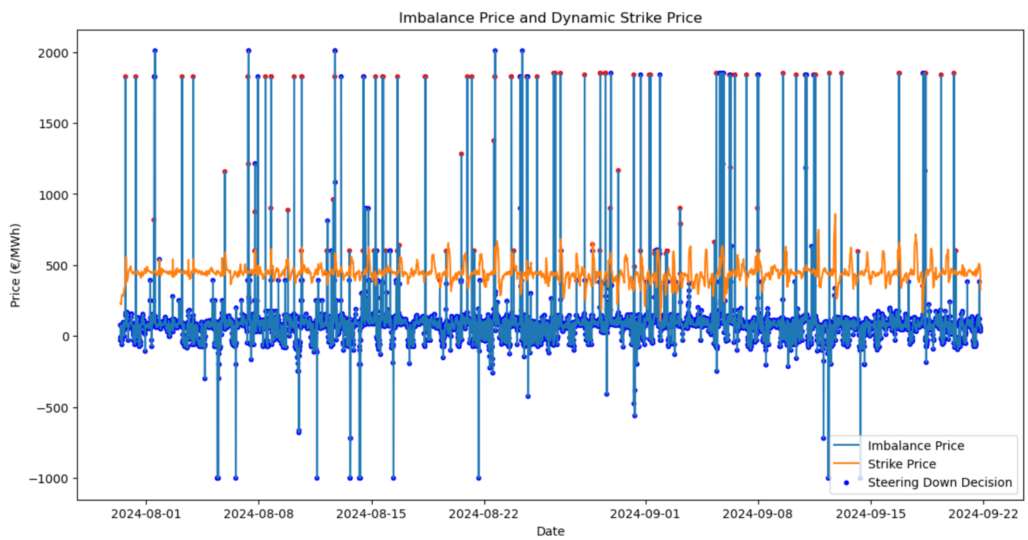


Figure 5.6: Development of Dynamic Strike Price.

5.5 Expected Lost Loads

An essential aspect of steering strategies is the risk of losing loads, which occurs when energy that would have been charged remains uncharged due to steering actions. Figure 5.7 illustrates the expected lost loads per PTU per day when steering down in that PTU and clarifies why steering-down actions are exclusively performed between 17:00 and 08:00.

As illustrated in Figure A18 in the Appendix, 3,113 kWh was expected to be lost out of the 228,940 kWh charged during the analyzed steering windows. This means the total value of the expected lost load amounted to €1,393.34 and represented 1.7% of the total charging revenue. Per steering down the action, the lost load had an average value of €8.3 in Model 1 and €10.53 in Models 2 and 3. This is significantly below average, as seen in Figure 5.7. Furthermore, from the load that would have been

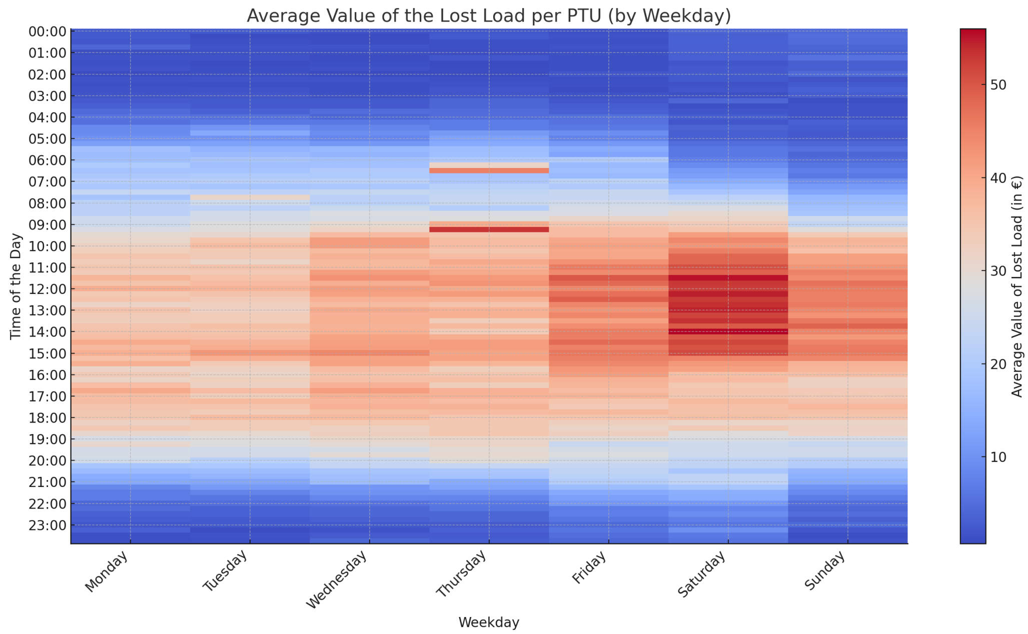


Figure 5.7: Heatmap of the Average Expected Lost Loads.

charged in a PTU, an average of 47.0% is expected to be lost when steering down.

Note that deviating (daily average) charging revenues cannot directly be linked to lost loads since the models are tested during summer and show strong seasonality. However, when comparing the realized load with the forecasted load for Model 1, a negative deviation of 11,485 kWh is seen. Assuming the forecast is perfect, this represents the actual lost load. Conversely, the steering-up actions of Model 2 steering-up actions increased the charged load by 6,747 kWh compared to the DAM-optimized load curve, resulting in a net increase in charging revenue of €3,019.65 over the tested period (or €71.90 per day). Additionally, Model 3 further increased charging revenue by €281.72 by trading on the IDM instead of steering to the forecast.

5.6 The Rebound Effect

The rebound effect forms one of the main cost factors of steering actions. For this research, the rebound volume is estimated as a fixed percentage of the steered load. By comparing the forecasted loads with the realized loads after steering down, the volume of the rebound is found to be, on average, 32.0% of the steered load. Additionally, it is observed that the rebound influences eight subsequent PTUs after a steering action.

The rebound volume ranged from -27.3 kWh to 29.6 kWh per PTU, with an impact ranging from -€39.16 to €36.00 for the non-optimized impact of the rebound. The average value of the rebound resulted to be €310.64. Notably, the most costly rebounds (highest impact of the rebound) are caused by negative rebounds with a strongly negative value of the rebound, which is the case when high compensation for regulating down. The most profitable rebounds (having a negative impact) are also mostly caused by high compensation for regulating down, combined with positive rebounds.

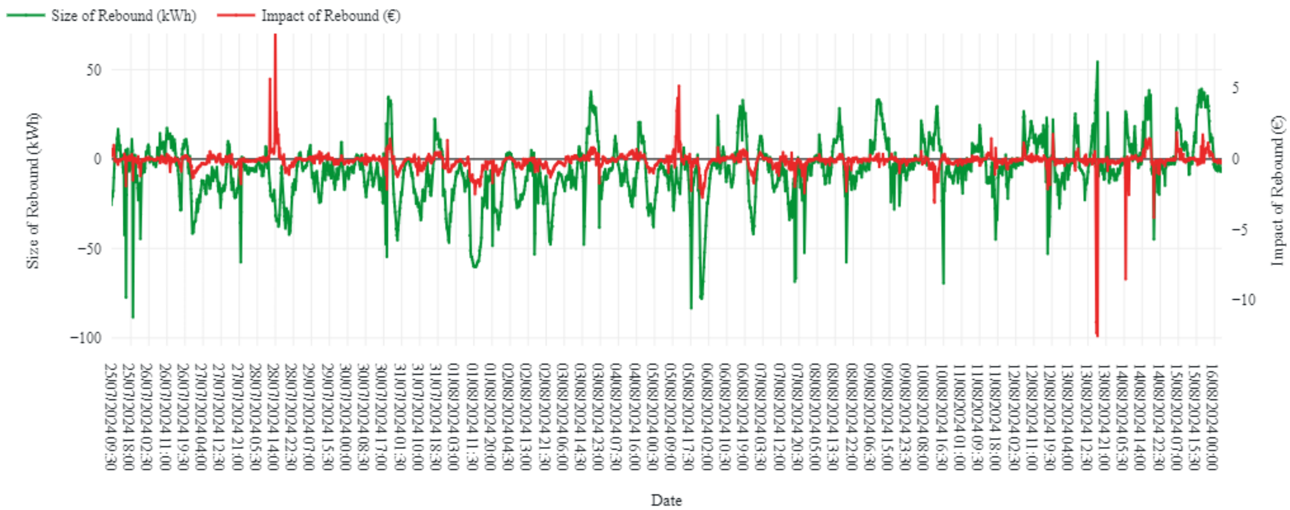


Figure 5.8: Volume and Impact of the Rebound.

Model 1 saw a total impact of the positive rebound of €488.10, or €14.79 per steering action and €24.41 per day. For Model 2, the total impact of both rebound directions was €1173.73 (€27.95 per day), whereas €1,070.72 came from the negative rebound and €103.01 from the positive rebound. Model 1 steered twice to the forecast, as the impact of the positive rebound was larger than the value of the expected lost loads in that PTU. Model 2 steered to the forecast in 6 PTUs, and Model 3 did not steer to the forecast.

As visualized in Figure A22, Model 3 optimizes the value of the rebound by purchasing 9,780.02 kWh and selling 2,515.94 kWh on the IDM. The optimized value decreased the rebound's impact by €1,553, to -€379.27 (-€9.03/day) and even made it profitable (negative). The impact of the optimized rebound ranged between -€132.14 and €12.99 per PTU, with rebound savings ranging up to €82.54 accordingly. The average purchase and selling price was €52.54/MWh and €139.91/MWh, respectively. As illustrated in Figure A23, IDM trading was utilized in 50.5% of the 2520 analyzed PTUs and covered 49.2% of the rebound volume.

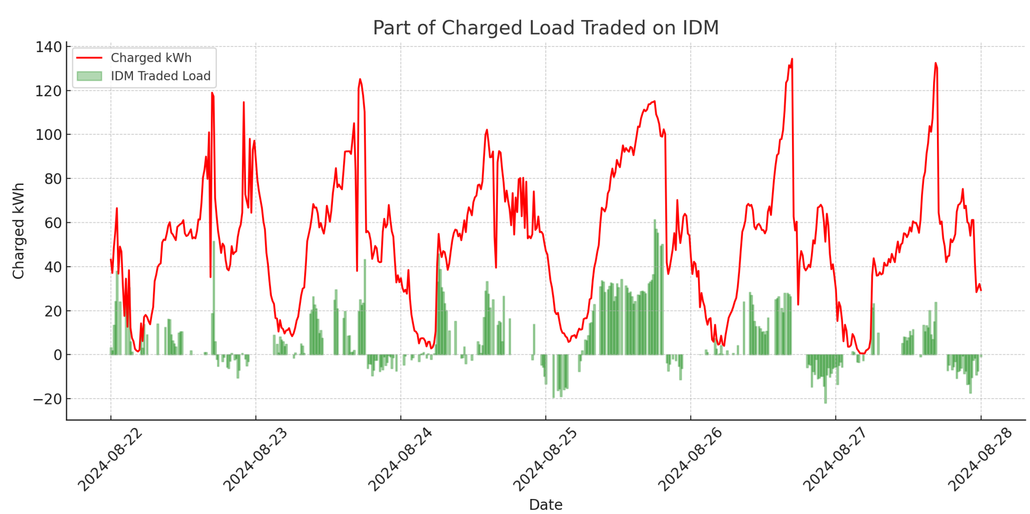


Figure 5.9: IDM Trading Load Profile.

5.7 Conclusion

This chapter evaluated the performance of the three steering strategies for managing EV charging sessions, revealing their performance and takeaways. Through a comparative analysis, valuable insights were gained into the impact of these strategies on various factors, such as load profiles and the elements that most significantly influence profits. Moreover, using the results of this chapter, more insights can be retrieved on the effects of the current steering strategies and how the more sophisticated models improve upon that situation. The current steering strategy, as represented by the policy of Model 1, offers limited flexibility and results in lower (total) rewards. While the policy of Model 1 limits the impact of the rebound and the expected value of the lost loads, its inability to steer up restricts monetizing regulate-down opportunities. This limitation results in decreased imbalance revenues and a lower total reward.

The policy of Model 2 shows improved performance by introducing the ability to steer up and down, along with DAM optimization. This additional flexibility creates a more complete strategy that leverages a wider range of market opportunities. The policy of Model 3 further enhances imbalance results and charging revenue by incorporating IDM trading and introducing a dynamic strike price for steering down. These features help to improve decision-making regarding the rebound and lower its impact.

However, the load shifts caused by DAM optimization have both benefits and drawbacks. While increasing the expected value of the lost loads and reducing the volume available for steering down during periods shown (in Figure 4.2a) to have higher regulating-up potential, they also enable steering up, which adds another layer of flexibility and a source of profit. Each successive policy, representing an increase in sophistication and intelligence, also shows an increase in total rewards. The policy of Model 3 achieves the highest total reward, mainly due to the dynamic strike price. Other features of Models 2 and 3 also effectively mitigate the impact of the rebound and minimize the value of the lost loads, ultimately enhancing the overall performance and efficiency of the steering strategies.

This chapter provides a further understanding of what factors mainly affect the performance of the steering strategy. Apart from the effects of deviating imbalance prices, several factors significantly impact the performance of the steering strategies. For instance, the ability to steer both up and down greatly improves the strategy's adaptability to volatile imbalance prices. This flexibility allows for more frequent and well-timed steering actions to increase imbalance results. Moreover, a dynamic strike price further improves the timing of steering decisions. By preventing sub-optimal steering actions, the effect of not being allowed to steer in the subsequent PTU and for a maximum of three times is limited. This helps to ensure that only high-value opportunities are acted upon.

Additionally, effective management of the rebound reduces its impact and mitigates costs. Model 3 incorporates the IDM to trade positive and negative rebounds, eventually turning it into a source of profit. Although the DAM optimization increases the expected value of the lost loads and reduces the available steering down volumes during periods with high regulating-up potential, it raises the number of steering opportunities. From Table 5.1, it follows that, on average, the flexibility for steering up is much more impactful than the lost loads or mentioned volume reduction. However, the effectiveness of the models remains uncertain. Given that these models employ heuristic-based decision rules for practical implementation, there exists the potential that even minor adjustments could lead to significant improvements in performance.

Chapter 6

Conclusion

This research aimed to develop a strategy that intelligently adjusts EV charging speeds to lower balancing costs, contribute to stabilizing the Dutch electricity grid, or create an additional source of profit for CPOs. The core problem addressed was the absence of a dynamic and intelligent strategy that steers EV charging sessions to monetize imbalance settlements.

6.1 Conclusion

The Netherlands faces significant challenges due to the rapid growth in EV charging sessions and required CPs, together with increasing (volatility) in imbalance prices. Currently, EV charging is a critical pain point in the energy transition, but it shows opportunities for innovations that could stimulate the transition. This highlights the urgency for intelligent EV charging strategies to contribute to stability on the grid, enhance profitability for CPOs, and support the integration of RES. This research aims to develop a strategy that intelligently steers EV charging sessions based on imbalance prices, representing the grid's balance.

The main contribution of this research lies in the development of a dynamic and effective steering strategy that allows TotalEnergies, as a CPO, to optimize EV charging speeds based on their current imbalance position, imbalance prices, IDM prices, the time of the day and the expected decrease in charged loads when steering. This strategy aims to transform volatile balancing costs into an additional source of profit. Moreover, the strategy enhances the company's operational efficiency and profitability, positioning it as a front-runner in smart EV charging technologies.

After answering the sub-research questions in previous chapters, we can conclude this research by answering the main research question:

"How can flexibility in EV charging be used to increase profits for CPOs through imbalance settlements while contributing to balance the Dutch electricity grid?"

Optimizing EV charging speeds based on imbalance settlement prices involves implementing a dynamic and intelligent steering strategy that adjusts charging rates in response to real-time market conditions. The developed strategy, represented by the policy of Model 3 in this research, integrates several key components to maximize profitability and manage potential costs.

A vital aspect of the strategy is the flexible adjustment of charging speeds (steering), allowing to charge faster (steer up), or pause the charging session (steer down). During periods of imbalance with high prices for regulating up (indicating high compensation for charging less than forecasted), charging sessions are paused to help balance the grid, minimize balancing costs, or even create an extra source of profit. Conversely, charging speeds are maximized when compensated to regulate down (indicating compensation for charging more than forecasted). This enables the strategy to adapt and monetize both directions of imbalance.

Furthermore, the strategy optimizes energy procurement costs from the DAM by adjusting charging speeds on DAM prices. Reducing energy consumption in periods with higher costs unlocks the opportunity to steer up and increases the number of steering opportunities. Although it requires careful consideration of the potential increase in expected lost loads due to longer charging durations, it provides another dimension of adaptability.

Incorporating IDM trading complements the adjustment of charging speeds by allowing for real-time buying or selling of energy to manage eventual imbalances. The inclusion of the IDM enhances the performance of the strategy by enabling the management of the risks from both the positive and negative rebound. Additionally, it optimizes profits associated with steering up (to regulate down) and covers eventual rebound costs more efficiently, eventually turning them into an additional source of profit.

A dynamic strike price is introduced for steering down (to regulate up). The strike price adjusts based on factors such as the volume of the rebound effect - the phenomenon where the deferred loads return in later periods - and the number of remaining periods in which steering is permitted. By optimizing the timing of charging speed adjustments, the strategy ensures that decisions to change charging rates are made when they are most profitable and least risky. This dynamic approach prevents sub-optimal steering actions, avoids reaching steering limits prematurely, and enhances overall decision-making.

Cost management is improved by quantifying the expected costs associated with steering actions, including potential lost revenues from unfinished charging sessions and the impact of the rebound. By comparing the imbalance (steering) results with the expected costs, the strategy further decreases uncertainties regarding imbalance prices.

By integrating these components - flexible adjustment of charging speeds, a dynamic strike price mechanism, comprehensive risk management, utilization of IDM trading, and DAM optimization - the developed strategy demonstrates how optimizing EV charging speeds based on imbalance settlement prices can create a strategy that maximizes profitability and manages risks. The strategy allows for dynamic and more effective responses to market conditions from enhanced flexibility in actions, coming from operating in different energy markets and monetization potential in case of both energy deficits and energy surpluses on the grid.

Hence, the inclusion of the IDM enhances the effectiveness of the strategy by permitting the management of potential costs from the negative rebound, optimizing profits that come along with regulating down, and more efficiently covering risks from the positive rebound.

6.2 Recommendations

Based on the findings of this research, it is recommended that TotalEnergies adopts the policy of Model 3 for managing EV charging speeds and on more of their CPs. This policy incorporates IDM trading and a dynamic strike price and is expected to increase imbalance results while effectively managing the rebound.

Furthermore, increased monitoring of actual real-time rebound volumes would increase the reactivity and adaptability to deviating imbalance prices. For instance, IDM trading outside the steering window can be used to trade away costly imbalance positions. Moreover, further examining rebound value dynamics through probability-weighted expectations or examining factors - apart from steering actions - that influence the volume of the rebound, would increase the ability to anticipate.

Lastly, quantifying the effect of the DAM optimization on imbalance results and evaluating DAM positions based on steering potential would be recommended. Since the decrease in steering down results cannot be directly compared to DAM profits, it is unclear if the DAM optimization contributes to the model's results.

6.3 Discussion and Limitations

It must be acknowledged that this research incorporates multiple assumptions to simplify real-world conditions and focus on the core objectives. These simplifications may cause practical situations to differ from this research's outcomes and the expected theoretical results.

The assumptions expected to have the most influence are the perfect information assumptions regarding demand per period and imbalance price forecasts. Subsequently, the rebound volume is assumed to be a fixed percentage of the steered load, which does not reflect reality. Additionally, the performance of each model is heavily influenced by external factors, such as imbalance prices, IDM prices, and charging demand, as well as by communication delays, technical limitations in charging speed adjustments, and grid (congestion) constraints. These factors may limit the models' ability to fully reflect their real-world effectiveness.

Additionally, the assumption that the results from the pilot field test on 200 real-world CPs during a limited period are representative for the actual performance of the models could be questioned. While the field test provided valuable real-world data on the models' performances, this research assumed that external factors (such as imbalance prices, charged loads per PTU and charging time per session) during the testing period are representative for the overall dynamics of these external factors. Even though the frequency of regulation states per month has shown to be comparable (Figure A11), and average imbalance prices per regulation state have - apart from during the energy crisis - shown to be relatively constant, it is not guaranteed that future regulation states will show similar dynamics. It could be the case that changed charging behaviour decreases charging times and takes away the flexibility required for steering down. Moreover, increased availability of battery storage systems might ease grid balancing and cause imbalance prices to be less volatile, making steering actions less profitable. Lastly, more frequent occurrences of regulation state 2 (in which every direction of imbalance is penalized), would decrease the profit opportunity of the model. Hence, the future performance of the model is not guaranteed to be as presented in Table 5.2.
An important limitation relates to calculating expected lost loads when optimizing charging speeds based on DAM prices. Since DAM optimization lowers charging speeds to align with lower-cost periods, charging sessions take longer to complete. The expected lost loads were calculated by comparing the number of periods in which the charging session was completed without DAM optimization or

steering. This comparison uses charging speeds when not optimized or adjusted, potentially underestimating expected lost loads. The impact on customer satisfaction and lost revenues may be greater than estimated, necessitating further investigation.

In addition, the assumption that steering actions might not influence imbalance prices may not hold when the strategy is expanded over the entire charging network. Since the the 17,500 CPs have an installed capacity of 193 MW, steering actions might resolve low imbalance volumes entirely or cause imbalance in the other direction. This state variable must be accounted for when starting a steering action, causing limited opportunities for steering during PTUs with low imbalance volumes.

Lastly, the impact of reputational damage from increased unfinished charging sessions is not fully explored. Adjusting charging speeds and accepting lost loads may increase profits, but it could harm TotalEnergies' reputation if customers experience frequent incomplete charging sessions. The extent to which reputational damage affects future demand and revenues is not considered.

6.4 Topics for Further Research

Although this research provides valuable insights into optimizing electric vehicle (EV) charging speeds based on imbalance settlement prices, there are several avenues for further investigation that could refine the presented steering strategy - which is represented by Model 3 - and enhance its applicability in practice. Improving the model on these topics in would make it more robust, efficient, and adaptive to varying grid conditions and forecast inaccuracies.

One area worth examining is the effects of regulation state 2 — where the electricity grid experiences complete imbalance, and penalizes all directions of imbalance — are not considered in the analysis of the performance of the models. Currently, the model considers the grid to experience a deficit (compensated to regulate up), surplus (compensated to regulate down), or balance (no compensation). Yet, the scenario of complete imbalance occurs in 10% of PTUs and forms a serious threat to the models' performance and profitability. The greatest difficulty comes from the unpredictability of this imbalance, which is caused by the different directions of imbalance within the PTU. However, imbalance prices for regulating up and regulating down are separated to make the model applicable also in that scenario. By further examining the scenarios in which Regulation State 2 occurs, future research could identify strategies to prevent unforeseen balancing costs.

Another topic that would be valuable to further investigate is the IDM trading strategy. Further refinement could involve exploring optimal ranges for selling negative rebounds — situations where previously surplus energy — and determine whether selling on the IDM or accepting the imbalance would be more profitable. Moreover, a dual-market approach for energy procurement on both the DAM and IDM would enhance the ability to correct inaccuracies in forecasted consumption and increase profitability. Additionally, examining other IDM periods and purchasing a portion of the forecasted consumption on the IDM could resolve the impact of forecast inaccuracies and ease managing the rebound.

Further enhancing the dynamic strike price mechanism presents another topic for improvement. The dynamic strike price has shown to significantly improve the total reward over the analyzed period. Hence, extending the usage of this mechanism to steering-up decisions and incorporating seasonal factors, as well as IDM or imbalance price volatilities, could further optimize the timing of steering decisions and improve profitability. Furthermore, integrating reinforcement learning techniques could optimize the model's coefficients and uncover non-linear patterns that traditional linear models might overlook. This would enable the strategy to adapt in real-time to evolving market conditions and demands and lead to a more complete and effective strategy.

A more extensive examination of customer behaviour after an unfinished charging session would be a valuable topic for further research. This allows to reevaluate the assumptions regarding the lost load, and is essential for validating those results. Currently, the models assume that uncharged loads remain uncharged indefinitely, which may not reflect actual customer behaviour. By determining the percentage of instances where uncharged energy is eventually sold and understanding how unfinished charging sessions influence future demand, the model can be adjusted to more accurately represent customer patterns. This insight would enhance demand forecasting and enable the consideration of lost loads in the model, ensuring that customer satisfaction remains sufficient while optimizing profits.

Lastly, examining the influence of forecast inaccuracies on imbalance prices and energy consumption can significantly improve the models' robustness. By considering the forecast errors in imbalance prices and consumption, and introducing penalties for these inaccuracies, the model can become more resilient to real-world uncertainties. Utilizing forecast errors as a parameter in the model could enable anticipation opportunities, allowing the model to adjust to inaccuracies and maintain profitable even under inaccurate forecasts.
In conclusion, delving into these areas of further research would not only refine the existing model but also contribute substantially to the practical implementation of advanced EV charging strategies. By addressing these topics, future studies can develop more nuanced and adaptable approaches that maximize profitability and manage costs more effectively. Such advancements would strengthen TotalEnergies' EV charging strategy by transforming volatile balancing costs into a source of profit while enhancing the stability of the Dutch electricity grid. Moreover, these improvements would support the energy transition in the Netherlands, aligning with national sustainability goals and contributing to a more resilient and efficient energy system.

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Appendix

Appendix A: Additional Problem Context Visualizations

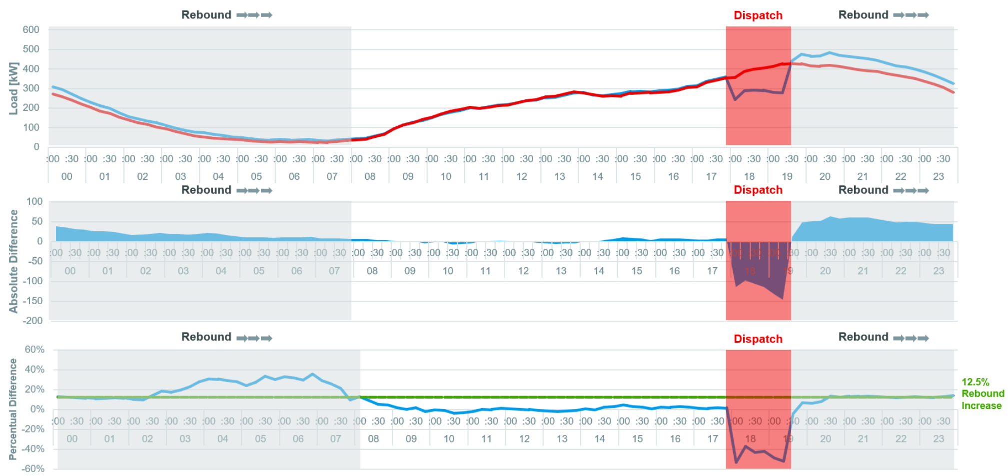

Figure A1: The Rebound Effect

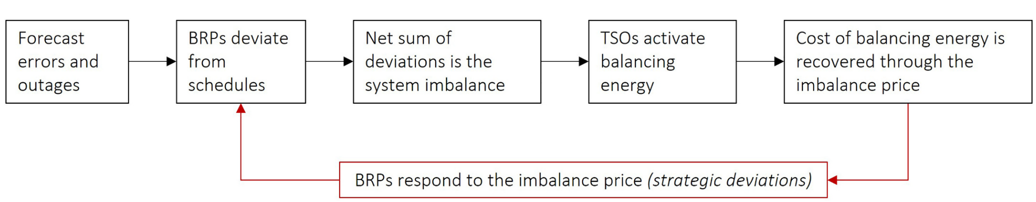

Figure A2: Flowchart of the Imbalance Monetization Process

Appendix B: Literature Study

Moreover, many reports from energy-related institutions like the International Energy Agency (IEA), the International Renewable Energy Agency (IREA), Dexter, and ElaadNL have been used. These provided more insight into the problem context than into the solution approach.

Literature Sources The relevant literature sources were as follows:

- Dexter's Knowledge Hub: Whitepapers and literature on forecasting processes, market dynamics and trend analyses.
- IEEE Transactions journals: Peer-reviewed research journals on smart grids, electricity markets and EVs. Research articles from IEEE Transactions journals are often more technical and provide more background knowledge.
- Energies: Research papers on energy-related topics with a more social orientation.
- IEA Energy and EV Outlook: These outlooks provide comprehensive analyses and forecasts on EV and energy markets, which highlight the effects of ongoing transitions
- Elaad EV Outlook: This outlook represents the latest findings on smart charging, the integration of EVs into the grid and the latest EV developments within the Netherlands.
- IEEE Electric Vehicle Conference and IEEE International Conference on Smart Grids: Conference papers regarding the latest findings on the applicability of EVs in smart grids and the development of models for energy trading.
- Energy Economics: Research papers focusing on finance-related topics in the energy sector.
- The Energy Journal: A journal that publishes quantitative research on the financial aspects of the energy sector.

Notable Authors

- Amory Lovins: Co-founder of the Rocky Mountain Institute, and finds its expertise in energy policy and RES.
- Paul Joskow: Professor of Economics at MIT, whose work on electricity markets and regulation has been highly influential.
- Benjamin F. Hobbs, Theodore M., and Kay W. Schad: Professors in Environmental Management and well-known for their work on electric power market modelling.

PRISMA Framework

To ensure the research's integrity, transparency, and repeatability, the PRISMA framework below 2.1 transparently provides the literature selection process and results.

1. **Reports identified from:** Conducting individual searches in various databases (with the search query of 2.1) using relevant search terms and finding the total number of reports. Moreover, several reports come from relevant institutions directly.
2. **Remove duplicates:** Use Mendeley to remove duplicate articles from the search results.
3. **Reports screened or title/abstract screening:** Determining the number of articles to be screened by subtracting the number of removed duplicates from the total number of records.
4. **Reports excluded or title/abstract screening:** Screening both the title and abstract of the remaining articles and excluding irrelevant ones.
5. **Reports sought for retrieval:** Calculate the number of articles for full-text screening by subtracting the number of excluded records from the total number screened at the title/abstract level.
6. **Reports not retrieved:** The number of articles that cannot acquire the complete text of.
7. **Reports assessed for eligibility - full-text screening:** Read the full text of the relevant reports to see if they qualify for the systematic review.
8. **Reports excluded:** After the full-text screening, write down the total number of excluded articles and provide reasons for their exclusion.
9. **Reports included in review:** The resulting number is calculated by subtracting the number of excluded records from the total number of articles assessed for eligibility. The resulting studies are expressed in the literature review and considered the most contributing to this research.

Appendix C: Policy Explanations

Appendix B represents the mathematical notations for the steering up and -down decisions for each model.

Model 1

Model 1 can steer down. However, this is only possible if the maximum number of steering times has not yet been reached ($\eta_t < \delta^{max}$), and no steering down action took place in the previous PTU ($\delta_{t-1} = 0$). When both conditions are satisfied, the model steers down. If one of those conditions is not met, the model steers to the forecast when a rebound is detected (indicating that $\Delta_t > 0$) or does not steer when no rebound is detected. When not having a rebound, or if $P_t^{up} < X_t^{up}$, the model does not steer and thus charges at full speed, accepting the eventual impact of the rebound in the form of imbalance costs.

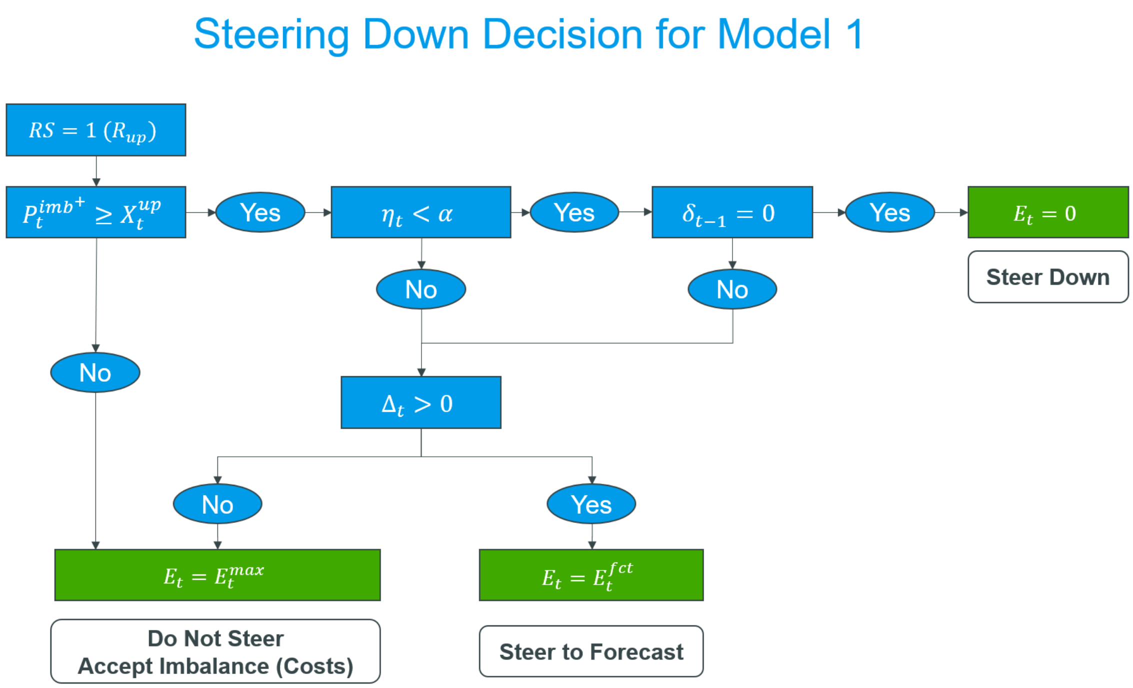

Figure A3: Mathematical Formulation for Steering Down Decision for Model 1.

Model 2

The policy for Model 2 extends on the policy of Model 1 and heavily relies on the underlying optimization of charging speeds based on DAM prices. When compensated for regulating up, the model follows the steering down flowchart below to determine its actions. The process begins similarly to Model 1 by assessing the regulation state, comparing the imbalance price for regulating up with the strike price and checking the feasibility of steering down. Steering down is feasible when the number of steering down actions is below the maximum allowance, and the previous PTU is not steered down. If possible, the model steers down by setting the energy consumption to zero.

Consequently, the model assesses the rebound. However, if there is a positive rebound, the model evaluates the expected value of the lost load ($\mathbb{E}[E_t^{fct} - E_t] \cdot \mathrm{SP}$) against the impact of the rebound ($\Delta_t \cdot P_t^{imb^+}$). If the value of the lost load is less, the model steers to the DAM-optimized consumption.

Otherwise, the model accepts the imbalance costs and charges at the maximum speed ($E_t = E_t^{max}$).

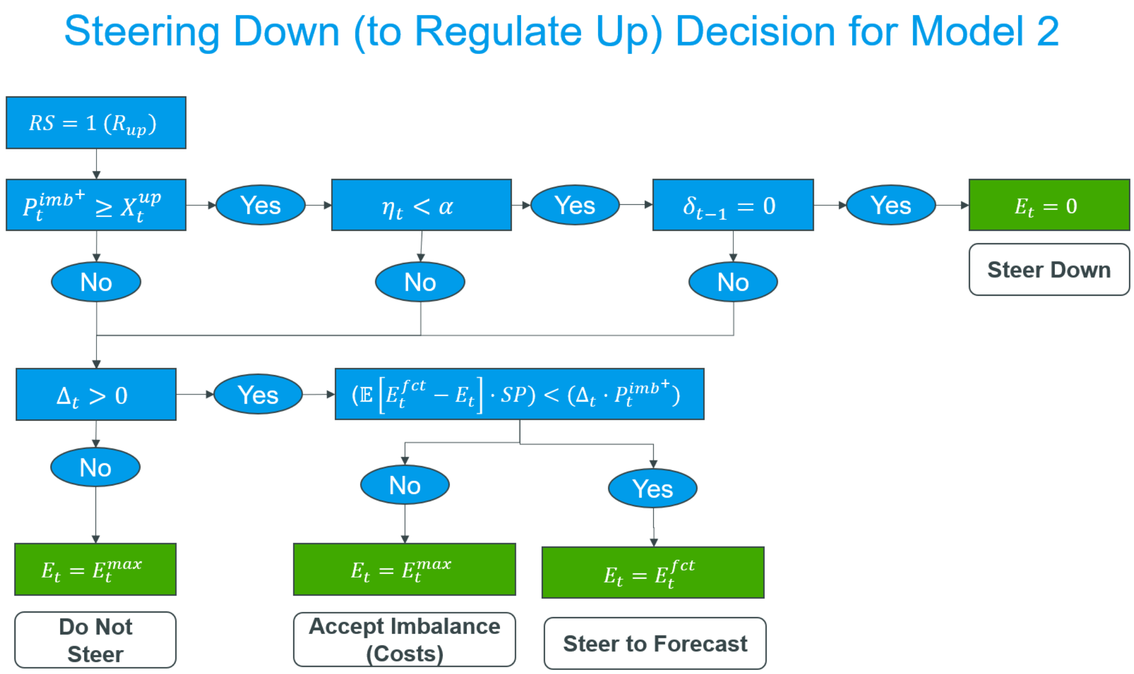

Figure A4: Mathematical Formulation for Steering Down Decision for Model 2.

As mentioned before, DAM price optimization default decreases charging speeds and enables steering-up decisions as presented in Figure A5. Model 2 uses this potential when compensated to regulate down and follows the steering up framework below to determine its actions. The process starts with setting the realized energy consumption to the maximum ($E_t = E_t^{max}$) to ensure that EVs charge at full speed.

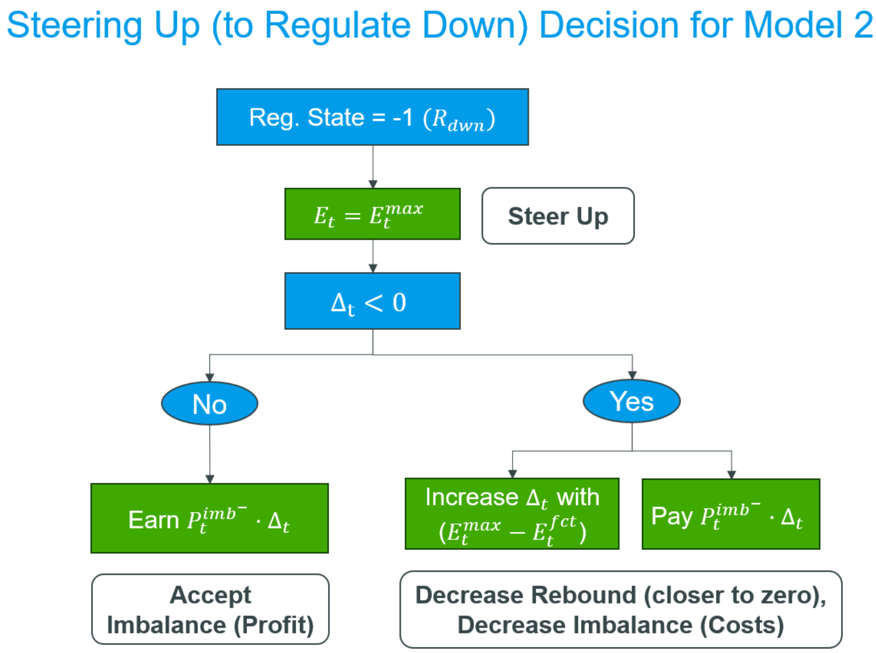

Figure A5: Mathematical Formulation for Steering Up Decision for Model 2.

In addition, the model checks for a negative rebound ($\Delta_t < 0$). If this is not the case, the model accepts the profit on the imbalance and earns $P_t^{dwn} \cdot \Delta_t$. If $\Delta_t < 0$, the model increases Δ_t with $(E_t^{max} - E_t^{fct})$ by charging at maximum speed. This decreases imbalance costs with $P_t^{dwn} \cdot (E_t^{max} - E_t^{fct})$, and leaves the costs of the inevitable imbalance of $P_t^{dwn} \cdot \Delta_t$. This action will decrease Δ_t for the following PTUs, which could form a risk when compensated for regulating down but also an opportunity when compensated for regulating up.

This policy could lead to the load profile shown in Figure A6.

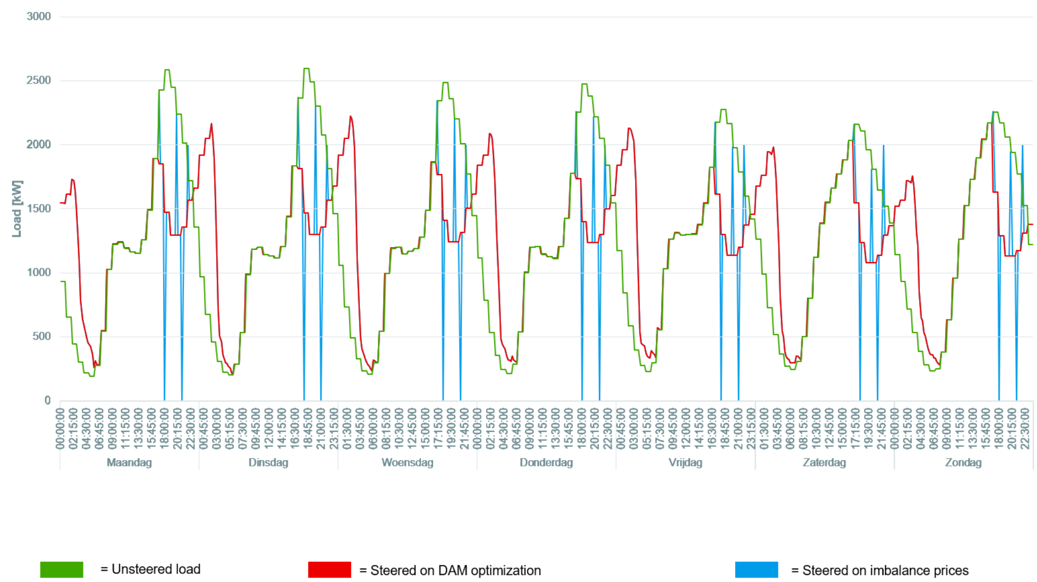

Figure A6: Expected Load Profile of Model 2.

Model 3

Model 3 follows the flowchart for steering down below if compensated for regulating up. If the regulation state is 1, indicating that one is compensated for regulating up, the model compares the imbalance price for regulating up ($P_t^{imb^+}$) with the strike price for regulating up (X_t^{up}). If the imbalance price is higher ($P_t^{imb^+} > X_t^{up}$), it is considered beneficial to steer down.

To determine if steering down is feasible, the model checks two conditions: the number of steering actions within the steering window being less than the stated maximum ($\eta_t < \delta^{max}$), and not having steered down in the previous PTU ($\delta_{t-1} = 0$). If both conditions are satisfied, the model steers down, meaning the energy consumption is set to zero ($E_t = 0$).

If the conditions to steer down are not met, the model assesses the volume of the rebound due to earlier steering events. If there is a positive rebound ($\Delta_t > 0$), the IDM price (P_t^{IDM}) is compared with the imbalance price for regulating up ($P_t^{imb^+}$). If ($P_t^{IDM} < P_t^{imb^+}$), the model charges on the maximum speed and buys a volume of Δ_t on the IDM to cover this rebound. If $P_t^{IDM} > P_t^{imb^+}$, the model evaluates the expected value of the lost load against the impact of the rebound ($\Delta_t \cdot P_t^{up}$). If the value of the lost load is less, the model steers to the optimized (forecasted) load ($E_t = E_t^{fct}$). Otherwise, the model accepts the costs of the impact of the rebound and charges at maximum speed.

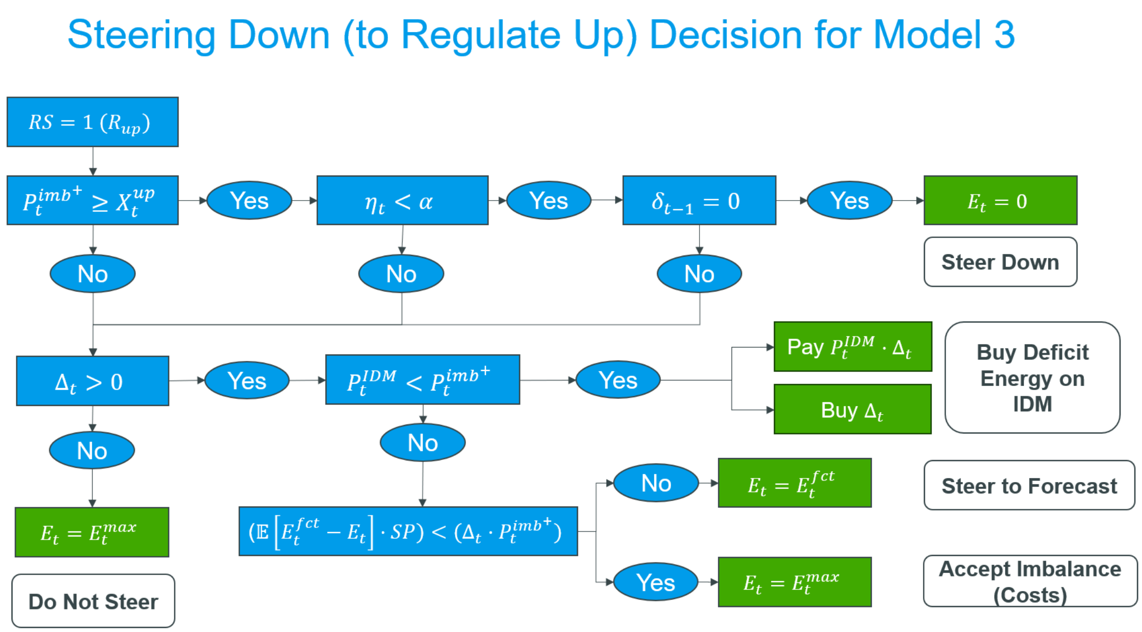

Figure A7: Mathematical Formulation for Steering Down Decision for Model 3.

If one is compensated to regulate down, the final model follows the steering up flow chart below. The process starts with an assessment of the regulation state. When this is -1, indicating being compensated to regulate down, the model sets the realized energy consumption to the maximum $(E_t) = (E_t^{max})$. This ensures that EVs charge at full speed, aligning with the grid's requirement to consume more energy.

Subsequently, the model checks for a negative rebound ($\Delta_t < 0$). If this is the case, the model compares the IDM price (P_t^{IDM}) with $P_t^{imb^-}$. If $P_t^{IDM} > P_t^{dwn}$, it indicates a favourable market condition to sell the excess energy on the IDM instead of accepting the imbalance, thereby earning $P_t^{IDM} \cdot \Delta_t$.

In situations where the IDM price is smaller than the imbalance price, the model attempts to decrease the volume of the negative rebound with $(E_t^{max} - E_t^{fct})$ by charging at maximum speed. Charging at maximum speed helps to bring realized consumption closer to optimized consumption. If there is no negative rebound or the IDM price is not favourable, the model accepts the imbalance and earns $\Delta_t \cdot P_t^{dwn}$.

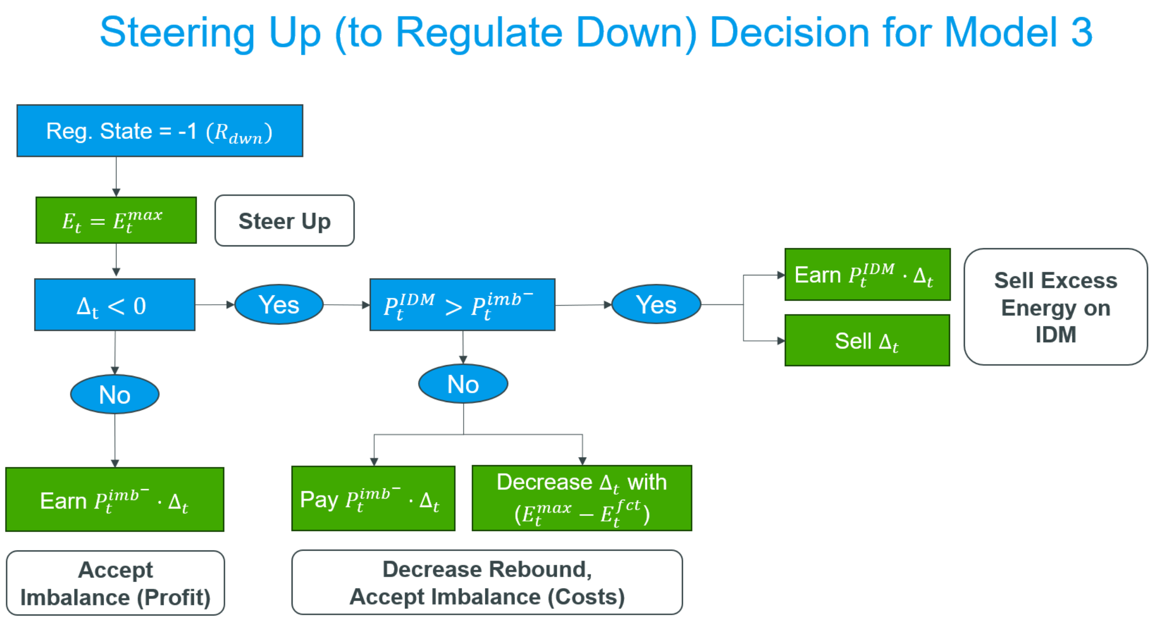

Figure A8: Mathematical Formulation for Steering Up Decision for Model 3.

Appendix D: Additional Data Set Evaluation

Additional Regulation States Analyses

The autocorrelation (the correlation between current and future regulation states) is represented in Figure A9. The figure shows (partial) autocorrelation scores of 0.5, which can be explained by random occurrences of regulating up (reg. state 1) and regulating down (reg. state -1) happening in the vast majority of cases.

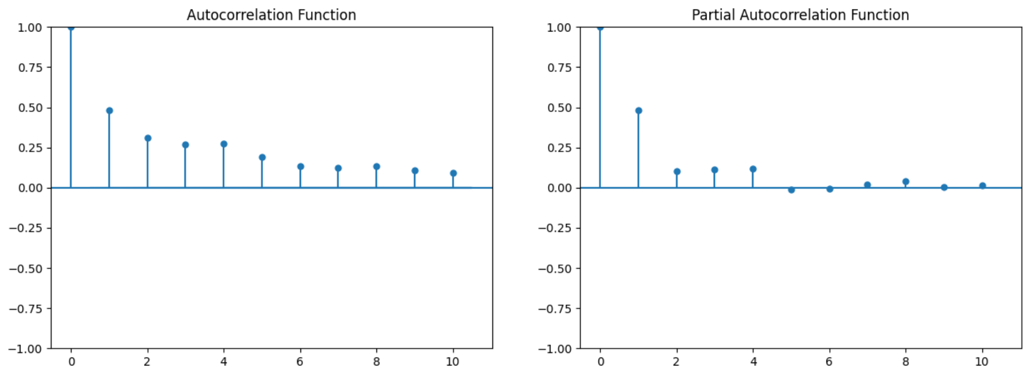

Figure A9: Autocorrelation of Regulation States.

As regulation states determine whether one is compensated for a negative or positive direction from the forecast, understanding the dynamics of regulation states helps to understand the operating environment of the models. The occurrence of each of the regulation states per day of the week and PTU throughout the day is examined, as this represents how often steering up and steering down would be compensated. Figure A10 shows that compensation for down-regulation (regulation state 1) occurs more often during workdays than weekend days. Moreover, it is seen in the right graph that compensation for regulating up (regulation state -1) is more often seen in peak hours (17:00 - 20:00).

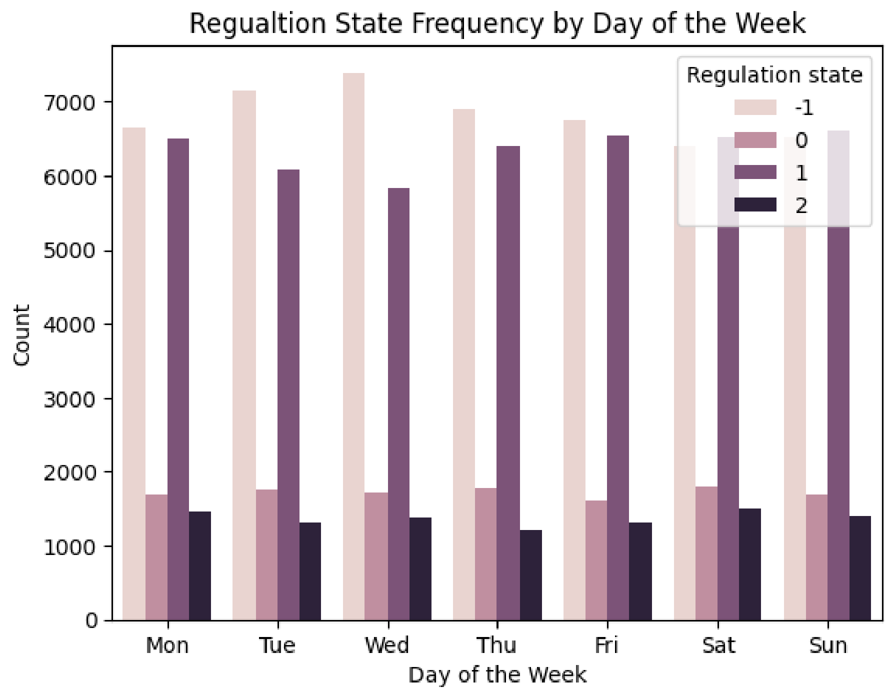

Figure A10: Frequency of Regulation States per Day of the Week.

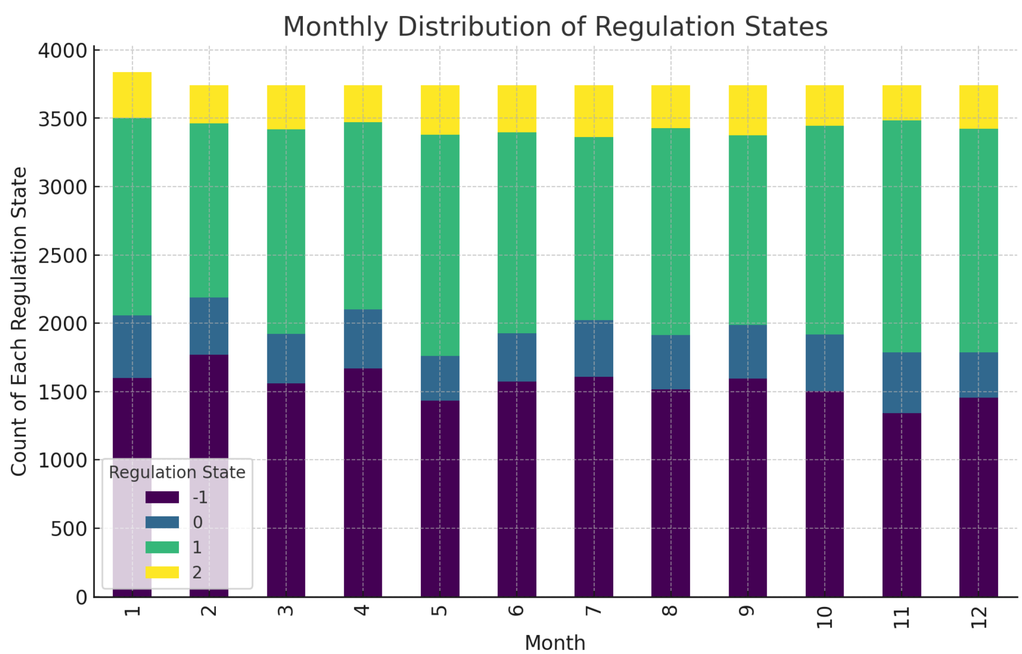

Figure A11: Frequency of Regulation States per Month

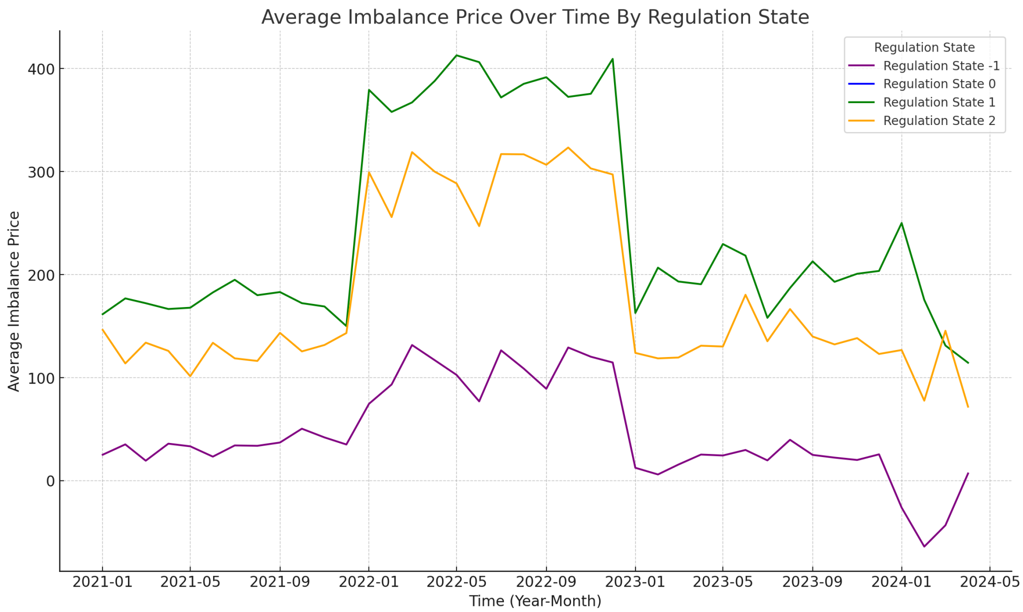

Figure A12: Monthly Average Imbalance Prices per Regulation State.

Additional Energy (Imbalance) Prices Analyses

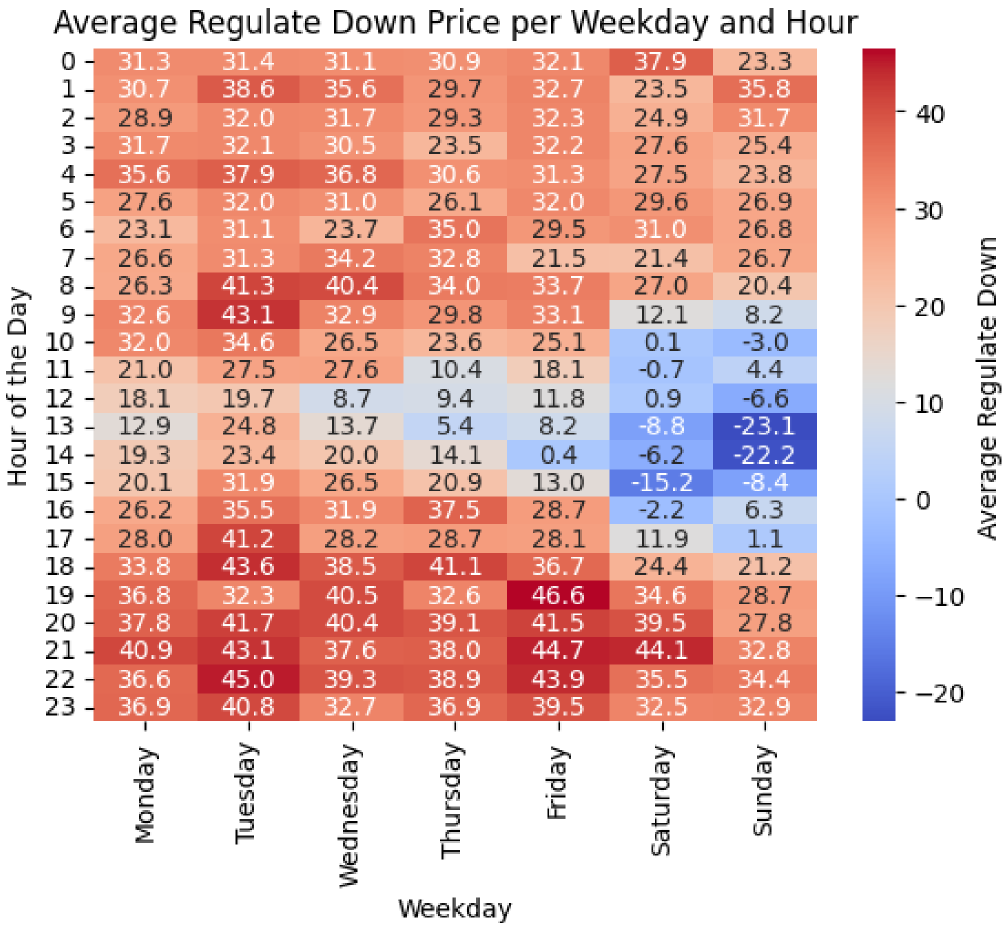

Figure A13: Heatmap of Average Regulate Down Prices per Weekday & Hour.

FigureA13 shows that regulating down prices are relatively stable across weekdays, particularly during the evening and night.

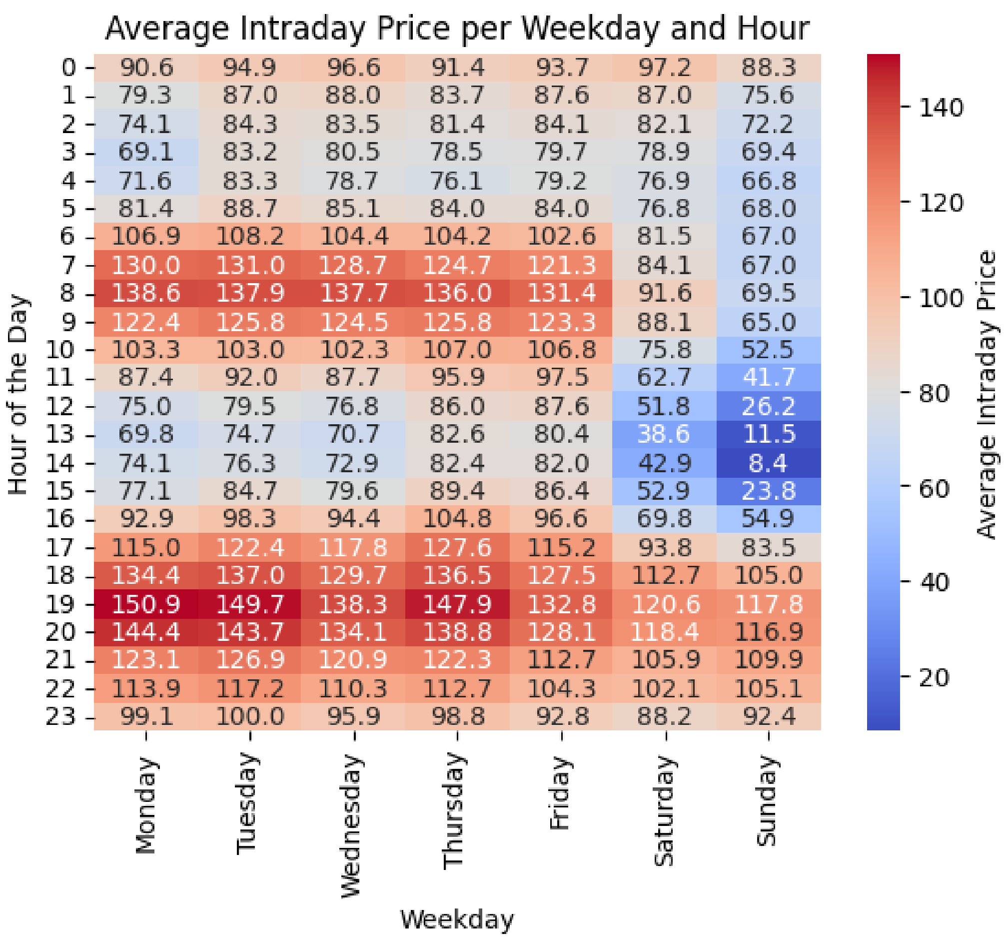

Figure A14: Heatmap on Average IDM Prices per Weekday & Hour.

Figure A14 shows that IDM prices fluctuate significantly across hours and days, with peaks during weekday evenings reaching €150/MWh. Lower average prices are seen during the weekends, with a minimum on Sunday midday of €8.40/MWh, which is nearly 90% lower than on several weekdays during that hour.

Figure A15 represents the price spreads (volatility) in imbalance prices per day.

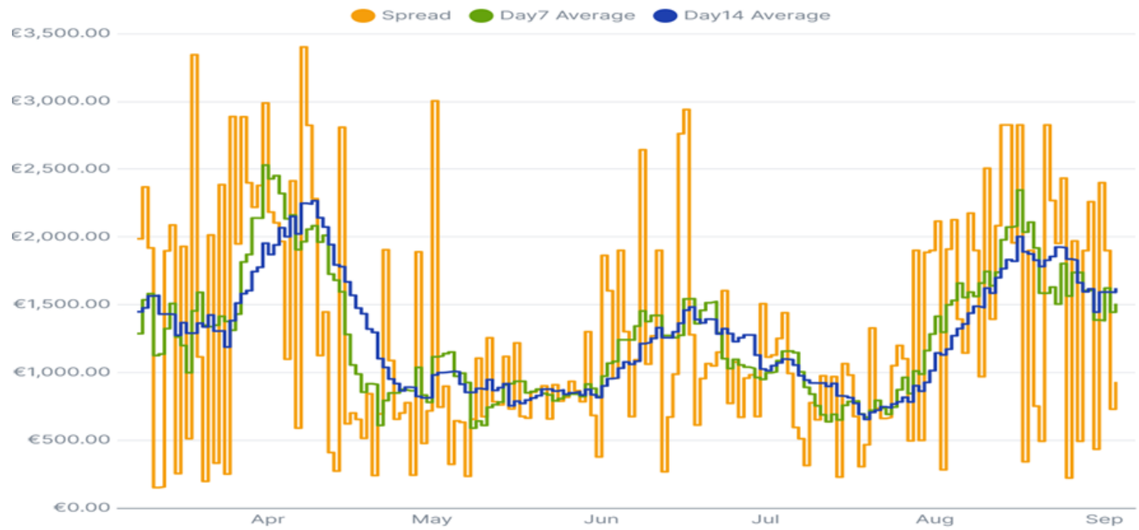

Figure A15: Imbalance Price Spreads.

Appendix E: Additional Results

Expected Lost Loads

By analyzing the time between the last PTU in which the EV was plugged in and the last PTU in which the EV was charging, the average flexibility for steering actions is determined. Table A16 represents the probability that the stated amount of flexibility is available within the EV charging session ι.

	maandag			dinsdag			woensdag			donderdag			vrijdag			zaterdag			zondag		
	15 min	30 min	45 min	15 min	30 min	45 min	15 min	30 min	45 min	15 min	30 min	45 min	15 min	30 min	45 min	15 min	30 min	45 min	15 min	30 min	45 min
00:00	0,82609	0,82609	0,82609	0,80488	0,80488	0,80488	0,93478	0,93478	0,93478	0,9	0,88333	0,86667	0,825	0,8125	0,8125	0,92647	0,89706	0,88971	0,89404	0,89404	0,89404
00:15	0,84884	0,82558	0,81395	0,90411	0,90411	0,90411	0,8875	0,8625	0,8625	0,84615	0,82906	0,82051	0,86441	0,85593	0,84746	0,89565	0,88261	0,87391	0,86195	0,85185	0,83838
00:30	0,91954	0,89655	0,86207	0,91176	0,88235	0,88235	0,86567	0,85075	0,8209	0,87179	0,87179	0,84615	0,83673	0,83673	0,78571	0,89427	0,89427	0,88546	0,89451	0,89451	0,88608
00:45	0,89231	0,89231	0,87692	0,89286	0,875	0,875	0,87273	0,83636	0,81818	0,77586	0,77586	0,74138	0,92771	0,87952	0,86747	0,84783	0,83152	0,83152	0,88021	0,88021	0,875
01:00	0,82143	0,80357	0,78571	0,875	0,84375	0,8125	0,89474	0,87719	0,87719	0,86364	0,84091	0,84091	0,82353	0,82353	0,82353	0,87273	0,86364	0,85455	0,87013	0,86364	0,85714
01:15	0,89091	0,89091	0,89091	0,8	0,8	0,8	0,86111	0,83333	0,83333	0,85714	0,81633	0,81633	0,8625	0,825	0,8125	0,84615	0,84615	0,83846	0,91096	0,91096	0,91096
01:30	0,82609	0,82609	0,82609	0,9375	0,9375	0,9375	0,86486	0,86486	0,86486	0,75	0,725	0,725	0,88889	0,88889	0,88889	0,84483	0,84483	0,81897	0,85271	0,85271	0,84496
01:45	0,89796	0,85714	0,83673	0,80952	0,80952	0,80952	0,9	0,875	0,825	0,72222	0,69444	0,66667	0,89796	0,85714	0,81633	0,83505	0,82474	0,78351	0,88696	0,88696	0,86087
02:00	0,76471	0,76471	0,76471	0,84	0,84	0,84	0,82759	0,82759	0,7931	0,83333	0,80556	0,77778	0,83333	0,83333	0,81667	0,82105	0,78947	0,76842	0,88298	0,88298	0,87234
02:15	0,87179	0,84615	0,79487	0,95	0,95	0,9	0,76667	0,76667	0,76667	0,82759	0,82759	0,82759	0,83721	0,83721	0,83721	0,87342	0,86076	0,86076	0,87234	0,87234	0,8617
02:30	0,8	0,8	0,8	0,75	0,75	0,75	0,78261	0,78261	0,78261	0,91304	0,91304	0,91304	0,91667	0,88889	0,80556	0,86076	0,86076	0,81013	0,84146	0,84146	0,82927
02:45	0,84	0,84	0,84	0,88235	0,88235	0,88235	0,91667	0,91667	0,83333	0,73913	0,73913	0,73913	0,67442	0,67442	0,67442	0,90909	0,89394	0,87879	0,87838	0,87838	0,86486
03:00	0,82609	0,82609	0,82609	0,94444	0,94444	0,94444	0,8125	0,8125	0,8125	0,77273	0,77273	0,77273	0,72973	0,72973	0,72973	0,85714	0,85714	0,84127	0,79452	0,76712	0,76712
03:15	0,78571	0,78571	0,78571	0,92857	0,92857	0,92857	0,85714	0,85714	0,78571	0,77778	0,77778	0,77778	0,76316	0,76316	0,76316	0,86364	0,86364	0,84848	0,90769	0,90769	0,87692
03:30	0,84615	0,76923	0,76923	0,8	0,8	0,8	0,5625	0,5625	0,5625	0,75	0,75	0,75	0,83871	0,83871	0,83871	0,81356	0,79661	0,77966	0,88889	0,86667	0,86667
03:45	0,90909	0,90909	0,86364	0,72727	0,72727	0,72727	0,7	0,65	0,6	0,8125	0,75	0,75	0,69231	0,65385	0,61538	0,7963	0,7963	0,7963	0,79365	0,77778	0,7619
04:00	0,65	0,65	0,65	0,73684	0,73684	0,73684	0,61538	0,53846	0,46154	0,625	0,58333	0,5	0,68182	0,68182	0,63636	0,88636	0,86364	0,86364	0,9	0,9	0,9
04:15	0,72727	0,72727	0,72727	0,42857	0,28571	0,28571	0,59375	0,59375	0,53125	0,70833	0,66667	0,66667	0,7	0,7	0,64	0,76786	0,75	0,73214	0,77941	0,76471	0,75
04:30	0,55263	0,55263	0,5	0,68421	0,63158	0,63158	0,66667	0,56667	0,53333	0,5814	0,51163	0,46512	0,65385	0,57692	0,55769	0,78947	0,75439	0,73684	0,7451	0,7451	0,72549
04:45	0,5814	0,55814	0,55814	0,425	0,4	0,4	0,5	0,47826	0,47826	0,525	0,475	0,45	0,63636	0,60606	0,5303	0,68966	0,68966	0,63793	0,83784	0,83784	0,81081
05:00	0,58571	0,52857	0,5	0,57377	0,57377	0,54098	0,57143	0,54545	0,53247	0,52055	0,49315	0,47945	0,57971	0,55072	0,53623	0,625	0,625	0,625	0,77612	0,77612	0,77612
05:15	0,56627	0,56627	0,54217	0,675	0,6625	0,6375	0,70787	0,69663	0,68539	0,63636	0,58182	0,54545	0,56044	0,52747	0,50549	0,73913	0,72464	0,68116	0,78125	0,78125	0,75
05:30	0,62937	0,62937	0,58741	0,64	0,624	0,608	0,66393	0,64754	0,63934	0,66216	0,63514	0,61486	0,68148	0,67407	0,65926	0,62963	0,60185	0,58333	0,67164	0,65672	0,62687
05:45	0,64433	0,60825	0,57732	0,63519	0,60944	0,57511	0,62766	0,60106	0,58511	0,63934	0,63115	0,59426	0,60622	0,58031	0,53368	0,66364	0,60909	0,57273	0,6413	0,61957	0,59783
06:00	0,60729	0,59109	0,56275	0,62846	0,6166	0,58498	0,61594	0,60507	0,57971	0,64401	0,62136	0,59547	0,57801	0,54965	0,53191	0,61667	0,575	0,54167	0,61905	0,59048	0,54286
06:15	0,65495	0,63259	0,61022	0,63333	0,61212	0,59091	0,59938	0,58385	0,55901	0,58713	0,56032	0,52815	0,62464	0,58166	0,55014	0,56204	0,54015	0,54015	0,58442	0,55844	0,50649
06:30	0,64286	0,6129	0,58065	0,66259	0,63814	0,58435	0,6211	0,59472	0,56835	0,59465	0,57407	0,53909	0,60091	0,56916	0,53741	0,58667	0,56	0,52667	0,56154	0,51538	0,46154
06:45	0,64931	0,63194	0,59201	0,67622	0,65767	0,63744	0,65094	0,62264	0,59906	0,67241	0,6442	0,61755	0,60954	0,58657	0,553	0,45887	0,42857	0,40693	0,51938	0,48062	0,46512
07:00	0,63818	0,61282	0,58879	0,65293	0,62422	0,60175	0,62723	0,6056	0,56997	0,67409	0,63892	0,61665	0,59736	0,56731	0,53606	0,40789	0,36184	0,33553	0,41038	0,37264	0,32547
07:15	0,62455	0,60048	0,56799	0,6218	0,60565	0,56797	0,61959	0,59033	0,56361	0,61458	0,59271	0,55833	0,59697	0,55905	0,51788	0,39348	0,37594	0,34586	0,396	0,356	0,32
07:30	0,60159	0,57619	0,54365	0,59296	0,5603	0,53099	0,58182	0,55257	0,50988	0,594	0,57541	0,53467	0,55587	0,52793	0,49162	0,43802	0,40083	0,34711	0,39706	0,37132	0,33456
07:45	0,6139	0,58431	0,54439	0,60884	0,57736	0,53985	0,54037	0,5085	0,46671	0,57288	0,5448	0,5006	0,55073	0,51848	0,4827	0,43761	0,40422	0,3638	0,37432	0,34426	0,30055
08:00	0,60926	0,58042	0,54552	0,58608	0,5538	0,50933	0,51714	0,47988	0,44486	0,58973	0,56309	0,51807	0,50066	0,47051	0,43447	0,38981	0,35537	0,32094	0,42056	0,40421	0,3528
08:15	0,54628	0,51815	0,48639	0,53903	0,5023	0,47291	0,49954	0,46203	0,42086	0,53696	0,50117	0,46926	0,50126	0,47014	0,42473	0,3879	0,35488	0,31224	0,41176	0,36812	0,33017
08:30	0,51992	0,49161	0,44025	0,53649	0,49949	0,4666	0,46937	0,43827	0,39491	0,4808	0,4543	0,41408	0,44986	0,41012	0,36314	0,39559	0,36706	0,32555	0,3955	0,36174	0,32154
08:45	0,4656	0,42546	0,39335	0,45795	0,43068	0,38864	0,47878	0,4407	0,39499	0,4322	0,39805	0,37268	0,4287	0,39531	0,36823	0,36025	0,32712	0,29917	0,42207	0,38621	0,33793
09:00	0,43917	0,41241	0,37591	0,44457	0,40466	0,37916	0,43584	0,40597	0,36836	0,43043	0,3964	0,35636	0,42523	0,38739	0,34955	0,38395	0,34288	0,30181	0,39572	0,35738	0,31567
09:15	0,46879	0,44204	0,41401	0,45797	0,42284	0,37892	0,51111	0,47284	0,41852	0,46288	0,42249	0,37882	0,38861	0,35465	0,31069	0,35778	0,33005	0,2907	0,40237	0,37864	0,33765
09:30	0,43225	0,41057	0,37398	0,48173	0,44114	0,40595	0,44309	0,41328	0,38211	0,41509	0,38797	0,35142	0,38304	0,3499	0,31871	0,37018	0,32831	0,29146	0,38129	0,35312	0,30584
09:45	0,4586	0,42675	0,3949	0,46879	0,43696	0,40147	0,41333	0,38182	0,34182	0,4223	0,3964	0,35698	0,38916	0,35862	0,31034	0,36386	0,31601	0,28795	0,39458	0,35843	0,31827
10:00	0,47704	0,44133	0,40561	0,39806	0,37171	0,33564	0,4359	0,40293	0,36874	0,41163	0,38883	0,33295	0,38419	0,35202	0,32353	0,33996	0,30905	0,26784	0,38223	0,33736	0,30802
10:15	0,4903	0,46572	0,43338	0,44733	0,41587	0,39261	0,40721	0,37917	0,35915	0,41226	0,38582	0,35577	0,35885	0,32803	0,29225	0,34537	0,31603	0,27991	0,44944	0,42437	0,38202
10:30	0,5195	0,48553	0,45535	0,40503	0,37989	0,34358	0,4443	0,40537	0,36242	0,42717	0,40147	0,36353	0,40851	0,37092	0,33828	0,36565	0,33143	0,3015	0,4287	0,38957	0,34696
10:45	0,50542	0,47774	0,44525	0,43776	0,41119	0,37203	0,43829	0,40428	0,36272	0,44564	0,41765	0,38967	0,39365	0,36285	0,32435	0,35058	0,31924	0,2879	0,41513	0,3861	0,34213
11:00	0,51667	0,49222	0,46333	0,43727	0,40682	0,3715	0,41116	0,38269	0,35649	0,43975	0,41092	0,36457	0,42489	0,39289	0,35378	0,33497	0,30056	0,27388	0,4299	0,39659	0,35709
11:15	0,53465	0,50605	0,47305	0,47437	0,43981	0,41001	0,44235	0,40881	0,37212	0,45921	0,43619	0,40481	0,41796	0,38515	0,3532	0,39208	0,35246	0,31352	0,44945	0,41232	0,37204
11:30	0,53283	0,50269	0,47147	0,49346	0,46136	0,42687	0,43718	0,40756	0,36466	0,45499	0,42788	0,394	0,39948	0,36928	0,33218	0,37801	0,35326	0,3079	0,45354	0,42441	0,39055
11:45	0,54676	0,50668	0,47901	0,44602	0,41221	0,37732	0,43053	0,40117	0,36693	0,47771	0,43992	0,4031	0,4048	0,37481	0,33883	0,39257	0,37145	0,32702	0,42814	0,39259	0,35098
12:00	0,48869	0,45821	0,42576	0,4454	0,41435	0,3833	0,43337	0,39878	0,37538	0,42967	0,39139	0,35407	0,39214	0,36842	0,33358	0,37483	0,34966	0,31769	0,42158	0,38751	0,35628
12:15	0,53512	0,5062	0,47107	0,4708	0,43266	0,40286	0,46763	0,44085	0,40625	0,41811	0,40488	0,36317	0,41235	0,3823	0,35225	0,3832	0,35074	0,3211	0,44136	0,4172	0,38806
12:30	0,57742	0,55914	0,52581	0,47002	0,44844	0,41607	0,4403	0,40512	0,36674	0,42887	0,3946	0,35929	0,42381	0,37968	0,35221	0,39124	0,3697	0,3294	0,42921	0,40697	0,35804
12:45	0,57046	0,54633	0,51062	0,46828	0,43714	0,39792	0,46218	0,43487	0,39076	0,45377	0,42295	0,38789	0,42667	0,38667	0,3525	0,3787	0,34697	0,31946	0,45208	0,42429	0,38478
13:00	0,58171	0,55447	0,52821	0,452	0,41312	0,38396	0,4299	0,40722	0,36907	0,46471	0,43529	0,39118	0,43472	0,41014	0,38556	0,38498	0,35345	0,32126	0,45646	0,42275	0,38343
13:15	0,58049	0,55208	0,5322	0,48627	0,45652	0,42334	0,45455	0,43182	0,40152	0,48119	0,45644	0,42475	0,43843	0,41098	0,38039	0,41774	0,38111	0,35154	0,47626	0,43555	0,40434
13:30	0,59835	0,57813	0,55055	0,5215	0,48953	0,45755	0,47908	0,4502	0,42032	0,4896	0,46692	0,43951	0,46712	0,43049	0,39761	0,43461	0,39906	0,36486	0,49515	0,46741	0,43204
13:45	0,60124	0,56852	0,53846	0,48901	0,46178	0,42932	0,48716	0,46147	0,42341	0,48092	0,45075	0,42236	0,47476	0,44461	0,40693	0,44227	0,42074	0,38748	0,49779	0,46907	0,43004
14:00	0,61496	0,59002	0,56508	0,50095	0,47148	0,43916	0,52589	0,49821	0,45804	0,49511	0,46819	0,43556	0,4881	0,46023	0,43236	0,43434	0,40341	0,37374	0,50206	0,48281	0,44979
14:15	0,61173	0,5902	0,55902	0,54857	0,51711	0,48566	0,51757	0,49098	0,46534	0,51028	0,4821	0,44935	0,52249	0,50035	0,46574	0,44743	0,42053	0,39549	0,51391	0,49166	0,46314
14:30	0,62482	0,59398	0,56241	0,57995	0,5551	0,52361	0,59063	0,56172	0,53672	0,56	0,54222	0,50889	0,51235	0,49718	0,47498	0,47111	0,43836	0,41275	0,53354	0,50316	0,47405
14:45	0,62851	0,60931	0,59232	0,59398	0,57282	0,54434	0,57744	0,55865	0,52481	0,53605	0,50619	0,47851	0,55966	0,53329	0,50231	0,5069	0,4835	0,45651	0,5666	0,54158	0,51927
15:00	0,64519	0,62222	0,58963	0,59839	0,5823	0,55816	0,60124	0,57576	0,55234	0,58362	0,55843	0,52974	0,59088	0,57094	0,54644	0,53125	0,5059	0,47936	0,57674	0,55349	0,53023
15:15	0,65364	0,63179	0,60993	0,61233	0,59391	0,57123	0,60724	0,58378	0,55965	0,5984	0,57305	0,5457	0,58357	0,56556	0,54024	0,54722	0,52604	0,50887	0,56443	0,54161	0,51275
15:30	0,67532	0,6507	0,62475	0,62844	0,58808	0,57527	0,64783	0,62649	0,60013	0,60275	0,57527	0,55465	0,62208	0,60135	0,57646	0,57529	0,54943	0,52299	0,62525	0,60489	0,58045
15:45	0,66972	0,65263	0,63004	0,64209	0,61602	0,59186	0,62719	0,60785	0,59094	0,64762	0,62801	0,60728	0,62594	0,60835	0,58824	0,6254	0,60512	0,58431	0,61519	0,59557	0,56519
16:00	0,66158	0,64407	0,61808	0,64899	0,6304	0,60798	0,63598	0,6115	0,595	0,63833	0,61978	0,60278	0,65093	0,62963	0,60694	0,63713	0,62025	0,5981	0,63847	0,62082	0,60499
16:15	0,65403	0,63191	0,61032	0,65389	0,63183	0,61397	0,66949	0,64709	0,62768	0,64574	0,61834	0,59791	0,654	0,63888	0,62289	0,64317	0,62297	0,60325	0,6463	0,62981	0,60965
16:30	0,66667	0,64205	0,61316	0,67538	0,65922	0,64116	0,69305	0,67464	0,65255	0,67701	0,65785	0,63869	0,68592	0,66721	0,6489	0,6748	0,66036	0,64343	0,66479	0,64724	0,62657
16:45	0,64894	0,62507	0,60879	0,68236	0,6662	0,64728	0,69662	0,67437	0,6564	0,69516	0,67903	0,65726	0,71571	0,69532	0,67813	0,72475	0,70464	0,68693	0,69052	0,67197	0,65739
17:00	0,63078	0,61161	0,58963	0,70295	0,68753	0,67122	0,72509	0,71134	0,69502	0,70119	0,68686	0,66926	0,72766	0,71238	0,68966	0,70921	0,69021	0,67706	0,67655	0,65836	0,64218
17:15	0,6383	0,62015	0,59825	0,71205	0,69829	0,68454	0,72655	0,71009	0,69542	0,70184	0,68683	0,66752	0,75502	0,74418	0,7249	0,72551	0,71071	0,69286	0,70673	0,69225	0,68067
17:30	0,67195	0,65281	0,63498	0,73889	0,72222	0,70455	0,74466	0,73137	0,71808	0,69212	0,67859	0,66554	0,73942	0,7242	0,70516	0,71523	0,70199	0,68653	0,71075	0,69369	0,67747
17:45	0,71176	0,69051	0,67989	0,70663	0,69388	0,68112	0,71974	0,70992	0,68866	0,69718	0,68202	0,66685	0,74099	0,7288	0,71407	0,72927	0,71697	0,69689	0,71109	0,70249	0,68272
18:00	0,72382	0,70675	0,69123	0,71614	0,70461	0,68948	0,72971	0,71949	0,70607	0,6864	0,67065	0,65617	0,73503	0,72178	0,70641	0,71965	0,70737	0,68759	0,71762	0,70594	0,68939
18:15	0,74806	0,73795	0,72784	0,71823	0,70324	0,69376	0,73191	0,72304	0,71196	0,71368	0,70234	0,68533	0,75029	0,73095	0,71512	0,72892	0,72214	0,70858	0,78008	0,76763	0,74793
18:30	0,76886	0,75774	0,74424	0,71903	0,70826	0,6921	0,74014	0,72813	0,71012	0,70187	0,68989	0,6779	0,73382	0,72391	0,7074	0,72063	0,70496	0,69278	0,78046	0,77387	0,76509
18:45	0,75933	0,74867	0,73357	0,72917	0,72064	0,70928	0,75109	0,73107	0,71366	0,72394	0,71743	0,70358	0,72799	0,71212	0,68687	0,7557	0,73954	0,71863	0,8012	0,79281	0,78323
19:00	0,80209	0,79076	0,78466	0,73326	0,72582	0,71413	0,71836	0,7098	0,70219	0,72085	0,71113	0,70141	0,76841	0,75482	0,73838	0,76114	0,74597	0,72891	0,78214	0,77619	0,77024
19:15	0,84356	0,83644	0,82222	0,76066	0,7541	0,74317	0,79444	0,78947	0,78054	0,7753	0,77066	0,76416	0,80335	0,79243	0,77932	0,77788	0,76549	0,75214	0,80073	0,78606	0,77751
19:30	0,85932	0,85305	0,84498	0,81877	0,81122	0,80367	0,81275	0,80567	0,7915	0,81281	0,8038	0,7958	0,81825	0,81212	0,80215	0,77544	0,76535	0,75252	0,82603	0,82238	0,81144
19:45	0,88235	0,87728	0,87221	0,83146	0,82697	0,81685	0,85441	0,85122	0,83953	0,83397	0,81862	0,80518	0,83442	0,82224	0,81331	0,81897	0,81034	0,79789	0,85214	0,84306	0,83528
20:00	0,87789	0,86947	0,86	0,87791	0,86744	0,86163	0,87751	0,87434	0,86484	0,84129	0,83642	0,8296	0,86441	0,85876	0,84988	0,83734	0,83188	0,81987	0,86466	0,85965	0,84962
20:15	0,87694	0,87361	0,8714	0,87362	0,86748	0,85767	0,88453	0,87892	0,86547	0,8907	0,88458	0,88151	0,8554	0,85215	0,84159	0,87295	0,86528	0,85433	0,86749	0,86066	0,85383
20:30	0,91278	0,90442	0,89725	0,89747	0,89171	0,88249	0,88763	0,88422	0,87968	0,89577	0,88545	0,88029	0,87983	0,8721	0,86524	0,85429	0,85076	0,84606	0,89886	0,89886	0,89174
20:45	0,87852	0,87596	0,87084	0,90969	0,90183	0,89529	0,90695	0,90481	0,90481	0,90206	0,89794	0,89588	0,8876	0,88046	0,87422	0,89227	0,88642	0,8829	0,90053	0,89257	0,88992
21:00	0,92645	0,92362	0,91655	0,91747	0,90922	0,90234	0,91047	0,90581	0,90233	0,91459	0,91027	0,90486	0,88113	0,87114	0,85935	0,8897	0,88848	0,88364	0,90442	0,89729	0,89301
21:15	0,9323	0,92525	0,91678	0,91233	0,90685	0,89863	0,92545	0,92288	0,91388	0,90959	0,90408	0,89857	0,89225	0,88941	0,87996	0,90037	0,89664	0,88792	0,92535	0,92068	0,91446
21:30	0,9374	0,9374	0,92751	0,93641	0,93005	0,92369	0,91942	0,91281	0,90621	0,91795	0,9141	0,90256	0,90671	0,90147	0,90042	0,90361	0,89759	0,89036	0,92087	0,91542	0,91132
21:45	0,91516	0,90975	0,90975	0,91652	0,91478	0,90783	0,91056	0,90469	0,89736	0,92151	0,91715	0,91424	0,92144	0,91401	0,91083	0,91795	0,91795	0,91667	0,92038	0,91228	0,90283
22:00	0,90302	0,8944	0,88793	0,93446	0,93446	0,926	0,9253	0,9202	0,91511	0,91205	0,90228	0,89577	0,90026	0,89258	0,88619	0,90755	0,90625	0,89844	0,91176	0,90882	0,90294
22:15	0,92105	0,91627	0,91388	0,91184	0,9068	0,89421	0,92418	0,91393	0,90984	0,88719	0,87954	0,86998	0,91727	0,91147	0,90131	0,8842	0,88283	0,88011	0,92151	0,9168	0,90895
22:30	0,89914	0,89049	0,87896	0,91563	0,90938	0,9	0,89516	0,89247	0,88978	0,9199	0,91019	0,90049	0,90034	0,8902	0,88514	0,92537	0,9209	0,91343	0,90148	0,89984	0,89819
22:45	0,9304	0,92674	0,92308	0,92446	0,92086	0,92086	0,92739	0,91749	0,90099	0,90265	0,89381	0,88791	0,9082	0,9043	0,89453	0,90842	0,90103	0,89956	0,93039	0,93039	0,92869
23:00	0,87705	0,86475	0,86066	0,93191	0,92766	0,9234	0,93916	0,93536	0,93156	0,91319	0,90972	0,90972	0,8753	0,86811	0,86091	0,93805	0,93451	0,91858	0,92776	0,92015	0,91255
23:15	0,90826	0,90367	0,8945	0,87654	0,87037	0,87037	0,8871	0,8871	0,8871	0,86512	0,86047	0,86047	0,88319	0,86325	0,84615	0,90309	0,89897	0,89691	0,9234	0,91915	0,91489
23:30	0,94388	0,92857	0,92347	0,91935	0,91129	0,91129	0,91241	0,91241	0,89781	0,89205	0,88636	0,86932	0,86154	0,86154	0,85769	0,90421	0,90421	0,89252	0,92214	0,91971	0,91484
23:45	0,88757	0,88166	0,86391	0,88119	0,88119	0,87129	0,89431	0,85366	0,8374	0,90909	0,90303	0,89091	0,91176	0,89706	0,89216	0,90426	0,89096	0,88032	0,92327	0,9156	0,91049

Figure A16: Flexibility Table.

Figure A17 presents the expected lost loads per PTU for every weekday, and shows that noticeable peaks on Tuesday morning.

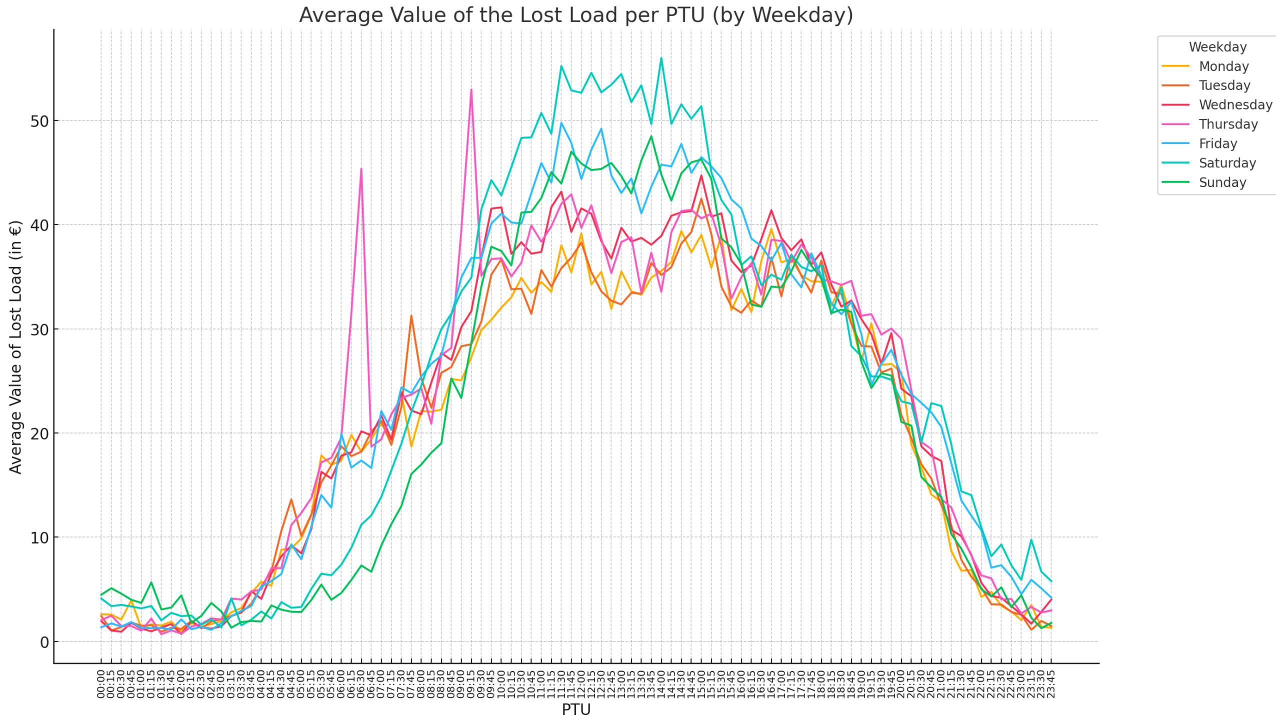

Figure A17: Average Value of the Expected Lost Loads per PTU on Weekdays.

Figure A18 compares the forecasted loads with the lost loads, providing insight into the effectiveness of the steering strategies in managing lost loads.

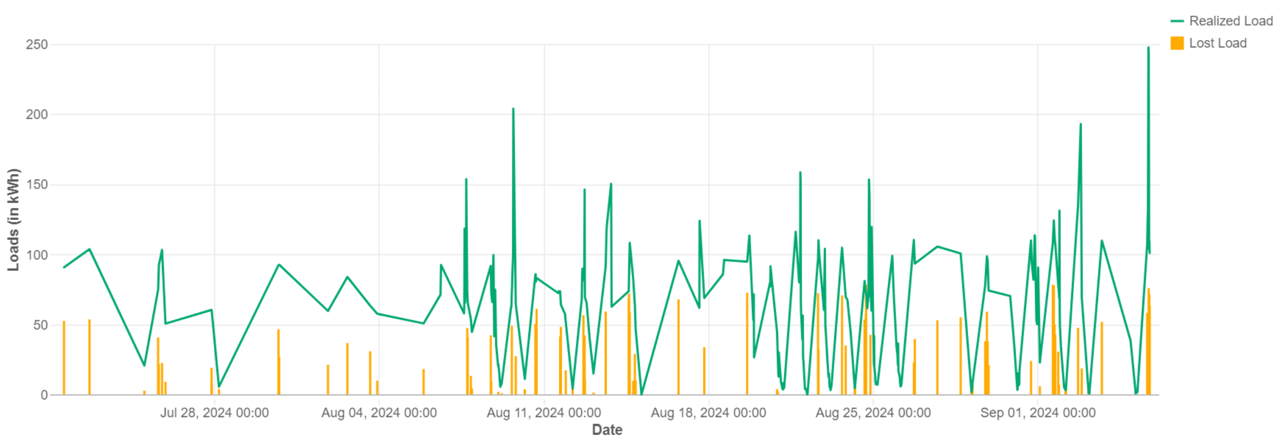

Figure A18: Forecasted and Lost Loads.

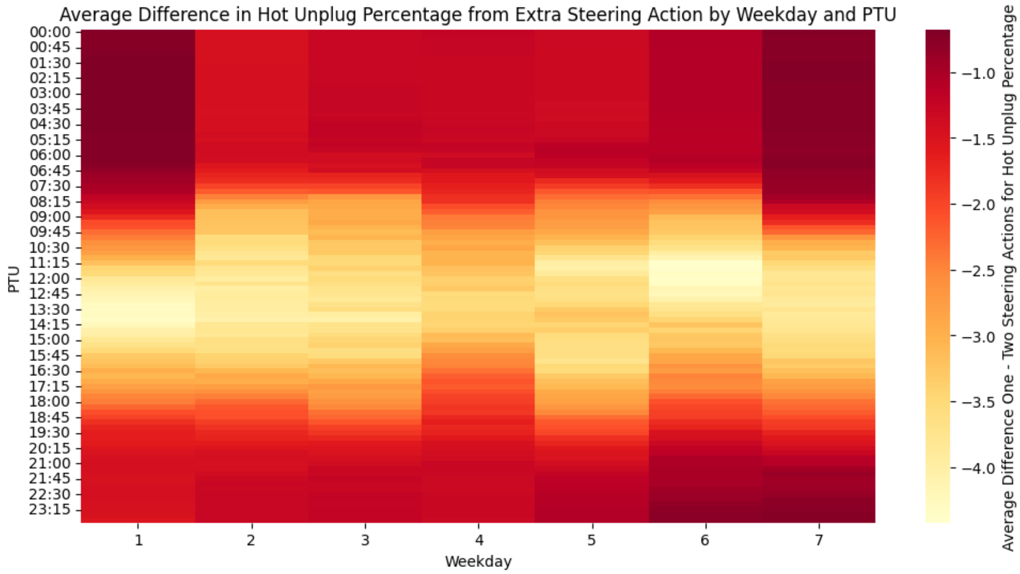

Figure A19: The Probability of Hot Unplug from Steering Action in PTUs throughout the Week.

Steering Profits

Figure A20 provides a detailed view of the financial impact of individual steering actions.

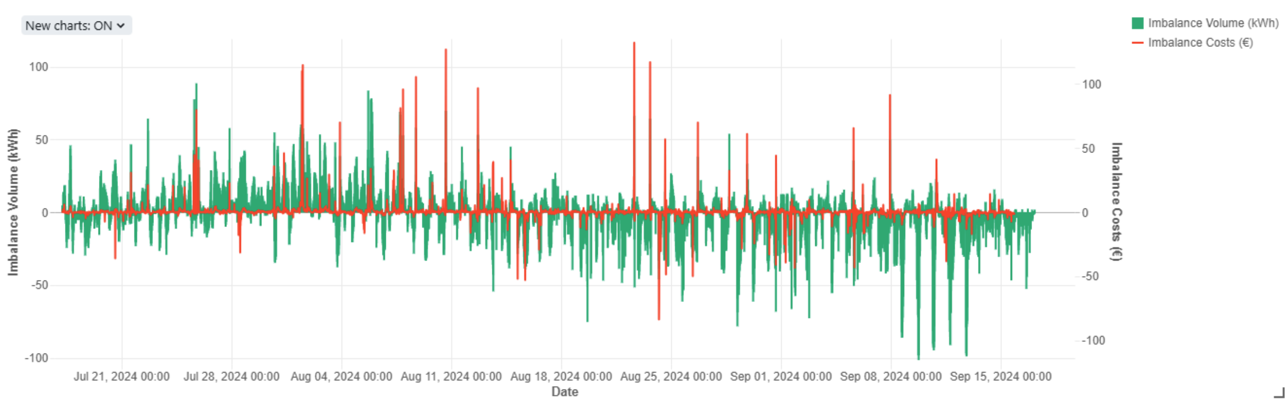

Figure A20: Imbalance Results

Figure A21 represents the imbalance prices that triggered a steering action.

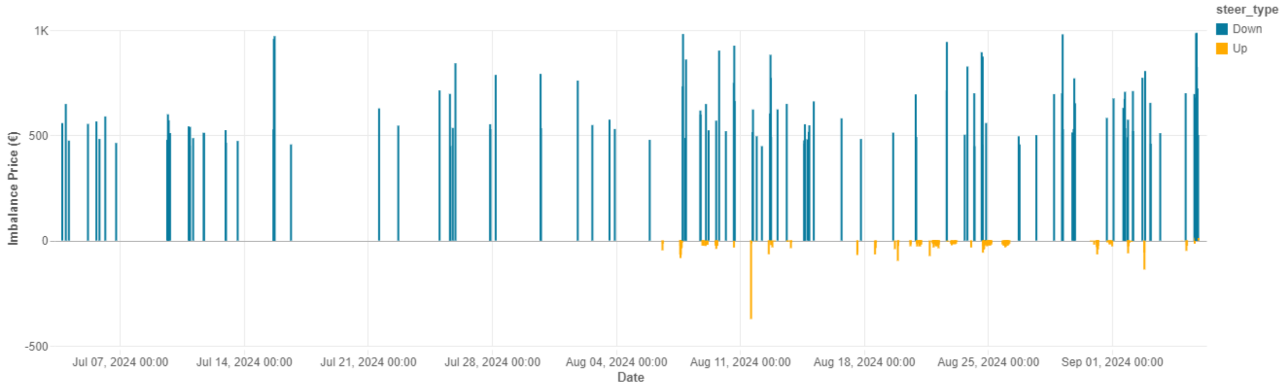

Figure A21: Imbalance Prices During Steering Actions.

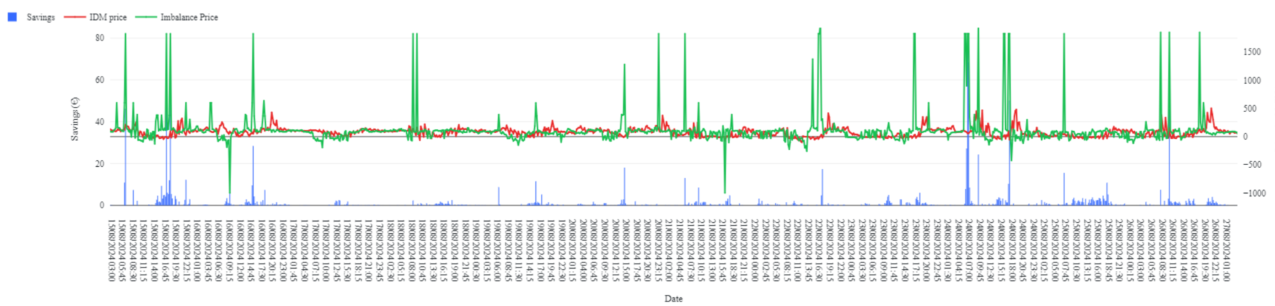

Figure A22: Impact of Rebound.

IDM Trading

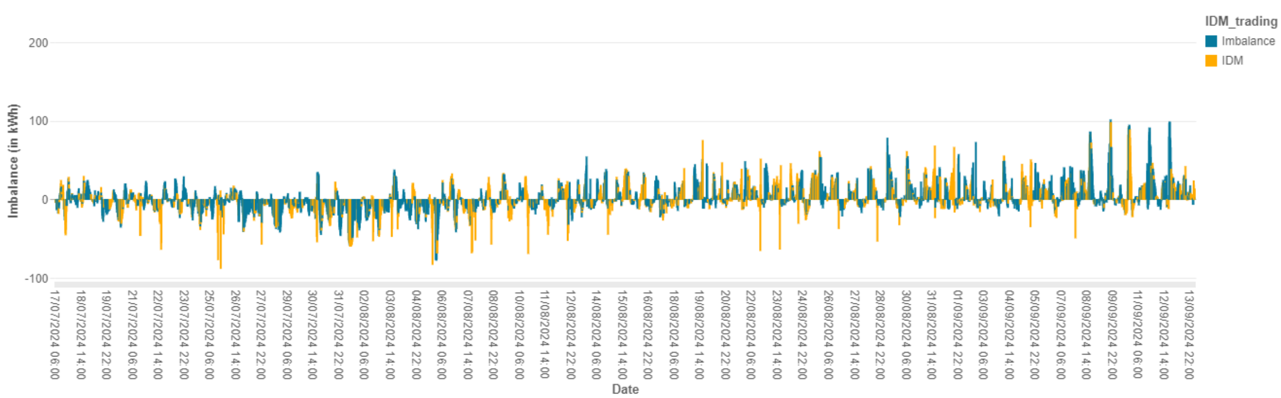

Figure A23: IDM Trading Frequency.

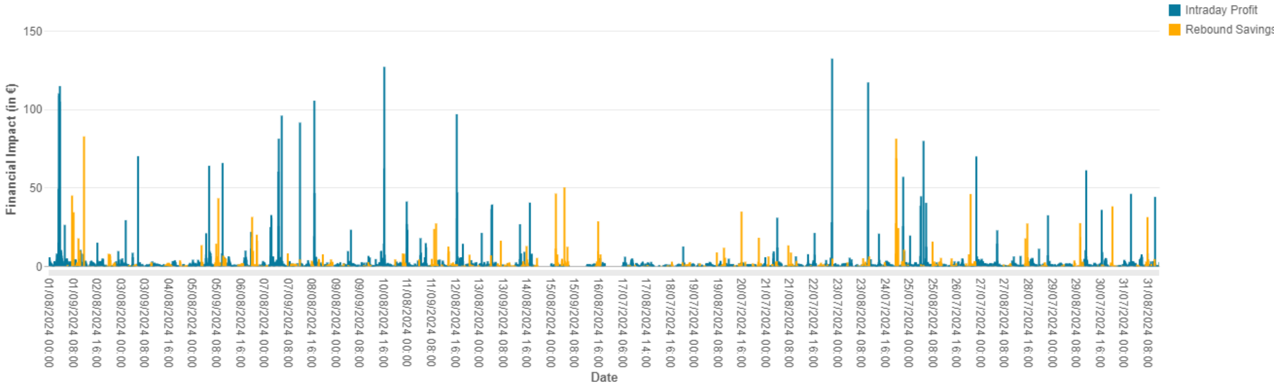

Figure A24: Effects of Model 3.

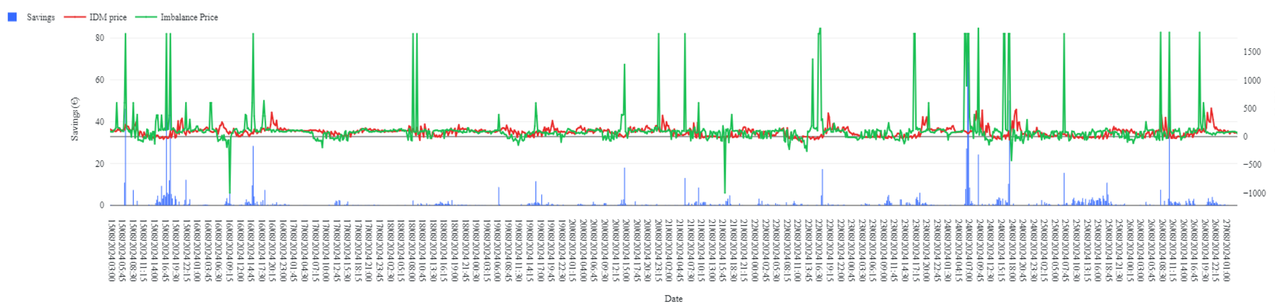

Figure A25: Savings per PTU from IDM Trading.