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Optimizing Electric Vehicle Charging: Managing User Behavior, Flexibility, Market Dynamics, and Costs

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"To my grandfather..."

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Abstract

The increasing adoption of electric vehicles (EVs) presents both challenges and opportunities for the power system. While the simultaneous charging of multiple EVs can increase peak demand, controlled charging—i.e., smart charging—allows EVs to serve as flexible assets. By implementing smart charging strategies, system operators and utilities can leverage EV flexibility to adapt the charging behavior in response to power system signals while ensuring user requirements are met. This thesis takes the perspective of an energy supplier, using smart charging to reduce their portfolio costs. However, achieving this goal requires addressing challenges on both the user and market sides. User-related challenges include willingness to participate and diverse driving and charging habits, which introduce variability in EV flexibility available for energy suppliers. On the market side, this variability, coupled with fluctuating electricity prices, makes it difficult to assess and monetize EV flexibility in the markets.

To address these challenges, this thesis, comprising seven research papers, investigates user factors influencing EV flexibility and integrates them into smart charging algorithms to enhance energy suppliers' trading strategies. Three papers focus on user behavior, analyzing factors that affect user participation in smart charging programs and the effectiveness of behavioral interventions in increasing flexibility provision. The remaining four papers quantify EV flexibility, assess its monetary value in wholesale electricity markets, and develop optimization models for energy procurement and imbalance management. By combining behavioral insights with optimization models and dynamic trading strategies, this thesis provides a comprehensive framework for energy suppliers to harness EV flexibility and reduce portfolio costs while maintaining user satisfaction.

Declaration

I, Raviteja Chemudupaty, declare that this thesis is solely my original work and has not been previously submitted for any other degree or professional qualification. I have acknowledged any contributions made by other authors in jointly-authored research papers and have provided accurate citations and references throughout the thesis.

To exclusively improve the readability and fix grammatical mistakes previously present in the text, I have utilized AI tools, including ChatGPT, and Grammarly during the preparation of this work. However, I have carefully reviewed and edited the generated content to ensure its accuracy, relevance, and alignment with the intended message of this dissertation. Thus, I assume full responsibility for the final content presented in this dissertation.

Moreover, I have no financial interests to declare and adhere to the principles of transparency and integrity in both public and professional life. I fully understand and commit to ethical research practices and academic honesty. This thesis represents the culmination of my efforts, and I am open to addressing any questions or concerns regarding its content or veracity in an honest and forthright manner

Luxembourg, July 16, 2025

Raviteja Chemudupaty

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I Introduction

1.1 Motivation

Energy fosters the global economy by driving industries, transportation, and infrastructure. Nevertheless, the energy sector has historically relied on fossil fuels, making it a major contributor to greenhouse gas (GHG) emissions. The rise in global temperatures, driven by GHG emissions, has underscored the urgent need to tackle climate change. In response, many nations have submitted nationally determined contributions (NDCs) following the Paris Agreement, outlining their plans to reduce GHG emissions (Horowitz, 2016). This accelerated the shift towards clean and alternative fuels, making significant strides in the energy transition to achieve a carbon-neutral energy system (Adefarati and Bansal, 2019).

In Europe, this energy transition led to an increase in renewable energy sources (RES), with their deployment expected to double over the past decade to help the Europe Union (EU) achieve its target of 45.5% renewable energy in final energy consumption by 2030 (EEA, 2025). Alongside the growth in renewable energy generation, the EU has promoted electrification as a key strategy to achieve its decarbonization goals (EUCOM, 2021). Electrification involves replacing fossil fuel-based technologies, such as internal combustion engines and gas boilers, with more efficient electric alternatives like electric vehicles (EVs) and heat pumps (IEA, 2023). These technologies improve energy efficiency and reduce emissions, primarily when powered by RES. Thus, the adoption of electrification is expected to grow rapidly, driven by ambitious climate goals, the enforcement of supportive legislation, ongoing technological advancements, and market incentives.

Nevertheless, the surge in electrification introduces new challenges to the power system and energy stakeholders. These challenges include managing peak demand, integrating variable RES, and addressing unpredictable consumption patterns, which could potentially destabilize the power system (Nour et al., 2020). These challenges due to electrification could be partially mitigated through demand-side flexibility, which allows consumers to adjust their energy use based on supply conditions and power system needs, reducing the need for additional infrastructure (Fridgen et al., 2020; Golmohamadi et al., 2024).

As part of ongoing electrification efforts, the penetration of EVs has increased (EAFO, 2025b). While their widespread adoption contributes to sustainability goals, their adoption increases electricity demand and may strain the power system, especially under simultaneous charging (Nutkani et al., 2024). However, when EVs are charged in a controlled manner, they serve as valuable flexible assets that system operators and utilities can leverage to optimize charging schedules according to both power system requirements and individual user needs (Haupt et al., 2020). This adaptation of EV user charging behavior to the conditions of the power system whilst adhering to user requirements is smart charging (IRENA, 2019).

Smart charging can assist system operators such as Distribution System Operators (DSOs) in reducing grid congestion (Galus et al., 2012; Menci et al., 2021), and provide Transmission System Operators (TSOs) with valuable flexibility services to maintain grid stability (Zhong et al., 2014). Furthermore, smart charging can also aid utilities such as energy suppliers or aggregators to reduce their portfolio costs by leveraging EV flexibility whilst trading in electricity markets (Fridgen et al., 2014; Pavić et al., 2015). Thus, smart charging helps system operators and utilities to optimize grid management, balance supply and demand, enhance stability, and reduce costs, benefiting both stakeholders and the power system.

While smart charging benefits stakeholders and the power system, its success relies on a thorough understanding of EV user behavior. The flexibility provided by EVs depends on individual driving and charging patterns, which vary widely among users (Daina et al., 2017; X. Li et al., 2023). This diversity creates uncertainty for system operators and utilities, complicating efforts to optimize EV charging. Additionally, some users might be reluctant to participate in smart charging programs due to behavioral factors such as concerns about losing control over their charging behavior, fearing that system operators or utilities could dictate their charging patterns (Delmonte et al., 2020). Lower participation rates ultimately limit the flexibility that EVs can provide, reducing the overall effectiveness of smart charging solutions.

Given these challenges, system operators or utilities seeking to leverage smart charging must account for the variability in user behavior and market conditions. In this thesis, I take the perspective of an energy supplier using smart charging to optimize residential EV charging and reduce their portfolio costs. The unpredictability of EV user behavior, combined with fluctuating market prices, complicates energy suppliers' ability to assess and monetize EV flexibility while trading in electricity markets. Thus, this thesis—comprising seven research papers (refer to Table I.1)—examines the behavioral factors influencing EV flexibility and explores their integration into smart charging algorithms to enhance energy suppliers' trading strategies in dynamic market environments.

Of the seven research papers, three (RP1, RP2, and RP3) explore behavioral factors influencing flexibility provision and investigate behavioral interventions that could enhance user flexibility provision. The remaining four papers (RP4, RP5, RP6, and RP7) focus on quantifying EV flexibility, analyzing the impact of behavioral factors on EV flexibility and its monetary value in wholesale electricity markets, and developing optimization models to facilitate trading in and reduce imbalances. By integrating these insights, this thesis aims to provide a framework for energy suppliers to design and implement effective smart charging programs that account for both user behavior and market dynamics.

Table I.1: List of research papers with roles and references

RP#	Title	Reference	Role
RP1	Towards an evaluation of incentives and nudges for smart charging	Marxen et al. (2022)	Non-primary
RP2	Empirical evaluation of behavioral interventions to enhance flexibility provision in smart charging	Marxen et al. (2023a)	Non-primary
RP3	Maximizing smart charging of EVs: The impact of privacy and money on data sharing	Marxen et al. (2023b)	Non-primary
RP4	Impact of minimum energy requirement on electric vehicle charging costs on spot markets	Chemudupaty et al. (2023)	Single primary
RP5	Uncertain electric vehicle charging flexibility, its value on spot markets, and the impact of user behaviour	Chemudupaty et al. (2025a)	Single primary
RP6	Optimizing trading of electric vehicle charging flexibility in the continuous intraday market under user and market uncertainties	Chemudupaty et al. (2025b)	Joint primary
RP7	Electric vehicle scheduling strategies to reduce the imbalances due to user uncertainties	Chemudupaty and Pavić (2024)	Single primary

1.2 Thesis Structure

This thesis is structured into five main chapters, followed by an Appendix. The thesis begins with Chapter I, which provides an overview of the research motivation, outlining the key research questions and objectives. Additionally, it presents the research papers included in this thesis, summarizing their respective topics, and concludes with a detailed explanation of the overall thesis structure.

Chapter II explores the concept of EV flexibility and the role of smart charging in harnessing this flexibility. It examines demand response strategies, the necessary communication infrastructure, and the critical aspects of information exchange required for effective smart charging implementation. Moreover, it discusses user privacy concerns related to data-sharing mechanisms for smart charging.

To effectively leverage EV flexibility in electricity markets, it is crucial to develop accurate models to quantify EV flexibility. Chapter III introduces a mathematical framework to model EV flexibility, outlining the key metrics and parameters involved in this process. The chapter further investigates how user uncertainties impact flexibility. Additionally, it discusses behavioral interventions to encourage more adaptable charging behaviors of EV users, ultimately enhancing the overall flexibility of the EVs fleet.

Building on the inputs from Chapter III, Chapter IV examines how EV flexibility can be utilized in electricity markets to optimize energy procurement and allocation. It covers two key aspects: aggregation, which focuses on procuring energy from the spot market, and disaggregation, which deals with optimal power allocation among individual EVs.

This thesis concludes with Chapter V, which summarizes the key contributions of this research. It also details the limitations of the proposed approaches in this thesis and outlines potential future research directions to improve EV flexibility modeling and trading strategies. Additionally, this chapter acknowledges related work conducted within the research group and collaborations.

Finally, Appendix A gives an overview of the publications included in this thesis, a detailed breakdown of individual contributions to each included research paper, and a complete draft of all the research papers.

II Smart Charging: From Basics to Information Exchange

The growing adoption of EVs presents both opportunities and challenges for the power system. While EVs can provide valuable flexibility through smart charging, their effective integration requires a well-structured framework. Section 2.1 introduces key smart charging concepts, emphasizing demand response strategies that maximize EV flexibility. Building on this, Section 2.2 gives an overview of the communication infrastructure and information exchange necessary for seamless smart charging implementation. Finally, Section 2.3 addresses the critical issue of user privacy, highlighting user concerns related to data sharing for smart charging programs.

2.1 Basic Concepts

EVs are classified based on their propulsion systems and energy sources. The main categories include Battery Electric Vehicles (BEVs), Plug-in Hybrid Electric Vehicles (PHEVs), and Fuel Cell Electric Vehicles (FCEVs) (EAFO, 2025a). BEVs operate solely on electric power, utilizing energy stored in rechargeable batteries. They produce zero tailpipe emissions and rely entirely on external charging infrastructure for energy replenishment. PHEVs combine internal combustion engines with electric motors and batteries, enabling both electric-only and hybrid operation. FCEVs generate electricity onboard using hydrogen fuel cells, emitting only water vapor as a byproduct. This thesis focuses exclusively on BEVs, which are referred to as EVs throughout this thesis.

The European market has witnessed rapid growth in EV adoption, with EVs accounting for 23.6% of total vehicle sales in 2023. Norway leads this transition, with up to 90% of its vehicle sales being EVs (EEA, 2024). Several European countries have established clear goals to decarbonize their transport sectors, accelerating EV penetration (EEA, 2024). As adoption continues to rise, the electricity demand for EV charging is projected to reach approximately 165 TWh by 2030 (McKinsey, 2022). This additional demand, especially if EVs are charged simultaneously, could increase peak demand and might have detrimental effects on the power system (Cheung, 2022).

To mitigate these challenges, smart charging offers a promising solution. Smart charging enables EVs to function as flexible assets, dynamically adjusting their charging schedules based on power system conditions. System operators (TSOs, DSOs) and utilities (energy suppliers and aggregators) can implement smart charging through two primary demand response strategies: implicit and explicit.

Implicit demand response relies on consumers adjusting their electricity consumption in response to time-based pricing schemes that can reflect market fluctuations (EUCommission, 2016). In the context of EV charging, utilities such as energy suppliers can encourage users to treat their vehicles as flexible assets and adapt their charging behavior by offering various pricing structures (Amin et al., 2020). The different pricing structures could include real-time pricing (RTP), time-of-use (ToU) tariffs, critical peak pricing (CPP), or peak time rebates (PTR) as I illustrate in Figure II.1.

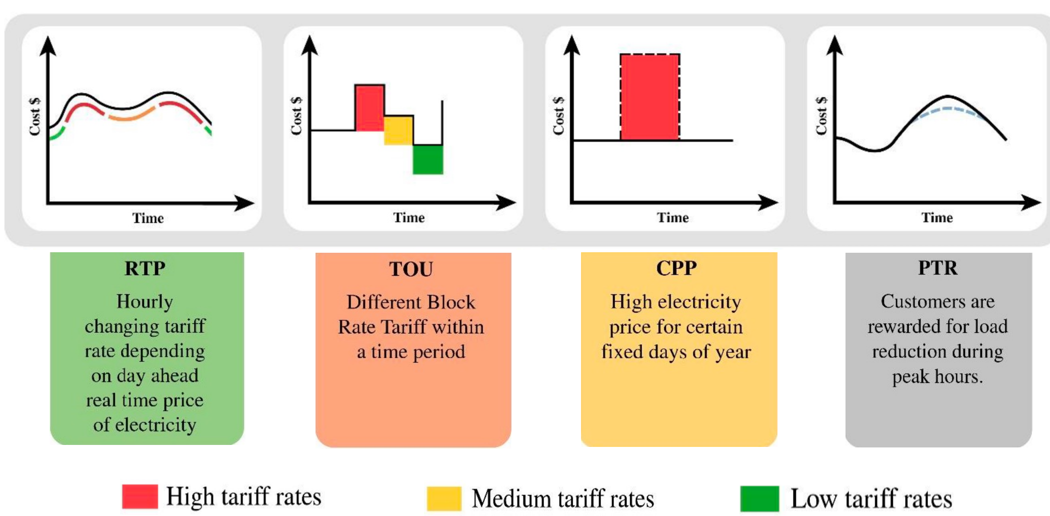


Figure II.1: Overview of different price mechanisms for implicit demand response programs extracted from Amin et al. (2020).[1]

[1]Open access CCBY 4.0.

RTP dynamically adjusts electricity rates at short intervals, such as hourly or every few minutes, reflecting real-time market prices. ToU pricing divides the day into predefined time blocks—off-peak, mid-peak, and peak—offering fixed rates announced in advance. CPP is a more dynamic variant of ToU, applying significantly higher rates during forecasted high-demand periods to reduce peak loads, though it requires accurate forecasting and consumer adaptation. Lastly, PTR incentivizes consumers by offering financial rewards for reducing electricity consumption during peak hours.

While these pricing structures encourage EV users to adapt their charging behavior based on price signals, their effectiveness depends on users' willingness and ability to respond (EUCommission, 2016). Factors such as convenience, awareness, and the perceived complexity of pricing structures can influence participation. Moreover, since the response is voluntary and not directly controlled by utilities, predicting and ensuring the desired load adjustments can be challenging (Amin et al., 2020).

Explicit demand response programs involve direct user participation—either individually or through aggregators or energy suppliers—in electricity markets (EUCommission, 2016). In these programs, EVs serve as controllable loads, providing flexibility services in wholesale energy, reserves, balancing, and capacity markets. Utilities such as energy suppliers can leverage EV flexibility to optimize the charging schedules, ensuring charging occurs during periods of lower electricity prices (Pavić et al., 2023). This strategic approach enables utilities such as energy suppliers to optimize their portfolio management and reduce overall costs.

To encourage participation in explicit demand response programs, energy suppliers can offer financial incentives such as direct payments, bill credits, or rebates (EUCommission, 2016). Additionally, users may gain access to specialized dynamic pricing programs that reward flexibility. These incentives ensure that users have a tangible financial motivation to adjust their charging behavior, making explicit demand response a more predictable and controllable strategy for utilities such as energy suppliers.

This thesis explores the implementation of smart charging within the framework of explicit demand response programs; focusing on how energy suppliers can leverage the flexibility of residential EV charging to optimize portfolio costs while participating in spot markets such as the DA and intraday (ID) markets.

2.2 Information Exchange

Implementing smart charging as an explicit demand response program requires a robust infrastructure enabling real-time communication between EVs and energy suppliers (Fridgen et al., 2016b). Central to this infrastructure are the standards and protocols that facilitate seamless data exchange, ensuring interoperability and reliability across different systems. Understanding these protocols and standards is critical for implementing smart charging programs.

The EV charging ecosystem involves various stakeholders and interconnections. As I illustrate in Figure II.2, ElaadNL (2016)'s study provides an overview of different protocols and market roles of the stakeholders. Their study analyzes the interoperability, maturity, and market adoption of various standards and protocols across four key use cases: Roaming, Smart Charging, Electric Vehicle Supply Equipment (EVSE)– Charging Point Operator (CPO), and EV–EVSE, primarily focusing on public charging scenarios. In the context of public charging, the CPO is the one who controls the charging of the EV fleet while collaborating with entities such as DSO and the Clearing House. As this thesis focuses on residential charging, the energy supplier is considered to be the CPO.

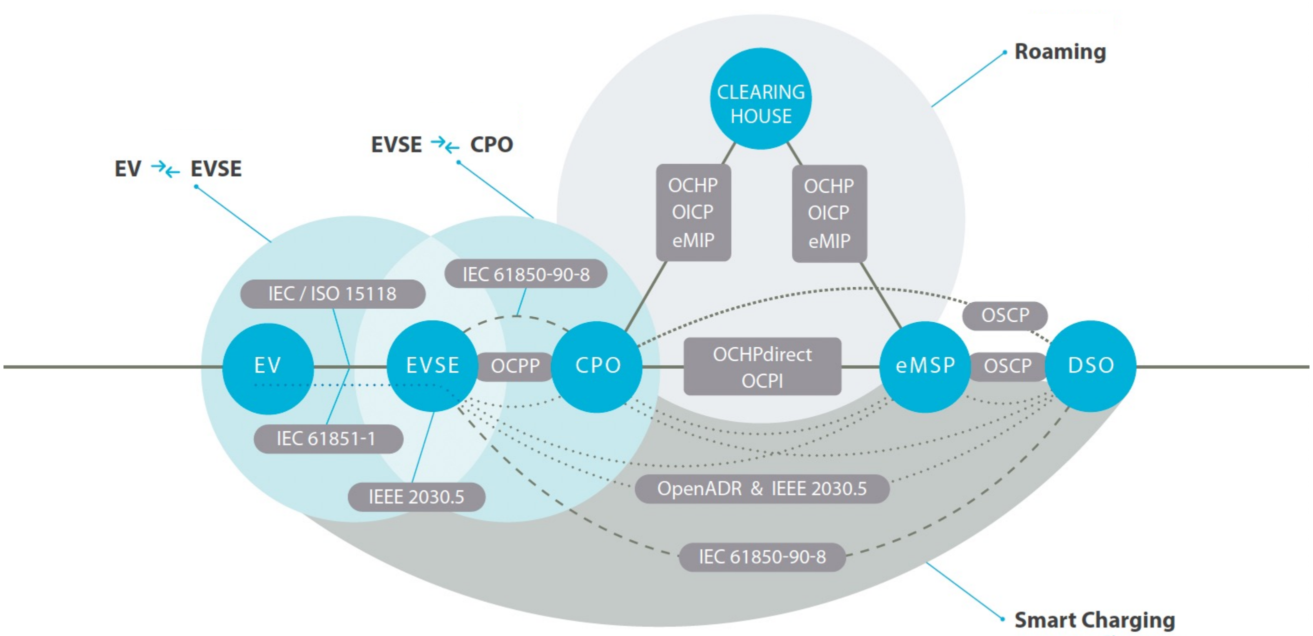


Figure II.2: EV charging protocols' representation extracted from ElaadNL (2016).

There are three possible connections for the energy supplier to control the charging of EVs. The first possible connection is the direct connection, where the energy supplier directly controls the charging of the EV via the EVSE i.e., wallbox in case of residential charging (see Figure II.3). In direct connection, the communication between the energy supplier and the EV is split into two parts - communication between the energy supplier and the EVSE, and the communication between the EVSE and the EV.

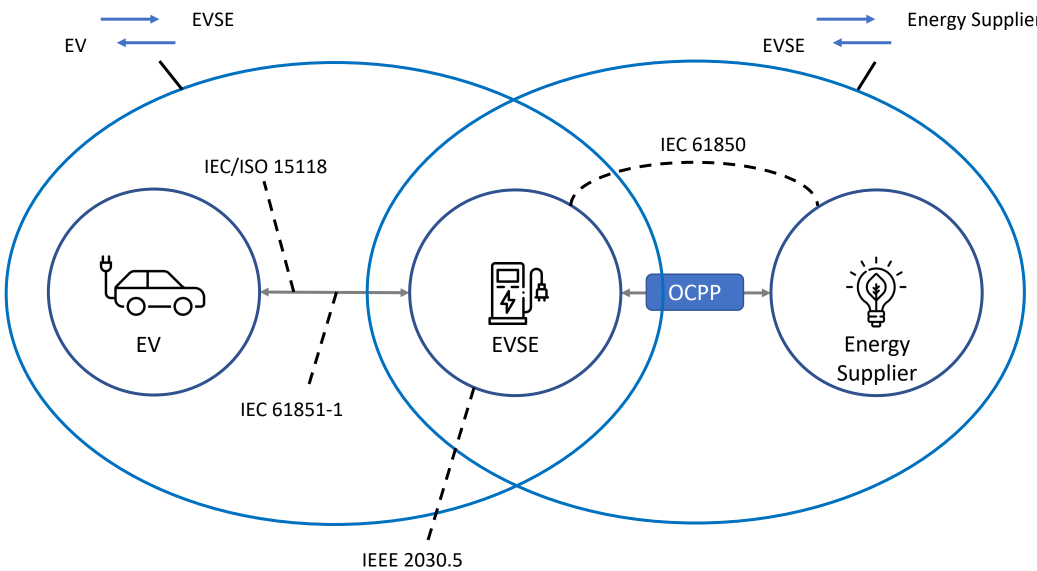


Figure II.3: Depiction of direct connection system including standards and protocols based on ElaadNL (2016).

The communication between the energy supplier and the EVSE is facilitated by two protocols - IEC 61850-90-8:2016 and the Open Charge Point Protocol (OCPP). The IEC 61850 standard focuses on grid automation, treating the EV as a distributed energy resource (DER) (ElaadNL, 2016). It establishes a robust communication stack for smart grid applications. On the other hand, the OCPP is specifically tailored to manage the EVSE, making it highly specialized for this single DER and ensuring efficient operation between the EVSE and the energy supplier (ElaadNL, 2016).

The communication between the EV and the EVSE is facilitated by three key standards: IEC 61850-1, IEC 62351, and ISO 15118. The IEC 61850-1 standard focuses on automating intelligent electronic devices (IEDs), including both EVs and EVSEs, with an emphasis on smart grid integration (ElaadNL, 2016). Meanwhile, IEC 62351 ensures secure communication by addressing critical security aspects such as authentication, digital signatures, and secure data transfer (IEC, 2025; Schmutzler et al., 2013). Finally, ISO 15118 provides a comprehensive framework for EV-to-EVSE communication, supporting both AC and DC charging, and enabling advanced features like Vehicle-to-Grid (V2G) functionality (ElaadNL, 2016).

The second possible connection for controlling EVs involves using an external device, typically a control box or a Home Energy Management System (HEMS). HEMS serves as a central hub, capable of connecting and managing various smart home devices, including photovoltaic (PV) inverters, battery management systems (BMS), and automation systems (Mahapatra and Nayyar, 2022). For EV charging, HEMS enables monitoring, control, and management of the charging process (see Figure II.4).

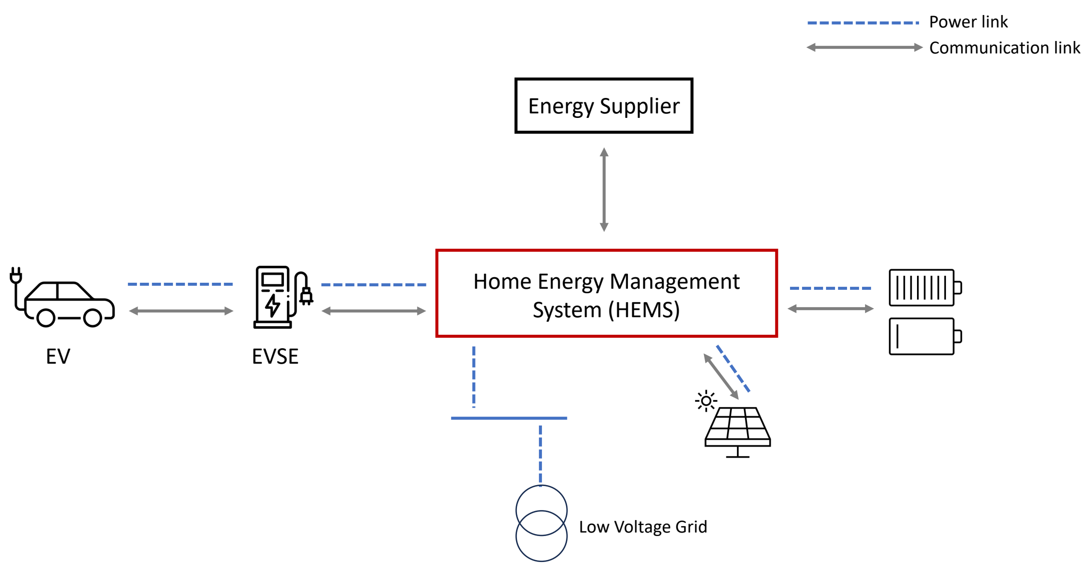


Figure II.4: Depiction of connection between EVs and energy supplier via HEMS based on ElaadNL (2016).

However, a key challenge with HEMS is interoperability, as different EV manufacturers often create unique solutions in partnership with OEMs, complicating device compatibility (Mahapatra and Nayyar, 2022). Protocols like EEBus (Europe), SEP2.0 (USA), and ECHONET Lite (Japan) are commonly used to connect EVSE with HEMS (Sole, 2017). Additionally, the connection between the energy supplier and HEMS is often facilitated by OpenADR 2.0, while many manufacturers also integrate OCPP to enable third-party access for energy suppliers or charge point operators (ElaadNL, 2016).

A third option for controlling EVs involves direct communication with the vehicle via application programming interfaces (APIs), bypassing the EVSE or HEMS. This approach leverages advancements in EV connectivity to enable new automation functionalities (Rutten and Cobbenhagen, 2019). However, a significant challenge is that car manufacturers typically restrict external access to their systems. To address this, some companies offer devices connected to the Controller Area Network (CAN bus), which act as gateways for third-party systems (Fixter, 2020). This technology is gaining traction, particularly among car-sharing companies. For instance, the Smartcar API provides basic functionalities like vehicle location, battery status, and lock/unlock features (Smartcar, 2025). While promising, this approach may be considered intrusive for private customers but is more suited for business fleets.

In this thesis, I assume that an energy supplier uses direct connection due to its simplicity, reliability, and compatibility with existing EVs and EVSE standards. Furthermore, using a direct connection enables secure and efficient communication between the energy supplier and EV. Figure II.5 provides an overview of the information exchanged between energy suppliers and users via the EVSE.

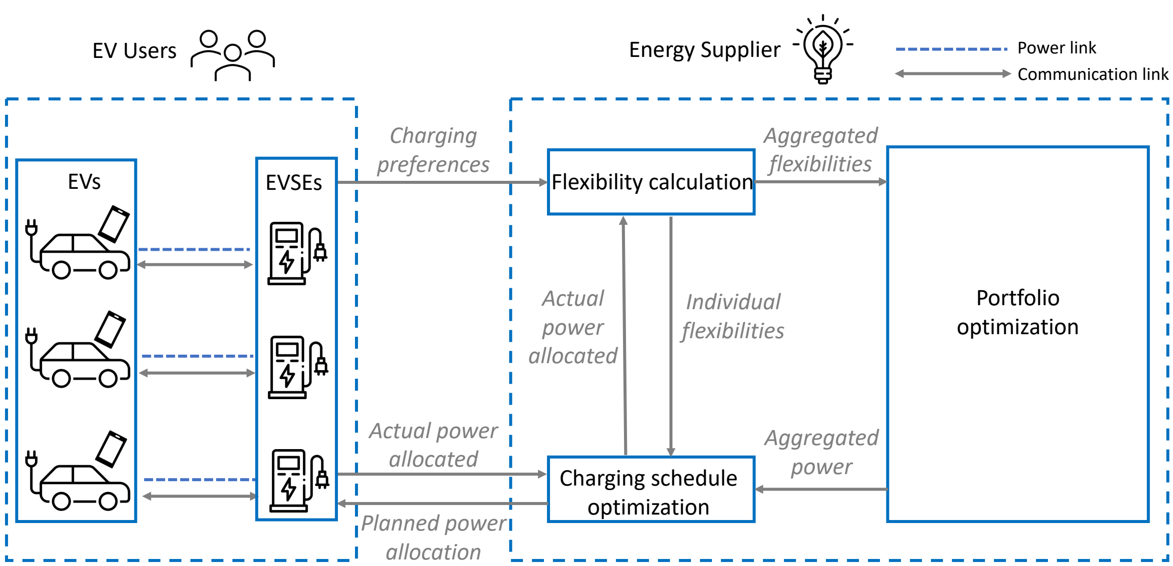


Figure II.5: Information exchange between EV users and Energy Supplier.

Users convey their charging preferences, such as parking duration and energy requirements, to the energy supplier. Across all my research papers, I assume that users communicate their preferences through a smart charging application. Using these preferences, the energy supplier calculates the aggregated flexibilities. Based on the aggregated flexibility, the energy supplier trades in the electricity markets to procure the required power for the entire fleet of EVs. Once the aggregated power is obtained, the energy supplier optimizes individual charging schedules and accordingly allocates power to each EV. Throughout this process, there is continuous information exchange between users and the energy supplier via EVSE to monitor the power delivered to each EV. This real-time data allows the supplier to update flexibility calculations and allocate the power to each EV based on their energy requirements.

2.3 User Information and Privacy Concerns

Bidirectional data exchange is crucial for implementing smart charging programs. Furthermore, for energy suppliers to accurately forecast the flexibility provided by EVs and improve smart charging algorithms, they may require additional personal data such as GPS location, distance traveled, and historical charging behavior. However, this data is sensitive as it reveals users' routines, movements, and daily schedules.

Despite technical privacy-enhancing techniques such as differential privacy (Dwork and Roth, 2014; Fernández et al., 2022), homomorphic encryption (Teng et al., 2022), and distributed learning techniques (McMahan et al., 2017) that aid in preserving user privacy, users may still be reluctant to share their data due to their privacy concerns. These concerns stem from fears of losing control over their information, illegal data disclosure, misuse by hackers, and increasing intrusion from smart devices (Aloise-Young et al., 2021; Cichy et al., 2021). Specifically, in the context of smart meters, which enable bidirectional communication— Quinn (2009) categorizes privacy concerns into four areas: individuated patterns, real-time surveillance, information detritus, and physical invasion. Given these challenges, understanding how users perceive and navigate data-sharing decisions for smart charging remains crucial, which was not explored by previous studies.

To explore this issue, RP3 investigated user willingness to share data with their energy supplier through a smart charging app. The study examined which types of data users were most willing to share and the sociotechnical measures that could encourage data sharing. Our survey considers three kinds of data, each with different sensitivity levels: charging data (least sensitive), location data, and calendar data (most sensitive). Based on the responses from 479 survey participants, my coauthors and I assessed their willingness to share these data types and the key factors influencing their decisions.

Findings from RP3 indicate that most participants were willing to share historical charging data, whereas they were ambivalent about sharing location data and generally unwilling to share calendar data. Perceived risks negatively influenced willingness to share all three data types, while perceived benefits increased willingness to share charging and location data. Furthermore, prior habits of location sharing played a significant role in users' willingness to disclose their location information.

Economic research has extensively explored willingness to pay for data privacy or the compensation required to accept data sharing (Acquisti et al., 2013; Hirschprung et al., 2016). However, such studies primarily focus on data sharing for websites rather than for demand response (DR) applications, particularly in the context of smart charging. To bridge this gap, RP3 examined whether users would share their data in exchange for monetary compensation and, if so, how much they would demand for charging, location, and calendar data.

The results from RP3 revealed that around 40% of participants expected 10–100% or more than 100% of their charging costs to be reimbursed in exchange for sharing their location or calendar data. For all data types, most participants in the experimental group expressed willingness to share their data for financial compensation. Notably, the more sensitive the data, the higher the amount requested.

Overall, these findings from RP3 highlight the complex balance between leveraging user data for improving smart charging programs and addressing privacy concerns. While most users are open to sharing charging data, they are cautious about more sensitive information. The high compensation demands, especially for sensitive data, highlight the challenge for energy suppliers in balancing the need for comprehensive data with users' privacy concerns.

III | EV Flexibility

Accurately estimating and quantifying the flexibility of EVs is crucial for energy suppliers. This foresight enables them to optimize trading strategies and reduce costs in electricity markets. This chapter delves into the key aspects of modeling EV flexibility, essential for improving energy suppliers' electricity market operations.

This chapter begins by describing a mathematical model to quantify EV flexibility, covering the metrics needed and approach to quantify EV flexibility in Section 3.1. Section 3.2 focuses on the practical implementation of the flexibility model to estimate fleet flexibility. It explores the modeling of input parameters essential for calculating EV flexibility, examines the impact of user uncertainties—such as variations in user preferences—on flexibility, and discusses behavioral interventions to enhance user flexibility provision.

3.1 Mathematical Model to Quantify EV Flexibility

Flexibility in power systems is crucial for ensuring a continuous balance between electricity generation and consumption (Akrami et al., 2019). Historically, flexibility was primarily achieved through controllable generation assets that could adjust their power output in response to fluctuating demand (Heggarty et al., 2020). As a result, flexibility was often perceived from the supply side, with authors (Heggarty et al., 2020) defining it as "the ability to adapt the system (both generation and transmission) quickly and at reasonable cost to any change in the conditions that prevailed at the time it was planned."

In recent years, however, the integration of variable RES into the power system has increased, alongside the decommissioning of controllable generation assets such as coal and gas plants. This shift has introduced uncertainty on the supply side (Papaefthymiou et al., 2018), creating a need for more flexibility in the system. Consequently, the definition of power system flexibility has evolved to include the system's ability to manage unpredictable changes in both supply and demand (Heggarty et al., 2020)

Quantifying flexibility is crucial for accurately estimating a system's ability to respond to power signals (Weidlich and Zaidi, 2019). To be a valuable, flexible asset, the metrics used to quantify flexibility must convey specific information that defines its effectiveness in delivering various flexibility services (J. Liu et al., 2022). The metrics should convey the following information: capacity - change in power output (Artelys, 2023); duration - time for sustaining full power change (Artelys, 2023; Bahmani et al., 2022; Faria et al., 2015; Schott et al., 2019); direction - upward or downward flexibility (Artelys, 2023; Bahmani et al., 2022; Schott et al., 2019); location -grid position of flexible loads (Fridgen et al., 2017; Fridgen et al., 2021a; Plaum et al., 2022); preparation time - time needed to initiate flexibility (Artelys, 2023; Bahmani et al., 2022; Schott et al., 2019; Tristán et al., 2020); ramping period - time to reach full power adjustment (Artelys, 2023; De Vos et al., 2022); full activation time - total time from notification to full delivery (Artelys, 2023); deactivation period - time to return to original state (Artelys, 2023; Schott et al., 2019); recovery time - interval before flexibility can be reactivated (Artelys, 2023); availability - time frames when flexibility can be provided, including daily/seasonal variations and activation limits (Artelys, 2023).

Nevertheless, not all the flexibility information is equally crucial in the context of smart charging, where an energy supplier leverages EV flexibility to reduce portfolio costs while trading in wholesale electricity markets. Some flexibility information, such as preparation time, ramping period, full activation time, deactivation period, recovery time, and location, is generally less critical. Since wholesale market trading does not require an immediate response, smart charging can operate with planned and gradual adjustments rather than rapid power changes. Energy suppliers can optimize charging schedules based on market conditions without strict constraints on activation timing, making metrics like ramping and recovery time less relevant. Similarly, location is not a primary concern for energy suppliers, as their focus is on portfolio cost optimization rather than addressing local grid constraints, which are more relevant for system operators managing congestion and voltage stability.

The key flexibility information required for smart charging includes capacity, duration, direction, and availability (Develder et al., 2016; Zhang et al., 2020). Additionally, energy level information is crucial from the user's perspective, as it ensures that the EV has enough energy to meet the user's requirements.

To better quantify EV flexibility, my coauthors and I developed a flexibility model in RP4 that assesses the flexibility provided by an aggregated EVs fleet. Our model calculates individual flexibility metrics for each EV based on user requirements, incorporating time-dependent power and energy metrics. These metrics provide insights into how much power can be adjusted while ensuring the vehicle retains the necessary energy levels to meet user needs. By aggregating these individual metrics, we derive comprehensive fleet-level flexibility metrics that offer a holistic view of the fleet's ability to adjust power levels while maintaining energy constraints.

The development of this flexibility model serves two primary purposes. First, it evaluates the EVs fleet's flexibility potential, helping to understand how much flexibility can be harnessed from aggregated EVs. Second, it facilitates optimal EVs scheduling for electricity market participation. While RP4 and RP5 focus on analyzing EVs flexibility potential, RP6 explores how this flexibility model can be applied to optimize EVs scheduling in wholesale electricity markets

The following subsections (3.1.1 to 3.1.3) replicate parts of the flexibility model presented in RP6. They are repeated here for completeness and to support a better understanding of the analysis and extensions discussed in the subsequent chapters of this thesis.

3.1.1 Input Parameters

The following parameters are required to quantify EV flexibility, as detailed in RP6. Please refer to RP6 for the rationale behind their selection.

- **Maximum charging power** ($P_v^{\max}$): The highest charging rate at which the EVs can charge.

- **Plugin duration**: The time that EV remains plugged in, estimated as the duration between arrival time (t^{arr}) and departure time (t^{dep}).

- **Energy transfer by departure** (E_v^{dep}): The energy required to meet the user's requested state of charge (SOC_{dep}) by the departure time (t^{dep}). SOC_{dep} is the percentage of battery capacity the user requests before the departure time (t^{dep}).

Figure III.1 illustrates the typical EV battery and its different energy values. E_v^{max} represents the total battery capacity, E_v^{arr} is the battery level at arrival time (t^{arr}), and E_v^{dep} is the energy transferred to meet the user's requirements.

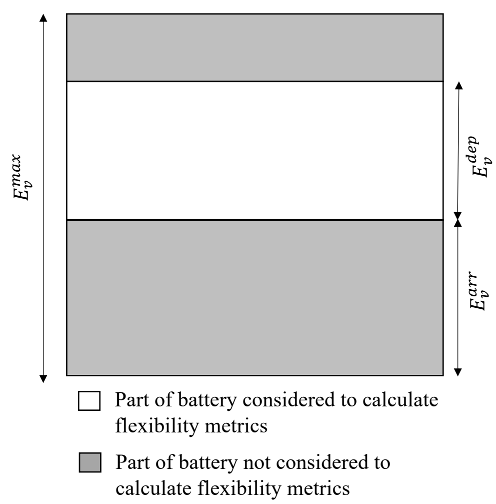


Figure III.1: Typical EV battery and different energy values extracted from RP6.

As this thesis only considers unidirectional charging, the battery's energy level can never drop below E_v^{arr}. Additionally, the user may not always request 100% state of charge at departure (SOC$^{\text{dep}}$). Thus, the sum of the E_v^{arr} and E_v^{dep} does not always equal the E_v^{max} of the vehicle (see Equation III.1):

$$E_v^{\text{arr}} + E_v^{\text{dep}} \leq E_v^{\text{max}} \tag{III.1}$$

Therefore, the flexibility calculation considers only the part of the battery that can be charged, i.e., E_v^{dep}.

3.1.2 Individual Quantification

To estimate the flexibility of an EV, time-dependent energy and power metrics are calculated based on the input parameters defined in Section 3.1.1. The energy metrics include minimum energy ($E_{t,v}^{\text{min}}$) and maximum energy ($E_{t,v}^{\text{max}}$) at time t, while the power metrics are minimum power ($P_{t,v}^{\text{min}}$) and maximum power ($P_{t,v}^{\text{max}}$) at time t. These metrics indicate the power with which an EV can be charged while maintaining the upper and lower limits of cumulative energy transfer.

$E_{t,v}^{\text{min}}$ is the minimum cumulative energy that must be transferred to meet the energy requirement E_v^{dep}. The calculation of $E_{t,v}^{\text{min}}$ follows two phases (i.e., Phase 1 and Phase 2) during the plugin duration, as illustrated in Figure III.2.

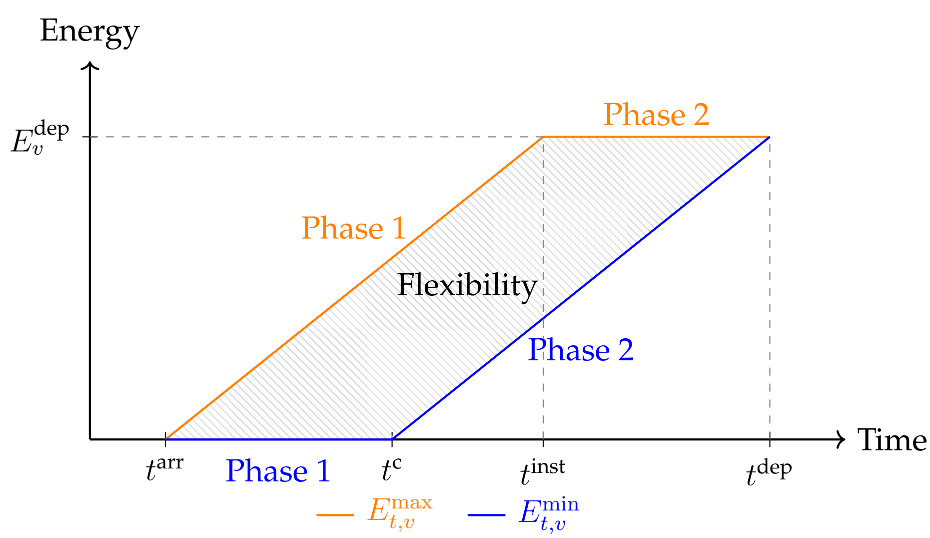


Figure III.2: Representation of EV flexibility in energy vs. time graph extracted from RP6.

In Phase 1, the EV remains idle until the critical time (t^{c}), after which EV should be charged at full power to meet the required energy level. This phase extends from t^{arr} to t^{c}. Meanwhile, Phase 2 lasts from t^{c} to t^{dep}, during which the EV charges at full power. The mathematical formulation for $E_{t,v}^{\text{min}}$ is given by Equations (III.2) and (III.3).

$$E_{t,v}^{\text{min}} = E_{t-1,v}^{\text{min}} + P_{t,v} \times \eta \times \Delta t \tag{III.2}$$

$$P_{t,v} = \begin{cases} 0 & t^{\text{arr}} < t \leq t^{c} \quad \text{(Phase 1)} \\ P_v^{\text{max}} & t^{c} < t \leq t^{\text{dep}} \quad \text{(Phase 2)} \end{cases} \tag{III.3}$$

As I assume linear charging, with continuous values for charging power. $P_{t,v}$ is the charging power at time t, where η is the charging efficiency, and Δt is the time interval during which charging power is delivered.

$E^{\text{max}}_{t,v}$ represents the maximum cumulative energy that can be transferred to the EV at time t. Similar to $E^{\text{min}}_{t,v}$, $E^{\text{max}}_{t,v}$ is calculated in two phases, as illustrated in Figure III.2. During the first phase, the EV charges instantaneously at maximum power until E^{dep}_{v} is met. Phase 2 occurs from t^{inst} to t^{dep}, where no charging occurs. The mathematical formulation for $E^{\text{max}}_{t,v}$ is provided in Equations (III.4) and (III.5).

$$E^{\text{max}}_{t,v} = E^{\text{max}}_{t-1,v} + P_{t,v} \times \eta \times \Delta t \tag{III.4}$$

$$P_{t,v} = \begin{cases} P^{\text{max}}_{v} & t^{\text{arr}} < t \leq t^{\text{inst}} \quad \text{(Phase 1)} \\ 0 & t^{\text{inst}} < t \leq t^{\text{dep}} \quad \text{(Phase 2)} \end{cases} \tag{III.5}$$

When plotting $E^{\text{max}}_{t,v}$ and $E^{\text{min}}_{t,v}$ on an energy vs. time graph, the area between these curves represents the flexibility region (see Figure III.2). The EV can adjust its charging power within this region, fluctuating between the maximum and minimum power values while maintaining the cumulative energy transfer limits. Therefore, the value of the minimum power flexibility metric - $P^{\text{min}}_{t,v}$, which represents the minimum allowable power at which the EV must be charged at time t, is equal to 0 for the whole plugin duration. The maximum power flexibility metric - $P^{\text{max}}_{t,v}$, represents the maximum allowable power at which the EV can be charged at time t. Therefore, $P^{\text{max}}_{t,v}$ for the whole plugin duration is equal to P^{max}_{v}.

3.1.3 Fleet Quantification

To manage a portfolio of an energy supplier, (which includes an EV fleet) aggregating their flexibilities becomes essential to facilitate trading in electricity markets. To obtain the aggregated flexibility of an EV fleet, the flexibilities of individual EVs are summed up. The resulting aggregated energy and power flexibility metrics are denoted as E^{min}_{t}, E^{max}_{t}, and P^{min}_{t}, P^{max}_{t}.

Quantifying flexibility through minimum and maximum power and energy metrics over time provides essential information—capacity, duration, direction, availability, and energy- necessary for enabling smart charging.

3.2 From Mathematical Model to Practice

3.2.1 Estimation of the Input Parameters to Calculate EV Flexibility

Calculating EV flexibility requires key input parameters such as plug-in duration and energy requirements. However, real-world EV data remains scarce, making it difficult to obtain these parameters directly from charging data. As a result, studies (Daina et al., 2017) rely on modeling approaches to simulate EV usage patterns and estimate the necessary input parameters.

Two primary modeling approaches represent EV usage: annual mileage models and daily pattern models (Daina et al., 2017). Annual mileage models estimate the total distance traveled per year and the corresponding energy consumption, providing a broad overview of EV charging demand (Taiebat et al., 2022). However, these models lack the temporal granularity needed for applications such as EV scheduling. In contrast, daily pattern models capture short-term variations in EV behavior by simulating hourly or quarter-hourly travel and charging activities (Daina et al., 2017; Nourinejad et al., 2016). Since real-world EV-specific data is limited, these models often rely on conventional vehicle driving patterns obtained from travel surveys, GPS data, or questionnaires.

To account for uncertainties in EV usage patterns, studies typically use either probability density functions (PDF) based models or Markov chain models (T. Li et al., 2021). PDF-based models fit statistical distributions, such as normal or exponential distributions, to observed data, estimating parameters like trip distance, frequency, duration, and parking times (Kelly et al., 2012; Rassaei et al., 2015). Monte Carlo simulations then generate diverse and realistic EV usage scenarios (Gjelaj et al., 2019; T. Li et al., 2021). Markov chain models, on the other hand, represent EV usage as transitions between states—such as driving, parked at home, work, or commercial areas—over fixed time intervals (Shepero and Munkhammar, 2018). These transitions, determined by regional traffic data, capture temporal dependencies and generate realistic mobility patterns (Müller et al., 2020).

In this thesis, specifically RP4 - RP7, uses a synthetic mobility dataset developed by Gaete-Morales et al. (2021) based on a German mobility survey (Nobis and Kuhnimhof, 2018) to model EV usage patterns. This dataset applies Monte Carlo simulations to generate unique EV mobility profiles, providing time-series data on vehicle location, travel distance, and energy consumption at 15-minute intervals over one year. In RP4 - RP7, my coauthors and I derive plug-in duration from arrival and departure times at their residence, while energy consumption data is used to estimate the vehicle's state of charge at arrival ($\mathrm{SOC}^{\mathrm{arr}}$). However, determining EV flexibility also requires estimating energy requirements, which depend on user charging preferences.

To estimate the energy requirements of users, it is crucial to understand their charging preferences. These preferences could include the desired $\mathrm{SOC}^{\mathrm{dep}}$, the $\mathrm{SOC}^{\mathrm{min}}$, and the frequency of EV connections to charging points (how often users choose to charge their EVs).

The $\mathrm{SOC}^{\mathrm{dep}}$ refers to the battery percentage users request by the end of the plug-in duration. In RP4 - RP7, EVs aim to reach the maximum possible $\mathrm{SOC}^{\mathrm{dep}}$ within the plug-in duration.

The $\mathrm{SOC}^{\mathrm{min}}$ represents the minimum battery state of charge to which a vehicle charges immediately at full power upon connection to a charging point (Ensslen et al., 2018; Fridgen et al., 2016b). This threshold ensures a basic level of readiness and addresses concerns such as range anxiety—the fear of not having enough charge for future trips (Delmonte et al., 2020). While many studies (Iversen et al., 2014; T. Li et al., 2021; Pavić et al., 2023) assume users participate in smart charging programs and provide complete control of their charging to energy suppliers, real-world behavior indicates otherwise. Users often hesitate to relinquish control due to concerns about insufficient power in emergencies (Libertson, 2022). To mitigate these concerns, the concept of $\mathrm{SOC}^{\mathrm{min}}$ offers a compromise: the battery charges immediately to a secure level, after which energy suppliers control the charging between $\mathrm{SOC}^{\mathrm{min}}$ and the desired departure state of charge ($\mathrm{SOC}^{\mathrm{dep}}$). However, the decisions of EV users are susceptible to behavioural factors like range anxiety (Herberz et al., 2022), which is related to risk aversity- a personality trait in which individuals tend to prefer lower risks over higher risks, even if there is a good chance of a more advantageous outcome (Werner, 2008). Risk-averse individuals may choose higher $\mathrm{SOC}^{\mathrm{min}}$ values than risk-prone individuals.

To quantify user preferences for the $\mathrm{SOC}^{\mathrm{min}}$, in RP2, my coauthors and I conducted a large-scale survey. Our survey gathered the responses to various variables, including risk aversion, from $n = 289$ EV users. In our survey, participants were asked: *"Which battery percentage should your EV always have as a minimum in case of unforeseen emergencies? (This implies that your EV would always be charged to that level at maximum charging power when plugged in.)"* Responses ranged from 0 to 100%. From their responses, I generated a frequency distribution that serves as the basis for modeling $\mathrm{SOC}^{\mathrm{min}}$ preferences in RP5.

The frequency of EV connections to charging points determines how often users charge their vehicles. While some studies (Ensslen et al., 2018; Foley et al., 2013) assume users charge whenever a station is available, studies indicate that EV users typically charge two to four times per week rather than daily (Franke and Krems, 2013). Charging frequency is influenced by both objective and subjective factors.

Regarding the objective factors, charging frequency correlates with daily driving distances, trip frequency, and other driving habits (Mandev et al., 2022). External conditions, such as weather, also play a role—for instance, EV owners with photovoltaic systems may charge more frequently on sunny days to maximize solar energy use (Dodson and Slater, 2019). Subjective factors like range anxiety might prompt risk-averse users to charge more frequently to maintain a buffer against unexpected trips (Marxen et al., 2023a). Since charging frequency affects both individual energy requirements and the aggregate number of EVs connected to charging points, it plays a critical role in flexibility modeling.

To model the frequency of EV connections, RP5 assumes that users prefer to charge when the battery level falls below a defined threshold, referred to as the charging threshold. The rationale behind this threshold aligns with the $\mathrm{SOC}^{\mathrm{min}}$, as both reflect the battery percentage users consider necessary for security. Therefore, the same distribution generated for $\mathrm{SOC}^{\mathrm{min}}$ values is used to model charging thresholds.

3.2.2 Impact of User Uncertainties on EV Flexibility

The uncertainties due to variable driving patterns and charging preferences will impact the flexibility provided by EVs. To assess this impact, RP4 examines how charging preferences, specifically how SOC^{min} influences EV flexibility, while RP5 extends the analysis to include uncertainties from both driving patterns and charging behaviors, focusing on SOC^{min} and the frequency of EV connections to charging point.

To model the variability in driving patterns in RP5, my coauthors and I generated 52 scenarios. Each scenario represents one week of driving patterns for the entire fleet, differing across scenarios. These scenarios, based on a synthetic mobility dataset, capture different driving patterns for a fleet size of 1000 EVs (Gaete-Morales et al., 2021). For further details on the scenario generation process, please refer to RP5.

Various possibilities exist regarding SOC^{min} and the frequency of EV connections to the charging point. For instance, the SOC^{min} requirement might vary among EV users; some may connect their EV every time they park, while others may not, both with or without an SOC^{min} requirement. RP5 captures these possibilities by developing four distinct cases in RP5:

- **Case 1:** All EVs connect to the charging point whenever parked at home, offering full flexibility, i.e., 0% SOC^{min} requirement.
- **Case 2:** All EVs connect to the charging point whenever parked at home, but each has a unique SOC^{min} requirement.
- **Case 3:** EVs are not always connected when parked at home and offer full flexibility when connected. Users plug in their vehicles after its battery capacity drops below a defined charging threshold.
- **Case 4:** EVs are not always connected when parked at home and have an SOC^{min} requirement when connected. This case considers both SOC^{min} and irregular connection behavior.

Using a frequency distribution derived from a survey conducted in RP2, my coauthors and I randomly assigned SOC^{min} and charging threshold values to the 1000 EVs. The values were randomly assigned to each vehicle as no clear correlation emerged with SOC^{min} response and risk aversion.

Using the flexibility model, my coauthors and I calculated the flexibility for each scenario across the four cases in RP5, quantifying the fleet's flexibility in terms of power and energy metrics—P_t^{min}, P_t^{max} and E_t^{min}, E_t^{max}. For further details on flexibility metrics calculations for each scenario, please refer to RP5.

Comparing these metrics against Case 1, which serves as the baseline, highlights the impact of SOC^{min} and irregular charging frequency on flexibility. Table III.1 presents the peak median values of each flexibility metric for a typical weekday, based on the results from RP5.

Table III.1: Peak median value of flexibility metrics for different user cases on typical weekday based on findings of RP5

Use cases	Power metrics		Energy metric	
	Pmax (MW)	Pmin (MW)	Emax (MWh)	Emin (MWh)
Case 1	7	0	11	3
Case 2	7	0.2	11	4
Case 3	2.25	0	11	4
Case 4	2.25	0.3	11	6

In Case 2, there is an increase in P_t^{min} and E_t^{min} due to the SOC^{min} requirement, which forces EVs to charge at full power until their battery capacity reaches the minimum required level. The change in P_t^{min} is minimal because most EVs already meet or exceed the SOC^{min}, and for those that don't, the required power to reach it is relatively low.

In Case 3, there is a decrease in P_t^{max} and an increase in E_t^{min}, primarily due to irregular EV connections. Since users are less likely to connect their EVs every day, the number of connected vehicles per day in Case 3 is much lower than Case 1, leading to a reduction in P_t^{max}. However, when the EVs do not connect regularly, they tend to require higher energy per charging session, as they need to meet their weekly energy requirements in fewer sessions. As a result, the E_t^{min} value is higher when compared to Case 1.

In Case 4, the value of $P_t^{\max}$ reduces, while there is an in the value of $P_t^{\min}$. The reduction in $P_t^{\max}$ is due to irregular connections as in for Case 3. The increase in $P_t^{\min}$ is predominantly due to SOC$^{\min}$ requirements as in Case 2. Furthermore, the value of $E_t^{\min}$ increases which is due to both SOC$^{\min}$ requirements (as in Case 2) and irregular EV connections (as in Case 3).

Considering that RP5 modelled aggregated flexibility metrics, EVs connected to the charging point collectively form a virtual battery. Hence, $E_t^{\min}$ and $E_t^{\max}$ represent the minimum and maximum energy capacities of this virtual battery, while $P_t^{\min}$ and $P_t^{\max}$ represent its minimum and maximum charging capacities. Any increase in $P_t^{\min}$ or decrease in $P_t^{\max}$ indicates a reduction in the power capacity of the virtual battery, signifying a decrease in flexibility. Similarly, an increase in $E_t^{\min}$ or a decrease in $E_t^{\max}$ suggests a reduction in the energy capacity of the virtual battery, also indicating a decrease in flexibility.

Thus, observed increases in $P_t^{\min}$ and $E_t^{\min}$ for cases with SOC$^{\min}$ requirements point to a reduction in flexibility due to these requirements. Likewise, a decrease in $P_t^{\max}$ and an increase in $E_t^{\min}$ for cases with irregular EV connections to the charging point suggest reduced flexibility due to the variability in EV connections.

3.2.3 Behavioral Interventions to Increase User Flexibility Provision

The analysis in RP4 and RP5 demonstrates that user preferences impact the flexibility of an EV fleet. To maximize the benefits of smart charging, energy suppliers must enhance users' flexibility provision. Behavioral interventions, such as incentives and nudges, can encourage users to adopt behaviors that increase flexibility provision (Huber et al., 2019b; Kacperski et al., 2022; Parrish et al., 2020).

Incentives provide financial rewards for choosing a certain option (Marxen et al., 2023a), while nudges influence decision-making by adjusting the way choices are presented, without restricting options or changing financial costs (Thaler and Sunstein, 2008). Nudges can focus on economic, environmental, or social benefits (Huber et al., 2019a). Economic nudges highlight cost savings, environmental nudges emphasize sustainability benefits, and social nudges stress positive effects on the community.

Monetary incentives and environmental nudges have been shown to encourage flexibility provision (Parrish et al., 2020) and increase acceptance of smart EV charging (Huber et al., 2019b). However, research on which specific incentives and nudges are most effective for increasing flexibility provision for smart charging remains limited. To address this gap, RP1 and RP2 examined which behavioral interventions are most effective in increasing residential flexibility provision.

A literature review in RP1 identified several behavioral interventions for smart EV charging, including monetary incentives, framing, feedback, default settings, and gamification.

Framing influences decisions by changing how choices are described. For example, smart charging can be presented in a way that emphasizes its benefits (Huber et al., 2019a). Feedback provides users with information about the effects of their choices, such as CO_2 savings or financial benefits (Huber et al., 2019a). Default settings make smart charging the standard option, requiring users to actively opt out if they do not wish to participate (Parrish et al., 2020). Gamification introduces game-like elements, such as rewards and challenges, to increase engagement (Deterding et al., 2011). Credit points act as a form of financial incentive, while tips provide users with behavioral recommendations (AlSkaif et al., 2018).

To gain initial insights into how current EV users perceive different incentives, nudges and tips, my coauthors and I conducted three focus groups (n= 13) as part of RP1. The findings indicated that most participants found monetary incentives and smart EV charging as the default most attractive. However, these results should be interpreted with caution due to the small sample size.

While previous studies (e.g., Huber et al. (2019a) and Wong et al. (2023)) have examined how incentives and nudges influence flexibility provision, few have tested multiple interventions within the same study. As a result, there is little understanding of which interventions are most effective when compared directly. Furthermore, some studies have measured perceptions (Delmonte et al., 2020) and others their effect (Huber et al., 2019b), yet both types of studies often interpret results as if they were measuring effects. However, preferences do not always reflect real-world behavior. For example, Tijs et al. (2017) found that while monetary and environmental incentives for water conservation were rated as appealing, their actual impact on behavior differed. This highlights the importance of distinguishing between user perception and real effects.

Thus, in RP2, my coauthors and I tested the effectiveness and perception of selected interventions through an experimental survey with 289 EV users. These interventions include high and low monetary incentives, environmental framing, environmental feedback, smart charging defaults, credit points, and behavioral tips.

Survey results demonstrated that only monetary incentives, including both high and low levels and credit points, significantly increased flexibility provision. Other interventions, such as nudges and tips, had no statistically significant effect. The effectiveness of high and low monetary incentives was comparable, consistent with prior findings that the presence of incentives matters more than their magnitude (Lagomarsino et al., 2022). Furthermore, we also found no correlation between the perception and effect of any behavioral intervention. This finding underscores the importance of testing the effects of incentives and nudges in experimental contexts rather than relying on measuring their perception.

IV EV Flexibility in European Electricity Markets

In Europe, power market participants, such as energy suppliers, can trade in short-term markets to reduce their demand and supply imbalances until just a few minutes before delivery. Although these markets are technically futures markets due to the time lag between trading and physical delivery, they are commonly referred to as spot markets (KULeuven, 2015).

Germany provides an illustrative example as one of Europe's largest power markets by traded volume (EPEX, 2024a). The German spot market consists of a DA auction and an ID market. The ID market is further divided into two segments: an auction market, known as the intraday auction (IDA) market, and a continuous market, referred to as the continuous intraday (CID) market. Products traded in the spot market differ in their delivery time intervals, which can be one hour, thirty minutes, or fifteen minutes (NEMO, 2023). In the German market, hourly products exhibit the highest liquidity, followed by quarter-hourly products (EPEX, 2024a; MCSC, 2023). Energy suppliers and other market participants can use these spot markets to meet their short-term power needs.

To participate in the European DA market, participants submit hourly orders to the DA auction, which is cleared through an auction mechanism. Orders consist of two types of offers: (1) bids, representing the prices participants are willing to pay to purchase power, and (2) asks, reflecting the prices they are willing to accept to sell power. In Germany, the DA auction is held daily at noon for all delivery hours of the following day (EPEX, 2022). Once the gate closure time is reached (the deadline for submitting orders), a clearing algorithm matches these bids and asks to determine a single clearing price for each market area, such as the German-Luxembourgish market area, following the merit order principle (Zachmann et al., 2023).

While only hourly products can be traded in the European DA market, the European ID market allows trading in products with shorter delivery intervals of thirty minutes and fifteen minutes (EPEX, 2024a). The IDA operates similarly to the DA auction and is conducted daily at 3 PM for products with delivery on the following day (EPEX, 2022). In contrast, the CID market facilitates continuous trading, where bids and asks are matched in real time throughout the trading period. Trading in the European CID market begins at 3 PM (NEMO, 2021). In this system, trades are executed immediately whenever a bid matches or exceeds an ask price (Neuhoff et al., 2016). In Germany, the CID market remains open until five minutes before delivery, allowing participants to adjust their positions close to real-time.

After the closure of the ID market, any remaining imbalances are managed by TSOs (ENTSO-E, 2022). All wholesale market participants are part of a Balancing Responsible Party (BRP), which is responsible for compensating TSOs for the balancing services required to correct any imbalances caused by market activity. This compensation can be negative, indicating a reversal in the direction of payment. In Germany, the imbalance price, which determines this compensation, is known as the reBAP (reBilanziertes Ausgleichsenergie-Preis) (50hertz et al., 2022).

Within this market framework, energy suppliers must efficiently manage the charging of EV fleet while balancing their portfolios. By leveraging EV flexibility, suppliers can participate in spot markets to procure energy at optimal prices while mitigating imbalances. However, this requires careful coordination to ensure that the procured energy is effectively allocated to individual vehicles.

This chapter is structured around two key aspects, as illustrated in Figure IV.1: aggregation— focused on procuring energy from the market, and disaggregation- which involves distributing the procured energy among individual EVs.

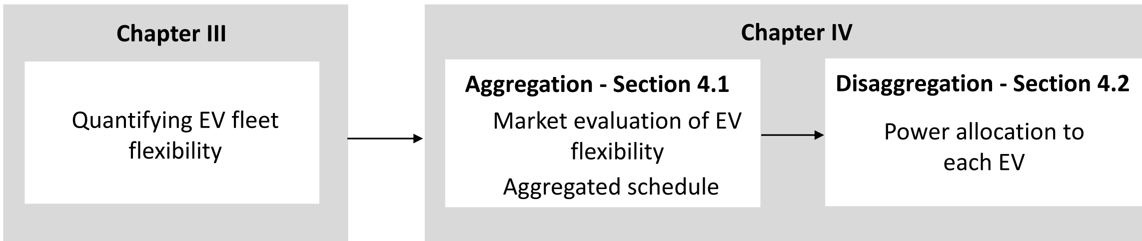


Figure IV.1: Overview of Chapter IV structure.

Section 4.1 focuses on aggregation, evaluating the monetary value of EV flexibility. It examines how charging preferences influence financial outcomes in the spot market and explores trading strategies to manage imbalances. These strategies help suppliers hedge against uncertainties arising from EV users and market fluctuations while leveraging arbitrage opportunities. Section 4.2 focuses on disaggregation, i.e., power allocation at the individual vehicle level. It introduces an optimization approach that efficiently distributes the procured energy among EVs while accounting for uncertainties between trading and actual delivery.

4.1 Spot Markets Exploration

4.1.1 Impact of Charging Preferences on Monetary Value

Smart charging enables energy suppliers to optimize EV charging, reducing electricity procurement costs (EPC) by scheduling charging during periods of lower electricity prices (Foley et al., 2013; Okur et al., 2021). This smart charging process can be formulated as an optimization problem because it involves allocating resources (i.e., charging power) to maximize the objectives (such as minimizing energy supplier EPC) while satisfying constraints (e.g. user requirements).

Accounting for user and market price uncertainties is crucial when developing optimization models for trading in electricity markets with EV scheduling. Stochastic optimization incorporates probability distributions to model uncertainties in market conditions and EV demand to address these challenges (Ding et al., 2018). By minimizing expected EPC across multiple demand scenarios, these models improve charging schedule reliability (Zheng et al., 2020). Some stochastic approaches also integrate risk measures, such as Conditional Value at Risk (CVaR) to minimize the EPC while trading in DA markets (Al-Awami and Sortomme, 2012).

Trading in both DA and ID enables energy providers to fully utilize the flexibility offered by EV across time horizons and market conditions (Z. Liu et al., 2019). Jin et al. (2020) and Sánchez-Martín et al. (2016) proposed two-stage stochastic optimization model to minimize the expected EPC of energy suppliers while trading in both DA and ID markets.

In contrast, robust optimization offers a more conservative approach to managing uncertainty in EV scheduling. Unlike stochastic models, which rely on probability distributions, robust optimization considers a worst-case scenario framework, ensuring feasible and cost-effective charging schedules under the most adverse conditions (Korolko and Sahinoglu, 2017). Energy suppliers use robust optimization to hedge against uncertainties in EV usage and electricity prices by optimizing charging schedules that remain viable across a predefined set of scenarios (Pavić et al., 2023). In this notion, Korolko and Sahinoglu (2017) formulated the objective function as a “min-max” model, aiming to minimize the energy provider’s EPC for the worst scenario across all scenarios while trading in DA markets. Morales et al. (2014) proposed scenario-based robust optimization to facilitate trading in DA and ID markets. Their scenario-based robust optimization model aims to minimize the worst scenarios EPC, which could include DA EPC and ID worst scenario costs.

Previous studies (Jin et al., 2020; Korolko and Sahinoglu, 2017; Z. Liu et al., 2019; Pavić et al., 2023; Sánchez-Martín et al., 2016) have developed optimization models to manage uncertainties related to EV usage and market and leveraged EV flexibility to minimize EPC. However, they have overlooked uncertainties arising from charging preferences, such as SOC^{min} and the frequency of EV connections to the charging point. Charging preferences are crucial in determining the flexibility available to energy suppliers. The flexibility is significantly reduced if users impose strict constraints—such as requiring a high SOC^{min} or charging infrequently. It could impact the monetary value of flexibility when trading in spot markets.

Thus, RP4 and RP5, investigated the impact of charging preferences on the monetary value of EV flexibility. Specifically, RP4 focuses on evaluating the impact of SOC^{min} requirement on the EPC while trading in DA and ID markets. To assess this, my coauthors and I employ a two-stage stochastic optimization model to minimize the EPC while accounting for user-defined SOC^{min} constraints and market price uncertainty.

Building upon RP4, RP5 evaluates the monetary value of EV flexibility while considering the uncertainties due to variable driving patterns and charging preferences. With respect to charging preferences, RP5 specifically focuses on evaluating the impact SOC^{min} and the frequency of EV connections to the charging point on the monetary value of EV flexibility while trading in spot markets. To evaluate the monetary value, RP5 develops a scenario-based robust optimization model aimed at minimizing the EPC while participating in both DA and ID. By incorporating flexibility scenarios into the optimization model, the model minimizes the EPC for the worst scenario, ensuring a robust assessment of the financial viability of trading EV flexibility in spot markets. For more details on the optimization model and relevant assumptions, please refer to RP5

To analyze the impact of charging preferences on the monetary value of EV flexibility, my coauthors and I conducted a cost sensitivity analysis by generating different use cases in RP5. These use cases are generated by varying two key parameters:

- **Charging threshold:** The charging threshold values were varied from 20% to 100% in increments of 20%. Higher thresholds correspond to more frequent EV connections to charging stations.
- **SOC^{min}:** This ranged from 0% (full flexibility) to 100% (no flexibility) in the increments of 20%.

For each use case, the study calculates the EPC required to charge 1,000 EVs for one week across all months in 2022 and 2023. The input data includes DA and ID3 index market price data from 2022 and 2023 (EPEX, 2024b), along with flexibility scenarios that represent the aggregated flexibility metrics of 1,000 EVs over one week. For more details on input data, flexibility scenario generation process, and relevant assumptions, please refer to RP5

Figure IV.2 presents one of the results from RP5, illustrating the EPC for various combinations of charging thresholds and SOC^{min} values in July 2023 (results for other months follow similar trends, though the specific values differ; refer to RP5 for details). The analysis indicates that EPC decreases with higher charging thresholds, while higher SOC^{min} values result in increased EPC.

Figure IV.2: Electricity procurement costs of one week in July 2023 for different SOC^{min} and charging thresholds, extracted from RP5.

A key observation is that EPC remains relatively stable for lower SOC^{min} values up to a critical threshold, beyond which costs rise sharply. For instance, at 80% and 100% charging thresholds, EPC remains nearly constant up to 80% SOC^{min}, after which it escalates. This trend arises because higher charging thresholds lead to higher state of charge upon arrival (SOC_{arr}), meaning that for most EVs, SOC_{arr} already exceeds SOC^{min}, thereby reducing the impact of SOC^{min} on EPC.

Figure IV.3 presents one of the results from RP5, illustrating the relative EPC reductions across different charging thresholds for July 2023 (results for other months follow similar trends, though the specific values differ; refer to RP5 for details). Under full flexibility (0% SOC^{min}), reductions range from 33.9% to 49.6%, while even with limited flexibility (80% SOC^{min}), savings between 11.8% and 36.9% are achieved compared to the no-flexibility case (100% SOC^{min}).

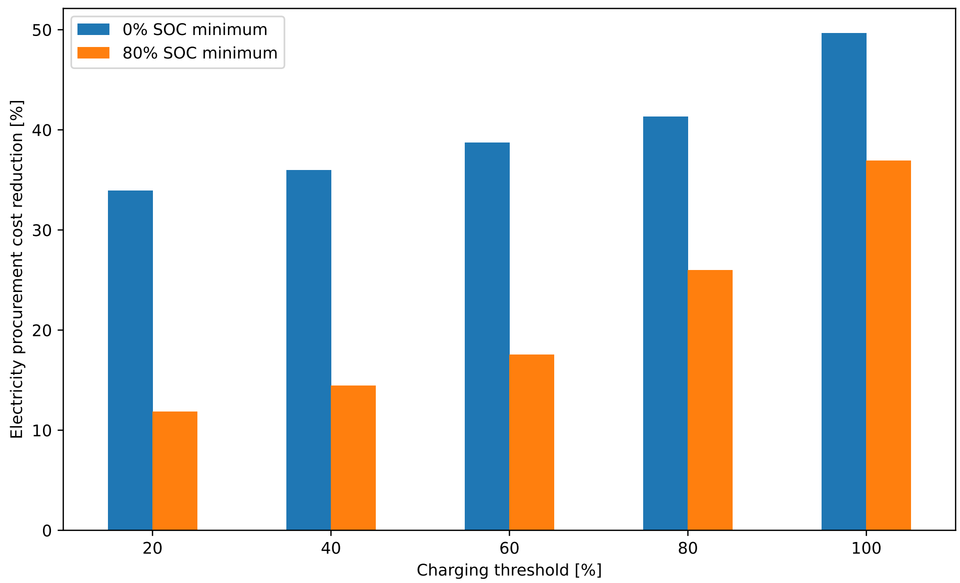


Figure IV.3: Relative cost reduction for one week in July 2023 of different SOC^{min} values compared to 100% SOC^{min} across different charging thresholds ,extracted from RP5.

These findings from RP5 demonstrate that EPC reductions depend on both the frequency of EV connections and the degree of charging flexibility. While full flexibility yields the highest savings, even low flexibility can lead to significant reductions, particularly when EVs charge more frequently. This enables energy suppliers to optimize costs without requiring users to relinquish full control over their charging schedules.

To illustrate this balance, I define three key SOC^{min} cases:

- **Full Flexibility (0% SOC^{min})** – Maximizes cost savings but reduces user control, as charging is entirely managed by suppliers.
- **No Flexibility (100% SOC^{min})** – Ensures full user convenience but eliminates supplier flexibility, leading to higher EPC.
- **Low Flexibility (80% SOC^{min})** – Provides a balanced approach, allowing suppliers to manage charging after 80% charge while ensuring users have sufficient battery for most trips, including emergencies.

Even at 80% SOC^{min}, suppliers can achieve up to a 33.9% reduction in EPC, with full flexibility offering slightly higher savings of 49.6%. The impact is most pronounced at higher charging thresholds (60%–100%), where frequent charging further enhances savings. While some users hesitate to charge often due to battery health concerns, studies (Kostopoulos et al., 2020) suggest the optimal operating range is 20%–80%. Encouraging charging within the 60%–80% range can help balance cost savings and battery longevity.

Overall, findings from RP5 imply that flexible EV charging offers significant economic benefits, enabling substantial cost reductions for energy suppliers while maintaining user convenience.

4.1.2 Trading Strategies to Maximize Energy Supplier's Profits

The analysis in RP5 underscores the substantial economic value of EV flexibility. However, energy suppliers must overcome challenges related to uncertain EV behavior and market prices to capitalize on this potential fully. To mitigate these risks and leverage flexibility for profit, energy suppliers need dynamic trading strategies that address market imbalances and optimize portfolio management.

The variable nature of EV user driving behaviors and evolving charging preferences causes discrepancies between actual and forecasted charging demand (Pareschi et al., 2020). These discrepancies can pose financial risks for energy suppliers, particularly in European markets where market participants incur penalties for imbalances between expected and actual demand (KULeuven, 2015). To manage these uncertainties, suppliers can participate in the DA and CID markets. The DA market allows for advance procurement, while the CID market enables suppliers to adjust schedules closer to real-time, mitigating imbalance penalties. Additionally, suppliers can leverage EV flexibility through smart charging, capitalizing on arbitrage opportunities in both the DA and CID markets to boost revenues.

To facilitate EV flexibility trading in the CID market, Naharudinsyah and Limmer (2018) and Tepe et al. (2022) proposed rolling window (RW) horizon optimization methods. These models enable energy suppliers to dynamically adapt to CID market conditions. By employing a sequential trading strategy, suppliers can first acquire most of the power needed for charging from the DA market, minimizing costs, and then capitalize on arbitrage opportunities in the CID market (Tepe et al., 2022; Vardanyan and Madsen, 2019).

Shinde et al. (2022) and Vardanyan and Madsen (2019) model price uncertainties in the CID market by considering different price scenarios and their associated probabilities. However, many studies (Shinde and Amelin, 2019; Tepe et al., 2022; Vardanyan and Madsen, 2019) assume that EV demand forecasts remain constant when trading in both the DA and CID markets, overlooking the inherent variability in EV behavior.

Relying solely on DA EV demand forecasts for CID trading is impractical since these forecasts are typically made 36 hours or more in advance, increasing the likelihood of inaccuracies. As the forecast is made closer to delivery time, its accuracy improves due to the inclusion of real-time user data, such as plug-in and plug-out times. Static forecasts may also overlook imbalance costs resulting from deviations in charging behavior. Additionally, price uncertainty in the CID market complicates forecasting, often leading to unrealistic scenarios based on perfect foresight. To address these challenges, RP6 proposes an optimization model that integrates real-time EV flexibility forecasts with dynamic price forecasting.

Figure IV.4 illustrates the sequence of trading and optimization steps my coauthors and I developed and applied in RP6 to determine the final EV charging schedule.

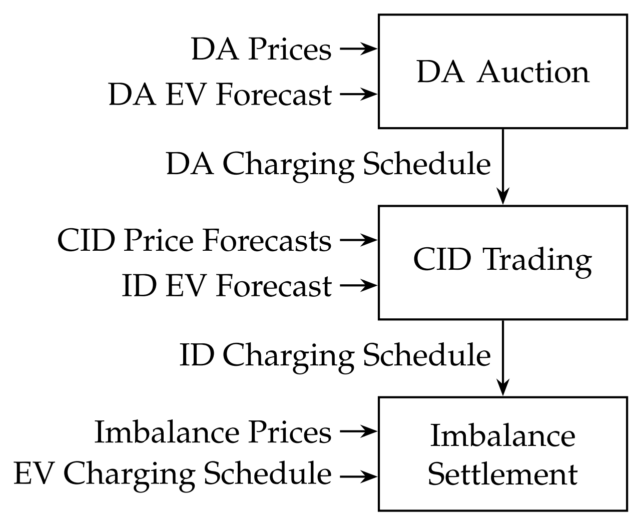


Figure IV.4: Overview of trading steps extracted from RP6.

The first step is securing energy in the DA market, which offers high liquidity and a single clearing price (EPEX, 2024a). The optimization model selects cost-effective charging periods within the DA timeframe, assuming perfect foresight of prices and an initial EV flexibility forecast, resulting in a preliminary charging schedule.

During the ID period, an updated EV flexibility forecast becomes available. For simplicity, RP6 assumes that this forecast aligns perfectly with actual EV flexibility at the time of charging (refer to RP6 for more details). Three distinct trading strategies are then proposed in RP6 to update the DA charging schedule based on new ID EV forecasts:

- **Baseline strategy ($BL_P^{\mathbf{reBAP}}$)** – This strategy settles power volumes required for the ID schedule at the imbalance price, known as reBAP in Germany (50hertz et al., 2022). It minimizes the difference between DA and ID power needs, thereby reducing imbalances and associated costs.

- **Static CID strategy ($BL_P^{\mathbf{ID}_1}$)** – Similar to the baseline strategy, this approach makes the same power volume adjustments but settles them in the CID market instead of treating them as imbalances. It uses the ID1, a price index published by EPEX, which reflects the price during the final trading hour of each product in the CID market (EPEX, 2025).

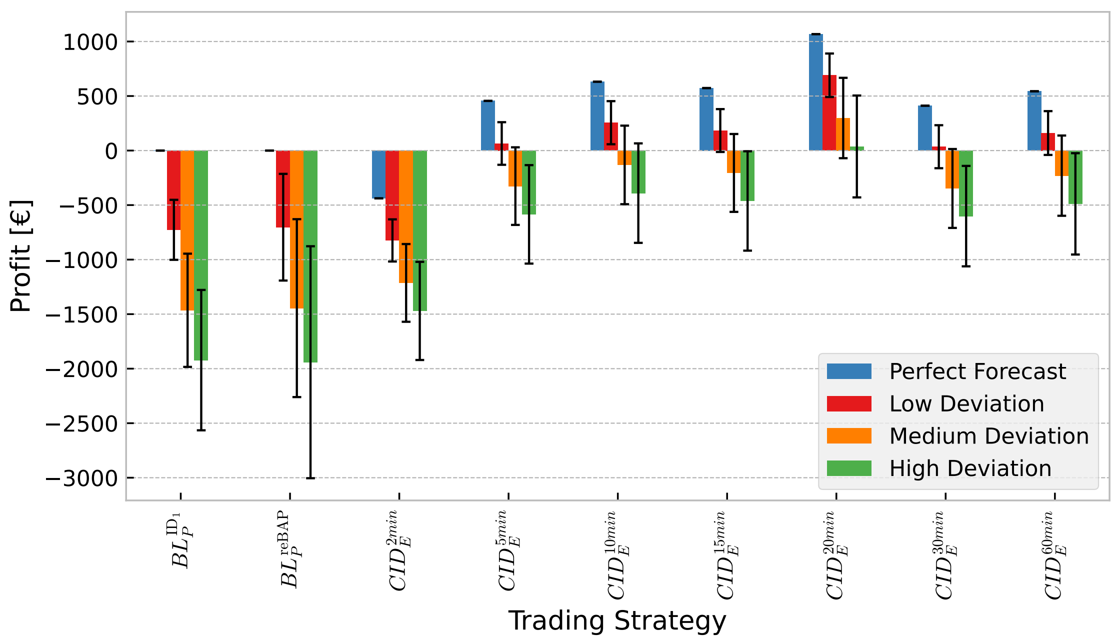
- **Dynamic CID strategy (CID_E^x)** – This strategy continuously adjusts positions in the CID market using a RW approach, allowing multiple re-optimizations during the CID trading window. It leverages EV charging flexibility to arbitrage from changing prices between products trading in parallel.

Each strategy results in a final ID charging schedule that determines when and how EVs are charged. The baseline and static CID strategies both aim to align the ID power schedule with the DA power schedule, but they differ in how they handle discrepancies. In contrast, the dynamic CID strategy continuously participates in the CID market, making adjustments based on trading frequency, with optimization intervals of 2, 5, 10, 15, 20, 30, or 60 minutes. For further details on the trading strategies and the optimization models developed to implement them, please refer to RP6.

Trading strategies are tested using market prices from 2019 and 2022 (EPEX, 2024b). Each strategy is evaluated across four different EV flexibility scenarios, each with increasing deviation from the DA flexibility forecast for a fleet of 1,000 EVs. For more details on input data and flexibility scenario generation process, please refer to RP6.

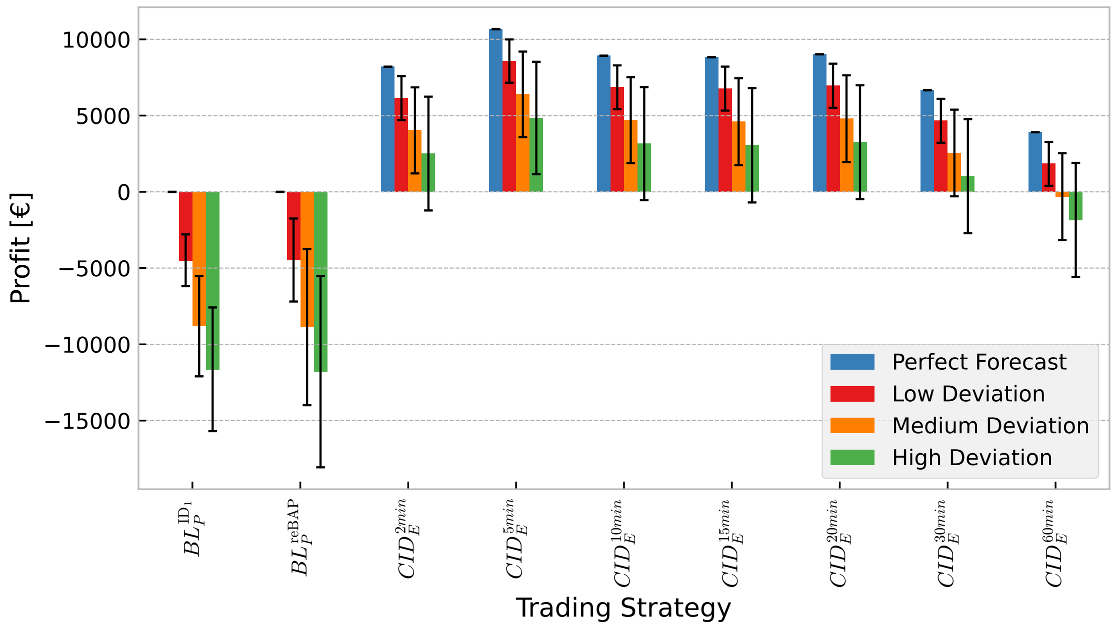
Our energy supplier's financial evaluation in RP6 involves calculating expected yearly profits for different trading strategies. Annual profits during the ID period are determined by aggregating all trade values, including CID fees and imbalance settlement costs. Profit dynamics depend on market prices—under positive prices, selling power increases profits while acquiring power reduces them; under negative prices, the relationship reverses. Our optimization models in RP6 rely on forecasts to compute schedules, while actual market prices determine final profit calculations.

Figure IV.5 illustrates the mean annual profits (based on the results from RP6) across various trading strategies, with four bars per strategy representing different levels of forecast deviation between DA and ID flexibility: perfect forecast (blue), low deviation (orange), medium deviation (green), and high deviation (red). Whiskers indicate two standard deviations above and below the mean profit, capturing uncertainty in outcomes.



(a) 2019

Figure IV.5: Comparison of yearly profits for different trading strategies, extracted from RP6 (Part 1).



(b) 2022

Figure IV.5: Comparison of yearly profits for different trading strategies, extracted from RP6 (Part 2).

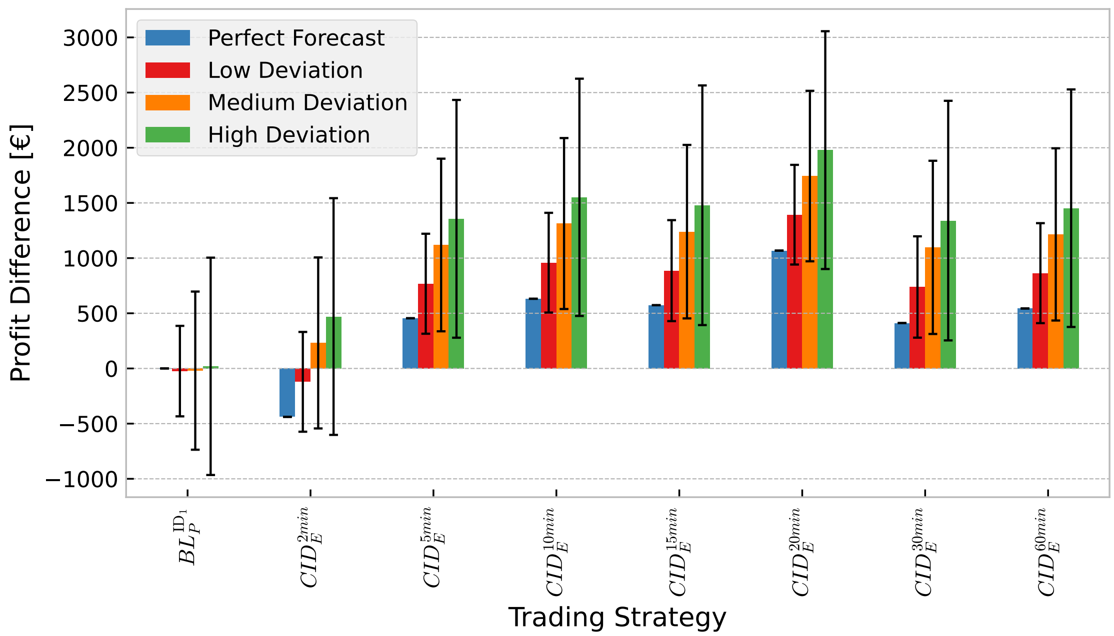
Profits decline as forecast deviations increase, leading to higher profit variability due to greater involuntary rescheduling. This reduces the available flexibility for voluntary rescheduling, increasing exposure to unfavorable market conditions. Baseline and static CID strategies (BL_P^{reBAP} and BL_P^{ID1}) yield zero profit under perfect forecasts since they minimize traded volumes. However, as deviations grow, these strategies become unprofitable due to limited flexibility and increased imbalance costs.

In contrast, dynamic CID strategies (CID_E^{2min} to CID_E^{60min}) adapt to ID market conditions, leveraging EV flexibility for arbitrage opportunities. In 2019, only CID_E^{20min} consistently generates positive profits, peaking at €1,067.98. By 2022, increased market volatility enhances profitability, with all dynamic strategies—except CID_E^{60min}—yielding positive returns. The CID_E^{5min} strategy achieves the highest profit, reaching €10,670.59.

A comparison between 2019 and 2022 reveals two key trends. First, profits are significantly higher in 2022 due to greater price volatility and market liquidity. Second, the optimal dynamic strategy shifts from CID_E^{20min} in 2019 to CID_E^{5min} in 2022, highlighting the advantage of higher trading frequency in more dynamic market conditions.

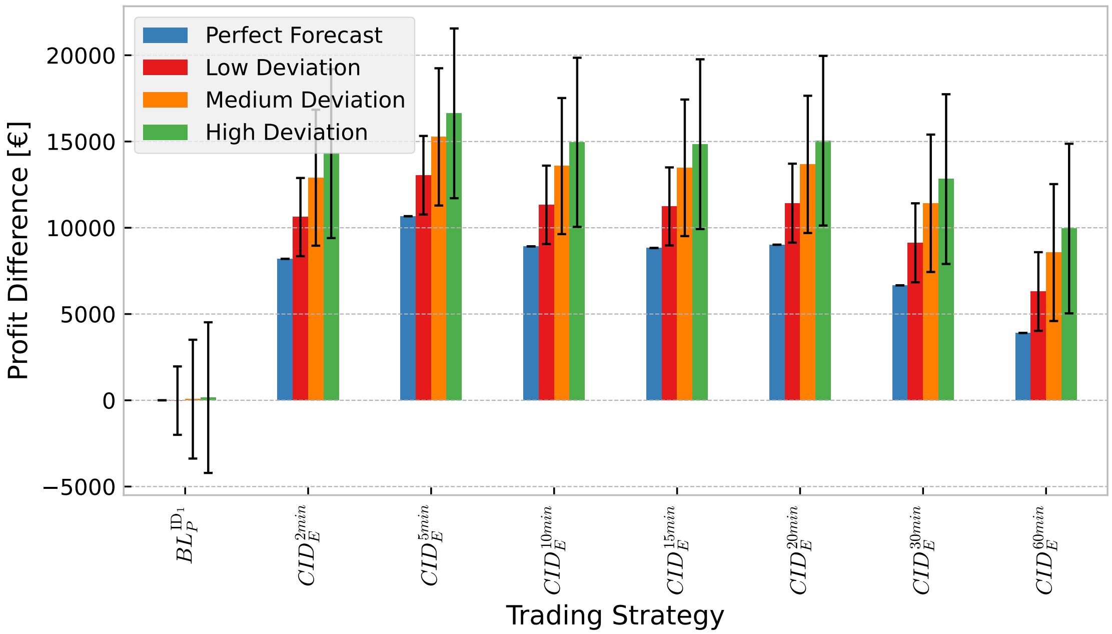
To further evaluate the financial benefits of trading in the CID market, each strategy's profitability is compared against the baseline (BL_P^{reBAP}), which settles imbalances at the reBAP price. This relative assessment that my coauthors and I conducted in RP6 highlights the advantages of proactive CID participation over passive imbalance settlement.

Figure IV.6, presents results from RP6, displaying the profit differences across different strategies in the CID market (BL_P^{ID1} and CID_E^{2min} to CID_E^{60min}) relative to the baseline. Uncertainty is depicted by whiskers extending two standard deviations above and below the mean profit differences, with results illustrated for varying deviations between DA and ID flexibility forecasts in 2019 and 2022.



(a) 2019

Figure IV.6: Comparison of yearly improvement over BL_P^{reBAP} as a share of DA costs, extracted from RP6 (Part 1).



(b) 2022

Figure IV.6: Comparison of yearly improvement over BL_P^{reBAP} as a share of DA costs, extracted from RP6 (Part 2).

The static CID strategy (BL_P^{ID1}), which settles at the ID1 price, yields similar profits to the baseline, offering minimal financial advantage. However, most dynamic CID strategies outperform the baseline, except CID_E^{2min} under perfect forecasts in 2019, which slightly underperforms. The increased profitability of dynamic strategies under uncertain EV schedules stems from their ability to exploit EV charging flexibility for arbitrage across products with different delivery intervals. This flexibility allows for strategic rescheduling that reduces imbalance costs while capitalizing on price differentials.

Thus, with an effective trading strategy, energy suppliers serving EV users can mitigate financial risks associated with forecast inaccuracies. The success of such a strategy depends on two critical factors: smart charging practices by EV users and strategic trading in the CID market. Encouraging flexible charging behavior enhances the ability to optimize schedules, while leveraging arbitrage opportunities across different market products improves profitability and reduces exposure to imbalance costs.

Overall, the results from RP6 underscore the importance of accurate EV flexibility forecasts and adaptive trading strategies. While baseline and static strategies fail to capture market benefits, dynamic strategies—especially those with higher trading frequencies—prove more effective in volatile markets. As market conditions evolve, aligning trading strategies with real-time flexibility and market liquidity will be crucial for maximizing financial returns.

4.2 From Fleet to Individual Schedule

After energy suppliers trade in the market and procure aggregated power for charging the EV fleet, they must optimally allocate this power to individual vehicles. However, a time lag exists between the trading and delivery periods. During this interval, initial user requirements predicted during trading may change. For example, users may update their plug-in durations or adjust their energy requests. These updates can lead to discrepancies between the procured power and the updated power demand at the time of delivery, resulting in imbalances and failing to satisfy users' energy requirements.

However, if EVs possess sufficient flexibility, energy providers can reschedule power allocation to accommodate these updated requirements and reduce imbalance costs. To investigate this, RP7 examines whether EVs have enough flexibility to address uncertainties in user demand, satisfy energy requirements, and minimize imbalance costs for energy providers.

Figure IV.7 gives an overview of our optimization approach implemented in RP7. The first step involves procuring aggregated power while trading in DA electricity market, where we developed a linear optimization model to procure the required power for EV charging based on predicted user requirements while minimizing procurement costs. The second step focuses on rescheduling, where we proposed three strategies to reallocate power among EVs, ensuring that updated energy needs are met while managing imbalances efficiently.

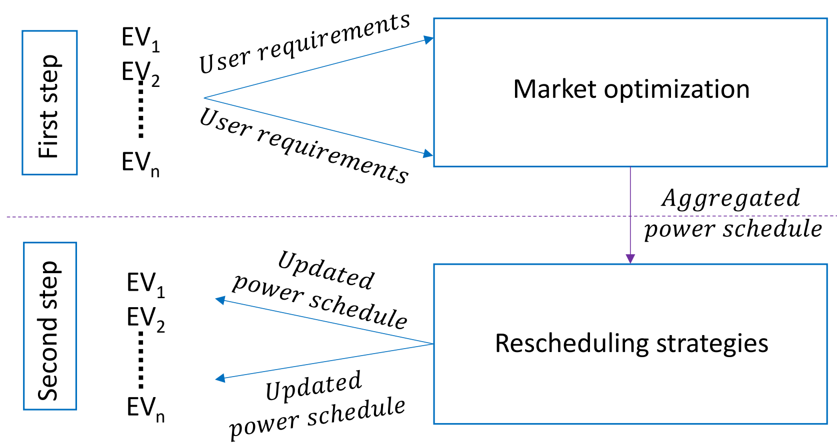


Figure IV.7: Overview of our two step optimization approach adopted in RP7.

The three rescheduling strategies that my coauthors and I proposed in RP7 were:

- **Strategy 1:** Uses the same aggregated DA schedule to satisfy the updated user requirements without settling imbalances in the market. Power is reallocated among EVs to minimize deviations between their updated energy needs and their actual energy levels at departure.
- **Strategy 2:** Settles imbalances in the imbalance market to fulfill updated user requirements while minimizing imbalance volume. This strategy adjusts the aggregated power schedule at the time of delivery to match the updated energy needs.
- **Strategy 3:** Settles imbalances in the imbalance market while minimizing imbalance costs. Similar to the second strategy, this approach modifies the aggregated power schedule at delivery but prioritizes cost reduction.

Using a synthetic mobility dataset (Gaete-Morales et al., 2021), we generate multiple scenarios in which the user requirements of the entire EV fleet vary across cases. One scenario represents the initial or predicted requirements used for market trading, while the remaining scenarios reflect updated user behavior. These scenarios allow us to test the rescheduling strategies under different conditions and evaluate their effectiveness in managing flexibility and minimizing imbalance costs. For further details on the scenario generation, rescheduling strategies, relevant assumptions, and the optimization models used, please refer to RP7.

Our optimization model incorporates German DA market price data from January 15–21, 2024 (EPEX, 2024b), and reBAP prices from the ENTSO-E Transparency Platform (ENTSOE-E, 2024) for the same period. Imbalance costs for all strategies are calculated ex-post using reBAP price data. For more information on the input data and modeling approach, refer to RP7.

Our findings from RP7 demonstrate that using the first strategy, energy suppliers can meet most user energy needs by redistributing the available power. However, some users may not receive their full requested energy, potentially affecting charging reliability and driving needs. If users are flexible in their energy requests, power can be reallocated to ensure all EVs receive enough energy for their next trip without major inconvenience. However, users are prone to discomfort when significant deviations remain between scheduled and actual energy levels at departure. In such cases, relying solely on this strategy may not be sufficient, prompting the need for imbalance market adjustments, as explored in the second strategy.

The second strategy in RP7 ensures users receive their requested energy by the end of the charging session by adjusting the power schedule through the imbalance market. While the model attempts to minimize deviations from the aggregated DA power schedule using EV flexibility, instances of both positive and negative imbalances still occur. A positive imbalance arises when the rescheduled power is less than the aggregated DA power, requiring energy suppliers to sell the excess power in the imbalance market. If the price during this period is positive, suppliers generate revenue, leading to negative imbalance costs. However, if the price is negative, the imbalance cost is positive, increasing overall costs. Conversely, a negative imbalance occurs when rescheduled power exceeds the aggregated DA power, requiring suppliers to buy additional energy from the imbalance market. A positive price results in a cost, whereas a negative price generates revenue.

As a result, overall imbalance costs varied across scenarios RP7 considers. In some cases, negative imbalance costs occur due to favorable combinations of imbalance prices and deviations. However, procuring excess power in the DA market does not always guarantee revenue, as positive imbalances do not necessarily coincide with profitable price conditions.

The third strategy in RP7 assumes perfect foresight of imbalance prices, allowing the model to strategically create positive and negative imbalances to minimize costs. As a result, the imbalance costs are negative across all scenarios. However, this assumption is purely theoretical, as energy suppliers cannot predict imbalance prices in real time. Despite its impracticality for direct implementation, this strategy highlights the potential of EV flexibility in providing balancing services. Since balancing energy prices influence imbalance prices, leveraging EV flexibility can help reduce overall system imbalances.

Overall, the findings from RP7 demonstrate that leveraging EV flexibility enables energy suppliers to meet most user energy requirements while reducing imbalance costs. Suppliers can minimize user impact and reduce imbalance costs by adjusting power allocation and using the imbalance market. These findings highlight the potential of EV flexibility to mitigate uncertainties in user behavior while supporting system reliability and cost efficiency.

V Conclusion

5.1 Contributions

This thesis advances the development of smart charging solutions for energy suppliers, enabling them to optimize EV charging, reduce portfolio costs, and effectively manage user behavior and market dynamics. The contributions span three key dimensions: understanding user preferences and factors influencing their EV flexibility provision, developing a quantitative model to assess EV flexibility, and designing trading strategies to mitigate uncertainties and optimize power allocation for EVs. These insights equip energy suppliers with the necessary tools to enhance market efficiency, improve portfolio performance, and maximize the economic benefits of EV flexibility while maintaining user satisfaction.

The first contribution of this thesis focuses on understanding user preferences and factors influencing their EV flexibility provision. A critical aspect of implementing smart charging is user willingness to participate in smart charging programs, provide flexibility, and share data. Through an experimental survey, this thesis empirically investigates different behavioral interventions that could enhance user flexibility provision. The findings from our survey reveal that financial incentives significantly increase user willingness to provide flexibility, whereas nudges and tips have limited impact. Additionally, a separate survey on data-sharing behavior indicates that while users are generally open to sharing less sensitive data like charging data, they are more reluctant to disclose sensitive information such as location and calendar details, often demanding high compensation. These findings underscore the need for energy suppliers to prioritize financial incentives for flexibility participation and develop data-sharing strategies that balance operational efficiency with user privacy concerns.

The second contribution of this thesis is developing a quantitative model to assess EV flexibility for market participation. This thesis introduces a mathematical model that quantifies flexibility using key metrics such as minimum and maximum power and energy values to support energy suppliers in leveraging flexibility. This model provides a structured approach for evaluating fleet-level flexibility and optimizing EV scheduling for electricity market participation. Furthermore, by applying this model, the thesis quantitatively demonstrates how variations in driving patterns and charging preferences impact flexibility potential. These insights offer energy suppliers a clearer understanding of how different user behaviors affect available flexibility and inform strategies to maximize flexibility utilization.

The third contribution of this thesis addresses the challenge energy suppliers face in managing uncertainties in user behavior and market conditions to optimize EV charging. To tackle this, the thesis proposes trading strategies enabling energy suppliers to participate in spot markets while accounting for user behavior and market price uncertainties. These strategies incorporate different EV flexibility scenarios to model user behavior variability and employ forecasting techniques to address price fluctuations. The findings demonstrate that, rather than relying solely on imbalance settlements, active participation in short-term markets such as CID markets allows energy suppliers to reduce imbalance costs and capitalize on arbitrage opportunities by leveraging both EV flexibility and market price volatility, ultimately improving overall revenues. Furthermore, this thesis introduces rescheduling strategies to address discrepancies between procured power from the market and actual demand due to trading and delivery time lags. These rescheduling strategies dynamically adjust individual EV power schedules by leveraging EV flexibility. These strategies minimize imbalance costs while ensuring minimal disruption to users.

Overall, this thesis demonstrates that integrating EV flexibility into electricity markets offers significant economic benefits for energy suppliers. By leveraging financial incentives, developing a flexibility model, and applying dynamic trading and scheduling strategies, suppliers can improve market performance while ensuring user satisfaction.

These contributions enable energy suppliers to fully capitalize on EV flexibility, paving the way for more efficient, user-centric smart charging solutions.

5.2 Limitations and outlook

While this thesis provides valuable insights into EV flexibility, several limitations must be acknowledged. One key constraint is the reliance on survey data to evaluate the effectiveness of interventions. Though the survey approach helps capture initial user intentions, there is an inherent gap between stated intentions and actual behavior. This inherent gap makes it challenging to assess user responses to incentives and smart charging programs accurately. Similarly, the evaluation of gamification is limited, as users did not directly interact with gamified elements, preventing a full assessment of their real-world impact. Future research should incorporate field studies or longitudinal data to understand better how users engage with smart charging over time.

Another limitation lies in using synthetic mobility datasets to estimate EV flexibility. While these datasets are useful for estimating key parameters, they may not fully capture real-world variations in driving behaviors. Factors such as seasonal fluctuations, holiday travel, and regional differences are often overlooked, potentially affecting the accuracy of flexibility assessments. Integrating real-world mobility data would improve the applicability of findings across diverse user groups and geographic locations.

Additionally, technical assumptions within my flexibility model also introduce some limitations. The flexibility model simplifies charging processes by assuming linear charging, whereas, in reality, charging power decreases as the battery approaches full capacity. This simplification may lead to overestimations of available flexibility. Furthermore, variations in battery size and vehicle specifications influence user charging preferences, affecting overall flexibility potential. Incorporating more detailed charging profiles and a wider range of vehicle characteristics would enhance the robustness of flexibility models.

While this thesis clearly demonstrates the value of EV flexibility and its potential system-level benefits, the exact monetary outcomes—such as cost savings or percentage reductions—are influenced by the specific input data and boundary conditions considered in the analysis.

Beyond modeling constraints, this thesis primarily focuses on spot markets for leveraging EV flexibility while trading. However, additional revenue streams remain underexplored. EVs could play a valuable role in reserve markets, where fast-response flexibility is highly valued. Integrating EV flexibility into ancillary services, such as frequency regulation and balancing markets, could enhance economic returns for energy suppliers while improving grid stability. Future research should investigate multi-market optimization strategies to maximize the value of EV flexibility across different market structures.

Another promising avenue for future exploration is vehicle-to-grid (V2G) technology, which enables EVs to supply electricity back to the grid. V2G has the potential to enhance grid stability further and create additional revenue opportunities for EV owners. However, its adoption depends on user willingness to allow battery discharge, concerns over battery degradation, and supportive regulatory frameworks. Future studies should explore strategies to integrate V2G into market mechanisms while addressing technical and behavioral challenges.

Despite these limitations, the findings in this thesis highlight the substantial flexibility potential of EVs. Addressing these challenges through improved data integration, refined modeling approaches, expanded market participation, and adopting V2G technology will further enhance the role of EV flexibility in future power systems.

5.3 Recognition of previous and related work

The foundational work of my colleagues in the FINATRAX group and previous institutions, along with collaborations with the University of Hohenheim/Forschungszentrum für Informationsmanagement, played a crucial role in shaping my research. Their prior investigations provided essential insights and methodologies, directly influencing my research questions, models, and analyses. Their work on behavioral interventions, data sharing in smart charging, and the monetary value of flexibility in electricity markets laid a strong theoretical and empirical foundation for my studies.

Research from studies (Bauer et al., 2017; Drasch et al., 2020; Fridgen et al., 2016a; Fridgen et al., 2020; Fridgen et al., 2021a; Heffron et al., 2020; Keller et al., 2020; Körner et al., 2019; Lindner et al., 2022; Rieger et al., 2016; Roesch et al., 2019; Wederhake et al., 2022) provided key insights into designing programs to harness demand-side flexibility to enhance power system reliability and value for stakeholders. These studies provided a strong conceptual and methodological basis for identifying, structuring, and operationalizing flexibility across different use cases. Building on this foundation, my thesis applies these concepts to EV smart charging, developing models and frameworks to leverage EV flexibility for reducing energy suppliers' portfolio costs.

User preferences play a critical role in developing effective smart charging solutions. Behavioral studies, particularly Graf et al. (2020) and Wagon et al. (2024), helped me understand how interventions such as gamification and financial incentives can motivate more sustainable charging behaviors. These insights shaped the behavioral focus of RP1 and RP2, where I explored user motivations and their willingness to provide flexibility. Similarly, the work of Fridgen et al. (2022) and Fridgen et al. (2014) helped identify which user data are most relevant for smart charging. This influenced the design of a privacy and data-sharing survey in RP3, which analyzed user willingness to share data for smart charging applications.

Additional studies (Bahmani et al., 2023; Fridgen et al., 2017; Schott et al., 2019; Thimmel et al., 2019) helped me understand the key information a flexibility model should provide while quantifying the flexibility of an asset to serve as a dependable grid asset. These insights supported the development of a flexibility model that quantifies EV flexibility, which I used to estimate potential and support scheduling strategies in RP4, RP5, and RP6.

Further prior research (Fridgen et al., 2016b; Fridgen et al., 2014; Fridgen et al., 2021b; Haupt et al., 2020; Pavić et al., 2018b; Pavić et al., 2020) on EV scheduling from both user and system operators/utilities perspectives helped me understand the key considerations and trade-offs involved in developing optimization models. These insights guided the design of my optimization models in RP4-RP7, enabling me to balance user needs with the operational goals of energy suppliers.

Another crucial aspect of my research involved developing strategies to harness EV flexibility in electricity markets, particularly by modeling uncertainties arising from EV usage and fluctuating market prices. The studies by Pavić et al. (2023), Pavić et al. (2015), Pavić et al. (2018a), and Pavić et al. (2021) provided a solid theoretical and methodological foundation for addressing these uncertainties. Their contributions guided the development of optimization models in RP4, RP5, RP6, and RP7, where I explored strategies to mitigate market price uncertainty (RP4, RP5) and user behavior uncertainty (RP5, RP6, and RP7).

Overall, the contributions of these previous studies provided a strong interdisciplinary foundation for this thesis. By building upon this foundational work, I developed novel perspectives and methodologies, furthering the understanding of how EV flexibility can be optimized to benefit both users and energy suppliers.

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A Appendix

A.1 Relevant publications

- RP1: H. Marxen, R. Chemudupaty, V. Graf-Drasch, G. Fridgen, and M. Schoepf (2022). "Towards an evaluation of incentives and nudges for smart charging". en. In: *ECIS 2022 Research-in-Progress Papers*
- RP2: H. Marxen, M. Ansarin, R. Chemudupaty, and G. Fridgen (2023a). "Empirical evaluation of behavioral interventions to enhance flexibility provision in smart charging". en. In: *Transportation Research Part D: Transport and Environment* 123, p. 103897. ISSN: 13619209. DOI: 10.1016/j.trd.2023.103897. URL: https://linkinghub.elsevier.com/retrieve/pii/S1361920923002948 (visited on 09/12/2023)
- RP3: H. Marxen, R. Chemudupaty, G. Fridgen, and T. Roth (2023b). "Maximizing Smart Charging of EVs: The Impact of Privacy and Money on Data Sharing". In: *ICIS 2023 Proceedings*. URL: https://aisel.aisnet.org/icis2023/iot_smartcity/iot_smartcity/5
- RP4: R. Chemudupaty, M. Ansarin, R. Bahmani, G. Fridgen, H. Marxen, and I. Pavić (2023). "Impact of Minimum Energy Requirement on Electric Vehicle Charging Costs on Spot Markets". In: *2023 IEEE Belgrade PowerTech*. Belgrade, Serbia: IEEE, pp. 01–06. ISBN: 978-1-66548-778-8. DOI: 10.1109/PowerTech55446.2023.10202936. URL: https://ieeexplore.ieee.org/document/10202936/ (visited on 09/13/2023)
- RP5: R. Chemudupaty, R. Bahmani, G. Fridgen, H. Marxen, and I. Pavić (2025a). "Uncertain electric vehicle charging flexibility, its value on spot markets, and the

impact of user behaviour”. In: *Applied Energy* 394, p. 126063. ISSN: 0306-2619. DOI: 10.1016/j.apenergy.2025.126063. URL: https://www.sciencedirect.com/science/article/pii/S0306261925007937 (visited on 07/08/2025)

- RP6: R. Chemudupaty, T. Hornek, I. Pavić, and S. Potenciano Menci (2025b). “Optimizing trading of electric vehicle charging flexibility in the continuous intraday market under user and market uncertainties”. In: *Applied Energy* 381, p. 125103. ISSN: 0306-2619. DOI: 10.1016/j.apenergy.2024.125103. URL: https://www.sciencedirect.com/science/article/pii/S0306261924024875 (visited on 12/27/2024)
- RP7: R. Chemudupaty and I. Pavić (2024). *Electric Vehicle Scheduling Strategies to Reduce the Imbalances due to User Uncertainties*. en. DOI: 10.46855/energy-proceedings-11394. URL: https://www.energy-proceedings.org/?p=11394 (visited on 12/27/2024)

A.2 Individual Contribution to the Included Research Papers

RP1 - Towards an Evaluation of Incentives and Nudges for Smart Charging

- **Hanna Marxen**: Investigation, Methodology, Conceptualization, Data curation, Formal analysis, Validation, Visualization, Writing – original draft, Writing – review & editing.
- **Raviteja Chemudupaty**: Conceptualization, Writing – original draft, Writing – review & editing.
- **Valerie Graf-Drasch**: Conceptualization, Writing – original draft, Writing – review & editing, Supervision.
- **Gilbert Fridgen**: Writing – review & editing, Supervision, Funding acquisition.
- **Michael Schöpf**: Conceptualization, Writing – review & editing, Supervision.

I contributed to the conceptualization of the paper and played an active role in its development through ongoing discussions throughout the process. Additionally, I wrote several sections of the paper and provided constructive feedback on the overall content.

RP2 - Empirical Evaluation of Behavioural Interventions to Enhance Flexibility Provision in Smart Charging

- **Hanna Marxen**: Investigation, Methodology, Conceptualization, Data curation, Formal analysis, Software, Validation, Visualization, Writing – original draft, Writing – review & editing.
- **Mohammad Ansarin**: Writing – review & editing, Supervision.
- **Raviteja Chemudupaty**: Conceptualization, Writing – original draft, Writing – review & editing.
- **Gilbert Fridgen**: Writing – review & editing, Supervision, Funding acquisition.

I contributed to the conceptualization of the paper and played an active role in its development through ongoing discussions throughout the process. Additionally, I wrote several sections of the paper and provided feedback on the overall content.

RP3 - Maximising Smart Charging of EVs: The Impact of Privacy and Money on Data Sharing

- **Hanna Marxen**: Investigation, Methodology, Conceptualization, Data curation, Formal analysis, Software, Validation, Visualization, Writing – original draft, Writing – review & editing.
- **Raviteja Chemudupaty**: Conceptualization, Writing – original draft, Writing – review & editing.
- **Tamara Roth**: Writing – original draft, Writing – review & editing, Supervision.
- **Gilbert Fridgen**: Writing – review & editing, Supervision, Funding acquisition.

I was responsible for devising the initial concept of the paper and contributed significantly to its evolution through continuous discussions. Throughout the process, I also authored several sections and provided valuable feedback on the paper's overall structure and content.

RP4 - Impact of Minimum Energy Requirement on Electric Vehicle Charging Costs on Spot Markets

- **Raviteja Chemudupaty**: Conceptualization, Methodology, Software, Validation, Formal analysis, Data curation, Writing – original draft, Writing – review & editing, Visualization.
- **Mohammad Ansarin**: Supervision.
- **Ramin Bahmani**: Conceptualization, Methodology, Writing – original draft, Writing – review & editing.
- **Gilbert Fridgen**: Writing – review & editing, Supervision, Funding acquisition.
- **Hanna Marxen**: Conceptualization, Writing – original draft, Writing – review & editing.
- **Ivan Pavić**: Conceptualization, Validation, Writing – review & editing, Supervision.

As primary author, I developed the initial concept of the paper and refined it through discussions with my co-authors. I was also responsible for data procurement, analysis, and cleaning, as well as writing the majority of the code. I conducted the simulations and analyzed the results. Additionally, I drafted the initial manuscript and further refined the text following multiple review sessions with my co-authors.

RP5 - Uncertain Electric Vehicle Charging Flexibility, its Value on Spot Markets, and the Impact of User Behaviour

- **Raviteja Chemudupaty**: Conceptualization, Methodology, Software, Validation, Formal analysis, Data curation, Writing – original draft, Writing – review & editing, Visualization.
- **Ramin Bahmani**: Conceptualization, Methodology, Validation, Writing – original draft.
- **Gilbert Fridgen**: Writing – review & editing, Supervision, Funding acquisition.
- **Hanna Marxen**: Conceptualization, Writing – original draft, Writing – review & editing.
- **Ivan Pavić**: Conceptualization, Validation, Writing – review & editing, Supervision.

As the primary author, I developed the initial concept of the paper and refined it through discussions with my co-authors. I was also responsible for data procurement, analysis, cleaning, and writing the code for simulations. I conducted the simulations and analyzed the results. Additionally, I drafted the initial manuscript and further refined the text following multiple review sessions with my co-authors.

RP6 - Optimizing Trading of Electric Vehicle Charging Flexibility in the Continuous Intraday Market under User and Market Uncertainties

- **Raviteja Chemudupaty**: Conceptualization, Methodology, Data curation, Writing – original draft, Software, Writing – review & editing, Visualization.
- **Timothée Hornek**: Conceptualization, Methodology, Data curation, Writing – original draft, Software, Writing – review & editing, Visualization.
- **Ivan Pavić**: Conceptualization, Writing – review & editing, Supervision.
- **Sergio Potenciano Menci**: Writing – review & editing, Supervision.

As a joint primary author, I was part of the development of the initial concept and conducted the literature review. In addition, I wrote key portions of the code for the simulations and was responsible for procuring the mobility data used in the analysis. I also authored most of the sections and contributed to reviewing and refining the entire paper.

RP7 - Electric Vehicle Scheduling Strategies to Reduce the Imbalances due to User Uncertainties

- **Raviteja Chemudupaty**: Conceptualization, Methodology, Data curation, Writing – original draft, Software, Writing – review & editing, Visualization.
- **Ivan Pavić**: Conceptualization, Writing – review & editing, Supervision.

As the primary author, I developed the initial concept of the paper and refined it through discussions with my co-author. I was also responsible for data procurement, analysis, cleaning, and writing the code for simulations. I conducted the simulations and analyzed the results. Additionally, I drafted the initial manuscript and further refined the text following multiple review sessions with my co-author.

A.3 Appended research publications

A.3.1 Research Paper 1 - Towards an Evaluation of Incentives and Nudges for Smart Charging

ECIS 2022 Research-in-Progress Papers

ECIS 2022 Proceedings

6-18-2022

Towards an evaluation of incentives and nudges for smart charging

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TOWARDS AN EVALUATION OF INCENTIVES AND NUDGES FOR SMART CHARGING

Research in Progress

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Abstract

Electric vehicles (EVs) are an important cornerstone to achieve transport decarbonization. Still, simultaneous charging of EVs when home charging increases peak demand, especially during evenings. Smart charging allows optimal distribution of load, thus preventing peak loads. Nevertheless, this incorporates certain risks for the EV user, e.g., unavailability of EVs for unplanned events. This might lead to a lack of user acceptance. This paper focuses on specific incentives and nudges, motivating users to adopt smart charging. We conducted an integrative literature review, bringing together literature from different areas. Possible incentives and nudges are monetary incentives, feedback, gamification, or smart charging as a default-setting. We conducted three focus groups with 13 EV users in Luxembourg to get first insights into which of those incentives and nudges they prefer. Preliminary results indicate that incentives and nudges should be individualized. In the future, we would use these first insights to develop a large-scale survey.

Keywords: Smart charging, incentives, nudges, user behaviour.

1 Introduction

A central step towards mitigating climate change includes the transformation of society towards carbon neutrality. Thereby, particularly the decarbonization of the transport sector is paramount, as this sector accounts for a quarter of the EU's total greenhouse gas emissions (European Environment Agency, 2021). Out of the many solutions to reduce the emissions associated with the transport sector, replacing the internal combustion engine with an electric drivetrain seems to be the most viable one (Wentland, 2016): When charged with renewable energy, the emissions of electric vehicle (EV) usage are almost negligible. Thus, electric vehicles (EVs) represent a key lever for putting the brakes on carbon emissions (Huber et al., 2019a). In that notion, favorable conditions such as EV-friendly policies, efficient drivetrains, or reduction in battery costs have rapidly increased the EV market penetration. This development is expected to accelerate in the forthcoming years (International Energy Agency, 2020).

Still, even if EVs address aspects of the climate crisis, the rapid electrification of the transport sector causes a rise in electricity demand. The situation further exacerbates when EVs charge simultaneously, thus causing a significant strain on the power grid (Huber et al., 2019b). This caveat could be tackled either from the supply side or the demand side: First, solutions associated with the supply side imply an increase in conventional generation capacity to meet the rising peak demand due to EV charging. This is quite expensive and incompatible with the renewable energy expansion goals (Amin et al., 2020). Second, solutions associated with the demand side refer to the control of EV charging by using demand response programs (Ireshika et al., 2019). Within such demand response programs, the EV load is controlled using indirect and direct load control strategies. In an indirect load control strategy, various dynamic pricing schemes are designed that positively correlate with peak demand, and users adapt their charging schedules to minimize their total cost (Amin et al., 2020). In a direct load control mechanism, the electricity provider alters the load based on the requirements of power systems, albeit adhering to the user requirements (Eid et al., 2016). The adaption of EV charge cycles to the conditions of power systems and the user requirements is known as 'Smart Charging' (IRENA, 2019).

Several studies have already investigated the economic feasibility of smart charging (e.g., Alghamdi et al., 2021; Eldeeb et al., 2018; Rashidizadeh-Kermani et al., 2018; van der Meer et al., 2018). All of them optimally scheduled the EV charging to maximize the profits of energy suppliers by considering the electricity market prices. Further studies ascertain that smart charging is feasible from both an economic and a technical perspective (Deilami et al., 2011; Franco et al., 2015; Richardson, 2011). These works developed an optimal solution for the efficient integration of EVs into the existing distribution systems. However, the acceptance of EV users, which is pivotal in large-scale adoption of smart charging, was rarely discussed in the studies mentioned above. This is somewhat counterintuitive since incentivizing the users is one of the most obvious ways to promote smart charging usage among EV users.

These studies on incentivizing the users to use smart charging mostly investigate the impact of monetary incentives on EV users' smart charging acceptance but less on the influence of non-monetary options. For example, Ensslen et al., (2018) developed a 'load-shifting-incentivizing' (dynamic) tariff which benefits both users and the energy suppliers. A smart charging trial in the UK found out that by implementing dynamic tariffs, most EV users shifted their charging events to off-peak periods (Greenflux, 2020). However, a recent report from the UK suggests that "over a quarter of EV users charge their vehicles during peak hours despite the cost benefits and carbon impacts" (Grundy, 2021, p.1). These contradictory results imply that monetary incentives alone might not suffice for large-scale adoption of smart charging (Will and Schuller, 2016). This ascertains that while developing an incentive scheme and strategies for smart charging, nudges should also be considered. Thaler and Sunstein (2008) define nudges as "any aspect of the choice architecture that alters people's behavior predictably without forbidding any options or significantly changing their economic incentives" (p.6). Incentives in contrast, refer to monetary benefits which arise from the choice of the desired alternative. Incentives and nudges could help ensure that smart charging is attractive to users and that they are willing to accept a certain degree of discomfort. Our research in progress study aims to better understand the behavioral component in smart charging systems and, specifically, the role of incentives and nudges for smart charging. We thus formulate two research questions:

RQ1: Which incentives and nudges in the context of smart charging are regarded as most attractive regarding user perception?

RQ2: What is the user's motivation for regarding certain incentives and nudges as attractive?

Figure 1 depicts an overview of our approach to answer these research questions. We first conducted an integrative literature review in different streams of research. Based on the literature review results, we identified incentives and nudges, which could be important from a smart charging perspective. We conducted three focus groups with 13 EV users in Luxembourg to get first insights into how attractive they perceive different incentives and nudges.

Preliminary results in this research in progress paper are that different motivations for EV usage seem to influence which incentives and nudges EV users prefer. The three motivations were ecological, economic, and technological. We will analyze focus group material using qualitative content analysis

(QCA) as a method. We will conduct a large-scale survey in a follow-up full paper to validate and determine which factors affect the perception of incentives and nudges.

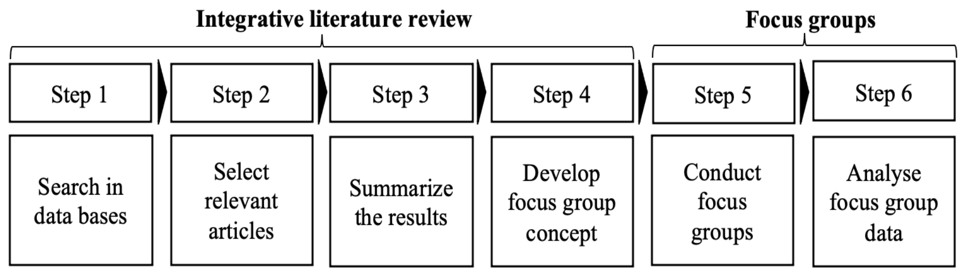

Figure 1. Research Approach.

2 Integrative literature review

Previous research has already described the impact of incentives and nudges on smart charging adoption to a small degree. Still, the number of those studies is limited. Therefore, we conducted a first integrative literature review, bringing together smart charging, energy saving and information system (IS) intersecting sustainability literature (e.g., Green IS, ICT4D). As a lens for our methodological proceeding, we used the guidelines for integrative literature reviews (Torraco, 2016). We searched in the SCOPUS and Google scholar data bases with combinations of search strings of two categories (Table 1). The search strings of the first category refer to smart charging and related concepts. Related concepts are similar to smart charging as they have the same underlying principle where the energy consumption is adapted based on the user requirements (e.g., residential). We also consider studies on energy savings. These are mostly referred to in the existing literature on incentives and nudges for smart charging (e.g., Huber et al., 2019b). The search strings of the second category are related to incentives and nudges.

Our search comprised two steps: The first step was structured with the aim to find as many relevant papers as possible about incentives and nudges for smart charging. We searched with the search strings of the first category (e.g., “smart charging”) and combined them with those of the second category (e.g., "incentive"). We looked further into the identified papers using the forward-backward search to find more relevant papers. We also included papers focusing on incentives and nudges for vehicle to grid technology, a further development of smart charging technology that allows the power flow from the EV batteries to the power grid. In the second step, we focused on the papers that designed incentives and nudges to other similar concepts that could be theoretically transferred to smart charging. We combined the search strings of the first category (e.g., “EV adoption”) with those of the second category (e.g., “nudge”). As there is a lot of literature on this in related fields, we aimed to get an overview of the literature and not cover the whole literature. Thus, we followed a narrative approach. In our team, we discussed and evaluated the applicability of incentives and nudges from other sectors to smart charging. The combination of the structured and narrative approach should yield a broad understanding on which incentives and nudges exist and are potentially effective for smart charging.

	Category 1		**Category 2**
Step 1 Structured approach	“smart charging” OR “flexible charging”	AND	“incentive” OR nudge” OR “behavior change” OR “consumer perspective” OR “user perspective” OR “motivation” OR “persuasion”
Step 1 Narrative approach	“load shift” OR “demand shift” OR “demand side management” OR “demand response” OR “EV adoption” OR “EV acceptance” OR “energy saving” OR “energy-efficient” OR “smart home management” OR “green information system”	AND	

Table 1. Search strings for the integrative literature review in step 1 and step 2.

Inclusion criteria for papers were the following: Papers needed to be in English or German and should state or measure the effect of incentives and nudges. In the first step, to find as much smart charging incentive literature as possible, we considered empirical papers, theoretical papers, conference papers, journal papers, doctoral theses, and university project reviews. In the second step, as fields related to smart charging were not the core focus of the paper, we mainly looked at the reviews and meta-analyses. In the first step, we found 12 papers[1]. In the second step, we selected 23 papers[2]. We looked more closely at those 35 papers. The results of the integrative literature review are that monetary incentives and the nudges *framing*, *feedback*, *gamification*, or *default-setting* can motivate people to use smart charging. In the following, we summarize this literature and provide details on related research.

First, *monetary incentives* in the context of smart charging, often refer to a discount on every kWh or the monthly base prize (Will and Schuller, 2016). Studies come to different conclusions regarding the effect of incentives and nudges on the use of smart charging. In the study of Schmalfuss et al., participants who tested smart charging for five months named monetary incentives most frequently as benefit for smart charging. Handke et al. (2012) claim that users need monetary incentives to accept smart charging. However, according to the survey results by Will and Schuller (2016), monetary incentives do not affect the acceptance of smart charging. Paetz et al. (2012b) tested a time-shifted charging concept for the charging of electric vehicles with 14 participants. The time-shifted charging mechanism allows users to adapt their charging schedule based on their requirements. For the participants of this study, however, monetary incentives were not the reason for time-shifted charging, but environmental aspects. The authors also doubt that time-shifted charging can work completely without monetary incentives.

Also, in the energy-saving literature, the effect of monetary incentives on energy-saving behavior is mixed. Some studies claim or find a positive effect (Alasseri et al., 2020; Azarova et al., 2020; Dütschke et al., 2013; Ito et al., 2018; Spandagos et al., 2021). However, a meta-analysis, which included 52 empirical studies, found a negative effect of monetary incentives on energy-saving behavior: Cost-saving information led even to higher energy consumption (Buckley, 2020). Despite disparate results, in the context of smart charging, monetary incentives may have a certain impact. According to Schmalfuß et al., (2015) and Tamis et al. (2018), EV users expect financial compensation for making their flexibility available to the energy provider. In summary, monetary incentives are potentially promising for smart charging. Previous smart charging studies mostly look at the perception of monetary incentives. Future studies on monetary incentives should also examine the impact of incentives on behavior change. But in practice, as monetary incentives are not effective for everyone, they should not be the only incentive (Tamis et al., 2018); nudges should also be considered.

Framing can be regarded as a nudge and "is the conscious formulation and description of the decision situation to encourage people to behave in a certain way" (Huber, 2020, p. 87). In the context of smart charging, this could mean using text messages to influence the decision-making situation so that EV users are more likely to use smart charging. Framing messages can be shown in an application before the user decides whether to use smart charging or not. In the study by Huber et al. (2019a), only cost frames were effective, environmental frames had no effect and social frames led even to a lower intention to use smart charging. Before charging, cost frames inform EV users to save money through smart charging (Huber et al., 2019b). Environmental frames make clear to the EV user that smart charging contributes to environmental protection (Huber et al., 2019b). Social frames show the user that the network is shared with other users and that everyone benefits from using smart charging (Huber et

[1] Selected papers in step 1: Antunes et al., 2018; Delmonte et al., 2020; Geske, 2014; Handke et al., 2012; Huber et al., 2019a; Huber et al., 2019b; Huber & Weinhardt, 2018; Jochem et al., 2012; Paetz et al., 2012b; Schmalfuß et al., 2015; Tamis et al., 2018; Will & Schuller, 2016.

[2] Selected papers in step 2: Alasseri et al., 2020; Allcott & Rogers, 2014; Azarova et al., 2020; Broman Toft et al., 2014; Buckley, 2020; Chatzigeorgiou & Andreou, 2021; Delmas et al., 2013; Dütschke et al., 2013; Frenzel et al., 2015; Günther et al., 2020; Horne & Kennedy, 2017; Ito et al., 2018; Johnson et al., 2017; Ming et al., 2020; Momsen & Stoerk, 2014; Morganti et al., 2017; Paetz et al., 2012a; Paetz et al., 2012c; Schaule & Meinzer, 2020; Soomro et al., 2021; Spandagos et al., 2021; Tiefenbeck et al., 2019; Vetter & Kutzner, 2016.

al., 2019b). In the energy-saving literature, Schaule and Meinzer (2020) had similar results: Cost frames led to an increased willingness to shift the run times of dishwashers and washing machines, and environmental frames showed no effect. "Social framing even showed a slight decrease in the readiness to shift run times for dishwashers" (Schaule and Meinzer, 2020, p. 1).

To summarize, especially cost framing messages seem to be successful. However, researchers should further investigate the effect of framing messages on the smart charging decision. Here, studies should investigate the effect of framing messages on real EV users' actual smart charging behavior.

Third, *Feedback* could be a significant nudge for smart charging. It can be given on the financial consequences or the respective carbon footprint of a user's charging behavior (Huber and Weinhardt, 2018). However, according to the meta-analysis of Delmas et al. (2013), feedback on cost savings in terms of energy savings leads to an increase in energy consumption and not a decrease (Delmas et al., 2013). Still, especially feedback on environmental contribution could be significant because eco-values, as well as ecological motives, are considered the main motivation for smart charging and the integration of renewable energy sources as the main acceptance factor (Frenzel et al., 2015; Geske, 2014; Huber et al., 2019a; Jochem et al., 2012; Paetz et al., 2012c; Schmalfuß et al., 2015; Tamis et al., 2018; Will and Schuller, 2016). Feedback on an environmental contribution would show users their contribution to environmental protection and motivate them to continue using smart charging. Schmalfuß et al. (2015) show in their survey study, for example, that EV users "are motivated by the feeling of doing something good" (p. 9) to use smart charging. The way feedback is given could be, e.g., historical, real-time, or socially comparative. Regarding the energy-saving literature, Chatzigeorgiou and Andreou (2021) regard historical feedback as a standard for feedback on energy consumption on mobile devices. Research results show that comparative social feedback and real-time feedback are particularly effective. Regarding comparative social feedback, US energy provider OPOWER received information every month about how their energy consumption varies compared to their neighbors (Allcott and Rogers, 2014). Even after the feedback reports were stopped for two years, there was an energy saving of 10-20% compared to when the feedback reports were received. According to Allcott and Rogers (2014), comparative social feedback could also be effective in the long term. Besides comparisons with other consumers, artificial norms can also be successful if the target group feels addressed (Soomro et al., 2021), e.g., encouraging hotel guests to reuse their towels. Concerning real-time feedback, Buckley (2020) concludes in his meta-analysis that real-time feedback is one of the most promising ways to give feedback. To give an example, hotel guests who "received real-time feedback on their energy consumption while showering used 11.4% (0.21kWh) less energy than guests in a control group" (Tiefenbeck et al., 2019, p.1). In addition to the distinction between historical, real-time, and social comparative feedback, feedback can be personalized or, for example, reflect the behavioral tendency. This is where personalized feedback seems most effective (Buckley, 2020; Delmas et al., 2013).

Fourth, gamification is "the use of game design elements in non-game contexts" (Deterding et al., 2011, p.9), e.g., tips, virtual currency, or badges (AlSkaif et al., 2018). It can be regarded as a form of feedback (Chatzigeorgiou and Andreou, 2021). The demarcations between gamification and feedback are blurred. Feedback and gamification differ, however, in their aims. Feedback aims to get the users to reflect on their behaviors. Gamification aims to engage the user and to enhance their activity and retention (Deterding et al., 2011). Game elements "vary widely in terms of the type of games, target, and features that might be appealing and motivating" (Morganti et al., 2017, p. 101). AlSkaif et al. (2018) classified the most important game elements for residential energy applications into the following categories: Information provision (e.g., tips), rewarding system (e.g., virtual currency), social connection (e.g., energy community), performance status (e.g., badges) and user interface (e.g., progress bar).

There is a lack of studies investigating the effect of gamification on the smart charging behavior of EV users. Still, in practice, current smart charging applications use numerous gamification elements (e.g., ev.energy, 2020). With regard to energy-saving behavior, studies find a positive effect of gamification elements (Chatzigeorgiou and Andreou, 2021; Johnson et al., 2017; Morganti et al., 2017). Gamification elements (e.g., personalized goals, feedback, social comparison, prizes, lottery) can enhance energy saving behavior and eco-driving (Günther et al., 2020; Ming et al., 2020). Regarding mobile energy applications, a limited number of studies examine the effect of gamification on behavior change (Beck et al., 2019). Also, existing studies often only consider individual gamification elements in isolation or differ in the combination of gamification elements they consider, e.g., compare the study of Ming et al. (2020) and Günther et al. (2020). It, therefore, seems difficult to describe the effect of the gamification elements on behavior change. However, some authors describe individual gamification elements further in literature and the effect on behavior: According to Buckley (2020), e.g. tips fall into the information provision category are very effective if individualized. According to their meta-analysis, general tips on saving energy even led to an increase in consumption. In general, the core principle behind tips is like feedback and framing. However, tips solely focus on improving user performance based on their behavioral patterns. Concerning social connection, Horne and Kennedy (2017) emphasize the role of social norms, which can be established via new technologies and can influence energy-related behavior. Peer pressure can be built up online and can impact the behavior of users (Spandagos et al., 2021).

Fifth, to set smart charging as a default is recommended by the UK Energy Task Force (Energy Task Force, 2019) and Delmonte et al. (2020), as this reduces user interaction with the smart charging system. In other areas, setting a desirable option as the default has proven effective, e.g., for organ donations (Shafir, 2013). Regarding the choice of environmentally friendly energy contracts, to set a contract with energy from renewables as the default was the only incentive that had an impact on whether people chose a contract where the energy came from renewable sources (Momsen and Stoerk, 2014): The default setting increased the proportion of those who opted for the green contract by 44.6%. In the study by Vetter and Kutzner (2016), the default setting also influenced whether a green contract was selected: Environmental attitudes did not influence the decision. For smart grids, the use of an opt-out frame leads to a significantly higher participation rate than the opt-in frame (Broman Toft et al., 2014). However, to make smart charging the default, smart meters and wall boxes should first be installed. If these conditions are met in the future, smart charging as a default could be possible. Still, EV users might just use it if there are no additional costs for purchasing infrastructure.

According to initial research results, different groups of people perceive incentives and nudges as differently attractive. Cultural and demographic factors and different motivations (e.g., ecological versus economic) influence, for example, how different they are perceived. Regarding cultural differences, e.g., monetary incentives are perceived as more attractive in Portugal than in the Netherlands; in contrast, social comparison is perceived as more negative in Portugal than in the Netherlands (Antunes et al., 2018). Besides cultural factors, different motivations for smart charging could also influence how attractive incentives and nudges are for different groups of EV users. Bailey and Axsen (2015) distinguish between EV users who could be motivated by cost-saving and those motivated by using electricity from renewable energy sources. In terms of how different consumers respond to demand response, Sharda et al. (2021) describe consumers based on the literature using four dimensions: Selfishness, importance of price, eco consumption, and demand responsiveness.

Concerning the price dimension, Sharda et al. (2021) distinguish between price optimizers (price prioritized over comfort), price-sensitive (tradeoff between comfort and price), and price-insensitive consumers (comfort prioritized over price). Regarding eco consumption, they distinguish between eco consumer (minimum power demand from the grid), the average consumer (average power demand from the grid), and waste consumer (comfort prioritized over price). Before incentives and nudges are applied, researchers need to conduct consumer research to investigate which incentives and nudges are appropriate for the respective target group. They "must fit the context and the targeted user group, as otherwise, they can backfire and even have adverse effects" (Huber, 2020, p. 68).

3 Focus groups

Focus groups are a well-established method to get customers' and users' perspectives on new technologies or products (Paetz et al., 2012a). In that, focus groups allow a deep investigation of reasons underlying a product evaluation and thus go far beyond superficial responses (Mert and Tritthart, 2009). Participants get the possibility to „ask questions and also to stimulate each other in evoking associations and perceptions to discuss them as a group" (Paetz et al., 2012a, p. 28).

To analyze the feedback and input received in the focus group, we later plan to use qualitative content analysis (QCA) as a deductive and an inductive approach to analyze data (Cho and Lee, 2014): We will first deductively develop categories according to which the data will be coded. Afterward, we will derive further categories with the help of an inductive procedure.

3.1 Conduct of focus groups

The primary goal of our focus groups was to perceive the users' preferences for different incentives and nudges in the context of EV charging and understand the factors driving these preferences. We conducted three focus groups ($n_1 = 4$, $n_2 = 4$, and $n_3 = 5$) in Luxembourg with 13 EV users (2 female, 11 male). We selected the EV users who drove their EV for at least several months. Participation was voluntary. All the focus groups were recorded and transcribed.

We conducted the focus groups onsite with a predefined agenda: After a short introduction, this agenda contained three central building blocks lasting 30, 15, and 90 minutes. First, we asked the participants to share their EV usage patterns as it also might influence the perceived attractiveness of incentives. Second, we described the concept of smart charging. We illustrated the importance of customer flexibility, which served as a transition for the third part, "discussion about incentives." Third, we selected the incentives and nudges based on the results of the integrative literature review. We discussed the five incentive and nudge groups *monetary incentives*, *framing*, *feedback*, *gamification*, and *smart charging as a default* with the participants. Regarding gamification, we discussed four gamification elements: badges, credit points, tips, and energy communities. Each gamification element reflects a category of AlSkaif et al. (2018). We created a presentation containing a brief description of the incentives and nudges and discussion questions to guide the discussion. Respective discussion questions were to deduce the rationale behind the participants' interest/disinterest towards a specific incentive or nudge. After the discussion, we asked participants to rank first the five incentives and nudges and second, the four gamification elements according to attractiveness using a survey.

4 Preliminary results and discussion

In the following, we provide some preliminary results of the focus groups and the participants' ranking of incentives and nudges. Regarding the first research question, "Which incentives and nudges in the context of smart charging are regarded as most attractive regarding user perception?", the rankings provide the first results (see table 2). For example, out of 13 participants, five participants ranked monetary incentives as first. Overall, the participants regarded monetary incentives and smart charging as default as most attractive. Concerning gamification, they considered tips as most attractive.

Incentives/ Nudges	Ranking results
Monetary incentives	ranked 1st (n = 5), 2nd (n = 1), 3rd (n = 1), 4th (n = 2), 5th (n = 1)
Smart charging as default	ranked 1st (n = 5), 2nd (n = 4), 3rd (n = 3), 4th (n = 0), 5th (n = 1)
Feedback	ranked 1st (n = 0), 2nd (n = 3), 3rd (n = 4), 4th (n = 4), 5th (n = 0)
Framing Messages	ranked 1st (n = 1), 2nd (n = 2), 3rd (n = 2), 4th (n = 2), 5th (n = 4)
Gamification	ranked 1st (n = 0), 2nd (n = 1), 3rd (n = 2), 4th (n = 3), 5th (n = 5)
1. Tips	ranked 1st (n = 6), 2nd (n = 2), 3rd (n = 2), 4th (n = 2)
2. Credit points	ranked 1st (n = 5), 2nd (n = 4), 3rd (n = 3), 4th (n = 0)
3. Energy communities	ranked 1st (n = 1), 2nd (n = 3), 3rd (n = 4), 4th (n = 4)
4. Badges	ranked 1st (n = 0), 2nd (n = 3), 3rd (n = 3), 4th (n = 6)

Table 2. Ranking perceived attractiveness of incentives and nudges.

The ranking of the incentives and nudges was mostly consistent with the participants' answers during the focus group discussions. About the focus group discussions, we want to highlight two striking features. First, the participants, in general, were concerned about information overload. Thus, in the context of feedback, framing, and tips, they wanted to receive only a limited number of messages on their smartphone, e.g., one message per week or just when they open their smart charging application. Second, participants largely rejected most gamification elements in the discussion. However, participants in all three focus groups considered gamification elements might be attractive for the younger generation.

Regarding the second research question, "*What is the user's motivation for regarding certain incentives and nudges as attractive?*", participants' motivation seemed to be related to their motivation to purchase an EV. Three motivations for purchasing an EV were ecological, economic, and technological. Participants with an ecological motivation had their EV for ideological reasons, to contribute to environmental protection. They were mainly interested in nudges indicating their contribution to environmental protection (e.g., feedback, framing). Participants with an economic motivation owned their EV mainly because their company covered most of their purchase costs and partly charged their EV at work. They had a higher preference for monetary incentives. Participants with technological motivation purchased EVs for their driving experience. It was not clear which incentives or nudges they preferred.

As the three motivations seem to be related to different incentives and nudges, it might be useful to incentivize and nudge EV users differently. Analog to different contexts, individualization approaches foster an effective EV user targeting for smart charging. Besides different underlying motivations, also socioeconomic characteristics (e.g., age) may influence the perception of incentives and nudges.

The results of the integrative literature review inform researchers and practitioners which incentives and nudges can potentially be effective. The review is comprehensive as we looked at the incentives and nudges literature for smart charging and other relevant sectors. A limitation of the integrative literature review is that we only used two data bases. Future research should extend the literature review and include data bases as AIS E-library, IEE Xplore, ScienceDirect and SAGE Journals.

The focus groups helped to get an insight into which incentives and nudges are attractive for EV users. One limitation of the focus groups is that the sample size of 13 is small, and therefore its results cannot be generalized. This is the reason why after analyzing the focus group transcripts, we want to design a large-scale survey based on the focus group's results. One main goal of this large-scale survey is to obtain generalizable results on users' perceptions of different incentives and nudges. We aim at investigating which incentives and nudges are attractive for different EV users and which factors (age, nationality, income, education level, occupation, ecological, economic, and technological motivation) influence individuals' perception. Incentives and nudges and the above-mentioned factors are independent variables. Using multiple regression, we then want to investigate the influence of these independent variables on the perception of incentives and nudges. Here, we want to investigate how both EV users and non-EV users perceive the incentives and nudges and compare their perceptions—the rationale behind including non-EV users as they could serve as potential EV users. In addition, however, we want to test in an experiment within the framework of the survey which incentives and nudges are effective.

The results will help practitioners develop individualized incentive schemes in different contexts (e.g., different countries). In the academic field, we want to initiate research that further investigates the behavioral aspects of smart charging. Such research is highly relevant, as smart charging cannot be established without the acceptance of EV users.

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A.3.2 Research Paper 2 - Empirical Evaluation of Behavioural Interventions to Enhance Flexibility Provision in Smart Charging

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Empirical evaluation of behavioral interventions to enhance flexibility provision in smart charging

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ABSTRACT

The growing adoption of Electric vehicles (EVs) puts pressure on the power grid, and implementing smart solutions can ease this pressure. Smart charging at home is a solution where users offer flexibility in their charging schedule, which energy suppliers and/or other aggregators can exploit by charging during times of low demand and low market prices. However, giving charging control to the energy provider can concern EV users, particularly about driving range, and give a sense of loss of control. We conducted an experimental online survey with EV users (n = 289), examining the effect and perception of different behavioral interventions to improve flexibility provision. We found that all monetary incentives (high, low, credit points) resulted in higher flexibility, while environmental framing, feedback and badges, default-setting, and battery-related tips had no effect. The perception of all behavioral interventions did not correlate significantly with the flexibility offered for any of the interventions.

1. Introduction

Many countries worldwide tackle climate change by aiming to reduce their greenhouse gas emissions (IEA, 2022). One relevant goal is to electrify the transportation sector, where burning fossil fuels contributes a large portion of greenhouse gas emissions. Here, electric vehicles (EVs) have the potential to make a significant impact (IEA, 2022). EV uptake is accelerated by EV-friendly regulations and improved EV range, especially in industrialized countries. The International Energy Agency projects that by 2030, EVs will account for 30% of all vehicle sales globally (IEA, 2022).

This tremendous rise in EVs increases electricity demand. When EVs charge simultaneously, a significant strain is imposed on the power grid (Huber et al., 2019b). Smart charging can help alleviate this issue. Smart charging involves adapting the charging schedule of EVs to both the conditions of the power system and the needs of the EV users (IRENA, 2019). This can drastically reduce the need for expanding grid capacity at both distribution and transmission system levels. As two examples, studies focused on Germany (Schmidt and Busse, 2013) and the United Kingdom (Greenflux, 2020) have illustrated that using smart charging algorithms can move charging to low demand periods and thus mitigate demand peaks.

To make the charging process smart, the EV user must provide charging flexibility to the energy provider. In the case of home charging, which is our focus, this includes leaving the EV plugged in while it is parked, selecting a low power for charging, and a low final state of charge (SOC). The more flexibility the EV user offers, the more the energy provider can charge the EV during periods of no grid congestion. Additional relevant benefits could also exist, such as when charging during periods with low electricity market prices and high renewable energy sources (RES) generation. For the EV user to provide flexibility means relinquishing control over

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when exactly the EV is charged. This lack of control and/or the possibility of having insufficient battery charge for the next trip can concern EV users (Delmonte et al., 2020; Bailey and Axsen, 2015; Libertson, 2022) who may thus be hesitant to provide flexibility.

Encouraging EV users to embrace flexibility (Kubli, 2022), despite any potential risks or discomfort is important. Flexibility provision can be achieved through monetary incentives, nudges and tips (Schuitema et al., 2017; Huber et al., 2019b,a; Huber and Weinhardt, 2018). Incentives are monetary benefits from choosing the desired alternative. In contrast, nudges focus on non-economic benefits. They are "any aspect of the choice architecture that alters people's behavior predictably without forbidding any options or significantly changing their economic incentives" (Thaler and Sunstein, 2008, p.6). It is thus a way to influence people's behavior without issuing prohibitions (e.g., feedback messages on previous energy consumption are supposed to influence future consumption). By tips, we refer to rational advice based on which users can make an informed decision (e.g. tips on what battery percentage is optimal for charging the EV).

Many studies have looked at incentives and/or nudges for smart charging decisions (Will and Schuller, 2016; Huber et al., 2019a; Huber and Weinhardt, 2018; Huber et al., 2019b; Kacperski and Kutzner, 2020; Kramer and Petzoldt, 2022; Kacperski et al., 2022; Ensslen et al., 2018; Verbong et al., 2013; Wong et al., 2023). These studies use different study designs to investigate the effect of incentives and nudges. They often do not consider several incentives and nudges in their study designs, making it difficult to compare their effectiveness.

Moreover, previous studies on these interventions mainly assess either the perception or efficacy, but not both. Studies also did not explicitly *distinguish* between perception and effectiveness. In our study, "perception" refers to how positively or negatively people assess interventions. With "effectiveness", we refer to its effect on people's behavior, in this case, flexibility provision. Effectiveness is typically assessed through experimental designs or real-life observations (Huber et al., 2019a; Kacperski et al., 2022). Perception, in contrast, is commonly measured through qualitative studies or those that do not employ experimental designs (Huber et al., 2019b; Delmonte et al., 2020). As the measurement can influence the outcome, we distinguish between them.

The link between the perception and effectiveness of incentives, nudges, and tips is especially relevant in practice: If incentives, nudges, and tips are viewed favorably but have no actual effect, there is no point in deploying them. For water saving, Tijs et al. (2017) point to a difference: Although people perceived the monetary appeal as most attractive, the environmental appeal was more effective in water saving while showering. Few studies in the smart charging domain look at both perception and effectiveness. Thus, it is uncertain whether the effectiveness of incentives, nudges, and tips is directly related to a positive perception of them.

In an experimental survey design, we investigate the effect of different behavioral interventions, (i) monetary incentives, (ii) nudges, and (iii) tips on flexibility decisions in the context of charging. We aim to identify which incentives, nudges, and tips are most effective in fostering smart charging. These results are particularly interesting for practitioners who aim for (increased) flexibility provision via home smart charging. Also, we investigate for which incentives, nudges, and tips a positive perception is related to a higher flexibility provision. These findings are of particular methodological relevance for consumer researchers designing studies to evaluate the impact of these behavioral interventions. Our research questions are as follows:

RQ1: Which incentives, nudges, and tips lead to a higher flexibility provision in electric vehicle charging?

RQ2: Is a positive perception of incentives, nudges, and tips associated with increased flexibility provision?

In the subsequent section, we discuss the literature surrounding different incentives, nudges, and tips for smart charging and derive our hypotheses. In Section 3, we describe our survey design based on the results of focus groups and the recruitment procedure for participants. In the results Section 4, we analyze if incentives, nudges, and tips lead to a higher flexibility provision and whether this is linked to their perception. This Section also contains an exploratory analysis of smart charging literacy and the minimum required state of charge. Section 5 discusses the survey results, illustrates practical and theoretical implications, and points out limitations.

2. Theoretical background and hypothesis development

So far, academic literature and real-world mobile applications have mainly focused on monetary incentives for smart charging. However, an increasing amount of authors also point to the importance of factors such as the integration of renewables (Will and Schuller, 2016; Huber et al., 2019b). In the study by Will and Schuller (2016), the integration of renewables affected the acceptance of smart charging, while monetary incentives did not. Verbong et al. (2013) even went as far to say that "too much focus on [...] economic incentives can become a barrier". Tarroja and Hittinger (2021, p.1) argued that "non-monetary incentives may be needed to increase smart charging participation". These non-monetary incentives may refer to nudges or tips. This study focuses on the monetary incentives and environmental nudges, which have been identified as the primary motivators for smart charging (Will and Schuller, 2016; Huber et al., 2019b). Additionally, we look at smart charging as a default option, battery-related tips and how the character trait risk aversion influences charging flexibility.

2.1. Monetary incentives

Literature has explored the effects of monetary incentives in various manners. These incentives refer to dynamic pricing schemes and discounts on the final energy bill (Will and Schuller, 2016). During peak periods, electricity prices are at their highest and vice versa during off-peak hours; thus, customers can reduce their electricity bills by shifting their load to off-peak times. The frequency of price variation is dependent on the particular dynamic tariff plan. In specific dynamic pricing systems, tariffs alter hourly or every few minutes to reflect the real-time energy market (e.g., real-time pricing) (Dutta and Mitra, 2017). While in other schemes, the different block rate tariffs are offered to consumers within a period (e.g., time of use, critical peak pricing) (Zhang et al., 2017;

Newsham and Bowker, 2010). A smart charging trial in the UK discovered that by utilizing dynamic tariffs, most of the EV users shifted their charging events to off-peak times (Greenflux, 2020). Another smart charging trial in Canada looked into the influence of dynamic pricing on the charging behavior of users (Goody et al., 2020). They found that, compared to a control group, the dynamic pricing group offered more flexibility and charged their EVs more often in the off-peak period around midnight. However, consumers might only be willing to accept dynamic tariffs if they perceive a significant difference in their final energy bills.

Incentives can also be given directly on the monthly energy bill. Will and Schuller (2016) conducted a survey asking EV users what the minimum discount would be on their electricity bill to participate in smart charging. Surprisingly, the anticipated discount had no notable influence on the willingness to participate in smart charging. Furthermore, in the interview study by Paetz et al. (2012a), EV smart charging was not motivated by cost savings but rather the desire to drive free of emissions.

In addition to reduced tariffs and cheaper electricity bills, incentives could be paid every time EV users allow smart charging, i.e., offer flexibility. Kramer and Petzoldt (2022) conducted an experimental survey where they examined the effect of cost saving on smart charging decisions: Cost savings had a statistically significant effect on the decision to select regular or smart charging for public charging (Kramer and Petzoldt, 2022).

EV users can also be rewarded with monetary incentives for participating in a smart charging program. Wong et al. (2023) conducted a survey and found that monetary incentives increased the interest to participate in a smart charging program for EV owners/lessees and EV interested buyers/lessees. Delmonte et al. (2020) conducted interviews with actual and potential EV users. Also, here, the EV users' willingness to participate in smart charging programs was related to reduced charging costs.

Overall, studies have differing results on the effectiveness of monetary incentives for smart charging. These discrepancies could be due to the different study designs and operationalizations of monetary incentives. However, as most studies state that monetary incentives lead individuals to participate in smart charging programs, we hypothesize:

H1: Monetary incentives lead to a higher flexibility provision.

The amount of monetary incentives may also affect the flexibility provision. Prior studies, for example Delmonte et al. (2020), mention that regular EV charging costs are already lower than refueling an internal combustion engine vehicle. With cheaper regular charging, motivating people to use smart charging further would require incentives significantly higher than those savings. Wong et al. (2023), who conducted a survey asking participants to join a smart charging program based on increasing monetary incentives, had similar results: Higher incentives were attributed to an increased interest in smart charging programs. To confirm this effect, we formulate the following hypothesis:

H2: High monetary incentives lead to a higher flexibility provision than low monetary incentives.

Monetary incentives can also be given in a fun and engaging manner on a digital interface using game elements. Game elements "vary widely in terms of the type of games, target, and features that might be appealing and motivating" (AlSkaif et al., 2018, p.101). Morganti et al. (2017) and AlSkaif et al. (2018) classified a rewarding system as a game element. These elements include credit points, which users can collect in an app through a desired behavior. The desired behavior would be smart charging in our study. These credit points have a monetary value and could be accumulated and utilized, for example, to charge EVs. With credit points, transparency (calculating and accumulating them) is important (Tamis et al., 2018). Credit points may function similarly to other monetary incentives because they have a monetary value. Therefore, we propose the following hypothesis:

H3: Credit points lead to a higher flexibility provision.

2.2. Nudges

Many studies have found that environmental values are essential for users of EVs. Eco-values, as well as ecological motives such as usage of RES while smart charging is considered highly relevant for the acceptance of smart charging (Frenzel et al., 2015; Geske, 2014; Huber et al., 2019b; Jochem et al., 2012; Paetz et al., 2012b; Schmalfuß et al., 2015; Tamis et al., 2018; Will and Schuller, 2016). In the following, we describe environmental nudges like framing, feedback, and badges, which might influence the charging choices of EV users.

First, framing "is the conscious formulation and description of the decision situation to encourage people to behave in a certain way" (Huber et al., 2019a, p.87). In the context of smart charging, framing can be using text messages to influence the EV users' decision-making so that they are more likely to provide high flexibility. Framing messages can be depicted in an application prior to the charging decision. Environmental frames make it clear to the EV user that smart charging contributes to environmental protection (Huber et al., 2019a). Huber et al. (2019a)'s study found that environmental frames did not affect the smart charging decision of participants. This result differs from results of studies in other adjacent research areas, such as energy-saving literature, where such frames were found to be effective (Schaule and Meinzer, 2020). In certain studies, environmental and monetary frames were both effective (Steinhorst and Klöckner, 2018), while in others, environmental frames were more effective (Asensio and Delmas, 2015). One possible explanation for the latter finding is that environmental frames enhance pro-environmental intrinsic motivation (Steinhorst and Klöckner, 2018). Steinhorst and Klöckner (2018) also hypothesized that environmental framing, contrary to monetary framing, influences long-term behavior change. However, they did not find any support in their study: The framing messages did not affect long-term self-reported energy-saving behavior and neither the yearly household electricity consumption. In a further experiment, Berger et al. (2022) tested the effectiveness of environmental framing when selecting programs for the washing machine and dishwasher. The use of environmental frames resulted in participants being more inclined to choose the eco-program over shorter alternatives. The effect of environmental frames was even more potent than default nudges. Based on these findings, we formulate the following hypothesis:

H4: Environmental framing leads to a higher flexibility provision.

Second, feedback allows users to be informed about their electricity consumption. It also assists them in interpreting their data and serves as a catalyst for behavioral change (Verbong et al., 2013). Environmental feedback could be provided on the corresponding carbon footprint, i.e., the amount of carbon emissions saved by smart charging when compared to regular charging (Huber and Weinhardt, 2018). Schmalfuß et al. (2015, p.9) indicate that EV users might use smart charging as they are "motivated by the feeling of doing something good". Seeing positive environmental consequences could be a motivator to use smart charging further. With reference to the energy-saving literature, Tiefenbeck et al. (2019, p.1) found environmental feedback to be specifically effective: Hotel guests who "received real-time feedback on their energy consumption while showering consumed 11.4% (0.21 kWh) less energy than guests in a control group", even without receiving any monetary incentives. Thus, we also hypothesize for smart charging:

H5: Environmental feedback leads to a higher flexibility provision.

Third, badges are a gamification element (AlSkaif et al., 2018) and should have their typical functions: to appeal, motivate, and include users (Morganti et al., 2017). This engagement is necessary as Lagomarsino et al. (2022, p.11) have pointed out that "a mere automatization of smart charging choices without user integration is likely to fail, and decrease[s] the acceptance of the technology". Badges can be considered as a 'nice-to-have functionality,' a feature that enhances the enjoyment of an application (Tamis et al., 2018) and displays the user's achievement level (Beck et al., 2019). In practice, some smart charging applications already use environmental badges. For example, the US-American application Fleetcarma awards badges to users for achieving minimum emission savings (FleetCarma, 2018). To the best of our knowledge, there is a lack of research on the impact of badges on smart charging behavior or similar behaviors such as energy-saving behavior. In the longitudinal study by Cominola et al. (2021), participants earned points, badges, and rewards and received recommendations for conserving water in a 6-month period. Two years later, 47% of households had reduced their consumption by 8% compared to before the project. Although the effect of all behavioral interventions was measured, it is possible that the badges may have contributed to this outcome. Based on this, we propose the following hypothesis:

H6: Environmental badges lead to a higher flexibility provision.

Fourth, we describe studies on the nudge smart charging as a default. Setting high charging flexibility as the default option for smart charging is a way to nudge users to choose this option. Users would have the option to opt-out for another choice, but the default option would encourage them to choose high flexibility. For example, when selecting an energy contract, energy providers often offer green energy contracts as the default option, where energy is generated using RES. In the study by Momsen and Stoerk (2014), by setting a contract with energy from RES as the default, the proportion of individuals who chose this contract increased by 44.6%. Vetter and Kutzner (2016) had similar results, which were independent of individuals' environmental attitudes. Similarly, default nudges can significantly increase participation in smart grids (Toft et al., 2014).

Smart charging as a default is recommended by the UK Energy Task Force (Force, 2019) and Delmonte et al. (2020). Currently, the standard practice is to charge EVs immediately, similar to how people are used to fully refueling their conventional cars (Lagomarsino et al., 2022). However, setting smart charging as the default option could reduce the number of decisions and cognitive effort required for the user and decrease interaction with the smart charging system (Delmonte et al., 2020). Based on this, we propose the following hypothesis:

H7: The default setting leads to a higher flexibility provision.

2.3. Battery-related tips

Battery-related tips can also be considered as gamification elements (AlSkaif et al., 2018). Strictly speaking, they are not nudges, as they provide the user with information that allows them to make a rational decision about charging. For some batteries, charging to a low battery percentage is better for the battery life (Tan et al., 2016) and offers more flexibility to the energy provider (Huber et al., 2019b). In focus groups conducted by Huber et al. (2019b), experts identified low battery degradation as one of the benefits of smart charging. Preserving the battery should also interest EV users.

Nevertheless, they must first be aware of the benefits of not fully charging the battery to make informed decisions. This information can be provided through battery-related tips. Therefore, we propose the following hypothesis:

H8: Battery-related tips lead to a higher flexibility provision.

2.4. Risk aversion and smart charging

Range anxiety, defined as "the worry that one will run out of battery before reaching the destination" (Herberz et al., 2022, p.2), is a frequently discussed topic. Range anxiety is related to risk aversion, a character trait in which people prefer low-risk alternatives to high-risk alternatives, even if the average outcome is equal or higher (Werner, 2008). As EV users become more risk-averse, they become more concerned about their remaining battery capacity, tend to charge more frequently, and draw more energy when charging (Xing et al., 2021). The counterparts of risk-averse individuals are risk-seeking ones. Risk-seeking people consider variables such as battery percentage, prices, and charging location when charging. In contrast, risk-averse people primarily focus on ensuring enough charge for the next trip (Pan et al., 2019). In the experiment by Huber et al. (2019a, p.11), "participants who consider[ed] themselves more willing to take risks [were] slightly more flexible" and selected a lower state of charge. Thus, we hypothesize:

H9: The lower the personal risk aversion, the higher the flexibility provision.[1]

[1] H9 was slightly adapted after the preregistration. Previous version: A high personal risk assessment negatively moderates the relationship between the nudge/incentive group and the flexibility provided.

2.5. Perception versus the effectiveness of incentives, nudges, and tips

The above-described studies differ in various characteristics, such as whether they use quantitative or qualitative analysis, whether they measure the effectiveness or perception of incentives or nudges, or how they operationalize the dependent variable flexibility or smart charging acceptance. Hence, it is difficult for these studies to compare the effectiveness of all the incentives and nudges. Also, most studies measure the perception or effectiveness of incentives and/or nudges. However, Tijs et al. (2017) demonstrate that the perception and effect of incentives and nudges do not always align for water-saving. In the flexibility field, we have not found any study investigating the perception and effectiveness of incentives, nudges, and tips. For this reason, in addition to examining the effect of these behavioral interventions, we aim to investigate how these perceptions relate to their effectiveness.

3. Methods

3.1. Focus groups and survey development

Before conducting the survey, we sought to gain a preliminary understanding of user preferences for different incentives, nudges, and tips in the context of EV smart charging and the factors driving these preferences. To do this, we conducted three focus groups ($n_1 = 4, n_2 = 4, n_3 = 5$) with 13 EV users in Luxembourg (2 women, 11 men). We took the help of one of our industry partner Enovos Luxembourg SA, who started a call for our focus groups. From the pool of participants, we selected all EV users who had been driving their EV for several months or more. The focus groups were recorded and transcribed and were conducted onsite with a predetermined agenda. Further information and results of the focus groups can be found in Appendix A and more detailed information in the paper by Marxen et al. (2022).

The results of the focus groups helped us design the survey but did not provide a clear indication of user preferences for different incentives, nudges, and tips. Therefore, the survey included all incentives, nudges, and tips. We also wanted to measure different motivations for EV usage (environmental, financial, technological, and social) in the survey, as the focus group results indicated that those are related to preferences for incentives, nudges, and tips.

We designed the survey material, and then discussed a first draft with five energy researchers/experts and three non-experts to ensure comprehensibility. Subsequently, we conducted the adapted survey in a pre-test with 25 participants, who left comments on various aspects of the survey. We simplified the content, including the definition of smart charging, and then preregistered our survey at Aspredicted.[2]

3.2. Recruitment, procedure for participants and measures

The questionnaire was available online from February 22, 2022, to June 29, 2022. The whole survey can be found in the supplementary material. Participants could answer the survey in English, German, or French. The primary goal was to obtain a sample of EV users from Luxembourg, Germany, Belgium, and France, all of whom speak French and/or German. So, we primarily shared the survey on German-and French-speaking platforms. However, we did not restrict participation from individuals residing in other countries. We shared the survey across various online platforms, such as Facebook groups, LinkedIn, Twitter, email distributions, and EV and university forums.

For the participants, the survey consisted of an experiment and a part in which they replied to items of questionnaires and further questions. Fig. 1 gives an overview of the experimental part of the survey. Before the experiment, participants indicated their familiarity with smart charging on a scale from 1 (“not familiar at all”) to 7 (“extremely familiar”). They read an explanation of the concept of smart charging (Appendix A) and answered an attention question to confirm their understanding. Afterward, we measured their willingness to allow their energy provider to control the charging process with one item: “I would have the charging process of my EV controlled by my energy supplier”. They indicated their agreement on a 7-point Likert scale (“strongly disagree” to “strongly agree”).

Participants then read a scenario in which they imagined the following smart charging situation: *You come home at 18:00 with your electric vehicle (EV). Your battery percentage is 15%. The next day, you have to leave at 8:00 and drive 200 km (round trip). You have told your smart charging app that you have to drive 200 km the next day*. We used the term “battery percentage” instead of “SOC” for a better understanding. For the scenario, EV users would need a SOC of 40%

In our study, flexibility relates to the charging flexibility of the energy provider. This charging flexibility is higher if the user requests a lower $SOC_{Departure}$ for a charging session. Within our paper, we use the term $SOC_{Departure}$ whenever users request a SOC for the end of the charging session. To simplify our study design, we set a $SOC_{Departure}$ of 65% as an anchor point to differentiate between high and low flexibility. Therefore, in our study, high flexibility entails that users select a $SOC_{Departure}$ of up to 65% and above and vice versa for low flexibility (Fig. 2). We intentionally have set the beneficial $SOC_{Departure}$ (anchor point) at an acceptable level. For example, if the beneficial $SOC_{Departure}$ is 90%, the small margin of 10% would greatly impact the effect size and make it difficult to test the effect of incentives, nudges, and tips with a suitable sample size and statistical power.

After reading the scenario, the participants were randomly assigned to either the control group or one of the eight experimental groups. In the control group, the participants saw a neutral message. An incentive, nudge, or tip message was given in the

[2] https://aspredicted.org/9ji4w.pdf.

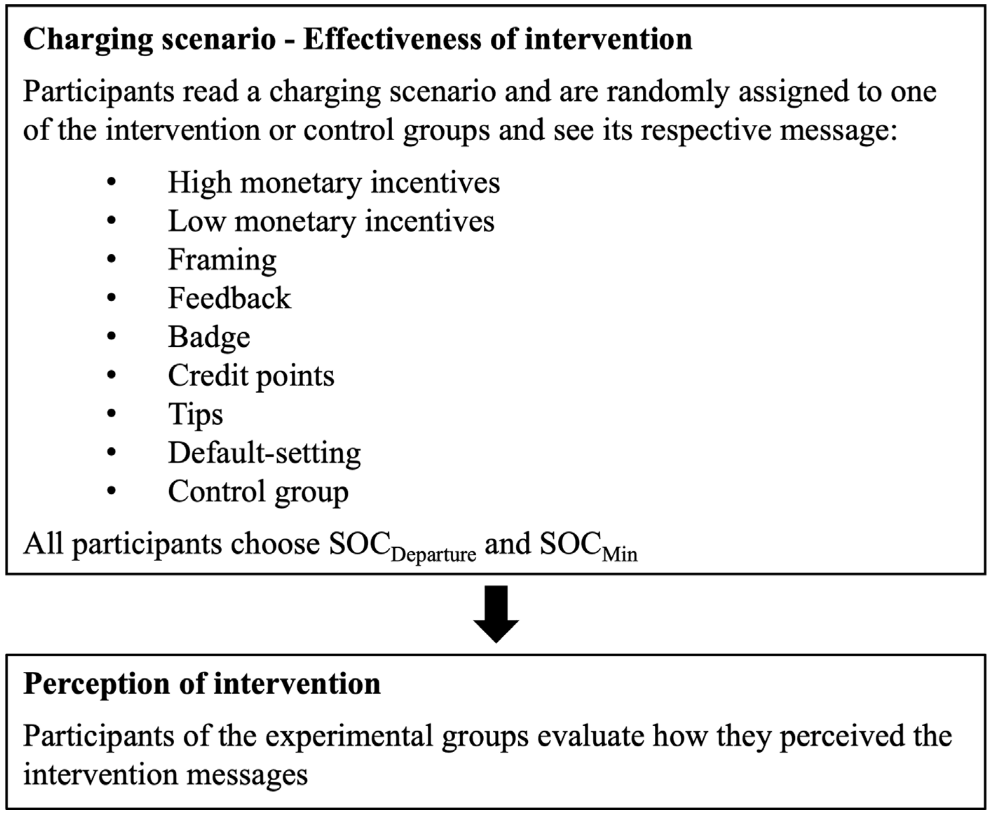

Fig. 1. Overview of the experimental survey design.

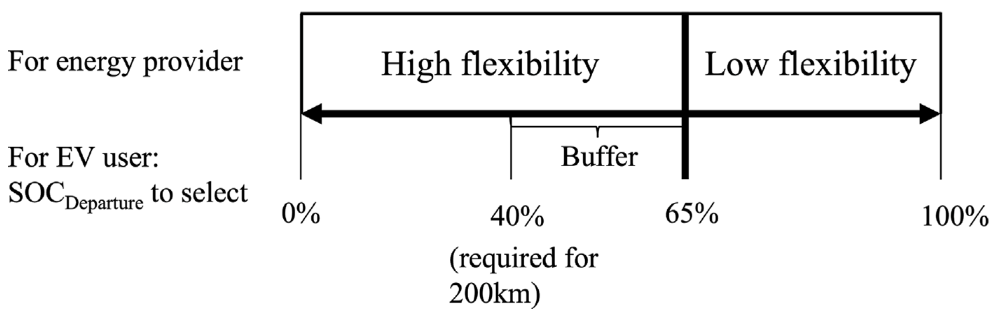

Fig. 2. Illustration of the simplified flexibility definition for the experimental design.

experimental groups regarding participants charging their EV only up to a $SOC_{Departure}$ of 65%. Fig. 3 depicts the messages for the high monetary incentives group, and other messages are in Appendix B (Fig. B.5). Regarding the high, low monetary incentives and credit points messages, we assumed a baseline electricity tariff of 25 ct/kWh. We established this baseline tariff after considering the electricity prices in Luxembourg and Germany during the years 2021–2022, which ranged roughly from 20–30 ct/kWh (Eurostat, 2022; Economy, 2022). In the high incentives group, participants got a reduction of 40% (15 ct/kWh) if they chose a $SOC_{Departure}$ up to 65%, and in the low incentives group, a reduction of 20% (20 ct/kWh). The participants also read the exact amounts they would save.

On the following page, participants in the experimental groups saw the message again, this time on a smartphone mock-up with an option to select the $SOC_{Departure}$ for the next day. We decided to repeat this message to ensure that all participants saw it; in the pretest survey, two participants missed it when it was only displayed once with further information. In addition to the smartphone mock-up, they saw an information table on how far they could travel with different SOC levels. Fig. 4 depicts this for the high incentives group. In the other groups, participants saw the exact mock-up and information table, respectively, with their group's message.

Then, all participants selected a $SOC_{Departure}$ (0%–100%) and a desired minimum SOC (SOC_{Min}) (0%–100%). $SOC_{Departure}$ is the desired battery percentage for the following day. SOC_{Min} is the battery percentage up to which the EV will be charged in an uncontrolled manner at full power right after it is connected to the charger (Fridgen et al., 2016).

Participants in the experimental groups then answered an attention question on the content of the message and questions on how they perceived the message. To measure the perception of the intervention message, we used the satisfaction sub-scale from Van

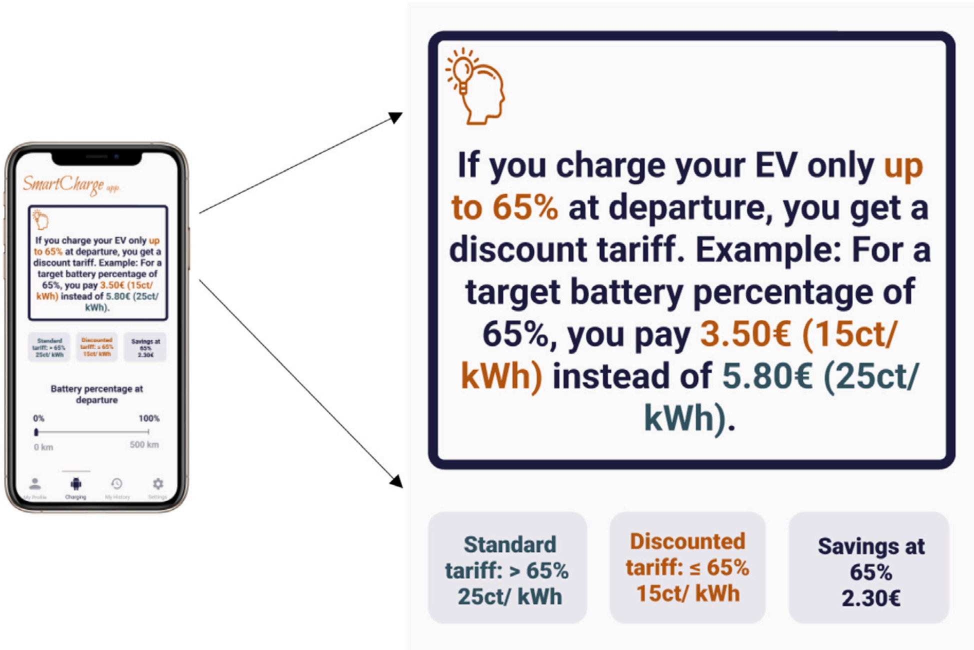

Fig. 3. Example of message for the high monetary incentives group.

Fig. 4. Example mock-up and information sheet for the high monetary incentives group.

Der Laan et al. (1997). On a scale from 1 to 7, participants evaluated the message based on four pairs of adjectives (e.g., "1 unpleasant – 7 pleasant"). The scale had satisfactory internal consistencies in the different experimental groups of our survey, with Cronbach's alphas above the threshold of $\alpha = .70$ (Hair et al., 2021): Perception of high incentives ($\alpha = .75$), low incentives ($\alpha = .83$), framing

Table 1
Distribution of participants in experimental and control groups.

Groups	Frequency	Percentage
High monetary incentives	24	8.30
Low monetary incentives	34	11.76
Framing	32	11.07
Feedback	30	10.38
Badges	31	10.73
Credit coins	37	12.80
Battery tips	28	9.69
Smart charging as default	39	13.49
Control group	34	11.76

(α = .90), feedback (α = .95), badge (α = .92), credit points (α = .96), battery tips (α = .87), and smart charging as a default (α = .92).

After the experiment, participants answered questions about their mobility behavior and vehicle and EV usage. These questions were about the most used transportation means, EV usage, number of vehicles, number of household members with a driving license, and daily kilometers driven. Participants additionally answered questions about their vehicle's range and battery capacity, the average distance they drive it, the time it spends at home on weekdays and weekends, and their usual charging location. They then answered questions about their motivations to drive an EV. These questions were presented on a 7-point Likert scale (ranging from "strongly disagree" to "strongly agree"). To measure technological motivation, we adapted four items from Kacperski and Kutzner (2020) (in our survey Cronbach's α = .77, example item: "I drive an electric vehicle because it is comfortable to drive due to its silent motor".). For environmental EV usage motivation, we adapted three items from Kacperski and Kutzner (2020) (in our survey α = .88, example item "…I can be part of the sustainability movement".). To measure financial EV usage motivation, we adapted three items by He et al. (2018) (in our survey α = .66, example item "…it helps me spend less on fuel".) and for social EV usage motivation four items from Wang et al. (2021) (in our survey α = .89, example item: "…I am judged favorably by others".). All participants then answered questions about their environmental concerns and risk aversion level. To measure environmental concern, we used the brief ecological paradigm scale (López-Bonilla and López-Bonilla, 2016), a short version of the new environmental paradigm (in our survey α = .80, example item: "Humans are severely abusing the environment".). To measure risk aversion, we used the general risk aversion scale by Mandrik and Bao (2005) (in our survey α = .83, example item: "I feel comfortable improvising in new situations"). Finally, participants answered demographic questions about their gender, age, nationality, highest level of education, occupation, industry, monthly income, and country of residence. In the end, participants were allowed to read about the background and research goals of the study. They could also provide feedback on the study and enter a raffle to win a voucher.

3.3. Sample

To determine the sample size for a multiple logistic regression a priori, we followed the method by Hsieh et al. (1998), which delivers accurate results for sample sizes of n > 200 (HHU, 2021). Using Python, we simulated all possible combinations of the following ranges: OR (2.0, 2.5 and 3.0) as similar studies used OR = 2.5 (Kramer and Petzoldt, 2022), Pr(Y = 1/X = 1) H0 (0.15, 0.2, 0.25), the proportion of the sample size experimental/control group (0.4, 0.45, 0.5, 0.55, 0.60), R^2 between the variables (0.01–0.2 in 0.01 steps). We aim for a sample size that covers at least 75% of the simulated cases. The simulations indicated we need a minimum sample of n = 282.

A total of n = 306 EV users completed the survey. We considered only participants who indicated that an EV was associated with their household. We also eliminated n = 17 participants for the following reasons: Participants answered both attention questions incorrectly (n = 12), were multivariate outliers according to the Mahalanobis statistic measure (n = 2) or said they did not understand the messages (n = 3). The final sample size was n = 289. The number of participants was similar across the different groups (Table 1).

Most of the participants are from Germany, Luxembourg, or France and reside in these countries (see Table C.5). The sample is predominantly male and highly educated, with an average age of 43.03. Our sample can be considered representative for EV users, as research from both Europe and the United States has found that EV users are typically male, middle-aged, well-educated, and have high incomes (Sovacool et al., 2018b; Shin et al., 2019; Plötz et al., 2014). The International Energy Agency also reports that EV users generally have high socio-economic status (IEA, 2022).

3.4. Analysis

We calculated a multiple logistic regression to answer research question 1 (*Which incentives, nudges, and tips are effective for individuals' flexibility provision in electric vehicle charging?*) and H1 and H3–H8. The aim was to ascertain the effects of seeing an incentive or nudge message on the likelihood of choosing a $SOC_{Departure}$ up to 65% (offering high flexibility) versus over 65% (offering low flexibility). To do this, we transformed the dependent variable $SOC_{Departure}$ into a categorical variable, with 1 representing a $SOC_{Departure}$ up to 65% and 0 representing a $SOC_{Departure}$ of 66%–100%. We created a dummy variable for each of the eight experimental groups, with the control group receiving a value of 0 for each dummy variable. We then compare the effect of each

Table 2
Results of multiple logistic regression testing the effect of incentives, nudges and tips on flexibility provision (Model 1) and with risk aversion (Model 2).

Dummy variable	Model 1 (H1, H3-8)				Model 2 (H9)			
	z	*p*	*OR*	*95% CI*	*z*	*p*	*OR*	*95% CI*
High monetary vs. Control	2.89	.004	5.42	[1.72; 17.02]	2.91	.004	5.57	[1.75; 17.72]
Low monetary vs. Control	2.44	.015	3.66	[1.29; 10.34]	2.60	.009	4.06	[1.41; 11.64]
Framing vs. Control	1.72	.085	2.53	[0.88; 7.27]	1.86	.064	2.75	[0.94; 8.03]
Feedback vs. Control	0.87	.386	1.63	[0.54; 4.87]	0.95	.343	1.71	[0.57; 5.18]
Badge vs. Control	−0.74	.458	0.63	[0.18; 2.17]	−0.72	.473	0.63	[0.18; 2.21]
Credit Coins vs. Control	2.37	.018	3.43	[1.24; 9.53]	2.49	.013	3.74	[1.33; 10.55]
Battery tips vs. Control	−0.20	.844	0.89	[0.27; 2.95]	−0.12	.901	0.93	[0.28; 3.11]
Default vs. Control	0.69	.490	1.44	[0.51; 4.10]	0.84	.399	1.58	[0.55; 4.53]
Constant	−2.92	.004	0.31		−0.10	.920	0.76	
Risk aversion					−2.30	.021	0.94	[0.60; 0.96]
Nagelkerke (Pseudo R^2)			.122				.146	

experimental group with the control group using logistic regression. We used the following multiple logistic regression formula as illustrated in Eq. (1) below[3]:

$$L = \ ln(p/1-p) = b_0 + \sum_{i=1}^{8} b_i x_i + e \tag{1}$$

In this context, L represents the log odds of p, which is the probability of choosing a $\text{SOC}_{Departure}$ up to 65%. b_0 indicates the (predicted) $\text{SOC}_{Departure}$ value of the control group. In contrast, b_i indicates the difference between the respective experimental and control groups concerning the selected $\text{SOC}_{Departure}$.

To test H9, we added risk aversion to the same logistic regression model to see if it increases the exploratory power. To test H2, we calculated a Chi-square test to compare the high and low monetary incentive groups concerning the chosen $\text{SOC}_{Departure}$.

To answer our second research question (*Is a positive perception of incentives, nudges, and tips associated with increased flexibility provision?*), we calculated Spearman's correlations (r_{Sp}) between the categorical variable $\text{SOC}_{Departure}$ and the perception of the respective intervention messages. We also conducted Independent-Sample Kruskal–Wallis Tests to determine whether the perception of the intervention message differed for the different types of intervention messages. This non-parametric test was used because the perception of the intervention message was not normally distributed for all eight groups.

As an exploratory analysis, we also calculated Pearson correlations (r) between SOC_{Min} and further variables as SOC_{Min} is part of the flexibility concept but less studied. Additionally, we calculated correlations between income, risk aversion, and further variables. If income was correlated with the main variables ($\text{SOC}_{Departure}$, risk aversion), we controlled for its influence in our analysis.

4. Results

We calculated a logistic regression to test H1, H3-H8 if seeing incentive, nudge, or tip messages leads to higher odds of choosing a $\text{SOC}_{Departure}$ up to 65% (offering high flexibility) versus over 65% (offering low flexibility). This is the Model 1, which was significant, X^2 (8, n = 289) = 27.13, p <.001 and explained 12.20% (Nagelkerke R^2) of the variance in the choice of $\text{SOC}_{Departure}$. Seeing the high monetary (*OR* = 5.42, *95% CI* [1.72, 17.02]), low monetary (*OR* = 3.66, *95% CI* [1.29, 10.34]), or credit point message (*OR* = 3.43, *95% CI* [1.24, 9.53]) increased the odds of offering high flexibility in comparison to the control group. Seeing the framing, feedback, badge, battery tips or default message did not increase likelihood to choose a high flexibility in comparison to the control group (Model 1, Table 2).

To test H9 (*The lower the personal risk aversion, the higher the flexibility provided*), we added risk aversion to the model (Model 2, Table 2). Adding the continuous predictor risk aversion to our logistic regression requires checking if the preconditions of logistic regression are observed: 1. No extreme outliers, 2. linearity of the logit, and 3. no multicollinearity. First, Cook's influence statistics were below 1.0, indicating no extreme outliers. Second, the Box-Tidwell test was non-significant, indicating the logit's linearity. Third, Variance Inflation Factor values are around 1, and tolerance values above 0.2, indicating no multicollinearity between the independent variables. By adding risk aversion, Model 2 was statistically significant, X^2 (9, n = 289) = 32.62, p <.001 and explained 14.60% (Nagelkerke R^2) of the variance in the choice of $\text{SOC}_{Departure}$. The change in comparison to Model 1 was statistically significant, X^2(1, n = 286) = 5.49, p = .019. High monetary incentives (*OR* = 5.57, *95% CI* [1.75, 17.72]), low monetary incentives (*OR* = 4.06, *95% CI* [1.41, 11.64]), credit points (*OR* = 3.74, *95% CI* [1.33, 10.55]), and lower risk aversion (*OR* = 0.76, *95% CI* [0.60, .96]) increased the odds of choosing high flexibility in comparison to the control group, whereas the framing, feedback, badge, battery tips, or default message did not.

[3] x_1: 1 if high monetary group, 0 otherwise, x_2: 1 if low monetary group, 0 otherwise, x_3: 1 if framing group, 0 otherwise, x_4: 1 if feedback group, 0 otherwise, x_5: 1 if badge group, 0 otherwise, x_6: 1 if credit points group, 0 otherwise, x_7: 1 if tips group, 0 otherwise, x_8: 1 if default group, 0 otherwise, e: random error.

Table 3
Overview on hypotheses related to RQ1: Which incentives, nudges, and tips lead to a higher flexibility provision in electric vehicle charging?

Hypotheses	Confirmed or rejected
H1: Monetary incentives lead to a higher flexibility provision.	Confirmed
H2: High monetary incentives lead to a higher flexibility provision than low monetary incentives.	Rejected
H3: Credit points lead to a higher flexibility provision.	Confirmed
H4: Environmental framing leads to a higher flexibility provision.	Rejected
H5: Environmental feedback leads to a higher flexibility provision.	Rejected
H6: Environmental badges lead to a higher flexibility provision.	Rejected
H7: The default setting leads to a higher flexibility provision.	Rejected
H8: Battery-related tips lead to a higher flexibility provision.	Rejected
H9: The lower the personal risk aversion, the higher the flexibility provision.	Confirmed

Table 4
Spearman correlations between perception of incentive, nudge or tips message and selected $SOC_{Departure}$.

Perception of message	$SOC_{Departure}$	
	Spearman's r	p-value
High monetary incentives	−.03	.908
Low monetary incentives	.21	.237
Environmental framing	.22	.236
Environmental feedback	.24	.198
Environmental badges	.23	.221
Credit coins	−.02	.917
Battery tips	.26	.182
Smart charging as default	−.03	.857

To test H2 (*High monetary incentives lead to a higher flexibility provision than low monetary incentives.*), the results of the Chi-squared association test indicate that subjects who saw the high monetary incentive message were not more likely to choose a high $SOC_{Departure}$ than subjects who saw the low monetary incentive message, $X^2(1, n = 67) = 0.15$, $p = .703$. Table 3 presents an overview on whether the hypotheses 1–9 were confirmed or rejected.

Concerning RQ2 (*Is a positive perception of incentives, nudges and tips associated with increased flexibility provision?*), the Spearman's correlations between $SOC_{Departure}$ and the perception of the respective stimulus messages were not significant for any of the stimulus messages (Table 4). Thus, the perception of the stimulus messages was not related to offering flexibility.

As an additional analysis, we conducted a Kruskal–Wallis test to identify if the perception of the message differed between participants of the different experimental groups. The test demonstrated that the perception of the stimulus messages did not differ based on the content EV users saw, H(7) = 7.51, $p = .378$. Thus, participants evaluated the eight messages equally well.

4.1. Exploratory analysis

In our exploratory analysis, we calculated correlations between 1. SOC_{Min}, 2. risk aversion, and 3. income with further variables. The higher the selected SOC_{Min} value, the more participants tended to be risk averse ($r = .13$, $p = .029$). Risk-averse participants tended to be generally older ($r = -.17$, $p = .005$).

Participants indicating a higher SOC_{Min} also tended to be less familiar with smart charging at the beginning of the survey, i.e., had a lower smart charging literacy, ($r = -.14$, $p = .014$) and were less willing to give their energy provider control on their charging process ($r = -.28$, $p < .001$). The selected $SOC_{Departure}$, however, was not related to familiarity with smart charging ($r_{Sp} = .05$, $p = .435$) and the willingness to give the energy supplier control on the charging process ($r_{Sp} = .09$, $p = .133$).

Those selecting higher SOC_{Min} values also tended to 1. provide a $SOC_{Departure}$ of above 65% ($r = -.25$, $p < .001$), to 2. have less environmental motivations to drive an EV ($r = -.15$, $p = .012$), and to 3. be less educated ($r = -.19$, $p = .001$).

Income was not correlated with $SOC_{Departure}$ ($r_{Sp} = -.05$, $p = .408$), SOC_{Min} ($r = -.03$, $p = .628$), or with risk aversion ($r = .01$, $p = .821$).

5. Discussion

Concerning the first research question (*RQ1: Which incentives, nudges, and tips are effective for individuals' flexibility provision in electric vehicle charging?*), H1 and H3 were confirmed. All monetary incentives, namely high incentives, low incentives, and credit points, led to a higher flexibility provision (choice of a $SOC_{Departure}$ of 65% vs. a $SOC_{Departure}$ of 66%–100%). H4-H8 were rejected: The nudges and battery-related tips did not lead to a higher flexibility provision. Nevertheless, they did not have a negative effect either. These results are in line with those of Bailey and Axsen (2015): For EV users, monetary incentives (reduced electricity bill) were more effective than environmental nudges. It appears that monetary incentives are generally more attractive to (mainstream) EV users than environmental or social nudges (Delmonte et al., 2020). Our study also demonstrated that this applies to various monetary incentives (low, high, and credit points).

Another question relates to whether a higher monetary incentive leads to better flexibility provision. In our study, H2 was rejected: There was no significant difference between groups given high and low monetary incentives regarding flexibility provision, i.e. low incentives were as effective as high incentives. This result is also supported by other academic studies (Kacperski and Kutzner, 2020; Kacperski et al., 2022). EV users seem to expect financial compensation for their flexibility, although this magnitude does not play a major role in whether or not they choose to provide this flexibility (Lagomarsino et al., 2022).

About the second research question (*RQ2: Is a positive perception of incentives, nudges, and tips associated with increased flexibility provision?*), perception of the incentives, nudges, and tips was not correlated with flexibility provision. This finding applied to all individual monetary incentives, nudges, and tips. The results align with Tijs et al. (2017), who also did not find a link between perception and effectiveness of nudges in a similar setting (water-saving while showering). This result implies that perceptions regarding these interventions might not play a crucial role for developing and designing behavioral interventions for smart charging as they might not be related to their actual effect.

The results confirmed H9, i.e. low risk aversion was related to high flexibility provision and explained additional variance. This finding aligns with the study by Huber et al. (2019a): People who consider themselves more willing to take risks are more likely to offer high flexibility.

Our exploratory analysis found that people who report lower $SOC_{Departure}$ values also report lower SOC_{Min} values and that SOC_{Min} correlates with risk aversion. These results suggest that factors associated with $SOC_{Departure}$, such as risk aversion, are also related to SOC_{Min}. Little research exists on SOC_{Min} in the behavioral context, although it is said that SOC_{Min} values increase the acceptance of smart charging (Will and Schuller, 2016; Ensslen et al., 2018; Geske and Schumann, 2018).

Another result of the exploratory correlation analysis was that participants with higher education levels and those more familiar with smart charging tended to choose a lower SOC_{Min}. Familiarity with smart charging is a form of smart charging literacy. Studies demonstrate that energy literacy is related to a higher flexibility provision (Reis et al., 2021). Our study further confirms that for smart charging. The correlation between SOC_{Min} and familiarity with smart charging indicates that people with higher smart charging literacy tend to provide higher flexibility. Our study is one of the first to demonstrate a relationship between smart charging literacy and the flexibility component SOC_{Min}. Another study by Baumgartner et al. (2022) examined the relationship between user experience and desired SOC_{Min} values. Surprisingly, the authors discovered no relationship between user experience and SOC_{Min} values. However, it is essential to note that in their study, user experience referred to the level of familiarity with EVs rather than knowledge specifically about smart charging.

5.1. Theoretical implications and directions for future research

Our results indicate that monetary incentives are most important to motivate EV users to provide charging flexibility.[4] Further research should focus on using monetary incentives for smart charging rather than on nudges and/or tips. In particular, research could be conducted to determine the minimum monetary incentive energy providers should offer to get charging flexibility. It would be further interesting to investigate how combining monetary incentives and environmental nudges impacts flexibility provision as explored by Kacperski et al. (2022) and to determine whether this combined approach is more effective than monetary incentives alone.

Our results also highlight the importance of appropriate experimental design for answering research questions. Although our results show the *effectiveness* of some behavioral interventions, we find no correlation between the *perception* of incentives, nudges, and tips and their effectiveness in improving flexibility provision. When the goal is to evaluate the effectiveness of such behavioral interventions, experimental approaches are highly valuable. Conducting a pilot study can also be beneficial. On the other hand, if the goal is to understand how incentives, nudges, and tips are perceived, focus groups or surveys without an experimental design might be a good choice. Measuring perception can be important in contexts where it is crucial for EV users to be engaged and to like the smart charging app.

Our study found a correlation between familiarity with smart charging and SOC_{Min}. Further research should be conducted to investigate this relationship in more depth. Instead of measuring familiarity with smart charging with a single item, it would be helpful to measure smart charging and energy literacy in more detail and investigate their relationship with flexibility provision. Smart charging literacy programs could also be explored to understand their impact on flexibility provision. It would be essential to determine the content and implementation of such programs, for example, by explaining to EV users how far they can travel with different $SOC_{Departure}$ values and how this relates to their specific profile. It is worth noting that participants who only drive short distances tend to overestimate the importance of SOC (Lagomarsino et al., 2022). Also Franke et al. (2017) did not find a significant correlation between daily travel distances and lower range satisfaction.

Regarding the link of risk aversion with flexibility provision, risk-averse people may particularly benefit from improved education and information. Additionally, it may be helpful to consider how this information is presented to users. As Lagomarsino et al. (2022) note, laypeople may need help understanding energy information presented in units like kWh or battery percentage (e.g., for how many kilometers which SOC would be sufficient). Therefore, future research should examine effective methods of transmitting information to EV users and the potential for educational programs to improve understanding. Studies can also be conducted on how information can be best transmitted to EV users about smart charging and related educational programs.

[4] Note however power limitations, discussed further below in the Limitations subsection.

5.2. Practical implications for energy providers

The results of the survey have several practical implications. For energy providers, our results indicate that offering monetary incentives can encourage users to provide higher levels of flexibility. The amount of the incentives does not appear to be as substantial as the fact that they are offered.

In this study, we only tested two realistically payable incentives by energy providers, so it cannot be ruled out that much higher incentives may lead to even higher levels of flexibility. The energy providers could design an incentive scheme for flexibility provision. Within this incentive scheme, energy providers can motivate EV users based on the monetary benefits the providers achieve while trading this flexibility in electricity markets.

Also, energy providers should provide their users with smart charging literacy programs, including a clear and easy-to-understand introduction to smart charging, perhaps through a smart charging application. These programs could include information about the risks and benefits of using smart charging and explanations of $SOC_{Departure}$ and SOC_{Min} data.

5.3. Limitations

There are several limitations to our study design. First, a simplification of the concept of flexibility was necessary to facilitate our experimental design. Flexibility is a continuous variable that includes factors other than $SOC_{Departure}$, such as SOC_{Min} and parking duration. Therefore, our study's categorical representation of flexibility gives an approximation of the reality of flexibility with EV smart charging.

Gamification elements must be analyzed engagingly within a dynamic setting; whereas our study allowed for gamification elements in a static and non-interactive setting. Since gamification elements are all about engagement, the best way to understand how they work is through direct interaction with an app. In our study, we only used a smart charging app interface, but participants did not have the opportunity to interact with the app and click through it. To more accurately assess the effectiveness of gamification elements, they should be tested in a more interactive experimental design.

Our sample size (n = 289) is relatively small. According to a posthoc power analysis in G Power (Faul et al., 2007) for the multiple logistic regression, only for the effect of the high monetary incentives group, a sufficient power of above 0.80 was reached. This value fell short of low monetary incentives and credit points (0.65, 0.64). The reasons for this are *a priori* unexpectedly high correlations between the independent variables. However, the results of the high monetary incentives are substantive. Since the slightly underpowered variables, low monetary incentives, and credit points are related in content with high monetary incentives; it can be assumed that monetary incentives generally work.

Even though our sample can be considered representative of current EV users, it might suffer from non-response errors. For this reason, individuals who voluntarily participated in the study might differ from those who decided not to do so (Sovacool et al., 2018a). EV users interested in our topic may have reacted differently to behavioral interventions than those who did not show this interest.

Furthermore, our study includes a sample of EV users from various countries, primarily Luxembourg and Germany, and other German- and French-speaking European countries. As a result, our sample predominantly represents EV users in Luxembourg and its border region. Samples per country are too small to perform a country comparison analysis with sufficient power.

The external validity of our study is also limited by the experimental design. The scenario-based nature of the experiment impacts the results (Lagomarsino et al., 2022). A field study (e.g., a pilot study) should be conducted to increase external validity.

Moreover, our study is a snapshot of a single decision, while users have to make multiple smart charging decisions over time. For smart charging to reach its full potential, it must be used regularly. Therefore, it is important to investigate how frequently EV users choose to use smart charging and what factors influence this decision (Lagomarsino et al., 2022).

6. Conclusion

In an experimental survey, we assessed whether various behavioral interventions, i.e. monetary incentives (low, high, credit points), framing, feedback, badge, smart charging as a default, and battery-related tips, lead to a high flexibility provision for smart home charging. We also explored whether the perceived effectiveness of these interventions is linked to their overall effectiveness.

Out of all the behavioral interventions, only the monetary incentives (low incentives, high incentives, and credit points) affected increased flexibility provision. At the same time, nudges and tips had neither a positive nor negative effect. Low and high monetary incentives were equally effective. The results indicate that energy providers should incentivize EV users for their flexibility, while the incentive amount does not appear to play a decisive role.

A positive perception of the behavioral intervention was not correlated with their effectiveness for any of the interventions. This result has theoretical and methodological implications for future research. If the effect of behavioral interventions is to be determined, experiments should be employed rather than relying on perceptions of hypothetical behavioral interventions.

In our exploratory correlation analysis, we found that participants with higher smart charging literacy and higher education level indicate lower SOC_{Min} values, i.e. higher flexibility provision. This result indicates that smart charging literacy programs could help to achieve higher charging flexibility.

Fig. B.5. Intervention messages and control group messages. 1. High monetary, 2. Low monetary, 3. Framing, 4. Feedback, 5. Badge, 6. Credit points, 7. Tips, 8. Default-setting, 9. Control group.

CRediT authorship contribution statement

Hanna Marxen: Investigation, Methodology, Conceptualization, Data curation, Formal analysis, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Mohammad Ansarin:** Writing – review & editing, Supervision. **Raviteja Chemudupaty:** Conceptualization, Writing – review & editing. **Gilbert Fridgen:** Writing – review & editing, Supervision, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Focus groups

Our focus groups followed a predefined agenda of 120 min. The focus was to discuss the incentives, nudges and tips. After the discussion, we asked the participants to rank those according to their perceived attractiveness using a short survey. Five participants

Table C.5
Description of the sample - EV users.

	Frequency	Percentage
Gender		
Male	235	81.31
Female	48	16.61
Transgender female	1	0.35
Gender variant/Non-conforming	2	0.69
Prefer not to disclose	1	0.69
Others	2	0.35
Highest degree of education		
Some high school	6	2.08
Highschool/GED	24	8.30
Some college	27	9.34
Associates' degree	53	18.34
Bachelor's degree	64	22.15
Master's degree	103	35.64
Doctoral degree'	12	4.15
Occupation		
Student	16	5.54
Working (full-time)	220	76.12
Working (part-time)	25	8.65
Housewife/househusband	18	6.23
Pensioner	7	2.42
Unemployed	3	1.04
Income (net)		
less than 1000 €	10	3.46
1000–2999 €	76	26.30
3000–4999 €	100	34.60
5000–6999 €	42	14.53
7000–8999 €	16	5.54
≥9000 €	12	4.15
No indication	33	11.42
Nationality		
German	165	57.09
Luxembourgish	46	15.92
French	17	5.88
US-American	12	4.15
Swiss	7	2.42
Austrian	6	2.08
Others	36	11.07
Residence country		
Luxembourg	158	54.67
Germany	69	23.88
France	17	5.88
US	13	4.50
Austria	9	3.11
Switzerland	5	1.73
Belgium	3	1.04
Others	18	6.23

indicated monetary incentives as most attractive, five participants smart charging as default, one participant framing, no one feedback and gamification, and one participant did not do the ranking. Looking at the next ranks, there was no clear ranking of the incentives, nudges and tips participants found most attractive. This was different for the ranking of the gamification elements. Here, six participants ranked tips first, five credit points, one energy communities, and no-one badges. These results were consistent with the next ranks. With regard to gamification, participants also mentioned the point that younger people might like it more. Furthermore, we investigate whether motivations for purchasing electric vehicles and incentives preferences are related. For this, we transcribed the focus group recordings and analyzed them using qualitative content analysis, a method that combines the deductive and inductive coding approach (Cho and Lee, 2014). We first deductively defined categories (e.g., different incentives, nudges, motivations) and coded them in the transcripts. Second, we inductively coded additional constructs, such as further motivations. Then we looked at the overlaps of different codes. In our analysis, the environmental and economic motivations to purchase an EV seemed to be related to the preference for incentives and nudges. Participants with environmental EV purchase motivation were mainly interested in nudges indicating their contribution to environmental protection (e.g., feedback, framing). Participants with economic motivation owned their EV mainly because their companies covered most of their purchase and charging costs. They had a higher preference for monetary incentives.

Appendix B. Survey material

See Fig. B.5.

Appendix C. Description of the sample

See Table C.5.

Appendix D. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.trd.2023.103897.

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Survey related to the paper “Empirical evaluation of behavioral interventions to enhance flexibility provision in smart charging”

Dear participant,

thank you for your interest in this study.

This study is conducted at the department FINATRAX of SnT, University of Luxembourg. By your participation, you support our research project on behaviors in electric vehicle charging. It takes a maximum of 10-15 minutes to complete the survey.

There are no right or wrong answers, we are only interested in your true and honest perspective. To ensure that the results of our study are meaningful, we would ask you to answer the survey completely and seriously. Participation in the survey is voluntary and open to anybody aged 18 and over. You can terminate the survey any time without stating reasons. All data will be kept strictly confidential.

At the end of the study you can take part in a lottery for five Amazon vouchers (1* 100€, 1* 40€, 3* 20€).

Thank you for your participation!

Part 1

How familiar are you with smart charging of electric vehicles?

Please rate yourself on a scale from 0 (not familiar at all) to 7 (extremely familiar). Please select 0 if you have never heard about it.

not familiar at all (1)	(2)	(3)	(4)	(5)	(6)	extremely familiar (7)

In order to be able to answer the questions in the survey, it is important to understand the explanation of smart charging. Please read it carefully:

Smart charging is a technology that allows the **energy supplier** to manage the charging of electric vehicles (EVs): The energy supplier considers both the **requirements of the power system** and the **EV user needs**.

Requirements of the power system: If most EVs are charged at the same time (e.g., after rush hour), this can overload the electricity grid. Imagine a residential neighbourhood with several EVs plugged in overnight at their home charging stations. By using smart charging, the load can be distributed across the time period EVs are plugged in. Some of those EVs can for example be charged between 22:00 and 1:00, some between 1:00 and 4:00 and some between 4:00 and 7:00.

EV user needs: Before charging, EV users enter their needs in a smart charging application:

- Departure time: The user says when to leave the next morning.
- Battery percentage: The user specifies how much battery percentage he/ she wants at departure time.

This way, the **energy supplier** knows which preferences to consider when managing the charging.

Based on the explanation of smart charging you just read, please select the appropriate answer.

Smart charging ...

- takes into account the requirements of the EV user and the power system.
- gives the energy provider complete control over the charging of EVs without considering EV user needs.
- exclusively maximises the EV users' profit.

Please indicate whether you would allow your energy supplier to control the charging process of your EV. Your energy supplier would ensure that your EV is charged to the desired battery percentage at departure.

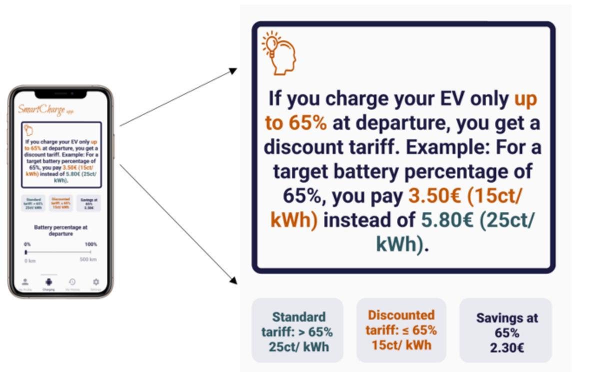
	Strongly disagree	Disagree	Some-what disagree	Neither agree nor disagree	Some-what agree	Agree	Strongly agree
I would have the charging process of my EV controlled by my energy supplier.							

Please imagine this scenario to answer the next questions:

You come home at 18:00 with your electric vehicle (EV). Your battery percentage is 15%. The next day, you have to leave at 8:00 and drive 200km (round trip).

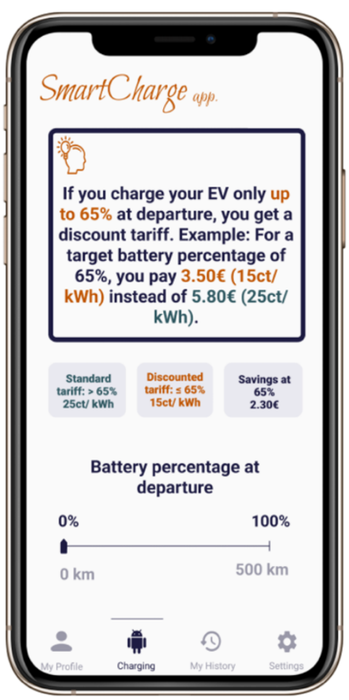
You have told your smart charging app that you have to drive 200km the next day.

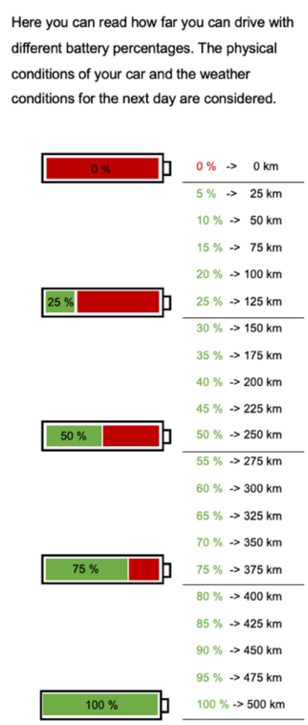
Your smart charging app displays the following message:[1]



Your smart charging app asks you what battery percentage you want the next morning.

Reminder scenario: You come home at 18:00 with your EV. Your battery percentage is 15%. The next day, you have to leave at 8:00 and drive 200km (round trip).





Which battery percentage would you like to have at departure the next morning?

Please choose a battery percentage from 0-100%. (Participants can select a value from 0-100%)

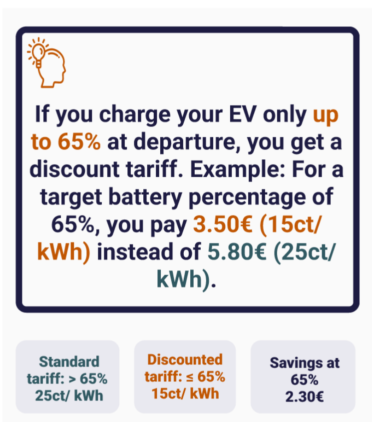
[1] The intervention message is just illustrated for the high incentives group, but the other messages can be found in the paper.

Which battery percentage should your EV always have as a mininum in case of unforeseen emergencies? (This implies that your EV would be always charged to that level at maximum charging power when plugged in.) This question does not refer to the previously described scenario.

Please choose an absolute minimum battery percentage from 0-100%. (Participants can select a value from 0-100%)

What information did you perceive on the mobile phone screen?

- Information on ...
- how I can save money.
- how I can get money in form of digital vouchers.
- that I saved CO2.
- how I can obtain more energy from renewables when charging.
- that I am among the 20% top smart chargers and received an environmental badge.
- the default battery percentage.
- that my EV is connected to the charging station.
- which battery percentage is best for the battery of my EV.



[2]

How did you perceive the following message (see screenshot below)? Your answers should reflect you personally and should not reflect any ideal case from your point of view. Please note that there are no right and wrong answers. Please choose a value from 1-7 in each row.

My judgement of this message is ...

Unpleasant (1)	(2)	(3)	(4)	(5)	(6)	Pleasant (7)
Annoying (1)	(2)	(3)	(4)	(5)	(6)	Nice (7)
Irritating (1)	(2)	(3)	(4)	(5)	(6)	Likeable (7)
Undesirable (1)	(2)	(3)	(4)	(5)	(6)	Desirable (7)

[2] The intervention message is just illustrated for the high incentives group, but the other messages can be found in the paper.

Part 2

The following questions are about your mobility behavior and vehicle usage.

Which of those transportation means cover currently the most of your mobility needs?

Please select 1-3 answers that apply to you.

- Electric vehicle
- Plug-in hybrid
- Combustion engine vehicle
- Public transport
- Bicycle
- Other:

How often do you drive an electric vehicle*?

Please select the answer that applies to you.

*Electric vehicles (EVs) are vehicles that are electrically powered (only fully battery-powered vehicles are considered in this study). They use electric motors for propulsion, which are powered by a battery.

- Never
- Once or twice a year
- Once or twice a month
- Once or twice a week
- Many times a week
- Every day
- Many times a day

How many vehicles does your household own?

- 0
- 1
- 2
- 3
- 4
- 5
- 6
- 7
- 8
- 9
- 10

How many of all your vehicles are electric vehicles?

- 0
- 1
- 2
- 3
- 4
- 5
- 6

How many people in your household have a driving licence?

- 0
- 1
- 2
- 3
- 4
- 5
- 6
- 7
- 8
- 9
- 10

Please indicate how many kilometres on average you daily drive your vehicle. (in km)

Part 3

The following questions are about your electric vehicle usage.

The electric vehicle I am using is ...

- a bought EV
- a leased EV
- a company EV
- Other:

How many kilometres can your electric vehicle roughly drive in electric mode? (in km)

What is the battery capacity of your electric vehicle in kWh? (in kWh)

Please indicate how many kilometres on average you daily drive your electric vehicle. (in km)

For how long is your electric vehicle standing at home on average on a weekday? (in hours)

(participants can select a value between 0-24h)

For how long is your electric vehicle standing at home on average on a weekend day? (in hours)

(participants can select a value between 0-24h)

Where do you mostly charge your electric vehicle?

- At home
- At work
- At a public charging station
- At commercial places
- Other:

Part 4

In the following, we ask you for your reasons to drive an electric vehicle. Your answers should reflect you personally and should not reflect any ideal case from your point of view. Please note that there are no right and wrong answers.

For each statement, please indicate how much you disagree or agree.

I drive an electric vehicle, because ...

	Strongly disagree	Disagree	Some-what disagree	Neither agree nor disagree	Some-what agree	Agree	Strongly agree
it is comfortable to drive due to its silent motor.							
it is easy to drive (e.g. no changing of the gears).							
it is fun to drive due to its quick acceleration.							
I like to try new technologies.							
I can be part of the sustainability movement.							
it is healthier due to lack of fumes and pollution.							
I can be environmentally friendly. it helps me spend less on fuel.							
it gives me governmental incentives (e.g. no taxes, no tolls, free parking spaces).							
considering all costs, it is cheaper for me than driving conventional cars.							
it helps me show others my personal values. it makes me feel proud. it is part							

of my identity. I am judged favourably by others.							
it gives me governmental incentives (e.g. no taxes, no tolls, free parking spaces).							
considering all costs, it is cheaper for me than driving conventional cars.							
it helps me show others my personal values. it makes me feel proud. it is part of my identity. I am judged favourably by others.							
it makes me feel proud. it is part of my identity.							
I am judged favourably by others.							

Are there other important reasons why you drive an electric vehicle?

If yes, please feel free to share them.

In the following, you see statements about environmental concerns and on the role of risk in life. Your answers should reflect you personally and should not reflect any ideal case from your point of view. There are no right and wrong answers.

For each statement, please indicate how much you disagree or agree.

	Strongly disagree	Disagree	Some-what disagree	Neither agree nor disagree	Somewh at agree	Agree	Strongly agree
Humans are severely abusing the environment.							
Despite our special abilities humans are still subject to the laws of nature.							
The earth is like a spaceship with very limited room and resources.							
The balance of nature is very delicate and easily upset.							
If things continue on their present course, we will soon experience a major ecological catastrophe.							

	Strongly disagree	Disagree	Some-what disagree	Neither agree nor disagree	Some-what agree	Agree	Strongly agree
I do not feel comfortable about taking chances.							
I prefer situations that have foreseeable outcomes.							

Before I make a decision, I like to be absolutely sure how things will turn out.							
I avoid situations that have uncertain outcomes.							
I feel comfortable improvising in new situations.							
I feel nervous when I have to make decisions in uncertain situations.							

Part 5

In this last part of this survey, we would like to ask you to provide some personal information. Your information will be kept anonymous and strictly confidential. However, this Information is important for our research.

What is your gender?

- Male
- Female
- Transgender Female
- Transgender Male
- Gender Variant/ Non-Conforming
- Prefer not to disclose
- Other:

How old are you? (in years)

(Participants can select a value between 18-100)

What is your nationality?

Please name the country or countries that apply. If you have several nationalities, please select the last option (other) and specify.

(Participants can select their nationalit(y)/(ies) out of a list of all nationalities)

Which highest degree of education do you have?

- No school diploma
- Some high school
- Highschool/ GED
- Some college
- Associates' degree
- Bachelor's degree
- Master's degree
- Doctoral degree
- Other:

What is your current occupation?

- Working professional (full-time)
- Working professional (part-time)
- Student Pensioner
- Housewife/ househusband

- Unemployed
- Other:

To which of the following industries is/ was your work or study field primarily related?

- Business, consultancy or management
- Accountancy, banking or finance
- Charity and voluntary work
- Creative arts or design
- Energy and utilities
- Engineering or manufacturing
- Environment or agriculture
- Healthcare
- Hospitality or events
- Computing or IT
- Law
- Law enforcement and security
- Leisure, sport or tourism
- Marketing, advertising or PR
- Media or digital
- Property or construction
- Public services or administration
- Recruitment or HR
- Retail
- Sales
- Science or pharmaceuticals
- Social care
- Teacher training or education
- Transport or logistics
- Other

What is your monthly net income?

- less than 1000 €
- 1000-2999 €
- 3000-4999 €
- 5000-6999 €
- 7000-8999 €
- ≥ 9000 €

In which country do you live?

(Participants could choose between all possible countries)

Do you feel that this survey has changed your attitude towards the topic of electric vehicles charging?

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
This survey has changed my attitude towards the topic of electric vehicles charging.							

Thank you for your participation in this study.

In the following, you are invited to read information about the background and aim of this study. If you want to participate in the lottery, you can enter your email address in the next comment field. You can also indicate whether you would like to take part in two more of our surveys on smart charging in the future.

A.3.3 Research Paper 3 - Maximising Smart Charging of EVs: The Impact of Privacy and Money on Data Sharing

Maximizing Smart Charging of EVs: The Impact of Privacy and Money on Data Sharing

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Maximizing Smart Charging of EVs: The Impact of Privacy and Money on Data Sharing

Completed Research Paper

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Abstract

Smart charging has the potential to shift peak load to times of lower demand, which better exploits renewable generation and enhances grid resilience. For increased effectiveness, smart charging requires access to data that consumers might be hesitant to share. To explore which data consumers would share and which factors influence this decision, we adopt the Barth and de Jong's risk-benefit calculation framework to smart charging and conduct an online-survey (n = 479). We find that most respondents who would share charging details with a smart charging application, are ambivalent about location data and would never share calendar details. When presented with concrete monetary rewards, participants lose their initial reservations and would share all data for an amount dependent on the data's sensitivity. Thus, our study contributes to research on the privacy paradox by highlighting the importance of calculations between perceived risks and benefits for the decision to share data.

Keywords: Smart charging, consumer data, data sharing, privacy concerns, monetary incentives

Introduction

The use of electric vehicles (EVs) has increased rapidly in recent years. Governmental incentive schemes and sales bans on combustion vehicles will likely bolster this trend (Shepardson et al., 2021). What appears at first glance to be a big step towards more sustainability also puts tremendous pressure on the energy grid (IEA, 2022). Managing thousands of simultaneous EV charging events combined with regular peaks in electricity consumption and volatility of renewable energy sources (RES) could strain the grid and threaten energy security (Papaefthymiou et al., 2018). However, if EVs are charged in a controlled manner, i.e., through smart charging, they could instead become a flexible asset and support grid stability. Smart charging means that energy providers can optimally adjust the EV charging schedule in response to power system signals (e.g., RES generation) while meeting user requirements (IRENA, 2019).

To fully exploit the flexibility potential of EVs and implement smart charging, it is imperative for energy providers to understand the charging patterns of EVs. Understanding and accurately predicting these charging patterns helps energy providers tailor their services to individual EV users and support grid resilience. Charging patterns typically manifest for different types of data: Historical charging behavior and smartphone location data will help predict future charging behavior. Data linked to a person's schedule (e.g., via a calendar) can be even more accurate and helpful to optimize EV charging. Advances in pattern prediction may further automate smart charging so EV users become less involved.

Despite the advantages of accurate charging pattern prediction, consumers might be reluctant to share their data due to privacy concerns (Aloise-Young et al., 2021; Barth et al., 2019; Smith, 2008; Smith et al., 2011). They fear losing control of who has access to and can use their data (Cichy et al., 2021). At the same time, consumers readily share data in online contexts, such as social media or e-commerce, sometimes forgetting their initial concerns about data privacy (Chakraborty et al., 2013; Kokolakis, 2017). This ambiguous relationship between privacy and data sharing is often termed as the 'privacy paradox' and is a well-researched phenomenon (Buckman et al., 2019; Kim et al., 2019; Wu et al., 2020). Moreover, studies on social-hedonic and financial rewards have indicated that risk-taking behavior, such as excessive private data sharing, depends on the ratio of perceived benefits versus perceived risks (Turel, 2021).

Most privacy paradox studies focus on the active sharing of information with an online service provider. However, the findings of these studies may not be fully applicable in the context of smart charging. Cichy et al. (2021) argue in their research on data sharing for connected cars, which – much like location data sharing for smart charging – relies on IoT devices, that common data sharing reservations in online service contexts may not apply to IoT devices. "IoT devices (1) tend to be 'always on' and generate continuous data streams, (2) give users little or no power to control the data flows, (3) require unrestricted data access to fully function, and (4) invade users' virtual and physical space given the increasingly powerful actuators—components that transform electric impulses into physical actions—they are equipped with" (p. 1864). These four characteristics distinguish data sharing mechanisms of IoT and connected cars from data sharing mechanisms in online contexts, such as social media and e-commerce (Cichy et al., 2021). For example, sharing data on social media or online shopping does not typically require a user's current location or access to their calendars. Thus, smart charging comes with different privacy concerns than social media or online shopping.

Since most observations focus on the privacy paradox in e-commerce and social media interactions, there is a need to investigate factors influencing the readiness to share data in an IoT context, such as smart charging. Although studies have highlighted the importance of sensitive data for smart charging (Bhusal et al., 2021; Habbak et al., 2022), we just found one study that examined whether privacy concerns, perceived risks, and potential environmental benefits influence data sharing with EVs (Alotaibi et al., 2023). The study explored the general data sharing behavior for different EV services. Still, it does not elaborate on the readiness to share data for smart charging nor does it say anything about the sharing behavior of different data types with varying degrees of sensitivity. The study also did not investigate whether people would be more willing to share their personal information when presented with some form of monetary compensation (Hirschprung et al., 2016; Wagner et al., 2018). The relevance of monetary compensation to balance perceived risks is well known from financial economics (e.g., Caraco et al. 1980; Payne et al. 2017), so our study aims to explore its applicability to data sharing with a smart charging application. We therefore asked the following research questions:

RQ1: What data types do individuals intend to share for smart charging?

RQ2: Which factors impact individual's intention to share data with their smart charging application?

RQ3: How much does the monetary incentive need to be for individuals to share different data types for smart charging?

We conducted a large-scale survey to answer our research questions. For RQ1, we explored which data types participants would be most comfortable sharing to enable smart charging. For this evaluation, we included three different types of data (charging history, smartphone location, calendar data). Each of these data types came with varying degrees of sensitivity. To answer RQ2, we used the theoretical framework of Barth and de Jong (2017), commonly applied in privacy paradox research, which integrated key theories on mobile computing. Unlike the thematically related framework of Cichy et al. (2021), the Barth and de Jong (2017) framework specifically focuses on data sharing in mobile computing, making it more suitable for our context. We also explored attitudes towards data sharing and perceived risks and benefits of using the smart charging application, building on theories like foraging and risk sensitivity (Turel, 2021). We additionally assessed data sharing habits and their effect on participants' data sharing intentions. To evaluate the impact of monetary incentives, we introduced an experimental setting to our survey with one experimental and one control group. To answer RQ3, we explored the amount participants would request from the energy provider for sharing data with varying degrees of sensitivity. Answering these research questions contributes to both theory and practice.

Our contributions are three-fold. First, we apply the framework of Barth and de Jong to the context of smart charging. We add to this framework by investigating data sharing behavior for data with varying degrees of sensitivity. Specifically, we look into the differences between moderately and highly sensitive data and how far the framework would still apply. Second, we provide a deeper understanding on the trade-off between perceived risks and benefits by applying a risk-sensitivity and foraging theory perspective. Third, we demonstrate the effect of monetary rewards on data sharing behavior, even for highly sensitive data.

The rest of the paper is structured as follows. The theoretical background elaborates on smart charging and the role of data, Barth and de Jong's (2017) theoretical framework and a short introduction to risk-sensitivity and foraging theory. In the third section, we describe our method, data collection, and analysis. In the fourth section, we present the findings of our SEM and the calculation of monetary incentives. In the fifth section, we critically discuss our findings, elaborate on our theoretical and practical contributions, and outline related limitations. We conclude with a summary of our study.

Theoretical Background

Smart charging and the role of data

Adapting the charging behavior of EVs in response to the power system signals whilst considering the user requirements is known as smart charging (IRENA, 2019). Smart charging algorithms help shift the EV charging process to low-demand periods, drastically reducing the need for additional generation capacities (Pawlowski & Dinther, 2020; Schmidt & Busse, 2013). Moreover, EV charging can be synchronized to the availability of energy from RES to reduce grid imbalances due to generation peaks and simultaneously maximize RES consumption (Eldeeb et al., 2018; van der Meer et al., 2018). To best leverage the potential of smart charging solutions, it is vital to accurately predict the flexibility provided by each EV. Flexibility in the context of smart charging describes the amount of energy that the energy provider can shift until the EV battery has reached the desired percentage within the indicated parking time (Develder et al., 2016; Guthoff et al., 2021; Saxena et al., 2015). Practitioners typically use mobility data (e.g., arrival time, departure time, distance traveled), charging requests (e.g., energy required at the departure time), EV specifications (e.g., battery capacity and maximum charging power) to calculate the flexibility (Daina et al., 2017; Fridgen et al., 2014).

For smart charging solutions to function efficiently, they require bidirectional data exchange between EV users and the energy provider. This data exchange comes with two obstacles: First, regulations, such as the GDPR (General Data Protection Regulations in Europe), require a high degree of user privacy, complicating the collection of relevant data. Second, users are often cautious when sharing sensitive data (Strüker & Kerschbaum, 2012).

There are a variety of technical and sociotechnical measures to overcome these obstacles. Studies on technical measures aim to increase privacy by design without impeding access to (relevant) data (Teng et al., 2022). Examples of such privacy measures are differential privacy (Fernández et al., 2022), homomorphic encryption (Teng et al., 2022), and distributed learning techniques (McMahan et al., 2017). These measures can also be leveraged for smart charging to improve confidence in the data sharing process. They are, however, not subject to this paper.

Sociotechnical measures typically support the acceptance of data sharing. Although sociotechnical measures have already been established in other contexts, they have not been tested for the acceptance of data sharing in smart charging. Monetary incentives are a prominent sociotechnical measure influencing users' intention to share data in various contexts. Thus, we also investigated their effect in our study along with the type of data people would share with the smart charging application and the factors influencing this decision.

We ground our investigations in the rational risk-benefit calculation framework (Barth and Jong, 2017) and make links to IS theories on risk-sensitivity and the privacy paradox. Based on these theories, we derive our hypotheses and research model.

Rational risk-benefit calculation framework (Barth and de Jong, 2017)

Our study is grounded in the theoretical framework of Barth and de Jong (2017), which is related to the privacy paradox, which describes the contradictory behavior of individuals who express concerns about privacy but often share their data freely. Barth and de Jong (2017) aimed to uncover the factors behind this paradox. They summarize and explain theories of private information sharing with mobile apps. They differentiated between rational and biased decision-making theories in the absence or presence of risk factors and consolidated these ideas in a theoretical framework. Barth and de Jong's framework was referred to in different contexts as health technologies (Fox, 2020) and e-commerce (Kolotylo-Kulkarni et al., 2021). Unlike social media and mobile apps, the privacy paradox hasn't been explored in smart charging, so we applied their rational decision-making framework to this context.

According to the rational decision making framework (Barth & de Jong, 2017), individuals choose the option with the greatest benefits. Attitudes towards information disclosure affect context factors and ultimately influence the readiness to disclose certain information. These attitudes can be privacy concerns, general (institutional) trust, or personality traits. Context factors encompass situational factors or individual and environmental characteristics. Individuals weigh perceived risks against perceived benefits, which affects their disclosure intentions and actions. While Barth and de Jong (2017) tie together multiple literature streams to elaborate on risk-benefit calculations, the perspective introduced by risk sensitivity and foraging theory might suit the context of smart charging. These theories include factors such as esteem and self-actualization that may present interesting angles of explanations for our observations in the users' strive to optimize their gains (Turel, 2021).

Risk sensitivity theory and foraging theory in information systems

The assessment of perceived risks and benefits is also at the core of two theories adapted from behavioral biology. Foraging theory suggests that individuals aim to maximize their benefits while considering the dangers of the activities involved in receiving the benefits (Payne et al., 2017; Stephens & Charnov, 1982). They typically base their decision-making on assessing one particular problem, a 'currency' by which they decide between options, and considering external and internal constraints (Stephens & Krebs, 1986).

Risk sensitivity theory (RST) extends foraging theory by adding flexibility to the interplay between internal and external motivators and constraints. Suppose that perceived benefits, for instance, social-hedonic rewards for displaying 'green' behavior in smart charging, outweigh the perceived risks, such as sharing personal data to maximize energy flexibility. In that case, the reward-utility curve may switch from risk averse to risk prone (Mishra & Fiddick, 2012). Thus, people may share sensitive data in high-risk high-reward contexts (Caraco et al., 1980).

Turel (2021) has only recently adapted both theories to analyze technology-mediated dangerous behaviors. More specifically, he explored the role of social-hedonic rewards on risk-taking in social media contexts and found significant overlap with foraging behavior. Such behavior depends on several external and internal context factors that influence the risk proneness and, dependent on their expression, may drive risk-shifting (Cartar, 1991). That is, the relationship between perceived risks and benefits fluctuates, highly dependent on the information provided (Turel, 2021). The level of provided information is also crucial for privacy considerations, especially in the context of smart charging. – where the use of data is unclear for EV users.

Development of hypotheses and research model

In the following section, we describe the development of our hypotheses derived from the literature. Figure 1 illustrates our research model and hypotheses. As noted earlier, attitudes towards disclosure of information play a crucial role in shaping the decision-making context and, consequently on the perception of risks and benefits (Barth & de Jong, 2017). Such attitudes can encompass general privacy awareness and trust towards the provider who manages the smart charging application. People who are generally more concerned about how their data are handled tend to perceive greater risks and have higher levels of risk awareness (Fortes et al., 2017; Van Slyke et al., 2006). Thus, we propose the following hypothesis:

H1a: Privacy awareness is positively related to perceived risks with the smart charging application.

An energy provider typically controls smart charging applications. The level of trust people have in their energy provider can significantly impact their perception of smart charging applications (Utz et al., 2023). Studies conducted in various areas, such as IoT and e-commerce, suggest that lower trust in the service provider leads to greater perceived privacy risks (Kim et al., 2019; Kim et al., 2008). This concept could be applied to smart charging applications since consumers would have a more direct relationship with their energy provider than with other online service providers. Thus, we hypothesize the following:

H1b: Trust in the energy provider is negatively related to perceived risks with the smart charging application.

If people's trust in their energy provider influences the perceived risks of smart charging applications, it can also affect the perceived benefits. Such benefits could encompass the optimal use of sustainable energy, contributing to stable and sustainable grid infrastructure, and reduced charging costs (Brey et al., 2021). Individuals who have built experience-based trust in their energy provider may perceive the potential benefits of the smart charging application more strongly (Utz et al., 2023). In the study by Söllner et al. (2016), trust in the application provider predicted the perceived usefulness of an application. Thus, we formulate the following hypothesis:

H1c: Trust in the energy provider is positively related to perceived benefits with the smart charging application.

Research indicates that prior behavior can be a reliable indicator of future behavior (Ouellette & Wood, 1998). In an experimental setting, Söllner et al. (2022) demonstrated that habitual use of an application positively influences continuous information system (IS) use. Such IS usage habits might also extend to data sharing habits. Barth and de Jong (2017) included this in their model as an antecedent for data sharing. For this reason, we suggest the following hypothesis:

H2: Prior data-sharing habits are positively related to the intention to share data for smart charging.

According to the framework of Barth and de Jong (2017), attitudes influence the intention to share data and resulting data sharing behavior (Theory of Reasoned Action/ Theory of Planned Behavior, Ajzen, 1985; Ajzen and Fishbein, 1980). Data sharing is often considered risky, as some personal data are sensitive. In the context of smart charging, different data types, such as charging history, smartphone location, and calendar data, can help identify behavioral patterns and create user profiles. We want to determine which types of data individuals would share with a smart charging application.

Data sharing decisions typically depend on evaluating risks against potential benefits (Privacy calculus theory, Culnan and Armstrong, 1999). In the context of smart charging, violation of user privacy could be the greatest perceived risks (Bailey & Axsen, 2015), along with the fear that personal data are used for purposes beyond smart charging (Xu et al., 2012). According to risk-benefit calculation theories, such as privacy calculus theory (Culnan & Armstrong, 1999) or risk-sensitivity theory (Mishra & Fiddick, 2012), the perceived risks and benefits of the smart charging application will influence the intention to share data. According to Alotaibi et al. (2023), the privacy calculus is also crucial to explain data sharing with EV services. Based on this, we formulate the following hypotheses:

H3: (H3a) Perceived risks are negatively, and (H3b) perceived benefits are positively related to the intention to share data for smart charging.

The theoretical framework of Barth and Jong (2017) assumes that contextual factors can influence decision making. In this study, we focus on two contextual factors: The desired level of automation of the smart charging application and monetary incentives. Some studies, for instance, Xu et al. (2008), have treated these factors as inherent benefits of data sharing. We did not include automation as a benefit, as it is unclear if it will become the norm. Instead, we explore the desired level of automation as a variable and its effect on the intention to share data.

Resource exchange theory suggests that users are willing to share some of their data in exchange for services (Donnenwerth & Foa, 1974; Foa, 1971). Services can be personalized and automated (Shah, 2015), or come in the form of monetary rewards. However, to increase service automation, the smart charging application requires more data that users who want automation should be willing to share. This assumption is supported by Kim et al. (2019), who found that people share their data for better personalized services without considering privacy risks. Thus, we hypothesize the following.

H4: The desired app automation is positively related to the intention to share data for smart charging.

We consider monetary incentives as both a context factor and a benefit of smart charging. This approach enables us to test how monetary incentives impact data sharing. Previous studies indicated that privacy comes at a cost with different 'price tags' depending on the sensitivity of shared data (Hirschprung et al., 2016) or the context in which the data are shared (Acquisti et al., 2013).

Other immaterial rewards could also play a role, such as increased user convenience or social-hedonic rewards (Turel, 2021). They are, however, difficult to measure in this context and may have different effects on the readiness to share data. Social-hedonic rewards, for instance, could backfire if users' social network criticizes their readiness to share important data for smart charging instead of applauding their contribution to the environment. Thus, we focus primarily on material rewards whose use is established in the literature (Acquisti et al., 2013; Hirschprung et al., 2016). Monetary rewards have also been proven to be effective in related contexts, such as the general acceptance of smart charging (Kramer & Petzoldt, 2022; Wong et al., 2023). They might effectively encourage data sharing (Cichy et al., 2021). We thus propose the following hypothesis:

H5: *Participants who receive monetary incentives have a higher intention to share data for smart charging than participants who do not.*

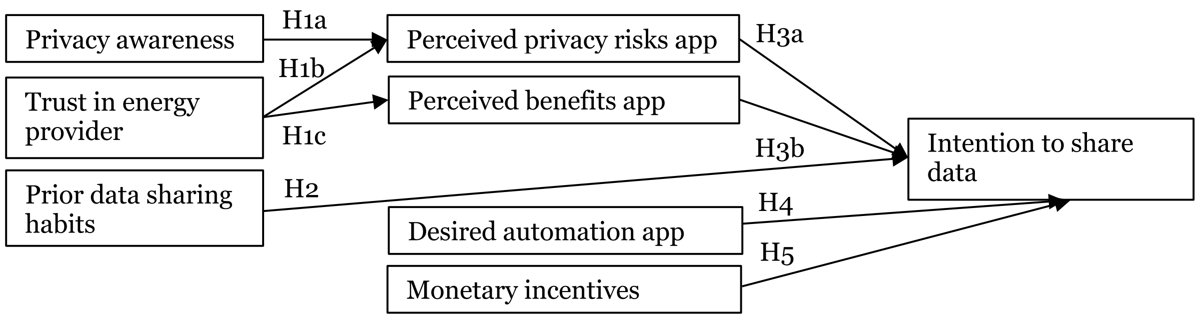

Figure 1. Representation of the hypotheses and research model

Methods

Before conducting the survey, we did a pre-test survey with 20 participants. We included a comment section in the survey to receive impromptu feedback from our pilot group. Feedback primarily concerned the complexity of questions and statements. We changed the survey accordingly and submitted the final draft to the university's ethics committee. After receiving approval from the ethics committee, we started disseminating the survey. Our goal was to get a sample of EV and non-EV users. To achieve this, we distributed the survey widely, including social media and EV user forums, as well as to prolific academics. The survey, which included a questionnaire and a related experiment, was available in English and German. It took about 10-15 minutes to complete the survey.

At the beginning of the survey, we asked participants if they were smartphone users. If they answered "Yes", they received questions about their data sharing habits, such as how many apps they use a month and how many continuously track their location. We measured data sharing habits, as people have many smartphone applications that require location sharing. Additionally, participants rated their familiarity with smart charging on a scale from 1 "not familiar at all" to 7 "extremely familiar". Regardless of their answer, they received a short explanation of smart charging, including potential benefits and requirements. In this way, we wanted to ensure they can make informed decisions when answering our survey.

Participants also received information on how sharing certain data can help the application become more automated and tailored to the charging patterns of users. We assure them that the data would only be shared with the energy provider and not transferred to a third party. Once they finished reading, participants rated the importance of three proposed benefits – facilitating an optimal use of sustainable energy, contributing to a stable energy grid, and reducing charging costs – when using the smart charging application (Brey et al., 2014). They also replied to items on perceived risks during usage (Secondary use of personnel information by Xu et al., 2012) and answered a related attention question. Participants responded to partially adapted scales on privacy awareness (Ponnurangam Kumaraguru & Cranor, 2005), and trust in the energy provider (Döbelt et al., 2015). They indicated their agreement to the respective items on a 7-point Likert scale (1 "Strongly disagree" – 7 – "Strongly agree").

The participants continued with a hypothetical smart charging scenario. They saw a screenshotted mock-up of the smart charging application, which depicted the charging preferences. They selected their preferences by responding to three questions written below the mock-up. These questions inquired about the state of charge (SOC) at arrival, desired SOC at departure, and parking duration. To measure the desired level of automation, participants replied to how often they would want to enter such information manually (1 "before every trip / settings manually" – 9 "once when installing the app / mostly automated").

For the experiment, we randomly assigned participants to the control or experimental group. Participants in the experimental group were notified that they could recover some of their electricity costs if they shared their data with the application. Participants in the control group did not receive this information. After that, we asked all participants which data they would share with the application. They each indicated their willingness to share charging times and preferences, smartphone's location, and full calendar details on a 7-point Likert scale (1 "Strongly disagree" – 7 – "Strongly agree"). In the experimental group, participants also had to imagine that they were frequent drivers with a monthly charging cost of 100 euros. We asked them to indicate how much of the total charging costs they wished to be redeemed for sharing each data type. They could also choose not to share any data type for money. At the end of the survey, participants were informed about the background and purpose of the study and could provide feedback on the survey. To honor their participation, they could sign up for a lottery.

We used structural equation modeling (SEM) to address RQ1 (*What data types do individuals intend to share?*) and answer H1-H5. To calculate the dependent variable, the intention of sharing data, we used a standardized mean of the three data sharing items (composite score). To answer RQ2 (*Which factors impact individual's intention to share data with their smart charging app?*) and RQ3 (*How much does the monetary incentive need to be for individuals to share different data types?*), we analyzed our results descriptively.

Sample

To determine the necessary sample size for the SEM, we used a sample size calculator (Soper, 2022) based on Cohen (2013) and Westland (2010). This analysis indicated that we needed a sample of n = 314 (considering a medium effect and a power of 0.8) to calculate our model and detect effects. 501 participants completed the survey. We eliminated participants (n = 22) for the following reasons: 1) Participants were not smartphone users (n = 10), 2) we detected multivariate outliers according to the Mahalonibis statistical measure (n = 12) and/or they answered the survey in less than three minutes or had evident response patterns for different items (n = 4). We conducted the analysis with 479 participants.

225 participants (46.97%) were in the experimental group to measure monetary incentives and 254 (53.03%) were in the control group. Most of the participants identified either as men (55.95%), female (40.71%) or diverse (3.34%). They were students (50.31%), worked full time (37.37%), or had other occupations (12.32%). Most of the participants had a master's (44.05%), a bachelor's (21.71%), or different degrees (34.24%). Participants predominantly lived in Luxembourg (50.73%), Germany (33.83%), France (6.26%), Belgium (2.71%), and other countries (6.89%). The three main nationalities were German (31.11%), Luxembourgish (16.70%), and French (6.26%). The mean age was 31.78 (SD = 13.03). While 28.18% of participants were EV users and 71.82% were non-EV users, our sample isn't specific to or representative of EV users. Our study primarily examines the willingness to share data for smart charging, irrespective of personal EV experience. Therefore, both EV and non-EV users can answer the survey in the same way.

Results

To answer RQ1, we calculated the mean values of the three data sharing variables for the control and experimental groups. We measured data sharing with a 7-point Likert scale (1 "Strongly disagree" – 7 – "Strongly agree"). Values above 4 indicate that people intend to share these data. The results indicate that the participants are comfortable sharing their charging history and patterns (Exp. Group: M = 5.47, SD =1.48, Md = 6 – "agree", Control group: M = 5.65, SD = 1.28, Md = 6 – "agree") and their location on the smartphone irrespective of monetary incentives (Exp. Group: M = 3.92, SD = 1.95, Md = 4 – "neither agree nor disagree", Control group: M = 4.13, SD = 1.85, Md = 5 – "somewhat agree"). In contrast, participants are not comfortable sharing full calendar details (Exp. Group: M = 2.75, SD = 1.86, Md = 2 – "disagree", Control group: M = 2.57, SD = 1.77, Md = 2 – "disagree").

To test RQ2 and hypotheses 1-5, we calculated a structural equation model, using the package "Lavaan" for "R" (Rosseel, 2012). We checked for the one-dimensionality of the measured items. Each item loaded on its respective underlying concept, and all loadings were significant (see Table 1). The scales' construct reliabilities (CR) were good (Hair, 2017), except for the composite score of intention to share data. Due to variance in the composite score of intention to share data, we additionally calculated three single SEMs with the dependent variables charging history (SEM2), location of the smartphone (SEM3), and calendar details (SEM4).

	Standardized factor loadings			
	SEM1	SEM2	SEM3	SEM4
	Composite score	Historical data	Location data	Calendar data
Privacy awareness	**(CR =.73)**	**(CR = .73)**	**(CR = .73)**	**(CR = .73)**
Consumers have lost all control over how personal information is collected and used by companies. (inverted)*deleted in the analysis				
Most businesses handle the personal information they collect about consumers in a proper and confidential way.	.773	.772	.773	.773
Existing laws and organizational practices provide a reasonable level of protection for consumer privacy today.	.740	.740	.740	.740
Trust Energy provider	**(CR =.81)**	**(CR = .81)**	**(CR = .81)**	**(CR = .81)**
My consumption data is being managed securely by my energy supplier.	.652	.652	.651	.650
My energy supplier is billing my consumption correctly.	.757	.757	.757	.756
I can rely on my energy supplier.	.884	.884	.885	.886
Perceived privacy risks with the application	**(CR =.92)**	**(CR = .92)**	**(CR = .92)**	**(CR = .92)**
I am concerned that a smart charging app may use my personal information for other purposes without notifying me or getting my authorization.	.873	.874	.874	.873
When I give personal information to a smart charging app, I am concerned that the app may use it for other purposes.	.910	.908	.910	.910
I am concerned that a smart charging app may share my personal information with other entities without getting my authorization.	.876	.878	.875	.876
Perceived benefits with the application	**(CR =.75)**	**(CR = .76)**	**(CR = .76)**	**(CR = .76)**
Facilitating optimal use of sustainable energy	.837	.822	.846	.859

	Standardized factor loadings			
	SEM1	SEM2	SEM3	SEM4
	Composite score	Historical data	Location data	Calendar data
Facilitating contribution to a stable energy grid	.689	.700	.685	.677
Facilitating reduced charging costs	.597	.604	.592	.586
Intention to share data	**(CR =.63)**			
The location of my smartphone	.726			
My charging times and preferences	.573			
Full details of my calendar (time, subject, location, and other details of all items in your calendar)	.508			

Table 1. Scales of the research model with respective factor loadings and composite reliability (CR). Note: All factor loadings are statistically significant.

The fit of the model with the composite score intention to share data as dependent variable suggests that the model fits the data (χ^2 = 237.598, *df* = 110, p < .001, Comparative Fit Index [CFI] = .945, Tucker Lewis Index [TLI] = .934, Root Mean Square Error of Approximation [RMSEA] = .053, Standardized Root Mean Square Residual [SRMR] = .068). Yet, fit indices for the three models with the single data sharing types as dependent variables suggest that the separate models fit even better to the data. The fit indices are as follows: For charging history and patterns as dependent variable (χ^2= 138.965, *df* = 82, p < .001, CFI = .972, TLI = .965, RMSEA = .041, SRMR = .057), for the location of the smartphone (χ^2 = 141.326, *df* = 82, p< .001, CFI = .971, TLI = .963, RMSEA = .042, SRMR = .059) and for the calendar details (χ^2 = 152.446, *df* = 82, p < .001, CFI = .965, TLI = .956, RMSEA = .046, SRMR = .060). Since privacy awareness and trust in the energy provider were highly correlated, we tested this correlation in all four models. Table 2 illustrates the standardized path coefficients and if the hypotheses could be confirmed or rejected for the four models.

	Composite score	Historical data	Location data	Calendar data
	SEM1	SEM2	SEM3	SEM4
	Standardized path coefficients (t-values)			
H1a: Privacy awareness -> Perceived privacy risks app use	.261***	.430***	.430***	.433***
H1b: Trust in energy provider -> Perceived risks app use	-.164**	-.163*	-.164**	-.166**
H1c: Trust in energy provider -> Perceived benefits app use	.261***	.260***	.255***	.247***
H2: Prior location sharing habits -> Intention to share data	.278***	.052 *p* = .089	.153***	.123***
H3a: Perceived privacy risks app use -> Intention to share data	-.457***	-.278***	-.277***	-.336***
H3b: Perceived benefits app use-> Intention to share data	.339***	.379***	.234***	-.025 *p* = .559
H4: Desired automation of the app -> Intention to share data	.047*	-.003 *p* = .872	.055**	.014 *p* = .452
H5: Monetary incentives message -> Intention to share data	-.049 *p* = .614	-.081 *p* = .321	-.083 *p* =.313	.149 *p* = .079
Privacy awareness <-> Trust in energy provider	-.356***	-.356***	-.356***	-.354***

	Composite score	Historical data	Location data	Calendar data
	SEM1	SEM2	SEM3	SEM4
	Standardized path coefficients (t-values)			

Table 2. Empirical evaluation of hypotheses and standardized path coefficients, ****p* **< .05, *****p* **< .01, ******p* **< .001.

To answer RQ3, we grouped the amount of money participants would need to recover from their charging bill to share data. We can interpret the desired amount as percentages since we asked participants to imagine that their electricity bill was 100 euros. Figure 2 illustrates the results. The more sensitive the data is (from charging history to calendar details), the more reluctant participants are to share their data, and the higher the monetary reward participants request. We observed that more than 50% of participants would share their data for money for all three data types,

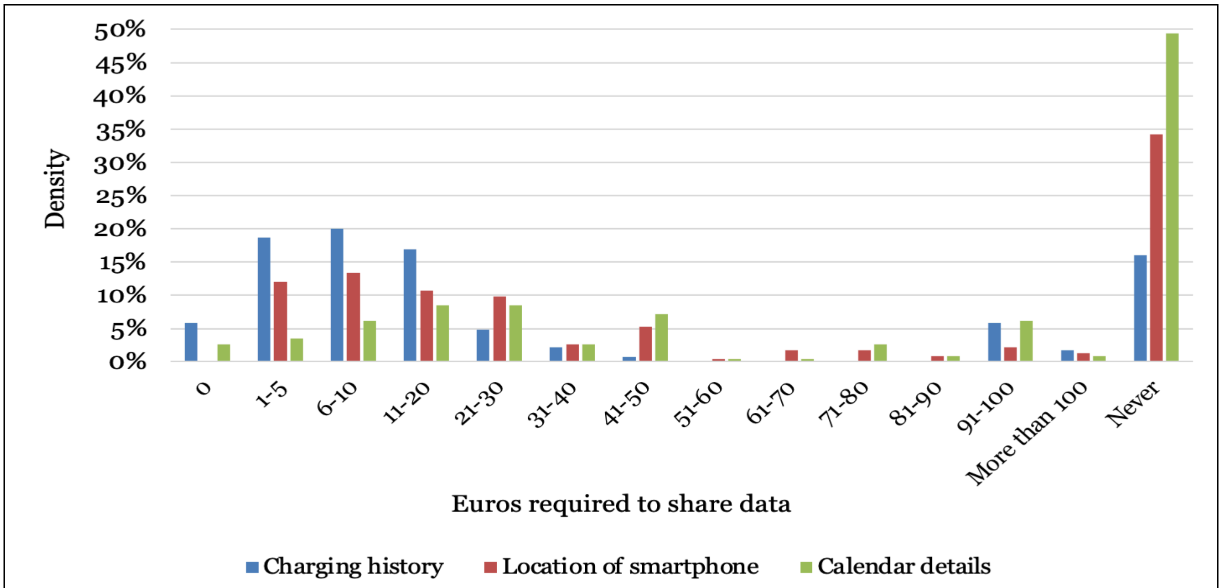

Figure 2. Euros which participants require back to share their data

We calculated the correlations between demographic variables and our main variables in an exploratory analysis. Women were less willing than men to share their calendar data (r_{Sp} = -.12, p = .012) and perceived more benefits with the smart charging application (r_{Sp} = .11, p = .017). Also, increasing age had a direct negative effect on the willingness to share location data (r = -.13, p = .005) and a direct positive effect with greater trust in their energy provider (r = .13, p = .006).

Discussion

Our findings provide food for thought about the applicability of the privacy paradox to smart charging. In our answer to RQ1 (*What data types do individuals intend to share for smart charging?),* we found that most people would share their charging history with a smart charging application. Participants are more ambivalent about their smartphone location data and are reluctant to share their calendar details. These findings are consistent with previous studies on data sharing with websites (Malhotra, 2012; Smith et al., 2011) and indicate that the readiness to share data decreases with increasing data sensitivity.

For RQ2 (*Which factors impact individual's intention to share data with their smart charging app?),* we calculated the structural equation model four times, once with the intention to share data composite score (SEM1), the intention to share charging history (SEM2), the intention to share the location of the smartphone (SEM3), and the intention to share calendar details (SEM4) as dependent variables. In general, our analysis indicates that Barth and de Jong's model is also valid in data sharing with a smart charging application. However, depending on the sensitivity of the data to be shared, not all factors, especially contextual ones, impact the intention to share data.

For all four models, trust and privacy awareness had a statistically significant negative impact on perceived risks and a positive effect on perceived benefits. That is, people who trusted their energy provider perceived fewer risks and more benefits with the smart charging application. While the role of institution-based trust is well-researched for customer loyalty (Utz et al., 2023) and e-commerce (McKnight & Choudhury, 2006), it also appears to play an important role for the readiness to share sensitive data with a service provider. Furthermore, people with greater awareness of privacy perceived greater risks. The general perception of greater risks in a data sharing context highlights the importance of information on data use and full transparency. This is in line with findings on risk-taking behavior, which show that the information available to individuals has a significant influence on their risk behavior (Turel, 2021).

For SEM1-3, perceived risks had a negative influence, and perceived benefits had a significant positive impact on the general intention to share data. These results align with the risk-benefit calculation since perceived benefits are often weighed against the risk probability. The higher the benefits, the easier it is to level perceived risks (Barth & de Jong, 2017; Culnan & Armstrong, 1999). However, for calendar data (SEM4), the perceived benefits of the smart charging application did not influence the intention to share data. They were insufficient to push the curve from high-risk low-benefit to high-risk high-benefit, which encouraged risk-averse behavior (Turel, 2021). The perceived risk of sharing sensitive data outweighed the perceived benefits of personalized charging, which has created a negative reward-utility balance and triggered risk averse behavior (Turel, 2021). These explanations from risk-sensitivity and foraging theory explicate risk-benefit calculations of Barth and de Jong's (2017) framework, wherein users refrain from sharing data when the risk probability is unfavorable. However, the underscoring of perceived benefits as opposed to the perceived risks of sharing sensitive data for smart charging can have significant implications for the design of smart charging applications. Either users enter their charging preferences for every charging event, which will be inconvenient, or smart charging will be limited. The success of smart charging depends on the ability to collect and analyze data to optimize charging processes.

Prior location-sharing habits had a statistically significant impact on the intention to share data for the composite score (SEM1), location data (SEM3), and calendar data (SEM4) but not for charging history (SEM2). This finding aligns with research on data sharing habits in the context of the privacy paradox (Awad & Krishnan, 2006). Despite privacy concerns, people overshare sensitive data on, for instance, social media (e.g., Chakraborty et al. 2013). Since experience-based trust might also be extendable to the action and not tied exclusively to the institution, people right- or wrongfully assume that sharing previously disclosed data does not carry any substantial risk (McKnight et al., 1998).

Our analysis of contextual factors demonstrated that the desired automation of the application positively influenced the intention to share data for the composite score (SEM1) and location data (SEM3) but not for historical data (SEM2) or calendar data (SEM4). This reflects findings from previous research on the privacy paradox wherein controlling the terms under which sensitive information is acquired and used was a key component of user privacy (Awad & Krishnan, 2006). While automation of data sharing would tremendously improve personalization and user experience, users appear reluctant to share such information unconditionally.

Despite the level of desired control, our analysis of RQ3 (*How much does the monetary incentive need to be for individuals to share different data types for smart charging?*) revealed that more than 50% of the participants would share all data types (historical data/pattern, location data, calendar data) in exchange for money. The more sensitive the data, the higher the expected monetary reward. For charging history data, over half of the participants required 20% of their monthly charging costs to be recovered. For the location of the smartphone, more than half of the participants wanted 40% of their monthly charging costs to be recovered. For calendar details, more than half of the participants required at least 100% of their monthly charging costs to be recovered. These findings reflect behavior explained in risk-sensitivity and foraging theory. The higher the risk, the higher the required benefits to switch from risk-averse to risk-prone behavior (Stephens & Charnov, 1982; Stephens & Krebs, 1986). However, the required monetary compensation may exceed what electricity companies would be willing to pay for the data.

Moreover, the results of RQ3 appear to contradict those of the model. Although the SEM model indicates that people would not share their data for money, more than 50% of our participants were willing to share all data types when explicitly asked how much (RQ3). However, the desired monetary compensation was exceptionally high for sensitive data, which is not always consistent with previous research. Dependending on the survey design, previous studies yielded different results: Braghin and Del Vecchio (2017), for instance, conducted a study in which only 36% of the participants agreed to share their browsing habits on an app for money. In contrast, Barak et al. (2013) conducted a field study asking participants for the amount required to share their location data. They found that 80% of the participants would share their location data for significant monetary rewards, while 20% would not share their data at all. Wagner et al. (2018) reviewed the existing literature on data monetarization and concluded that the monetary value of privacy is still unclear. They noted that the value people assign to their private information is generally low and that some people would sell data for only a little money. Also, Acquisti et al. (2013) suggest that privacy valuation depends on the situation's context and framing.

Theoretical and practical implications

Our research has both theoretical and practical implications. The theoretical implications of our study lie in the extension of Barth and de Jong's (2017) theoretical framework for smart charging applications. Since Cichy et al. (2021) argue in their study on data sharing for connected cars that common data sharing reservations in online service contexts do not apply to IoT devices, we demonstrated that the privacy paradox and typical data sharing reservations apply to smart charging applications. Depending on the type of data they share, users can decide on the level of personalization with a high level of control over their private information (Awad & Krishnan, 2006; McKnight et al., 1998).

However, the framework does not apply to highly sensitive calendar data. In this case, the perceived benefits of the smart charging app had no impact on the intention to share data. This demonstrates the influence of behavioral principles from foraging theory and risk-sensitivity on the data sharing intention. More specifically, some data carry inherent high-risk characteristics, which cannot be balanced even by high perceived rewards from a usability and knowledge perspective (Stephens & Charnov, 1982; Stephens & Krebs, 1986). However, findings on the effects of monetary rewards indicate differences in the value of rewards. That is, experience-based values, such as usability or convenience, appear less influential than material values in the form of concrete monetary rewards. Thus, adding of foraging and risk-sensitivity theory principles to the framework enhances Barth and de Jong's (2017) explainability of discrepancies between perceived risks and benefits.

Our findings on the effect of monetary rewards also highlight the importance of the research design to reliably catch such tendencies despite self-reporting bias. While undefined monetary rewards did not affect the readiness to share data, a direct question on the amount of money for which participants would share their data yielded different results. More than 50% of the participants were willing to share all data types. Thus, researchers might require more direct questions in their studies on the privacy paradox to reliably capture the impact of monetary incentives on data sharing.

Regarding practical implications, we found that customers are willing to share their data if they receive monetary compensation. However, the requested amount is often unrealistically high, especially for sensitive data such as calendar and smartphone, and may not be financially attractive to energy providers.

In addition, we found that perceived risks and benefits of the smart charging app have a significant impact on people's willingness to share data. Energy providers should, therefore, ensure that customers are well-informed about the benefits of their application and the use of data for smart charging to lower perceived risks. Explanatory videos might help convey the required information.

Furthermore, it is a good idea for energy providers to limit data collection to only the essential information needed to further optimize the charging process. This approach will help to avoid the unnecessary collection of data that may concern users.

Trust in the energy provider also influences how participants perceive the risks and benefits of the application. It is therefore important for energy providers to build trust with their customers. This can be done by being transparent about how they collect, process, and use data, or through, for instance, customer loyalty programs based on transparency-enhancing technology (e.g. Utz et al. 2023).

Limitations and future work

Our research comes with some limitations. First, we measured the intention to share data but not the actual behavior. There may be a gap between intention and actual behavior (Sheeran & Webb, 2016). A field study measuring the actual behavior could help us fill the gap but would have to be postponed until smart charging is more widely adopted. This is also the reason why we restricted our study to the intention of sharing data.

Second, we applied the rational decision-making framework to smart charging, which assumes that data sharing is rational. However, our decisions are also influenced by biases such as heuristics and situational cues (Barth & de Jong, 2017). To meet this limitation, future research could carry out a pilot focusing on irrational factors influencing decision-making.

Third, we asked participants for the amount of money rewards required to share their data. However, this self-assessment may not necessarily correspond to the actual values at which they would share their data. To overcome this limitation, a randomized experimental study could be conducted to test for how much money participants would be willing to share their data.

Fourth, we need to consider the possibility that our findings may not generalize to other cultural groups. Researchers claim that people from individualistic cultures value privacy more and show more privacy-protective behaviors, while in collectivistic cultures, privacy is less protected (Li, 2022). A cross-cultural study would help us evaluate the generalizability of our findings. However, previous cross-cultural studies on social networks often did not show differences between individualist and collectivist cultures (Li, 2022).

Conclusion

Our research aimed to investigate the types of data individuals would share with a smart charging application for EVs, such as charging patterns, smartphone location, and calendar details, and the factors influencing their decision. We applied the theoretical framework of Barth and de Jong (2017) and conducted a large-scale online survey to explore our hypotheses. We also investigated if participants would share their data for monetary rewards and, dependent on the data type, for how much. We used the IS theories of the privacy paradox (e.g., Barth and de Jong, 2017), foraging theory, and risk sensitivity theory to explore this behavior (e.g., Turel 2021)

We found that most individuals would share their charging history but would not share more sensitive data, such as calendar details. Participants were also ambivalent about sharing the location data. To determine which factors influenced the decision to share data, we calculated four SEM models, each with one dependent variable – charging details, smartphone location, calendar data – and a composite score of all three variables. The perceived risks and benefits of the smart charging application determined the intention to share charging details and smartphone location. However, perceived benefits did not influence the decision to share sensitive calendar data, while perceived risks had a significant influence.

Moreover, we discovered that different contextual factors influenced the data sharing decision for different data types. For instance, the desired degree of automation, influenced the intention to share location data but not the intention to share the charging history and calendar data. Interestingly, proposed monetary rewards did not have a significant impact on the intention to share data in any of the SEM models. However, when we asked participants from the monetary rewards group how much money they would share their data, most participants indicated willingness to share data for a monetary reward. The requested amount increased with the sensitivity of the data. Therefore, the energy supplier needs to decide if it is worth paying these rewards to get access to relevant data for smart charging.

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A.3.4 Research Paper 4 - Impact of Minimum Energy Requirement on Electric Vehicle Charging Costs on Spot Markets

Impact of minimum energy requirement on electric vehicle charging costs on spot markets

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***Abstract*—Simultaneous charging of electric vehicles (EVs) increases the peak demand and might lead to higher electricity prices. This could increase EV charging costs and make EVs unattractive. Smart charging utilizes the flexibility provided by EVs and adapts charging behavior in response to the electricity market price signals. However, some studies indicate users' reluctance to participate in smart charging programs, as they perceive the risk of their vehicle not being charged sufficiently at required times. As a countermeasure, several researchers use the concept of minimum state of charge (SOC_{min}). It is the percentage of the battery up to which the EV is charged uncontrollably at full power right after it is connected to the charger. Depending on the users' SOC_{min} requirement, there might be an impact on EV flexibility and subsequently on EV charging costs. We developed a novel flexibility algorithm which quantifies EV flexibility in terms of both energy and power as a function of time. To calculate the EV charging costs, we developed a two-stage scenario-based stochastic optimization model. Optimization utilizes flexibility input and minimizes charging costs while participating in both day-ahead and intraday markets. We found that in most cases where EVs provide some flexibility, there was no significant increase in charging costs. However, we observed a 50% increase in costs when EVs do not provide flexibility. Therefore, EVs possess high flexibility potential. This flexibility can be provided almost without any loss of user comfort for high monetary gains.**

***Index Terms*—Electric vehicles, Flexibility, Electricity markets**

I. Introduction

During the last couple of years due to its environmentally positive effects, we have seen a rapid increase in electric vehicle (EV) penetration. This trend is expected to continue in the coming years [1]. However, the introduction of EVs brings new challenges to the existing power system. When EVs charge simultaneously, it could lead to an increase in peak power demand. This could subsequently lead to significant increase in wholesale market prices [2]. Furthermore, existing power grid capacities should be increased to prevent the grid from overloading and voltage issues [3]. All these factors would increase the costs of electricity procurement, which is reflected in the user's bill, making EVs unattractive.

This caveat could be addressed by using demand response (DR) programs [4]. DR refers to the alteration of user demand in response to signals coming from the power system. In that notion, the charging behavior of EVs can be used as flexibility service where charging adapts to the power system conditions and to the user mobility requirements. This is commonly termed as smart charging. The electricity prices are usually lower during the off-peak periods. Therefore, charging EVs at lower prices would simultaneously reduce the procurement costs of energy suppliers and reduce the peak demand.

Several studies have developed optimization models for smart charging of EVs with the objective to maximize the revenue of EV aggregator while participating in electricity markets [5], [6]. To consider uncertainties of electricity market prices and vehicle availability, [7]–[9] proposed two-stage stochastic optimization models with objective to maximize the revenue of EV aggregators. These studies optimally scheduled EV charging while considering price uncertainty in electricity markets and different travel patterns for EVs. However, all the above studies assumed that users would participate in smart charging programs and thus provide full flexibility throughout the charging session.

There are some studies that indicate users' reluctance to participate in smart charging programs [10], [11]. This is because users perceive certain risks in smart charging programs, including fear of losing control and not being charged sufficiently at the required times. As a countermeasure, several researchers and practitioners use the concept of SOC_{min} [12]–[14]. SOC_{min} is the percentage of the battery up to which the EV will be charged in an uncontrolled manner at full power right after it is connected to the charger. SOC_{min} plays a large role in the acceptance of smart charging and counteracting range anxiety [15]. [15] evaluated the charging costs incurred for smart charging with this additional user requirement, i.e. SOC_{min}, while participating in the German day-ahead electricity market. We extend their work by considering several cases with different possible SOC_{min} values and we evaluate EV flexibility for each of the cases. Additionally, we evaluate monetary value of EV flexibility when participating in both day-ahead and intraday markets. In our paper, we strive to answer the following research questions:

- RQ1: How does the SOC_{min} requirement impact the EVs flexibility potential?
- RQ2: What is the monetary value of EV flexibility depending on SOC_{min} when participating in wholesale electricity spot markets?

To answer RQ 1, we propose a novel flexibility algorithm to quantify flexibility. We quantify EV flexibility in terms of both energy and power as a function of time. This will tell us the amount of power that can be varied in each timestep whilst maintaining the required energy level to satisfy user requirements. To evaluate the flexibility algorithm, we use synthetic mobility dataset based on German mobility behavior. We then use this flexibility as an input to our optimization model to simulate EV charging.

To answer RQ 2, we developed a two-stage scenario-based stochastic optimization model with the objective to minimize the charging costs while participating in both day-ahead and intraday markets. To consider the uncertainty in the intraday market, we modelled different prices scenarios. We used German day-ahead and intraday electricity market data to evaluate our optimization model.

II. Mathematical framework

In this section, we present the mathematical formulation used for flexibility algorithm and optimization model used to optimize the EV charging behavior.

A. Flexibility algorithm

The flexibility provided by an EV varies for each charging session based on the user charging requirements. These requirements include $E^{arrival}$, the energy level of the EV battery at the time of arrival ($t^{arrival}$). $E^{departure}$, the energy that should be transferred to EV by the time of departure ($t^{departure}$). $E^{minimum}$, the energy that should be transferred to satisfy the $\mathrm{SOC_{min}}$ requirement. The maximum charging power of EV is $P^{EV,max}$. As we only consider unidirectional charging, we can only use $E^{departure}$ for flexibility provision.

We only consider the part of EV battery capacity which offers flexibility, $E^{departure}$, and model the flexibility metrics - energy and power metrics accordingly. The energy metrics are minimum energy level (E_t^{min}) and maximum energy level (E_t^{max}). The minimum energy level represents the minimum cumulative energy that must be transferred to the EV at time t to satisfy the user's energy requirements. As we assume a linear charging of the EV, we calculate E_t^{min} by using Equation (1), where charging power at time t is P_t. The charging process to determine E_t^{min} is divided into three phases within its plugin duration (Equation (2)). The first phase is between $t^{arrival}$ and time taken for the minimum energy transfer, which is t^{min}. The second phase is between t^{min} and $t^{critical}$, where $t^{critical}$ is the time after which the P_t should be maximum to satisfy the user's energy requirement. The third phase is the time between $t^{critical}$ and $t^{departure}$. Hence, the P_t in the first phase, second phase, and third phase are $P^{EV,max}$, 0, and $P^{EV,max}$ respectively.

$$E_t^{min} = E_{t-1}^{min} + P_t \times \Delta t \tag{1}$$

$$P_t = \begin{cases} P^{EV,max} & t^{arrival} < t \leq t^{min} \\ 0 & t^{min} < t \leq t^{critical} \\ P^{EV,max} & t^{critical} < t \leq t^{departure} \end{cases} \tag{2}$$

The maximum energy level (E_t^{max}) represents the maximum cumulative energy that can be transferred to the EV at time t. As we assume a linear charging of EV, the maximum energy level at time t , E_t^{max} is calculated by Equation (3). The charging process to determine E_t^{min} is divided into two phases (Equation (4)). The first phase is between $t^{arrival}$ and $t^{instant}$. $t^{instant}$ is the time it takes to transfer $E^{departure}$ when charged at full power. The second phase is between $t^{instant}$ and $t^{departure}$ where there is no energy transfer. Hence, the charging power in first phase and second phase is $P^{EV,max}$ and 0 respectively.

$$E_t^{max} = E_{t-1}^{max} + P_t \times \Delta t \tag{3}$$

$$P_t = \begin{cases} P^{EV,max} & t^{arrival} < t \leq t^{inst} \\ 0 & t^{inst} < t \leq t^{departure} \end{cases} \tag{4}$$

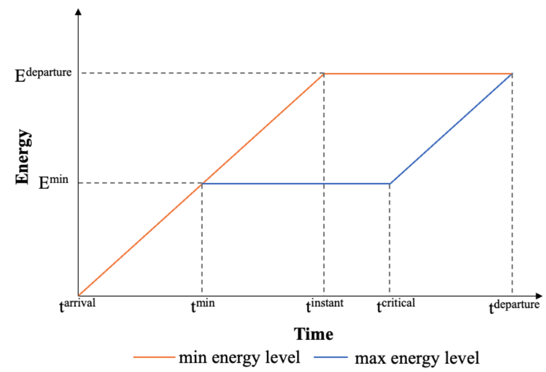

Fig. 1. Representing EV flexibility in energy vs. time graph.

The minimum and maximum energy levels can be represented in the energy vs. time graph as illustrated in Figure 1 above. From the Figure 1 it is quite evident that EV does not provide any flexibility until t^{min}. The power flexibility metrics are minimum power (P_t^{min}) and maximum power (P_t^{max}) at time t. The (P_t^{min}) when there is no flexibility, that is until t^{min}, is equal to $P^{EV,max}$. When EV offers flexibility, from t^{min} to $t^{departure}$, (P_t^{min}) is equal to 0. The maximum power (P_t^{max}) during the whole plugin duration is equal to $P^{EV,max}$.

The flexibility provided by an EV during its plugin duration is quantified by using energy (E_t^{min}, E_t^{max}) and power parameters (P_t^{min}, P_t^{max}). These parameters will convey the amount of power with which EV can be charged while maintaining upper and lower limits of cumulative energy transfer.

In our study, we calculate the individual flexibilities of each EV separately and then aggregate them (i.e, summation of the flexibility metrics of individual EV) to obtain the aggregated flexibility of all EVs. We represent the corresponding aggregated energy and power flexibility metrics as $E_t^{min,agg}$, $E_t^{max,agg}$ and $P_t^{min,agg}$, $P_t^{max,agg}$. Thus, it represents a virtual battery with minimum and maximum power and energy levels.

B. Optimization model

This section presents the mathematical model to minimze the energy provider's costs incurred for EV charging. We developed a two-stage scenario-based stochastic optimization model considering the price uncertainty of the intraday market. To consider intraday price uncertainty, we generate scenarios for intraday electricity prices first and employ them as optimization input afterwards.

We consider the uncertainty of intraday prices by utilizing probability density function (PDF) to create scenarios based on historical data and to model probabilistic nature of intraday market behavior. We employ normal PDF to generate scenarios for intraday prices as illustrated in Equation (5) below [16].

$$PDF(x) = \ 1/(\delta\sqrt{2\pi})\ exp(-(x-\mu)^2/(2\delta^2\ )). \quad (5)$$

using normal PDF, we generate different scenarios for intraday price. The value for each scenario and its corresponding probability are calculated using Equations (6) and (7) respectively:

$$\chi_{x,\ n_x} = \frac{1}{\rho_{x,\ n_x}} \times \left(\int_{x_{start,\ n_x}}^{x_{end,\ n_x}} x.PDF\,(x)\,dx \right), \quad n_x = 1, 2,\ \ldots,\ N_x \quad (6)$$

$$\rho_{x,\ n_x} = \int_{x_{start,\ n_x}}^{x_{end,\ n_x}} PDF\,(x)\,dx \quad , \qquad n_x = 1, 2,\ \ldots,\ N_x. \quad (7)$$

where $\chi_{x,\ n_x}$, $\rho_{x,\ n_x}$, and n_x are value, probability, and number of intervals for the scenario x,respectively. In this paper, we consider 7 intervals illustrating 7 scenarios for intraday prices of each time period.

The objective function in this paper is to minimize the costs of energy provider using our two-stage scenario-based stochastic optimization method. One prominent feature of two-stage stochastic optimization is the division of decisions in two stages. The energy provider takes some decisions in the first stage, and compensates any unfulfilled resource allocation in the second stage of the optimization. The objective function used in our paper is illustrated in Equation (8):

$$\sum_{t\in T} (P_t^{DA} \times c_t^{DA}\ )\Delta t + \sum_{w\in W}\sum_{t\in T}\ \rho_w \times (P_{t,w}^{RT} \times c_{t,w}^{RT}\ )\Delta t. \quad (8)$$

The objective function is divided into two parts. The first part is the total cost of energy provider in day-ahead market in the optimization period T, and the second part is expected cost of the energy provider in intraday market under various scenarios, W. The energy provider purchases the required power from the day-ahead market in the first stage, and compensates the rest of the required power based on the occurring scenario in the second stage. We use the generated scenarios from the previous section as input for the stochastic optimization. P_t^{DA} and c_t^{DA} are power purchased from the day-ahead and day-ahead price, respectively at time t. ρ_w is the probability of occurrence of each scenario w. Moreover, $P_{t,w}^{RT}$ and $c_{t,w}^{RT}$ are variable and parameter illustrating the purchased power from intraday market and intraday market prices at time t for scenario w.

In the scenario-based stochastic optimization used in this paper, P_t^{DA} is the same for all the scenarios. Therefore, the power balance between day-ahead and intraday is attained by using the Equation (9) below:

$$P_t^{DA} + P_{t,w}^{RT} = \quad P_{t,w}^{agg} \quad \forall\ t \in T, w \in W. \quad (9)$$

$P_{t,w}^{agg}$ is the variable for aggregated charging power of EVs, which is restricted by the connected vehicles to the grid, illustrated in the Equation (10):

$$P_t^{min,agg} \ \leq P_{t,w}^{agg} \ \leq \ P_t^{max,agg} \ \ \forall\ t \in T, w \in W. \quad (10)$$

$P_t^{min,agg}$ and $P_t^{max,agg}$ are inputs from the flexibility algorithm from previous section and are restricting the allowed charging power for EVs.

In this paper, we assume that all the EVs connected to the grid create a large virtual battery. This virtual battery can describe the characteristics of the connected vehicles while giving a proper understanding for mathematical modeling of EVs. By aggregating the effect of all connected EVs in $E_{t,w}^{agg}$ variable, Equation (11) can depict the virtual battery energy balance:

$$E_{t,w}^{agg} = E_{t-1,w}^{agg} + P_{t,w}^{agg} \times \Delta t - E_t^{cars,disconnected} \quad \forall\ t \in T, w \in W. \quad (11)$$

In this regard, $E_{t,w}^{agg}$ is the variable illustrating the energy capacity of virtual battery which is affected by $E_{t-1,w}^{agg}$, $P_{t,w}^{agg}$, and $E_t^{cars,disconnected}$ which are energy capacity of virtual battery in prior time step, aggregated charging power of EVs at current time step t for scenario w, and the energy capacity related to EVs which left their chargers at current time step t, respectively. $E_t^{cars,disconnected}$ resulted from the flexibility calculations and is the same for all scenarios. Moreover, $E_{t,w}^{agg}$ is restricted by the aggregated energy metrics of connected EVs as illustrated in the following Equation (12):

$$E_t^{min,agg} \leq \ E_{t,w}^{agg} \leq \ E_t^{max,agg} \ \ \forall\ t \in T, w \in W \quad (12)$$

where $E_t^{min,agg}$ and $E_t^{max,agg}$ are minimum and maximum energy levels of connected EVs, respectively.

III. Testing and Validation

A. Datasets

We use existing synthetic mobility data to derive the required inputs for calculating the EV flexibilities [17]. We consider mobility data of 1000 EVs with battery capacity of 75 kWh and max charging power of 7.4 kW. For the SOC_{min} values, we generate different cases where all the EV users chose a specific SOC_{min} value in each case. The cases are illustrated in Table I below. We analyze only the home charging case, with following assumptions 1. all vehicles will predominantly charge at home, and 2. all vehicles are always plugged in while parked at home. 3. all vehicles are charged until 100% SOC is reached or max SOC that can be reached within parking duration.

Please note that our model results hold, even if users decide to charge their battery only up to, e.g., 80% of their capacity to avoid battery degradation. In that case, 100% SOC would just correspond to 80% of the battery capacity. However, for reasons of simplicity, we will not make this distinction in the following.

TABLE I
EV CASES BASED ON SOC_{MIN} REQUIREMENT

Case	Description
0% SOC_{min}	All vehicles offer full flexibility
x% SOC_{min}	All vehicles have SOC minimum requirement of x%
100% SOC_{min}	All vehicles offer zero flexibility (uncontrolled charging)

We used German wholesale electricity market price data to calculate procurement costs. For day-ahead prices, we use historical data for January 2020 [18]. We generate scenarios individually for one day and compile intraday price scenarios for the whole month. In Figure 2, we illustrate the average electricity prices of German day-ahead and intraday market of a typical representative day of January.

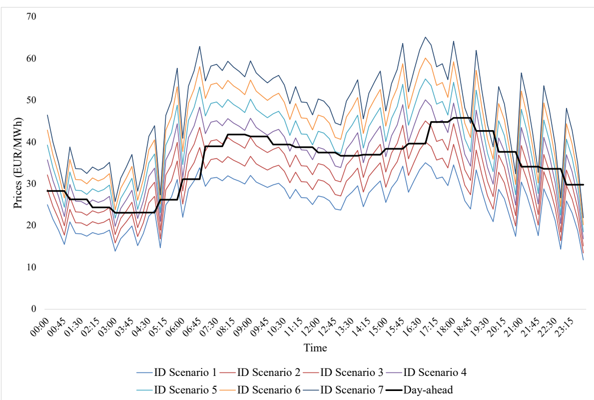

Fig. 2. Average day-ahead and intraday scnearios electricity prices.

B. Results

We calculate EV flexibilities for all the SOC_{min} cases for one month using the flexibility algorithm described in Section II-A. EV flexibilities are timeseries of energy ($E_t^{min,agg}$ and $E_t^{max,agg}$) and power ($P_t^{min,agg}$ and $P_t^{max,agg}$) flexibility metrics. Used timeseries data are for the range of one month and resolution of 15 minutes.

We model the EV as virtual battery, albeit only with the possibility of charging. Therefore, the energy metrics - $E_t^{min,agg}$ and $E_t^{max,agg}$, can be interpreted as minimum and maximum energy level of the virtual battery at time t. The power metrics - $P_t^{min,agg}$ and $P_t^{max,agg}$, can be interpreted as minimum and maximum charging capacity of the virtual battery.

Figure 3 illustrates the average power metrics for a typical day in month of January. As depicted in Figure 3, the maximum power curve for all the cases is the same. This is because maximum power is simply the sum of maximum charging power of all EVs connected to the charger. The value of $P_t^{max,agg}$ is maximum between midnight and 06:00, which is basically when the most EVs are connected to the charger. The $P_t^{min,agg}$ is zero when all EVs offer full flexibility at time t. Therefore, in the 0% SOC_{min} case the minimum power curve is always zero. In other SOC_{min} cases, EVs do not offer full flexibility until their SOC_{min} requirement is satisfied. Therefore, there are very few instances where $P_t^{min,agg}$ value is little over zero. This is because for most EVs, the $SOC_{arrival}$ is already greater than or equal to the SOC_{min} values. For EVs, whose $SOC_{arrival}$ value is already less than their SOC_{min} values; the power required to satisfy their SOC_{min} requirement is not significant. Therefore, the variation in minimum power curves for all SOC_{min} cases is not very significant.

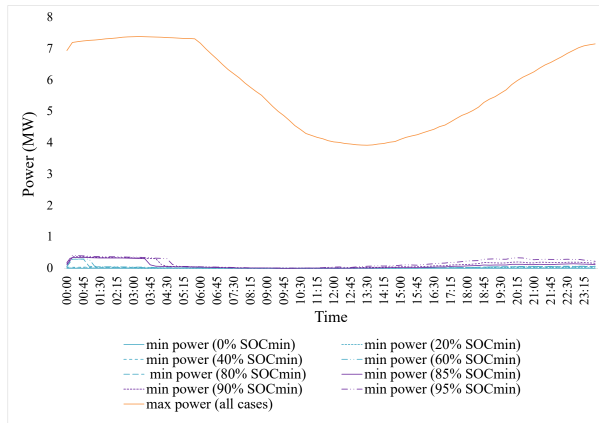

Fig. 3. Power metrics.

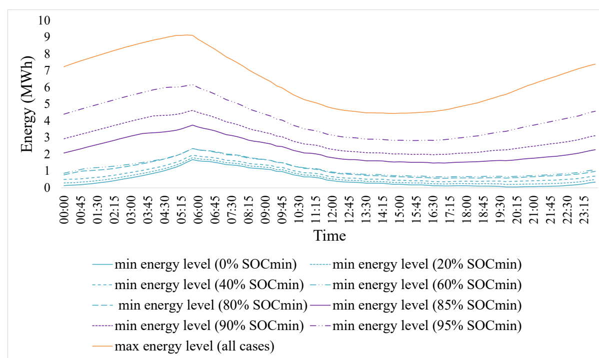

Fig. 4. Energy metrics.

Figure 4 illustrates the average energy metrics of a typical day in January. The maximum energy curve is the same for all cases as it just gives the sum of maximum allowable energy level of the EVs connected to the charger. The minimum energy level gives the cumulative energy that must be transferred at each time interval to satisfy the user requirements. Therefore, as the value of SOC_{min} increases, the value of the minimum energy level curve also increases. The difference between minimum and maximum energy gives the operational energy capacity of the virtual battery. As power metrics are almost similar for all cases, a higher operational energy capacity represents greater flexibility. Therefore, we can see a reduction in flexibility as the value of SOC_{min} increases.

We will illustrate how we optimally scheduled the electric vehicle charging using the modelled flexibilities. In Figures 5 and 6, we can observe the power procured from day-ahead and intraday market for EV charging on a random day (y axis scales are different in two figures, values in y-axis of Figure 5 are lower). The objective of energy provider is to minimize the overall costs. Therefore, the energy provider prefers to procure the power when the prices are low. Due to lower prices in the intraday market, most of the power is purchased from intraday market. In this regard, as illustrated in figure 6, most of the power for charging EVs is procured at 00:45, 04:00, 20:45, and 21:45, when the prices are lowest. Moreover, at times such as 02:00 and 04:00 some part of the required power can be provided from the day-ahead market, where the prices are lower in the day-ahead market.

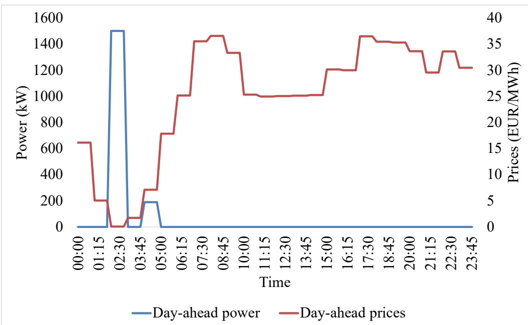

Fig. 5. Aggregated power procured for EV charging on a random day from day-ahead market

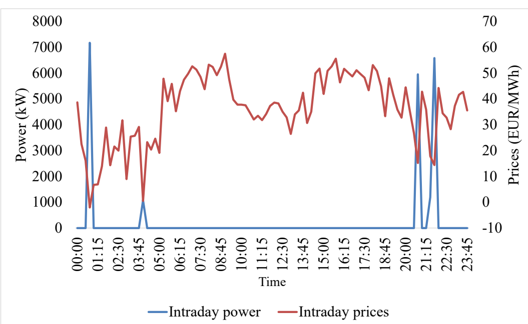

Fig. 6. Aggregated power procured for EV charging on a random day from intraday market

The total energy consumed to charge the EVs is 200 MWh for one month. From Figure 7, we can observe that the majority of the energy is procured from the intraday market for all SOC_{min} cases. However, as the flexibility decreases, the share of energy procured from the day-ahead market increases. It is evident that the intraday market prices are quite volatile as depicted in Figure 2. Prices can be extremely high or extremely low compared to the day-ahead market. As flexibility decreases, the probability of purchasing energy at lower prices decreases. This results in a slight increase in share of energy procured from the day-ahead market.

We illustrate the corresponding costs incurred to procure the required energy from the electricity markets for all SOC_{min} cases in Figure 8. We can observe that as the flexibility decreases, the costs increase. The charging costs until 80% SOC_{min} are almost similar. The charging costs starts to increase from 85% SOC_{min} case. However, the difference in

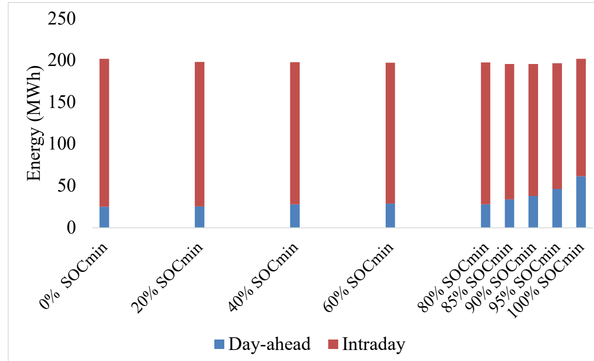

Fig. 7. Energy procured for EV charging

costs between the cases where the EVs offer flexibility and no flexibility is quite considerable. Costs increased by almost 50% for the 100% SOC_{min} case even when compared to the 95% SOC_{min} case.

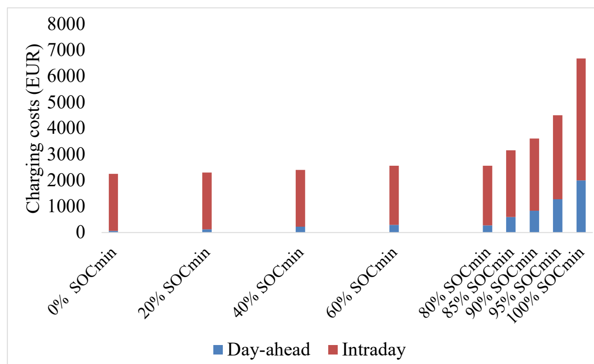

Fig. 8. EV charging costs

IV. Discussion

We found that as the SOC_{min} value increases, the flexibility decreases. However, the reduction in flexibility was considerable only for the cases where SOC_{min} value was greater than 80% compared to 0% SOC_{min} case. This is because for most EVs, the battery percentage rarely drops below 80% due to their mobility patterns, given available charging options. The same holds true for charging costs where the costs were almost similar until the 80% SOC_{min} case and increased only for the cases where the SOC_{min} was above 85%. However, even compared to the case of 95% SOC_{min}, the charging costs for the case where EVs do not offer flexibility were 50% higher. This further ascertains the importance of flexibility for the energy providers.

For EV users, it makes little difference whether their EV is charged instantaneously every day to a SOC_{min} of 80% or 100%. Even for an emergency at night (e.g., to the nearby hospital), a SOC_{min} of 80% would be sufficient for most. However, people are used to fill the tank of conventional cars immediately to their full capacity; thus, full charging of EVs is rather standard [19]. This standard needs to be changed as it is quite evident that it might not affect user comfort to a relevant amount.

There are some limitations in our paper that we would like to address in our future research. We assumed that all vehicles have the same specifications and undergo the linear charging process without efficiency losses. In reality, vehicle specifications will be different and the charging process is not linear. In principle, all EVs do not charge every day, but only a couple of times a week, depending on the user. We assumed that we know the user mobility patterns and corresponding requirements. However, these limitations will not have a major influence on the final outcome, i.e., high monetary value for the flexibility of EVs. In future research, we will consider more stochastic user scenarios and evaluate their impact on EV flexibility and charging costs.

V. Conclusion

In our paper, we evaluate the impact of the minimum SOC requirement on EV flexibility potential and charging costs. We developed a flexibility algorithm to quantify flexibility using energy and power metrics as a function of time. We then calculated the flexibility for each case and use it as input to the optimization model to simulate EV charging. To evaluate the monetary value of flexibility, we developed scenario-based stochastic optimization model with the objective of minimizing EV charging costs while participating in both the day-ahead and intraday markets. We modelled 7 different intraday prices scenarios to consider the uncertainty in the intraday market.

In summary, EVs possess high flexibility that can be provided without almost any loss of comfort (80% of the SOC is sufficient for almost all daily driving needs) for high monetary gains (160% reduction in charging costs). Therefore, it is vital that EV users provide this kind of flexibility. Energy providers could motivate users to provide flexibility by incentivizing them. These incentives can be financed by revenues generated from the flexibility of EV users.

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A.3.5 Research Paper 5 - Uncertain Electric Vehicle Charging Flexibility, its Value on Spot Markets, and the Impact on User Behaviour

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Uncertain electric vehicle charging flexibility, its value on spot markets, and the impact of user behaviour

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HIGHLIGHTS

- Integration of behavioural factors while estimating the user charging preferences.
- Focus on two charging preferences: minimum state of charge and charging frequency.
- Flexibility model to quantify the flexibility provided by electric vehicles.
- Robust optimisation model facilitating energy providers to trade in spot markets.
- Flexible charging offers high economic value with minimal user inconvenience.

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ABSTRACT

Simultaneous charging of electric vehicles (EVs) increases peak demand, potentially causing higher electricity prices and increased procurement costs for charging, making EVs less economically appealing. Smart charging addresses this challenge by utilising EVs as flexible assets, adjusting their charging behaviour in response to both power system conditions and user requirements. In our paper, we take the perspective of an energy provider using smart charging algorithms to reduce their electricity procurement costs (EPC) by charging the EVs when the electricity prices are lower. However, EV usage uncertainties introduce variability in the flexibility EVs provide and subsequently impact the energy providers' EPC when trading in electricity markets. Our paper considers uncertainties arising due to variable driving patterns and charging preferences. Within the charging preferences, we specifically focus on two charging preferences such as a minimum state of charge (SOC^{min}) requirement – the percentage of the battery up to which EV needs to be charged immediately at full power when connected to the charging point; and the frequency of EV connection to the charging point – how often EV users connect their EV to the charging point. We develop a flexibility model that quantifies the flexibility in terms of energy and power as a function of time. To calculate the energy provider's EPC, we develop a scenario-based robust optimisation model, minimising the energy provider's EPC while trading in German day-ahead and intraday markets. As expected, an increase in SOC^{min} requirements and a decrease in frequency of EV connections results in reduced EV flexibility and subsequently increases the EPC. However, our cost sensitivity analysis reveals that even with an 80 % SOC^{min}, EPC can be reduced by up to 33.5 % and 36.9 % for the years 2022 and 2023, respectively, compared to fully uncontrolled charging. When EVs offer full flexibility (0 % SOC^{min}), the cost reduction is only slightly higher, at around 43.6 % and 49.6 % for the years 2022 and 2023, respectively. Flexible EV charging, even with low flexibility, thus possesses high economic value, allowing energy providers to achieve substantial monetary gains with minimal impact on user convenience.

1. Introduction

Electric vehicles (EVs) are a cornerstone of transport decarbonisation as they aid in reducing greenhouse gas emissions, particularly when charged with renewable energy sources (RES). The positive impact on the environment and targeted political measures have led to a significant rise in EV market penetration in recent years. This trend is expected to gain even more traction in forthcoming years [1]. However,

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Nomenclature

Indices/sets

t	Index of time step
T	Set of time steps
w	Index of electric vehicle uncertain scenarios
W	Set of electric vehicle uncertain scenarios

Parameters

$E_{t,w}^{\text{min,agg}}$	Aggregated minimum energy flexibility metric at time t for scenario w, in MWh
$E_{t,w}^{\text{max,agg}}$	Aggregated maximum energy flexibility metric at time t for scenario w, in MWh
$P_{t,w}^{\text{min,agg}}$	Aggregated minimum power flexibility metric at time t for scenario w, in MW
$P_{t,w}^{\text{max,agg}}$	Aggregated maximum power flexibility metric at time t for scenario w, in MW
$E_{t,w}^{\text{vehicles,dis}}$	Cumulative energy transferred to EVs disconnected from charging point at time t for scenario w, in MWh
C_t^{DA}	Day-ahead market price at time t, in EUR/MWh
C_t^{ID}	Intraday market price at time t, in EUR/MWh
Δt	Length of time step, in hour

Variables

β	Auxiliary decision variable to capture worst scenario in intraday market
P_t^{DA}	Power procured from day-ahead market at time t, in MW
$P_{t,w}^{\text{ID}}$	Power procured from intraday market at time t, in MW
$P_{t,w}^{\text{agg}}$	Aggregated charging power procured for the electric vehicle fleet at time t for scenario w, in MW
$E_{t,w}^{\text{agg}}$	Cumulative energy transferred to the electric vehicle fleet at time t for scenario w, in MWh

the simultaneous charging of multiple EVs raises concerns, as it contributes to higher peak power demand, leading to increased wholesale prices [2,3]. These factors can increase electricity procurement costs (EPC), potentially affecting users' bills and making the transition to EVs less economically appealing.

Smart charging addresses the challenges of simultaneous charging by utilising EVs as flexible assets, adjusting their charging behaviour in response to both power system conditions and user mobility requirements [4,5]. In this paper, we take the perspective of the energy provider (such as aggregators and energy suppliers), who uses smart charging algorithms to control the charging behaviour of EVs. Typically, electricity market prices are lower during off-peak periods. Smart charging algorithms leverage the flexibility of EVs by scheduling their charging during these periods of low electricity prices, thereby reducing EPC for energy providers and possibly overall peak demand [6]. These algorithms can employ linear optimisation models, assuming deterministic EV usage behaviour, with the objective of minimising EPC while trading in electricity markets such as day-ahead markets [7,8].

EV usage is subject to several uncertainties due to diverse driving patterns and charging preferences. Uncertainties stem from EV user trip distances, parking durations, arrival and departure times, and energy requirements [9]. Being inherent in EV usage, uncertainties introduce variability in the flexibility offered by EVs, posing challenges for energy providers in predicting and managing the EV schedules [10,11]. Energy providers can employ stochastic or robust optimisation models to address the challenges associated with EV uncertainties. Stochastic optimisation models represent uncertainties using probability distribution functions (PDFs), allowing energy providers to account for a spectrum of scenarios and minimize their average EPC while trading in electricity markets [12]. Conversely, robust optimisation models characterize uncertainties using an uncertainty set or range of scenarios to minimize EPC while preparing for worst-case scenarios [13,14]. However, while modelling the uncertainties due to charging preferences, authors often assume that users would provide full flexibility - meaning no minimum state of charge (SOC$^{\text{min}}$) requirement, and that users always connect their EVs to the charging point when the vehicle is parked [10–14].

However, EV users could be reluctant to provide flexibility for smart charging due to behavioural aspects such as range anxiety and loss of control [15–17]. As a countermeasure, authors have introduced the concept of the minimum state of charge (SOC$^{\text{min}}$) [18–20]. SOC$^{\text{min}}$ represents the percentage of the battery capacity up to which an EV is charged at full power immediately upon connection to the charging point. SOC$^{\text{min}}$ provides users with a sense of security, as it ensures that their required battery capacity will be available to them as soon as possible. The SOC$^{\text{min}}$ values that EV users choose could vary, introducing uncertainty in energy requirements.

Moreover, users might not always connect their EVs to the charging point whenever it is parked, especially in the context of residential charging, which is the primary focus of our paper [21]. The frequency of EV connections can vary due to various factors. Users with higher range anxiety opt for more frequent charging and vice versa [21]. While, some users could plug in their vehicles less frequently due to concerns about potential battery damage [22]. The frequency of EV connections influences the energy requirements and the total number of EVs connected to the grid.

Both the SOC$^{\text{min}}$ and the frequency of EV connections to the charging point introduce uncertainties in the EV usage and impact the overall flexibility available to the energy provider. Consequently, these additional behavioural uncertainties pose significant challenges for energy providers in accurately assessing the monetary value of EV flexibility while trading in the spot markets (day-ahead and intraday electricity markets). Thus, in our paper, we aim to answer the following two research questions:

RQ1: What is the impact of behavioural uncertainties on overall EV flexibility?
- RQ1a: What is the impact of SOC$^{\text{min}}$ requirements on overall EV flexibility?
- RQ1b: What is the impact of the frequency of EVs connections to the charging point on overall EV flexibility?

RQ2: What is the impact of behavioural uncertainties on the monetary value of EV flexibility in spot markets?
- RQ2a: What is the impact of SOC$^{\text{min}}$ requirements on the monetary value of EV flexibility in spot markets?
- RQ2b: What is the impact of the frequency of EVs connections to the charging point on the monetary value of EV flexibility in spot markets?

To answer RQ1, we propose a flexibility model that quantifies flexibility in terms of energy and power as a function of time. This model provides insights into the dynamic power adjustment at each time step while ensuring the necessary energy levels to meet user requirements. To evaluate the flexibility model, we use an existing mobility dataset based on German mobility behaviour for driving patterns [23]. Additionally, we derive user charging preferences, such as SOC$^{\text{min}}$ requirements and the frequency of EV connections to the charging point, from the "large scale survey data on behavioural aspects of charging" [17]. We first represent the variability in driving patterns by generating distinct scenarios. We assume different user charging preferences and calculate the flexibility for each scenario. In our paper, we assume unidirectional charging and accordingly calculate the flexibility of the EVs in each scenario. We then incorporate these flexibility scenarios into our optimisation model for evaluating the monetary value of EV flexibility.

To answer RQ2, we develop a scenario-based robust optimisation model with the objective of minimising the EPC while participating in both day-ahead and intraday markets. By implementing a robust optimisation approach, we optimise the EPC over the worst scenario, helping energy providers to clearly assess the financial viability of trading EV flexibility in spot markets. We used the German day-ahead and intraday electricity market data to evaluate our optimisation model and to test the impact of EV user uncertainties on the technical and financial indicators of flexibility provision.

The remainder of the paper is structured as follows. In Section 2, we discuss the literature on modelling EV usage patterns, EV scheduling algorithms, and different user charging preferences. Section 3 introduces our flexibility and scenario-based robust optimisation models. Section 4 gives an overview of scenarios and the data used for our simulations. Section 5 presents our results, and we discuss them in Section 6. Section 7 concludes the paper.

2. Related work

In this section, we first outline the different methods employed in the previous publications for modelling EV usage, accounting for inherent uncertainties. We then present how different papers utilised these EV usage models to estimate EV flexibility and develop smart charging algorithms. We primarily focus on optimisation/scheduling models that optimised the EV charging with the objective to minimise the EPC or maximise the revenue of the energy provider while participating in electricity markets. Lastly, we explore the impact of behavioural factors on charging preferences, highlighting their potential effects on the provision of EV flexibility and its corresponding monetary value.

2.1. EV usage models

The models to generate EV usage patterns are classified into annual mileage models and daily pattern models based on their time resolution [9]. Annual mileage models typically model vehicle usage as annual distances travelled by vehicles [24]. In contrast, daily pattern models, employed to develop EV scheduling algorithms typically focus on modelling the usage metrics such as the number of trips, daily mileage, daily activity-travel schedules (i.e., trip chains interspersed with non-travel activities) [9,25]. Daily pattern models are usually referred to as short-period models, as the time resolution typically ranges from hours to quarter hours [26,27].

Due to the limited availability of EV data, short-period models often rely on conventional vehicle usage patterns to generate EV usage patterns. These patterns, extracted from travel journals, are obtained through travel surveys, questionnaires, or GPS data. Authors [28–31] analyse these conventional patterns, focusing on parameters such as trip distance, trip frequency, trip duration, trip start and end times, and parking duration. The two predominant approaches to capture the variability in these parameters are PDFs and Markov chains [32]. In the first approach, authors in [33] used different types of PDFs such as uniform, normal, exponential, Gaussian, and Rician. Authors in [33] fit these PDFs to the observed data to find the distribution that best represents the different parameters. To simulate the stochastic behaviour of EV usage, authors in [11,29–31] employed Monte Carlo simulations, drawing random samples from the PDFs of various EV parameters.

The second approach to model the stochastic usage of EVs is by using a Markov chain. A Markov chain's next state is solely determined by the current state, based on the Markov property [34]. To generate a consistent EV usage pattern, authors in [10,35] used discrete time state Markov chain, which gives the state of each EV for each time interval (e.g., 15 min, 30 min, 1 h) over a defined period (e.g., week, month, year). These EV states can include information on whether the EV is driving, parked at work, at home, or in commercial areas. Transition probabilities, which indicate the likelihood of moving from one state to another for a given period, are usually derived from statistical information on traffic patterns in the region of analysis [23,26].

The energy that an EV consumes while driving can be estimated by multiplying its consumption rate by the distance travelled. To calculate the consumption rate, authors in [23,36,37] developed complex models that consider several factors like average velocity, aerodynamic efficiency, ambient temperature, and power consumption of auxiliary equipment. To estimate the charging demand of EVs, authors in [38–40] often assume an uncontrolled charging regime, where an EV is charged at full power until its energy requirement is fulfilled. The energy required for a charging session is assumed to be either equal to the estimated energy consumption of the EV for its next trip or the energy needed to reach maximum battery capacity. The required charging time is calculated based on the maximum charging power and the needed energy. In reality, EV maximum charging power is not always equal to the rated charging capacity of the charging point. The charging process typically involves various stages, including constant current and voltage, to preserve battery health and safety [41]. For simplicity, the authors [42] usually assume that maximum charging power is constant throughout the charging process and equal to the maximum rated charging capacity. The load profile for each EV, which gives the electricity consumption pattern of each EV, is computed and superimposed, representing the overall EVs demand at each time step for a given period.

2.2. EV charging scheduling algorithms

The actual charging duration of EVs is usually less than their parking duration, which makes the EV charging temporally flexible. This flexibility allows the energy providers to alter the EV charging schedule within a specific time period [43]. Consequently, using smart charging, energy providers can leverage the flexibility provided by EVs to minimise their EPC by scheduling the charging at times when market prices are low [44]. To smart charge, the EVs, the EV charging schedule can be formulated as a mathematical optimisation problem while considering various uncertainties [45]. Smart charging can be formulated as an optimisation problem because it typically involves allocating resources (i.e., charging power) to optimise the objectives (such as minimising energy supplier EPC) while satisfying constraints (e.g., user requirements). The performance of these optimised charging schedules is then compared with an uncontrolled charging schedule derived directly from the EV usage models [6,46].

Energy providers can use stochastic optimisation models to deal with uncertainties associated with EV usage in EV scheduling problems [12,47]. The stochastic optimisation model utilises probability distributions to represent uncertainties in EV behaviour, enabling the model to account for a spectrum of potential scenarios [48,49]. The energy provider could implement diverse approaches to formulating objective functions to minimise EPC when trading in electricity markets. For example, authors in [49] formulated the objective function to maximise the expected revenue of the energy provider in the reserve market by calculating the average performance across different EV demand scenarios based on their respective probabilities. Additionally, some stochastic optimisation models incorporate risk measures such as conditional value at risk (CVaR) [12,48,50] or variance [47] into the objective function. This inclusion serves to maximise energy provider's revenue in the day-ahead market [12,48,50] or reserve markets [47] while penalising outcomes with high variability or undesirable characteristics. Authors in [31,51] proposed two-staged stochastic optimisation models. The goal of these optimisation models is to minimise the expected EPC of energy providers while trading in both day-ahead and real-time/intraday markets. In the first stage, decisions aim to minimise the energy provider's EPC in the day-ahead market scheduling [51]. In the second stage, decisions correspond to the real-time/intraday markets where energy providers minimise the expected EPC of the anticipated energy procured in the real-time/intraday markets markets [31,51,52]. Trading in both day-ahead and intraday markets enables energy providers to fully utilise the flexibility offered by EVs across time horizons and market conditions [53].

In contrast to stochastic optimisation, energy providers can employ robust optimisation models in EV scheduling problems to adopt a more conservative and resilient strategy to address the uncertainties [13,14]. Within robust optimisation models, energy providers can model the uncertainties in EV usage [14] and market prices [13] by considering a set of uncertain scenarios without explicitly relying on probability distributions. While robust optimisation does not rely on probability distributions as stochastic optimisation does, its effectiveness is highly dependent on the chosen uncertainty set. A narrowly defined uncertainty set may only protect against a limited range of outcomes, similar to how scenario selection in stochastic optimisation can restrict the model's scope [54]. This connection parallels chance-constrained optimisation approaches, which address uncertainty without assuming a single probability distribution function and extend the applicability and robustness of the model [55]. The uncertainties related to EV usage could be, for example, the number of vehicles charging, the arrival or departure times, and the required energy [56]. Robust optimisation models aim to optimise the EV charging schedules to perform well under the worst-case scenarios. In this notion, authors in [57,58] formulated the objective function as a "min-max" model, aiming to minimise the energy provider's EPC for the worst-case scenario across all scenarios while trading in day-ahead markets. Another approach to model the objective function in robust optimisation models is by introducing a penalty term or robustness term in the original objective function [14]. Introducing a penalty or robustness term would penalise the deviations from the expected values within the uncertainty set. Authors in [59] proposed scenario-based robust optimisation to facilitate trading in day-ahead and intraday markets. Their scenario-based robust optimisation model aims to minimise the worst scenarios EPC, which could include day-ahead EPC and intraday worst scenario costs.

Our literature review reveals that most papers primarily relied on statistical models to derive the charging requirements and, consequently, to estimate the flexibility provided by EVs. They did not comprehensively consider the effect of behavioural factors on the charging preferences, such as $\mathrm{SOC}^{\mathrm{min}}$ requirements and frequency of charging events, and consequently their influence on the EV flexibility potential.

2.3. Charging preferences as an uncertainty

In our paper, the primary objective is to address limitations in previous research by integrating more realistic behavioural uncertainties into our charging algorithms. In this subsection, we elaborate on how specific behavioural factors can shape charging preferences, subsequently impacting both EV flexibility provision and EPC.

First, as previously mentioned, papers indicate that users are reluctant to participate in smart charging programs and thus provide flexibility [15,16]. Some users feel they lose control of the charging process and are concerned that the charge provided by the energy provider will not be sufficient in an emergency [15], such as a night-time hospital visit. To counteract this range anxiety, papers introduced the concept of $\mathrm{SOC}^{\mathrm{min}}$ [18,20]. $\mathrm{SOC}^{\mathrm{min}}$ offers users assurance that their EV will be instantly charged to their desired $\mathrm{SOC}^{\mathrm{min}}$, ensuring sufficiency in emergency situations [15]. By implementing this $\mathrm{SOC}^{\mathrm{min}}$ requirement, energy providers anticipate that users will provide some flexibility for smart charging from $\mathrm{SOC}^{\mathrm{min}}$ to the required state of charge at departure $\mathrm{SOC}^{\mathrm{dep}}$. However, the decisions of EV users are susceptible to behavioural factors like range anxiety [60], which is related to risk aversity – a personality trait in which individuals tend to prefer lower risks over higher risks, even if there is a good chance of a more advantageous outcome [61]. Risk-averse individuals may choose higher $\mathrm{SOC}^{\mathrm{min}}$ values than risk-prone individuals, impacting EV flexibility provision and the energy provider's EPC.

Second, papers indicate that EV users do not charge daily, but rather two to four times a week [21,62]. The charging frequency might depend on objective and subjective reasons. Regarding objective reasons, charging frequency correlates with the number of kilometres people drive per day [63]. It may also depend on other driving habits, such as the radius they drive from home and the number of trips they make. Weather and temperature as external factors could also influence the charging behaviour of EV users [64]. When the sun is shining, those with photovoltaic installations and the ability to charge at home can charge for free. Besides objective reasons, a subjective reason influencing the charging frequency might be range anxiety [21], which might be influenced by risk aversity [17]. Risk-averse people might tend to charge their EV more often to reduce the risk that the range will not be sufficient for upcoming trips. The frequency of EV connections influences the number of EVs connecting to the grid and their energy requirements, consequently impacting the EV flexibility potential.

3. Mathematical framework

In this section, we present the mathematical formulation of our flexibility model, which quantifies the EV flexibility in terms of power and energy flexibility metrics as a function of time. These flexibility metrics convey information on the amount of power that can be varied in each time step while maintaining the required energy level to meet the users' requirements. We then present the mathematical formulation of our scenario-based robust optimisation model, which uses this flexibility information for different scenarios and electricity market price data as an input to minimise the EPC for EV charging.

3.1. Flexibility model

The necessity of developing our flexibility model is twofold. Firstly, to evaluate the EV flexibility potential and secondly, to aid in EV flexibility trading. Within our model, we calculate individual flexibility metrics for each EV based on the user requirements. These flexibility metrics include time-dependent power and energy metrics, providing insights into how much power can be varied while maintaining energy levels required to meet EV user needs. By aggregating these individual flexibility metrics, we derive aggregated flexibility metrics. These aggregated flexibility metrics give a comprehensive view of the fleet's capacity to adjust power levels while maintaining energy requirements, allowing us to estimate the flexibility potential. Furthermore, these aggregated metrics serve as direct inputs to our optimisation model, reducing the complexity of our optimisation model by eliminating the need for individual-level computations for each EV.

3.1.1. Input data to quantify individual EV flexibility

The level of flexibility an EV offers varies with each charging session, influenced by the user's driving patterns and charging preferences, EV battery and charging point specifications.

To quantify EV flexibility, we require maximum charging power, energy requirements and parking duration. The maximum charging power (P^{max}) is the maximum power at which an EV can be charged. We derive the energy requirements from the user's $\mathrm{SOC}^{\mathrm{min}}$ and $\mathrm{SOC}^{\mathrm{dep}}$ requirements. $\mathrm{SOC}^{\mathrm{min}}$ represents the battery percentage up to which an EV will be charged at full power immediately upon connection to the charging point. $\mathrm{SOC}^{\mathrm{dep}}$ is the battery percentage requested by the user that should be fulfilled at departure time (t^{dep}). E^{SOCmin} denotes the energy that should be transferred to satisfy the $\mathrm{SOC}^{\mathrm{min}}$ requirement. The energy that should be transferred to satisfy the user's $\mathrm{SOC}^{\mathrm{dep}}$ requirement is denoted by E^{dep}. Plugin duration is the time throughout which the EV is connected to the charging point. We calculate the plugin duration using the user's arrival time (t^{arr}) and departure time (t^{dep}).

In Fig. 1, we illustrate the typical EV battery with different energy values at the time of arrival. E^{max} is the total battery capacity of the EV, E^{arr} is the energy level of EV battery at t^{arr}, and E^{dep} is the energy that should be transferred to satisfy the $\mathrm{SOC}^{\mathrm{dep}}$ requirement.

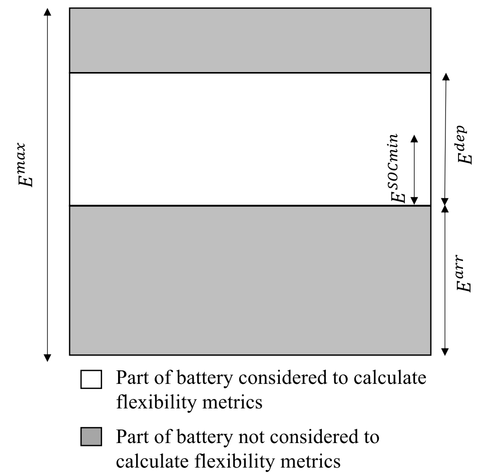


Fig. 1. Typical EV battery and different energy values.

As we only consider unidirectional charging, the overall energy capacity of the battery can never drop below E^{arr}. Furthermore, the user might not always request 100 % SOC^{dep}. This would mean that the sum of E^{arr} and E^{dep} would not always be equal to E^{max}. Therefore, when evaluating the flexibility metrics, we only consider the part of the battery that can be charged, i.e., E^{dep}.

3.1.2. Mathematical formulation to quantify individual EV flexibility

We derive time-dependent energy and power flexibility metrics to quantify the flexibility provided by an EV during its plugin duration, using the parameters introduced in the previous Section 3.1.1. The energy flexibility metrics are minimum energy (E_t^{min}) and maximum energy (E_t^{max}) at time t. The power flexibility metrics are minimum power (P_t^{min}) and maximum power (P_t^{max}) at time t. These flexibility metrics will convey the amount of power with which an EV can be charged while maintaining upper and lower limits of cumulative energy transfer. E_t^{min} represents the minimum cumulative energy that must be transferred to the EV at time t to fulfil the user's energy requirements, i.e. E^{dep} and E^{SOCmin}. The process to determine E_t^{min} is divided into three phases within its plugin duration as we illustrate in Fig. 2. The first phase is between t^{arr} and the time taken to transfer E^{SOCmin}, which is t^{min}. In the first phase, the vehicle is charged at full power until E^{SOCmin} is transferred. The second phase is between t^{min} and t^{c}, where t^{c} is the time after which the P_t should be maximum to transfer the remaining energy to fulfil E^{dep}. In the second phase, the vehicle is in an idle state. The third phase is the time between t^{c} and t^{dep}. In the third phase, the vehicle is charged at full power until it transfers the remaining energy required to fulfil E^{dep}. We present the mathematical formulation for the process to determine E_t^{min} in Eqs. (1) and (2).

$$E_t^{\text{min}} = E_{t-1}^{\text{min}} + P_t \times \eta \times \Delta t \tag{1}$$

$$P_t = \begin{cases} P^{\text{max}}, & t^{\text{arr}} < t \le t^{\text{min}} \quad \text{(Phase 1)} \\ 0, & t^{\text{min}} < t \le t^{\text{c}} \quad \text{(Phase 2)} \\ P^{\text{max}}, & t^{\text{c}} < t \le t^{\text{dep}} \quad \text{(Phase 3)} \end{cases} \tag{2}$$

In reality, EV charging is not linear and involves different stages, such as constant current and voltage, to optimise the charging process for battery health and safety [41]. However, for simplicity, we assume a linear charging of the EV where the charging power takes continuous values. Therefore, we calculate E_t^{min} using the Eq. (1), where charging power at time t is P_t, and η is the charging efficiency to account for power losses while charging. The value of P_t to calculate E_t^{min} in the first phase, second phase, and third phase is P^{max}, 0, and P^{max} respectively, as depicted in Eq. (2).

E_t^{max} represents the maximum cumulative energy that can be transferred to the EV at time t to satisfy the user's energy requirement, i.e., E^{dep}. The process to determine E_t^{max} is divided into two phases as illustrated in Fig. 2. The first phase is between t^{arr} and t^{inst}. t^{inst} is the time it takes to transfer E^{dep} when charged at full power. The second phase is between t^{inst} and t^{dep} where there is no energy transfer. We present the mathematical formulation to calculate E_t^{max} in Eqs. (3) and (4).

$$E_t^{\text{max}} = E_{t-1}^{\text{max}} + P_t \times \eta \times \Delta t \tag{3}$$

$$P_t = \begin{cases} P^{\text{max}}, & t^{\text{arr}} < t \le t^{\text{inst}} \quad \text{(Phase 1)} \\ 0, & t^{\text{inst}} < t \le t^{\text{dep}} \quad \text{(Phase 2)} \end{cases} \tag{4}$$

As we assume a linear charging of EV, E_t^{max} is calculated by Eq. (3). The value of P_t to calculate E_t^{max} in the first and the second phase is equal to P^{max} and 0, respectively, as depicted in Eq. (4).

When plotting E_t^{min} and E_t^{max} on the energy vs time graph, the region bounded by these two energy metrics represents the flexibility (see Fig. 2). From the Fig. 2, we can observe that EV does not provide any flexibility until t^{min}.

P_t^{min} represents the minimum allowable power at which EV can be charged at time t. When there is no flexibility, until t^{min}, P_t^{min} is equal to P^{max}. When EV offers flexibility, from t^{min} to t^{dep}, P_t^{min} is equal to 0.

P_t^{max} represents the maximum allowable power at which EV can be charged at time t. Therefore, P_t^{max} for the whole plugin duration equals P^{max}.

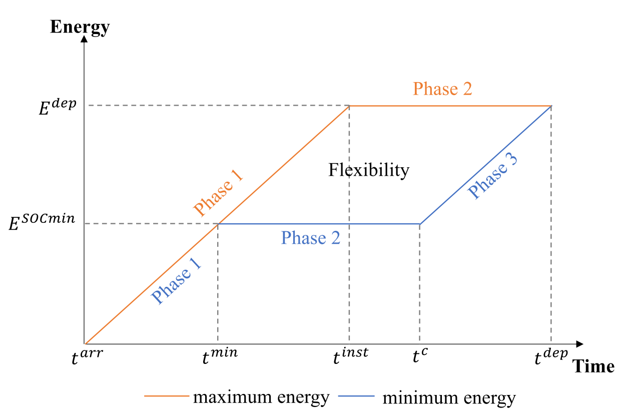


Fig. 2. Representing EV flexibility in energy vs. time graph.

3.1.3. Aggregated flexibilities for an EV fleet

In our paper, we consider different scenarios where the energy requirements, time of arrival and time of departure of the EVs are different in each scenario. For each scenario, we calculate the aggregated flexibility of the EV fleet as depicted in Fig. 3. We compute the individual flexibilities for each EV separately using user input data (refer to Section 3.1.2) for each specific scenario. We then aggregate the flexibility metrics of the EV fleet for a given scenario by summing up the individual flexibility metrics of each EV.

We repeat the same process for all scenarios and calculate the aggregated flexibility metrics for each scenario. The corresponding aggregated energy and power flexibility metrics for each scenario ω are denoted as $E_{t,\omega}^{\text{min,agg}}$, $E_{t,\omega}^{\text{max,agg}}$ and $P_{t,\omega}^{\text{min,agg}}$, $P_{t,\omega}^{\text{max,agg}}$ which serves as an input to our optimisation model. We will present our optimisation model in the next Section 3.2.

3.2. Optimisation model

Our paper aims to assess the monetary value of EV flexibility in electricity spot markets considering inherent uncertainties in EV usage. To

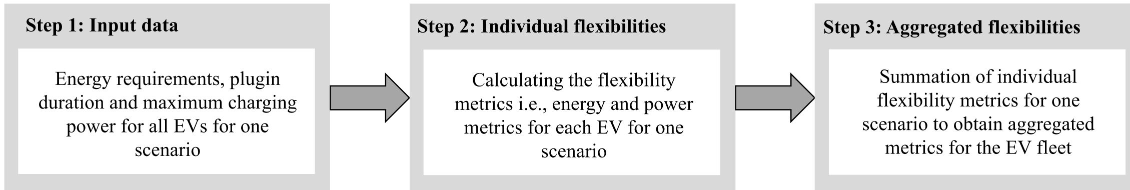


Fig. 3. Flexibility model to calculate aggregated flexibilities.

achieve this, we opt for a scenario-based robust optimisation model to minimise the EPC for the worst case while trading in day-ahead and intraday markets. We consider predetermined scenarios across which we calculate the aggregated flexibility metrics by varying the time of arrival, time of departure and energy requirements of each EV as discussed in Section 3.1.3

The robust optimisation model enables us to evaluate the worst-case scenario in terms of cost, providing a conservative estimate of the value of flexibility. Moreover, the robust optimisation approach allows us to develop charging schedules by considering various potential scenarios, providing resilience against different uncertainties related to EV usage. By accounting for these uncertainties in the optimisation model and optimising for the worst-case scenario, we can further ascertain if it is worthwhile to trade EV flexibility in electricity markets despite the uncertainties.

In line with prevalent scenario-based robust optimisation models, we assume that power acquired in the day-ahead market is the same for all scenarios, and the power is varied for each scenario while trading in the intraday market [59]. We assume perfect foresight of day-ahead and intraday market prices. Fig. 4 gives an overview of our optimisation model, illustrating the input data, objective function, relevant constraints and the resulting output.

Accordingly, we formulate the objective function of our optimisation model using Eq. (5). The first part is the energy provider's EPC of the day-ahead market, and β is an auxiliary decision variable used to capture the worst scenario intraday market EPC. In other words, β is a robustness variable that identifies the solution optimised for the worst scenario among all the modelled scenarios in the robust optimisation framework. The variable P_t^{DA} represents the power procured from the day-ahead market at time t, while C_t^{DA} denotes the corresponding day-ahead market price at time t. T gives the set of time steps, and Δt gives the length of the time step. In our paper, the time resolution is 15 min, and the time period is one week. Thus, the set $T = \{1, \ldots, 672\}$, and value of Δt is equal to 0.25 h

$$\min \sum_{t \in T} (P_t^{\mathrm{DA}} \times C_t^{\mathrm{DA}}) \Delta t + \beta \tag{5}$$

We formulate the constraint that relates the decisions taken in the intraday market to the objective function using Eq. (6). This constraint ensures that intraday EPC for all scenarios are less than or equal to the auxiliary decision variable . $P_{t,w}^{\mathrm{ID}}$ represents the power procured from the intraday market at time t for scenario w, and the parameter C_t^{ID} represents intraday market prices at time t. W is the set of scenarios; we model 52 EV flexibility scenarios, which we describe in detail in Section 4.1. Thus, the set $W = \{1, \ldots, 52\}$.

$$\sum_{t \in T} (P_{t,w}^{\mathrm{ID}} \times C_t^{\mathrm{ID}}) \Delta t \leq \beta \;\forall w \in W \tag{6}$$

As we assume P_t^{DA} to be the same for all the scenarios, the power balance between day-ahead and intraday market for each scenario w is attained using the Eq. (7). $P_{t,w}^{\mathrm{agg}}$ is the variable for the aggregated charging power of EVs for scenario w at time t.

$$P_t^{\mathrm{DA}} + P_{t,w}^{\mathrm{ID}} = P_{t,w}^{\mathrm{agg}} \quad \forall\, t \in T, w \in W. \tag{7}$$

The number of vehicles connected to the charging point limits the variable $P_{t,w}^{\mathrm{agg}}$. The constraint, which we illustrate in the Eq. (8), ensures the $P_{t,w}^{\mathrm{agg}}$ is always within the values of aggregated power flexibility metrics. $P_{t,w}^{\mathrm{min,agg}}$ and $P_{t,w}^{\mathrm{max,agg}}$ are the aggregated power flexibility parameters at time t for each scenario w within which $P_{t,w}^{\mathrm{agg}}$ can vary. We determine these power flexibility metrics using the flexibility model described in Section 3.1.

$$P_{t,w}^{\mathrm{min,agg}} \leq P_{t,w}^{\mathrm{agg}} \leq P_{t,w}^{\mathrm{max,agg}} \quad \forall\, t \in T\; w \in W. \tag{8}$$

As we trade the aggregated flexibility of the EV fleet, we assume that all the EVs connected to their respective charging points at the residential level create a large virtual battery [65]. This virtual battery can describe the connected vehicles' characteristics while properly understanding the mathematical modelling of EVs. The variable $E_{t,w}^{\mathrm{agg}}$ illustrates the cumulative energy transferred to this virtual battery at time t for each scenario w. $E_{t,w}^{\mathrm{agg}}$ is restricted by the aggregated energy flexibility metrics as illustrated in the Eq. (9). $E_{t,w}^{\mathrm{min,agg}}$ and $E_{t,w}^{\mathrm{max,agg}}$ are

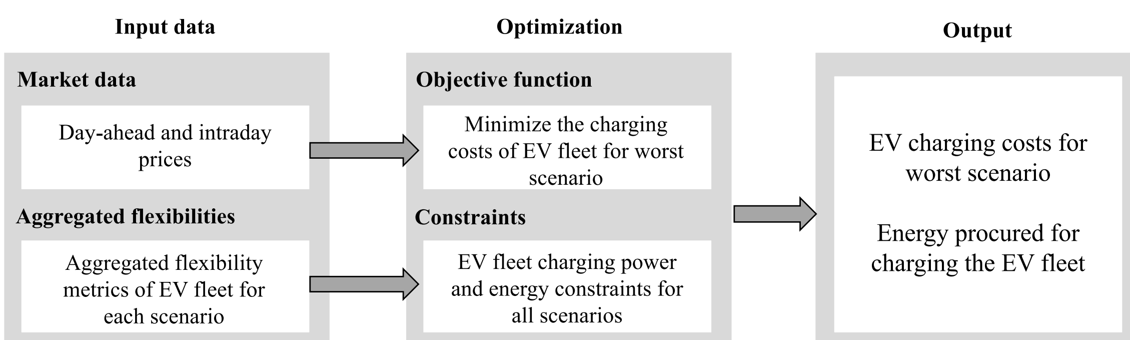


Fig. 4. Optimisation model.

the aggregated energy flexibility metrics at time t for scenario w. We determine these energy flexibility metrics using the flexibility model described in Section 3.1.

$$E^{\text{min,agg}}_{t,w} \leq E^{\text{agg}}_{t,w} \leq E^{\text{max,agg}}_{t,w} \quad \forall\, t \in T\; w \in W \tag{9}$$

The following Eq. (10) depicts the energy balance of the virtual battery:

$$E^{\text{agg}}_{t,w} = E^{\text{agg}}_{t-1,w} + P^{\text{agg}}_{t,w} \times \Delta t - E^{\text{vehicles,dis}}_{t,w} \;\forall\, t \in T, w \in W. \tag{10}$$

$E^{\text{agg}}_{t,w}$ is the variable illustrating the cumulative energy transferred to this virtual battery at time t for each scenario w. Its value is affected by $E^{\text{agg}}_{t-1,w}$, $P^{\text{agg}}_{t,w}$, and $E^{\text{vehicles,dis}}_{t,w}$. $E^{\text{agg}}_{t-1,w}$ is the cumulative energy transferred to the virtual battery in the previous time step for scenario w. $P^{\text{agg}}_{t,w}$ is the aggregated charging power of EVs or power procured to charge the virtual battery at the current time step t for scenario w. $E^{\text{vehicles,dis}}_{t,w}$ is the cumulative energy transferred to EVs disconnected from the charging points at the current time step t for scenario w, respectively.

4. Scenario generation and datasets

This section describes the approach and relevant datasets for generating flexibility scenarios and calculating the EPC.

We model uncertainties due to driving patterns by generating scenarios with different EV user driving patterns. We explain the methodology used to generate different scenarios in Section 4.1. These driving patterns provide information on the plugin duration of individual EV across different scenarios. We also need energy requirements to calculate flexibility for each scenario, which depends on charging preferences. Section 4.2 outlines the different charging preferences we assume, from which we derive the energy requirements for each EV across the scenarios. The information on plugin duration and energy requirements, derived from driving pattern scenarios and charging preferences, serves as input to the flexibility model, allowing us to calculate the aggregated flexibility metrics for each scenario.

Section 4.3 provides an overview of the electricity market price data used in our optimisation model to calculate EPC.

4.1. Modelling uncertainties due to driving patterns

To model uncertainties stemming from diverse driving patterns, we generate diverse scenarios reflecting various EV user driving patterns. We create the scenarios using synthetic mobility data derived from the German mobility survey [23]. We consider the mobility data of 1000 EVs. The mobility data comprises one-year mobility profiles for each EV. Each mobility profile represents a year-long time series capturing vehicle location, distance travelled, and energy consumption at 15-minute intervals. Our paper exclusively focuses on home charging, assuming all EVs charge when parked at home. Additionally, we assume the following specifications for all EVs.

- The battery capacity E^{max} of all vehicles is 75 kWh, which is similar to Tesla Model S [66].
- As per IEC 61851–1:2017 standard, we consider a Level 2 charger with a mean power rating of 7.4 kW, typically used for home charging [67].
- The charging efficiency η is 95 % which is within the efficiency range of Level 2 charger [68].

Fig. 5 outlines our approach to generate 52 scenarios to capture the uncertainties arising from variable driving patterns. We divide the mobility dataset – which contains individual profiles for the entire fleet (1000 EVs) over one year, into weekly datasets. This results in 52 datasets comprising the individual mobility profiles for the entire EV fleet over one week each. We utilise weekly datasets to better represent real-world charging behaviour, as EV users commonly plan their charging schedules every week. It also allows us to capture variations in charging behaviour between weekdays and weekends, which can differ significantly. Each weekly dataset is assigned to a unique scenario, totalling 52 scenarios. This approach introduces uncertainties in arrival and departure times, trip distances, and trip start and end times.

These driving pattern scenarios allow us to estimate the energy consumed by an EV during driving and the plugin duration for charging sessions in different scenarios. However, to quantify flexibility across all scenarios, we also require the energy requirements of EV users. The energy requirements depend on different charging preferences, which we discuss in the next section.

Overall, using our approach, we generate 52 different flexibility scenarios to model the uncertainty. These 52 scenarios serve as potential scenarios for one week that energy provider should consider while making the procurement decisions for that week. These scenarios serve as inputs for our robust optimisation model, which calculates the EPC for the worst scenario over the week (refer to Section 3.2).

4.2. Use cases for charging preferences

4.2.1. Definition of the use cases

EV users' charging preferences include SOC^{dep}, SOC^{min}, and the frequency of EV connection to the charging point. To determine SOC^{dep}, we assume that all EV users charge their vehicles until they reach either 100 % SOC or the maximum SOC at departure. Various possibilities exist regarding SOC^{min} and the frequency of EV connection to the charging point. For instance, the SOC^{min} requirement might vary between different EV users; some EV users may connect to the charging point every time they park with/without SOC^{min} requirement; some EV users may not connect to the charging point every time they park with/without SOC^{min} requirement. To deal with these different possibilities, we develop four different cases to cover all these possibilities.

- Case 1: We assume that all EVs are connected to the charging point whenever they are parked at home and offer full flexibility, i.e. 0 % SOC^{min} requirement.
- Case 2: We assume that all EVs are connected to the charging point whenever parked at home, each having a unique SOC^{min} requirement. We explain the methodology used to derive the SOC^{min} values in Section 4.2.2.
- Case 3: We assume that EVs are not always connected to the charging point when parked at home and offer full flexibility (i.e., no SOC^{min} requirement) when connected to the charging point. Connection occurs when state of charge at arrival SOC^{arr} values drop below a certain state of charge (SOC) value, which we define as the charging threshold. Thus, we assume that EV users plugin the vehicle when the SOC^{arr} is below the charging threshold. The charging threshold is unique for each EV, and Section 4.2.2 explains the approach to derive this value.
- Case 4: We assume that EVs are not always connected to the charging point when parked at home and have an SOC^{min} requirement when connected. In other words, here we consider both SOC^{min} and irregular EV connection to the charging point.

Table 1 provides an overview of the assumed charging preferences for each case. We consider Case 1 as the base case with no SOC^{min} requirement and with the assumption that EVs are always connected to the charging point when they are at home. Hence, we compare the results of other cases with Case 1 to analyse the impact of charging preferences on EV flexibility potential and its monetary value.

4.2.2. Deriving input data for each use case

We obtained the values for SOC^{min} requirements and charging thresholds from our large-scale survey data [17]. The survey, detailed in the paper by Marxen et al. [17], gathered data on various variables, including risk aversion, from $n = 289$ participants. To derive SOC^{min} requirements and charging thresholds, we used participants' responses to the question: "Which battery percentage should your EV always have as a minimum in case of unforeseen emergencies? (This implies that

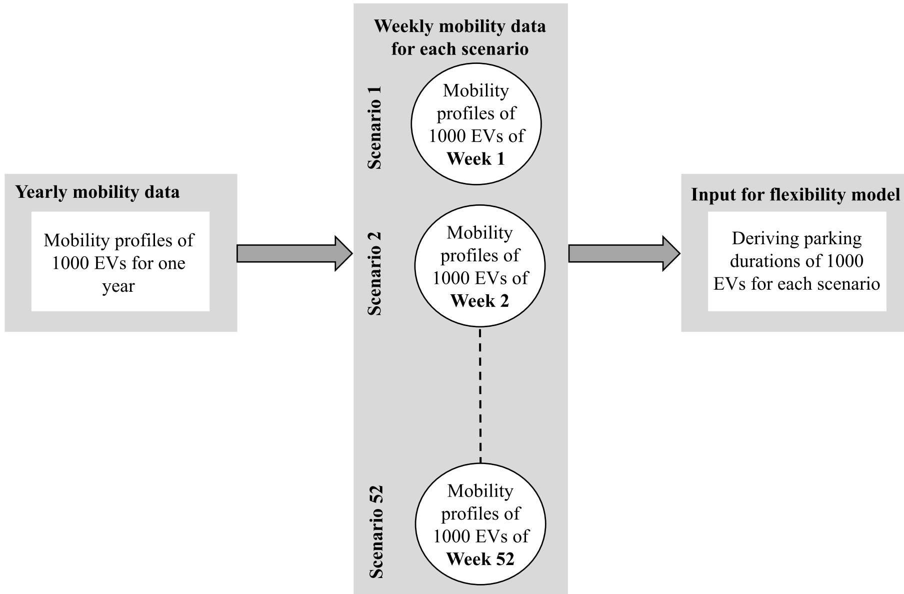


Fig. 5. Our approach to generating different scenarios.

Table 1
Charging preferences for different cases.

	SOC^{min} requirement	Irregular connection
Case 1	✗	✗
Case 2	✓	✗
Case 3	✗	✓
Case 4	✓	✓

your EV would always be charged to that level at maximum charging power when plugged in.)" Participants selected values between 0 % and 100 %. We then created a frequency distribution of their responses and randomly assigned SOC^{min} and charging threshold values to the 1000 EVs. In our survey, we also asked the participants about the battery capacity of their EV and the kilometres which they daily drive their EV. As these values did not correlate with SOC^{min}, we randomly assigned the SOC^{min} values for the scenarios. Fig. 6 illustrates the distribution of SOC^{min}/charging threshold values for 1000 EVs.

This distribution guides the definition of both SOC^{min} and charging threshold values, as the rationale behind the charging threshold is similar to that of SOC^{min}. The charging threshold also represents the battery percentage users would like to have for a sense of security. Therefore, we assumed that the values of SOC^{min} and the charging threshold would be the same for an individual EV. An assumption in our study is that the SOC^{min} values are based on survey data, which reflect behavioural intentions rather than actual behaviour. While behavioural intentions are generally considered a good proxy for actual behaviour [69], we acknowledge that a gap may exist between intentions and actual behaviour.

4.3. Electricity market price data

We use German wholesale electricity market price data from the day-ahead and intraday (ID3 index) markets for the years 2022 and 2023 [70] to calculate EPC. We include 2022 due to its high prices and increased market price volatility and analyse its impact on EPC [71]. The resolution of the prices is a quarter-hour.

Since our uncertain EV flexibility scenarios are modelled over a one-week period (refer to Section 4.1), we perform the optimisation for a single week to determine EPC over that time frame. To avoid bias from choosing a specific week, we use the weekly median price for a given month as input to our optimisation model. The weekly median price is calculated with a 15-minute resolution. For each 15-minute interval within the week, we take the corresponding prices from all weeks in the given month and calculate their median. To analyse the seasonal price impact on EPC, we run the optimisation separately for each month. For each run, we use that month's weekly median price data to calculate the EPC incurred by the energy provider to charge the vehicles for one week. Fig. 7 illustrates the price data (median value) for a typical week in September 2022 (see Fig. 7(a)) and September 2023 (see Fig. 7(b)).

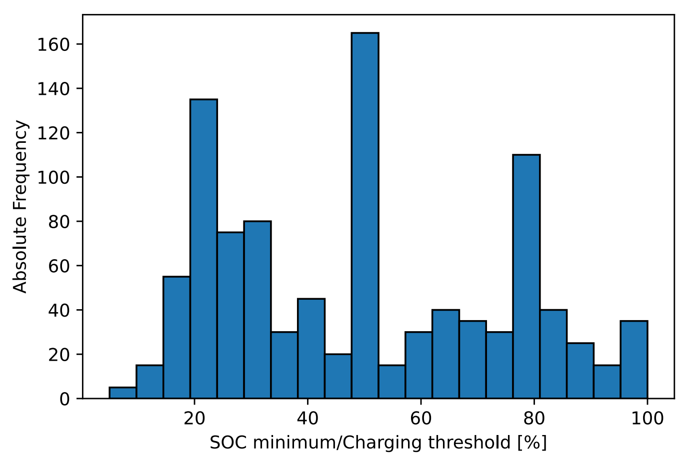
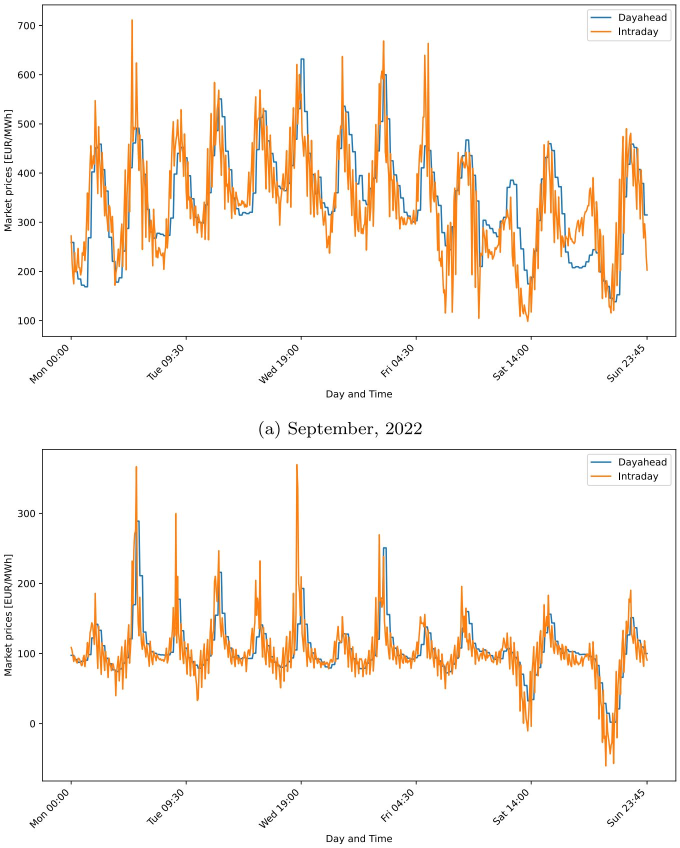


Fig. 6. Frequency distribution of SOC^{min} and charging thresholds derived from our survey data.

4.4. Simulation setup

Fig. 8 gives an overview of our methodology for calculating aggregated flexibilities and EPC for a single use case. We generate different scenarios and obtain the plugin duration of all EVs for each scenario (refer to Section 4.1). By considering one of the four charging preference use cases (refer to Section 4.2, we determine the energy requirements of all EVs for each scenario. These user requirements, such as plugin duration and energy requirements, serve as an input to calculate the aggregated flexibility metrics for each scenario using our flexibility



(a) September, 2022

(b) September 2023

Fig. 7: Electricity market price data for a typical week.

model (refer to Section 3.1). Subsequently, we employ our optimisation model to compute the worst scenario EPC (refer to Section 3.2) for one week in a specific month. We run the optimisation model separately for one month based on the weekly price input in each month (refer to Section 4.3) and calculate the worst-scenario EPC costs for all months in both 2022 and 2023.

We replicate this approach for each charging preference use case, determining flexibility scenarios for each use case separately.

5. Results

This section addresses our two research questions by presenting the results. We begin in Section 5.1 with the aggregated flexibility metrics calculated for all use cases using our flexibility model (refer to Section 3.1). Section 5.2 presents the EPC incurred for charging the EVs across all use cases. Finally, Section 5.3 explores the results of our cost-sensitivity analysis, where we determine the EPC incurred by varying the $\mathrm{SOC}^{\min}$ and charging threshold values.

5.1. EV flexibilities

In this section, we present quantile distribution graphs illustrating aggregated flexibility metrics for all cases (refer to Section 4.2) we consider in our paper. As we describe in Section 3.1.3, the aggregated flexibility metrics are energy metrics - $E_{t,w}^{\max,agg}$ and $E_{t,w}^{\min,agg}$; power metrics - $P_{t,w}^{\max,agg}$ and $P_{t,w}^{\max,agg}$. We create these quantile distribution plots for typical weekdays and weekends to showcase the variability of EV flexibility across the 52 scenarios. To analyse the impact of $\mathrm{SOC}^{\min}$ requirements and frequency of EV connections to the charging point on the flexibility, we compare the aggregated flexibility metrics of different cases with Case 1, the base case.

For the quantile distribution plots, we group weekdays (Monday to Friday) and weekends (Saturday and Sunday) separately and calculate the median value of the aggregated flexibility metrics for each scenario. We then plot the quantile distribution of these medians for weekdays and weekends. We use these typical plots to generalise the results across all weekdays and weekends. A solid red/orange line represents each flexibility metric's median (q50) value in these quantile distribution plots. Different shades of green around the central line indicate various quantile values for the flexibility metric. For example, in Fig. 9(c), the red line represents median (q50) of $E_{t,w}^{\max,agg}$ metric, and adjacent green shades are different quantiles of $E_{t,w}^{\max,agg}$ metric.

In the subsequent subsections, we detail the quantile distributions of all flexibility metrics for Cases 1–4, depicted in Figs. 9–12, respectively.

5.1.1. EV flexibilities for case 1

Figs. 9(a) and (b) illustrate the quantile distribution of power metrics for Case 1 on a typical weekday and weekend, respectively.

The $P_{t,w}^{\max,agg}$ metric displays slight variability for weekdays and weekends. Variability occurs due to different arrival and departure times of EVs in different scenarios, resulting in the difference in the number of vehicles connected to the charging point for a given period in different scenarios. On weekdays, the median value of $P_{t,w}^{\max,agg}$ is highest (7 MW) between midnight and 06:15 when most EVs are at home and connected to the charging point. Then it decreases as many people go to work. The median value increases again after 15:00 as people return home from work. On weekends, the median value of $P_{t,w}^{\max,agg}$ is highest (7 MW) just after midnight and remains constant until 08:45, when most EVs are at home. Its value drops slightly after 08:45, possibly due to short leisure trips some EV users take on weekends.

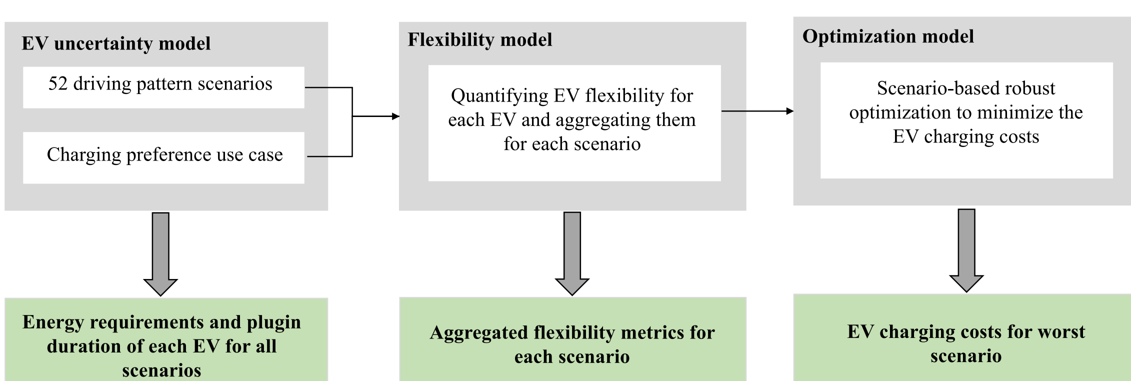
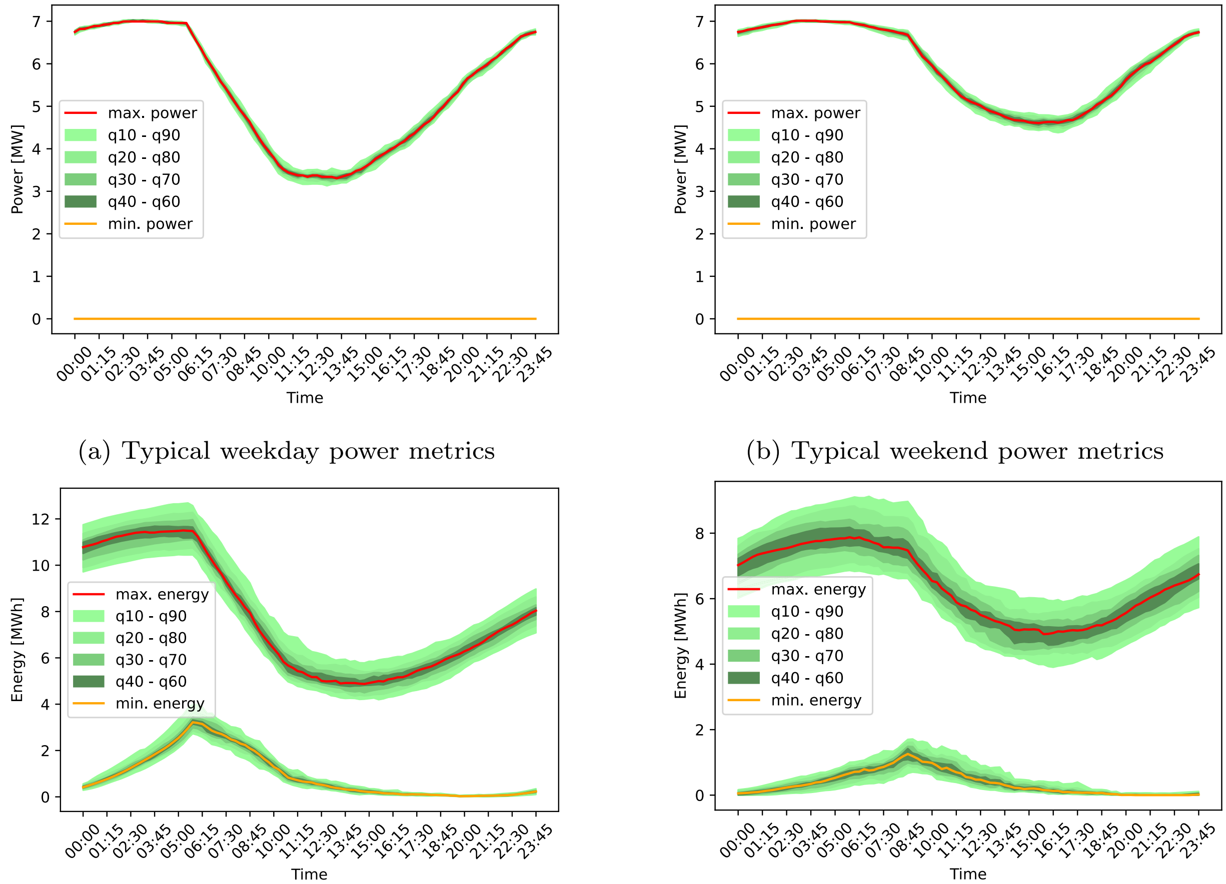


Fig. 8. Overview of our methodology for one use case.



(a) Typical weekday power metrics

(b) Typical weekend power metrics

(c) Typical weekday energy metrics

(d) Typical weekend energy metrics

Fig. 9. Quantile distribution of flexibility metrics for Case 1.

$P_{t,w}^{\max,\text{agg}}$ is zero during both weekdays and weekends during all hours, as all EVs offer full flexibility throughout the plugin duration.

The energy metric for Case 1, especially $E_{t,w}^{\max,\text{agg}}$, exhibits some variability throughout the day, with its values varying by ± 1 MWh from the median value for both weekdays (refer to Fig. 9(c)) and weekends (refer to Fig. 9(d)). The variability is predominantly due to the different energy requirements (E^{dep}) caused by variable driving patterns of each EV across the scenarios. The median values are highest around 06:15 (11 MWh) and 08:45 (7 MWh) for weekdays and weekends, respectively. $E_{t,w}^{\max,\text{agg}}$ is the sum of the maximum cumulative energy that could be transferred to all connected EVs. Therefore, its value increases when more vehicles start connecting to the charging point, reaches a peak, and decreases when the number of vehicles leaving is relatively higher than the number of connected vehicles. The $E_{t,w}^{\max,\text{agg}}$ values are higher on weekdays than weekends. These high values at weekends can be attributed to the fact that many EVs are more active on weekdays than weekends.

For weekdays, the median value of $E_{t,w}^{\min,\text{agg}}$ is almost close to zero from 17:30 to 23:45 and only increases after midnight with a peak (3 MWh) around 06:15, although many users connect their EVs to their charging points. The increase in the value only after midnight suggests that most EVs only need to be charged for a fraction of their plugin time. On weekends, the $E_{t,w}^{\min,\text{agg}}$ curve is much flatter than on weekdays, with a small peak (1 MWh) around 08:45, and the values are also much lower. These low values are because the energy requirements of the EVs are much lower on weekdays, likely due to short leisure trips taken by the EV users on weekends.

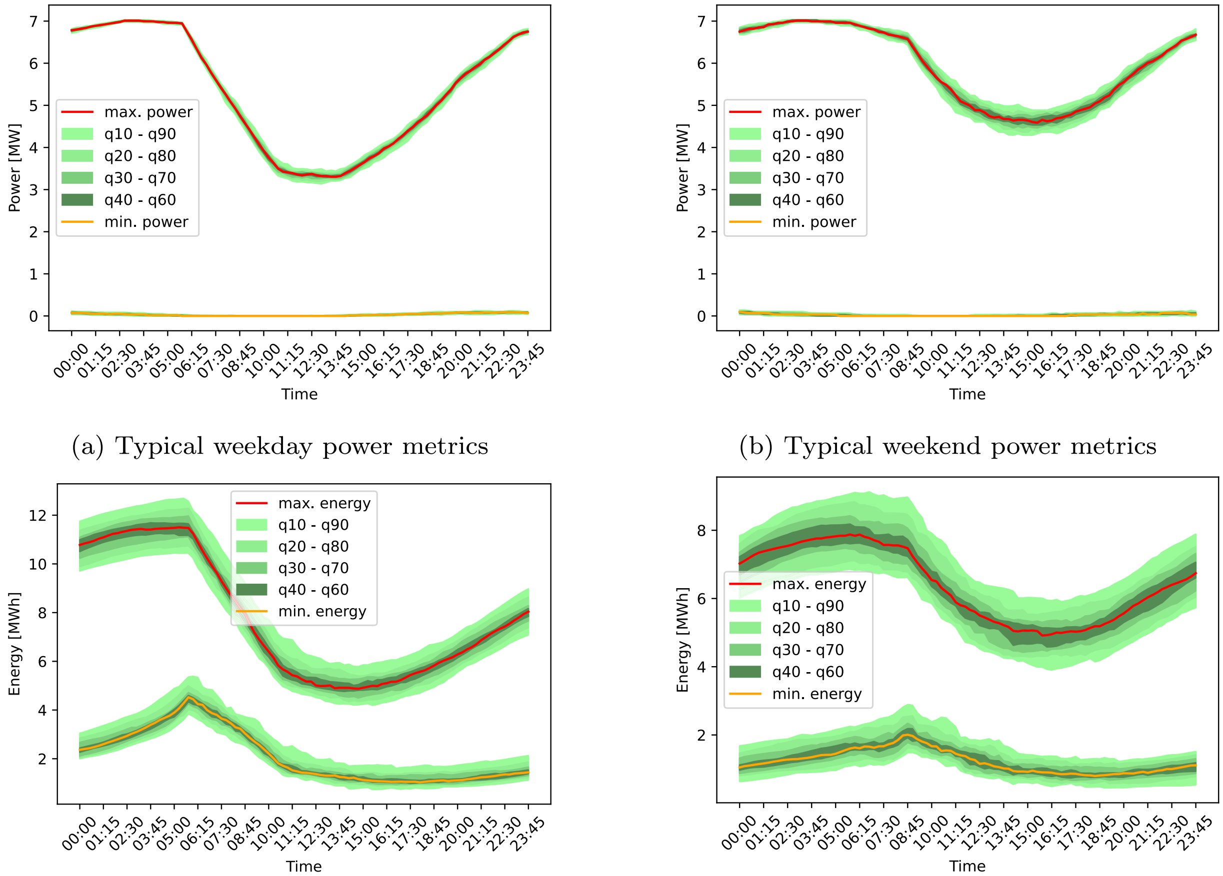
5.1.2. EV flexibilities for case 2

For Case 2, the $P_{t,w}^{\max,\text{agg}}$ values for both weekday (refer Fig. 10(a)) and weekend (refer Fig. 10(b)) are the same as those of Case 1. The similarity is because the number of EVs connected in Case 2 is identical to that in Case 1.

However, the $P_{t,w}^{\max,\text{agg}}$ values are slightly higher in Case 2 compared to Case 1 for weekdays and weekends. The increase in $P_{t,w}^{\max,\text{agg}}$ values is due to the $\text{SOC}^{\min}$ requirement in Case 2, which mandates that EVs charge at full power until their SOC value reaches $\text{SOC}^{\min}$. Nevertheless, the increase in $P_{t,w}^{\max,\text{agg}}$ is marginal, with a median value just above zero. This minimal increase could be attributed to two main factors: first, most EVs already have SOC^{arr} values greater than or equal to $\text{SOC}^{\min}$; second, for EVs where SOC^{arr} is less than $\text{SOC}^{\min}$, the power required to meet $\text{SOC}^{\min}$ is not very high.

The $E_{t,w}^{\max,\text{agg}}$ values for both weekdays (refer Fig. 10(c)) and weekends (refer 10(d)) are the same as in Case 1. The similarity is because $E_{t,w}^{\max,\text{agg}}$ is the sum of the maximum cumulative energy of all the EVs, and the number of EVs connected and their E^{dep} requirements are similar to those of Case 1.

The $E_{t,w}^{\min,\text{agg}}$ values for both weekdays and weekends are higher than those of Case 1 due to the $\text{SOC}^{\min}$ requirement. The peak median value of $E_{t,w}^{\min,\text{agg}}$ is 4 MWh and 2 MWh for weekdays and weekends, respectively,



(a) Typical weekday power metrics

(b) Typical weekend power metrics

(c) Typical weekday energy metrics

(d) Typical weekend energy metrics

Fig. 10. Quantile distribution of flexibility metrics for Case 2.

which is 1 MWh higher than in Case 1. The values are higher in Case 2 because, unlike Case 1, the amount of energy (E^{SOCmin}) needed to meet SOC$^{\mathrm{min}}$ requirement should be immediately transferred to each EV. Since $E^{\mathrm{min,agg}}_{t,\omega}$ represents the minimum cumulative energy transfer, this additional transfer of E^{SOCmin} for each EV at the start of the plugin duration contributes to higher overall values.

5.1.3. EV flexibilities for case 3

For Case 3, the shape of the $P^{\mathrm{max,agg}}_{t,\omega}$ quantile distribution is similar to that of Case 1, both for weekdays (refer Fig. 11(a)) and weekends (refer Fig. 11(b)), due to similar driving patterns. However, there is slightly higher variability in the quantile distribution, and the values of $P^{\mathrm{max,agg}}_{t,\omega}$ metric are notably lower than those of Case 1. The peak median value of $P^{\mathrm{max,agg}}_{t,\omega}$ is 2.25 MW and 1.75 MW for weekdays and weekends, respectively, 4.75 MW and 5.25 MW lower than in Case 1.

The variable frequency of EV connections means that most users do not connect their EVs to the charging point daily, which was the situation in Case 1. This varying number of connected vehicles leads to variability in the $P^{\mathrm{max,agg}}_{t,\omega}$ metric. Consequently, these irregular connections also lead to a reduced number of EVs connected to the charging point, contributing to lower $P^{\mathrm{max,agg}}_{t,\omega}$ values.

$P^{\mathrm{max,agg}}_{t,\omega}$ values are equal to zero, which is similar to those of Case 1 because EVs offers full flexibility throughout the plugin duration.

The variability of different quantile values of $E^{\mathrm{max,agg}}_{t,\omega}$ in Case 3 is slightly higher than that of Case 1, both for weekdays (refer to Fig. 11(c)) and weekends (refer to Fig. 11(d)). This difference could be primarily due to the varying number of EVs connected to the charging point on a given day, with more diverse energy requirements (E^{dep}) across different scenarios.

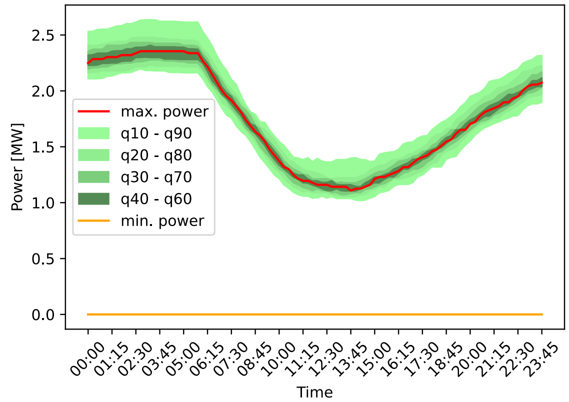
However, the peak median value of $E^{\mathrm{max,agg}}_{t,\omega}$, particularly for weekdays, is similar (11 MWh) to that of Case 1. Although the number of connected EVs is lower than in Case 1, their energy requirement, i.e., E^{dep} value, within a charging session is higher than in Case 1. In Case 3, the E^{dep} value for each user is higher because they have to meet the energy required for their weekly driving needs in fewer charging sessions than in Case 1. Therefore, at the aggregate level, the total energy could be similar.

The values of $E^{\mathrm{min,agg}}_{t,\omega}$ are significantly higher for weekdays and weekends in Case 3 than in Case 1. The peak median value of $E^{\mathrm{min,agg}}_{t,\omega}$ is 4 MWh and 2 MWh for weekdays and weekends, respectively, 2 MWh and 1 MWh higher than in Case 1. This disparity is due to the higher energy requirements (E^{dep}) of EVs in Case 3, where these vehicles need more time to meet their energy requirements compared to Case 1.

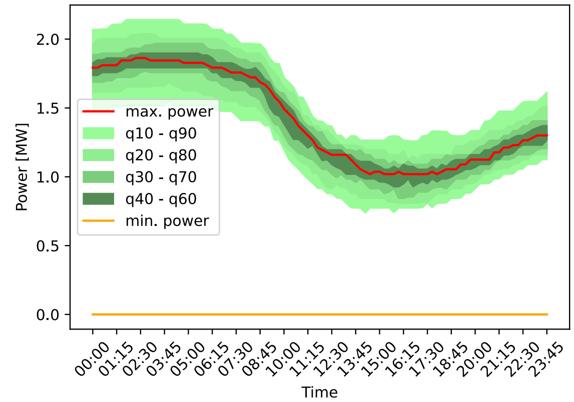
5.1.4. EV flexibilities for case 4

For Case 4, the values of $P^{\mathrm{max,agg}}_{t,\omega}$ are similar to those of Case 3, both for weekdays (refer to Fig. 12(a)) and for weekends (refer to Fig. 12(b)). The values in both cases are similar because the number of EVs connected to the charging point is similar to Case 3. Therefore, the reason for the difference in values compared to Case 1 is similar to Case 3.

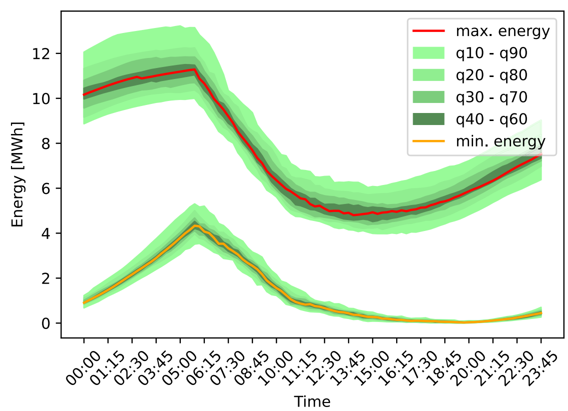
However, the $P^{\mathrm{max,agg}}_{t,\omega}$ values are slightly higher in Case 4 compared to Case 1 for both weekdays and weekends. This increase could be



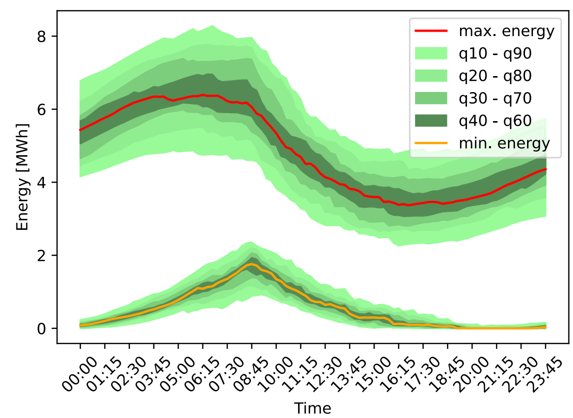
(a) Typical weekday power metrics



(b) Typical weekend power metrics



(c) Typical weekday energy metrics



(d) Typical weekend energy metrics

Fig. 11. Quantile distribution of flexibility metrics for Case 3.

primarily attributed to the $\mathrm{SOC}^{\min}$ requirement, which forces EVs to charge at full power until the $\mathrm{SOC}^{\min}$ requirement is met. Nevertheless, the increase in $P_{t,w}^{\max,\mathrm{agg}}$ is marginal, with a median value just above zero. The increase in $P_{t,w}^{\max,\mathrm{agg}}$ is minimal because the power required to meet $\mathrm{SOC}^{\min}$ is low.

The $E_{t,w}^{\max,\mathrm{agg}}$ values for Case 4 are the same as those in Case 3, both for weekdays (refer to Fig. 12(c)) and weekends (refer to Fig. 12(d)). The similarity in both cases is because the number of EVs connected to the charging point and the energy requirement (E^{dep}) of EVs is similar to that of Case 3. Therefore, the rationale behind the differences in values compared to Case 1 is similar to that of Case 3.

The $E_{t,w}^{\min,\mathrm{agg}}$ values for weekdays and weekends are higher than in Case 1. The peak median value of $E_{t,w}^{\min,\mathrm{agg}}$ is 6 MWh and 3 MWh for weekdays and weekends, respectively, 4 MWh and 2 MWh higher than in Case 1. The values in Case 4 are higher because the combination of irregular charging and $\mathrm{SOC}^{\min}$ leads to higher energy requirements (E^{SOCmin} and E^{dep}) within a charging session, which would mean that the minimum cumulative energy that should be transferred to EV would be higher compared to Case 1.

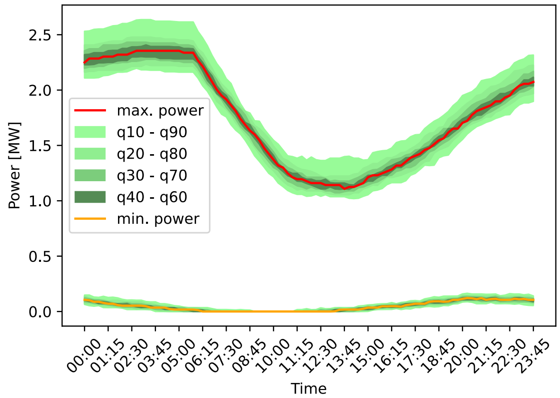
5.1.5. Comparison of EV flexibilities for all cases

When comparing the aggregated flexibility of cases with Case 1, we observe changes in both power and energy flexibility metrics for all three cases. Specifically, Case 2 exhibits an increase in $P_{t,w}^{\max,\mathrm{agg}}$ and $E_{t,w}^{\min,\mathrm{agg}}$ values compared to Case 1, attributed to the requirements of $\mathrm{SOC}^{\min}$. Case 3 exhibits a decrease in $P_{t,w}^{\max,\mathrm{agg}}$ and an increase in $E_{t,w}^{\min,\mathrm{agg}}$ values, compared to Case 1, owing to irregular EV connection to the charging point. Case 4 indicates a decrease in $P_{t,w}^{\max,\mathrm{agg}}$ and an increase in both $P_{t,w}^{\max,\mathrm{agg}}$ and $E_{t,w}^{\min,\mathrm{agg}}$ values, compared to Case 1, influenced by $\mathrm{SOC}^{\min}$ requirements and irregular EV connections to the charging point.

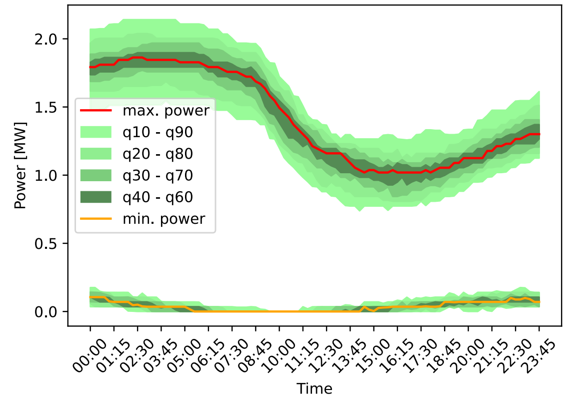
Considering that we model aggregated flexibility metrics, we can assume that all EVs connected to the charging point create a sizeable virtual battery. Hence, $E_{t,w}^{\min,\mathrm{agg}}$ and $E_{t,w}^{\max,\mathrm{agg}}$ represent the minimum and maximum energy capacity of this virtual battery, while $P_{t,w}^{\max,\mathrm{agg}}$ and $P_{t,w}^{\max,\mathrm{agg}}$ signify its minimum and maximum charging capacity. Any increase in $P_{t,w}^{\max,\mathrm{agg}}$ or decrease in $P_{t,w}^{\max,\mathrm{agg}}$ suggests a reduction in the power capacity of this virtual battery, indicating decreased flexibility. Similarly, an increase in $E_{t,w}^{\min,\mathrm{agg}}$ or a decrease in $E_{t,w}^{\max,\mathrm{agg}}$ implies a reduction in the energy capacity of the virtual battery, signifying decreased flexibility. Thus, observed increases in $P_{t,w}^{\max,\mathrm{agg}}$ and $E_{t,w}^{\min,\mathrm{agg}}$ for cases with $\mathrm{SOC}^{\min}$ requirements indicate a reduction in flexibility due to $\mathrm{SOC}^{\min}$ requirements. A decrease in $P_{t,w}^{\max,\mathrm{agg}}$ and an increase in $E_{t,w}^{\min,\mathrm{agg}}$ for cases with irregular EV connections to the charging point, indicate reduced flexibility due to irregular EV connections to the charging point.

5.2. Monetary value of EV flexibility

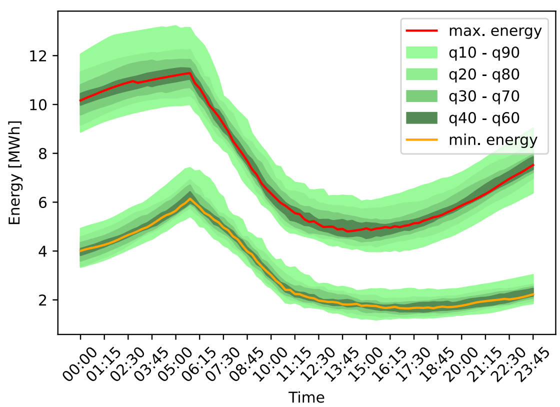
Fig. 13 illustrates the corresponding EPC incurred for procuring the energy required (87.16 MWh) to charge the EVs for one week in each month across the years 2022 and 2023. The bars represent the absolute EPC and the dashed lines represent the average EPC incurred for each case.



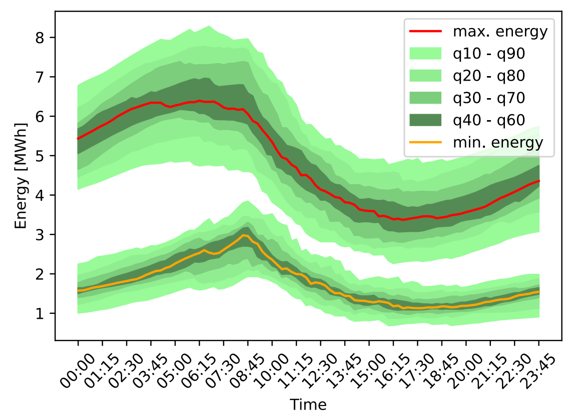
(a) Typical weekday power metrics



(b) Typical weekend power metrics



(c) Typical weekday energy metrics



(d) Typical weekend energy metrics

Fig. 12. Quantile distribution of flexibility metrics for Case 4.

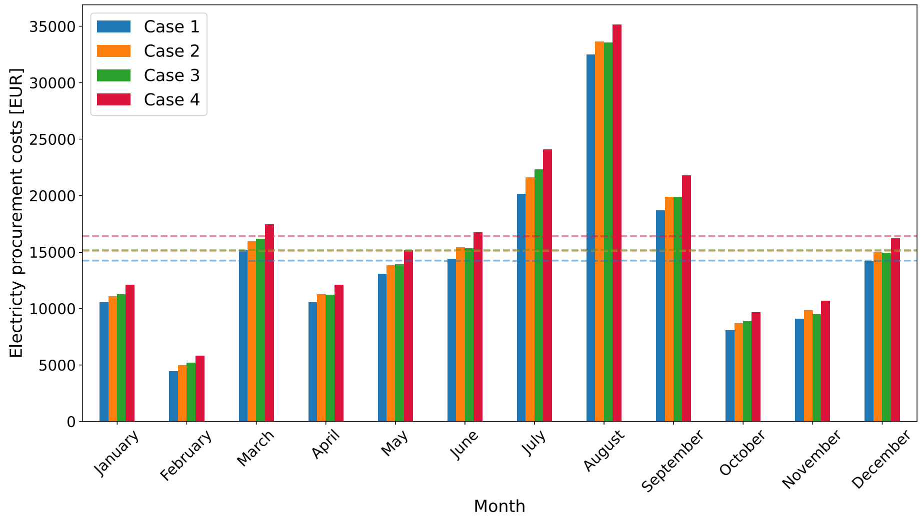
From Fig. 13(a), we can observe that in 2022, EPC are highest for August and lowest for February. In all cases, the EPC exhibit a similar trend for all three months. This trend persists in all three months, with EPC increasing for cases with SOC^{min} requirements and irregular EV connection frequency to charging points. To analyse the impact of SOC^{min} requirements and charging frequency on EPC, we compare the EPC of the different cases with Case 1, which is the base case. We selected August and February for a detailed comparison, as these months depict the lowest and highest cost increases, respectively, compared to other months in 2022 (Appendix A illustrates the relative increase in EPC when compared to Case 1 for all the months in the year 2022).

First, comparing Case 2 with Case 1 reveals that EPC increases by 3.6 % (1166 EUR) in August and 11.3 % (505 EUR) in February, demonstrating the effect of SOC^{min} requirements. Second, comparing Case 3 with Case 1 exhibits a rise of 3.3 % (1075 EUR) in August and 16.5 % (736 EUR) in February, demonstrating the effect of the frequency of EV connection to the charging point. Third, comparing Case 4 with Case 1 reveals an increase of 8.1 % (2644 EUR) in August and 30.3 % (1350 EUR) in February, demonstrating the effect of the SOC^{min} requirement and charging frequency.

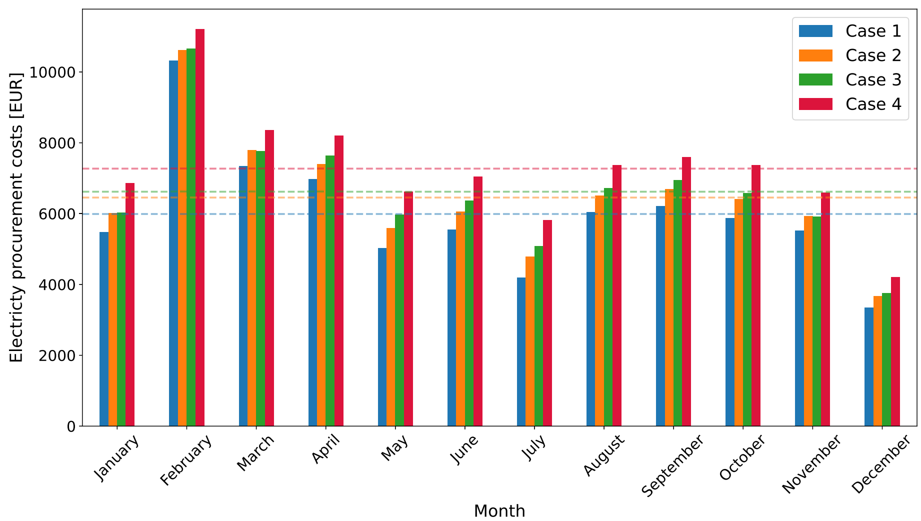
From Fig. 13(b), we can observe that in 2023, EPC are highest for February and lowest for December. In all cases, the EPC exhibit a similar trend for all the months. Although the EPC for the different cases exhibit a similar trend as in 2022, the EPC are much lower than those of 2022. Similar to the year 2022, to analyse the impact of SOC^{min} requirements and charging frequency on EPC, we compare the EPC of the different cases with Case 1, which is the base case. We selected February and July for detailed comparison, as these months depict the lowest and highest cost increases, respectively, compared to other months in 2023 (Appendix A illustrates the relative increase in EPC when compared to Case 1 for all the months in the year 2023).

First, comparing Case 2 with Case 1 reveals that EPC increases by 2.8 % (296 EUR) in February and 14 % (589 EUR) in July, demonstrating the effect of SOC^{min} requirements. Second, comparing Case 3 with Case 1 exhibits a rise of 3.3 % (341 EUR) in February and 21 % (882 EUR) in July, demonstrating the effect of the frequency of EV connection to the charging point. Third, comparing Case 4 with Case 1 reveals an increase of 8.6 % (891 EUR) in February and 38.4 % (1613 EUR) in July, demonstrating the effect of the SOC^{min} requirement and charging frequency.

In both years, the EPC are higher for the cases with SOC^{min} requirements, variable frequency of the EV connection, and combination of SOC^{min} and variable frequency of the EV connection when compared to Case 1. The increase in EPC implies that as the EV flexibility decreases, the EPC increases. When comparing the EPC between the two years, the EPC are much higher for 2022 due to high market prices, yet we still observed a notable reduction in the EPC for the cases offering higher flexibility.



(a) 2022



(b) 2023

Fig. 13. Electricity procurement costs for one week across all months.

5.3. Cost sensitivity analysis

We perform a sensitivity analysis to assess how varying the SOC^{min} and charging threshold values will affect the EPC. In our cost sensitivity analysis, we vary the charging thresholds and SOC^{min} values for all EVs. We vary the charging threshold values from 20 % to 100 % in 20 % increments, while SOC^{min} values vary from 0 % to 100 % in the same increments. The higher charging threshold implies that users connect their EVs more frequently. An SOC^{min} requirement of 100 % is similar to uncontrolled charging, where an EV does not offer flexibility, whereas 0 % is when the EV offers full flexibility i.e., energy provider can control the charging throughout the plugin duration.

Fig. 14 illustrates the EPC incurred for different combinations of charging thresholds and SOC^{min} values for February 2022 and July 2023. We selected February and July for our detailed analysis, as these months depict the highest cost variation compared to other months in 2022 and 2023, respectively (refer to Appendix B for the analysis of other months). From the sensitivity analysis of two months (refer to Figs. 14(a) and (b), we observe a trend where EPC decreases as the charging threshold value increases, and conversely, EPC tends to rise with higher SOC^{min} requirements.

From the sensitivity analysis, it is evident that the EPC varies considerably. We observe the highest EPC is 7917.68 EUR and 8335.05 EUR for February 2022 and July 2023, respectively, reflecting uncontrolled charging where EVs provide no flexibility. The lowest EPC are 4464 EUR and 4197.37 EUR, for February 2022 and July 2023, respectively, representing the combination with the highest overall flexibility (0 % SOC^{min} and 100 % charging threshold).

Furthermore, we observe a notable trend in the EPC variations concerning SOC^{min} values. The EPC remains relatively stable for certain charging thresholds until a particular value of SOC^{min}, after which the EPC escalates rapidly. For instance, for charging thresholds 80 % and 100 %, EPC is almost similar up to 80 % SOC^{min}, after which it increases significantly. This is because higher charging thresholds entail a higher SOC^{arr} value, which means that for most of EVs when they arrive, the SOC^{arr} might be already higher than SOC^{min} requirement, thus not having much impact on the EPC.

Expanding our cost sensitivity analysis, we evaluate the relative reduction of EPC for the cases with 0 % SOC^{min} and 80 % SOC^{min} compared to the EPC of 100 % SOC^{min} across various charging threshold values. With 0 % SOC^{min} reflecting a full flexibility and 80 % SOC^{min} a low flexibility case. This comparison allows us to estimate a range for potential EPC reductions when EVs provide flexibility for smart charging as opposed to uncontrolled charging where EVs provide no flexibility (100 % SOC^{min}).

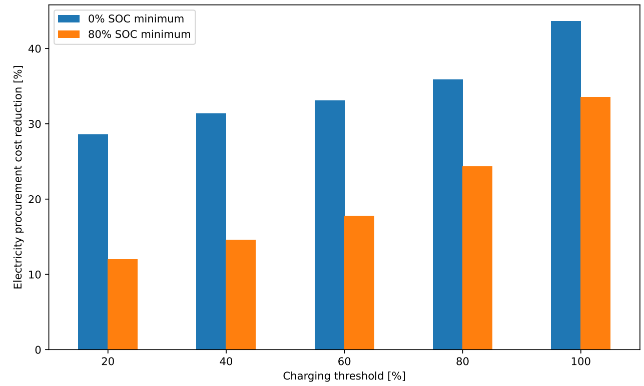
Fig. 15 illustrates the relative EPC reduction for February 2022 and July 2023 (refer to C for the analysis of other months). For 0 % SOC^{min}, the EPC reduction ranges from 28.6 % to 43.6 % in February 2022 (refer to Fig. 15(a)) and from 33.9 % to 49.6 % in July 2023 (refer to Fig. 15(b)).

Even with low flexibility (80 % SOC^{min}), we observe a substantial reduction in EPC compared to uncontrolled charging. The EPC reduction ranges from 11.9 % to 33.5 % for February 2022 (refer to Fig. 15(a)) and from 11.8 % to 36.9 % for July 2023 (refer to Fig. 15(b)).

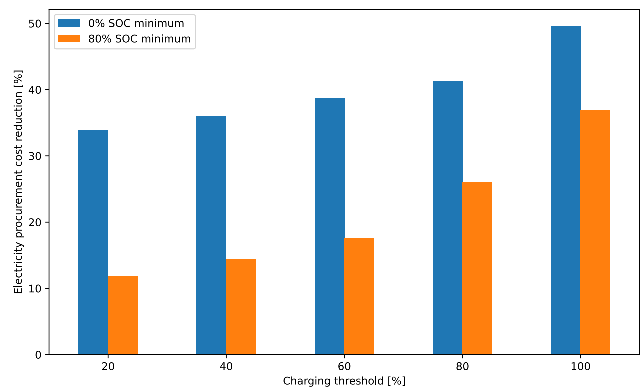
6. Discussion and limitations

6.1. Implications to energy providers

In our analysis, an increase in SOC^{min} requirements and a decrease in the frequency of EV connections to the charging point result in reduced EV flexibility, which subsequently increases overall EPC. Therefore, high flexibility, i.e., low SOC^{min} requirements and high frequency of EV connections, is desirable for energy providers. While energy providers cannot directly control the EV user charging preferences, they can incentivise users to adapt their preferences in a certain way, resulting in higher flexibility provision. Thus, users could be persuaded with monetary incentives to provide low SOC^{min} values and frequently connect their EV to the charging point.

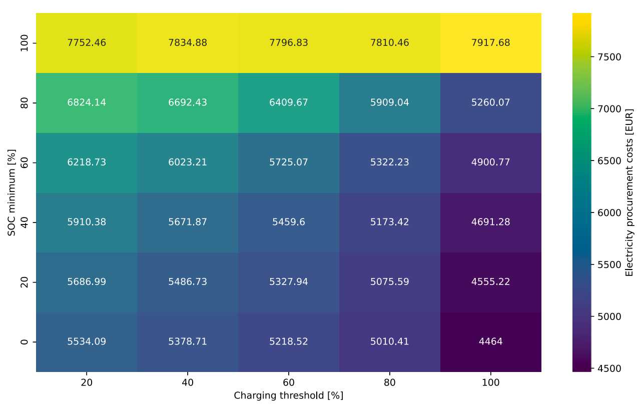


(a) February 2022



(b) July 2023

Fig. 15. Relative cost reduction of different SOC^{min} values compared to 100 % SOC^{min} values across different charging thresholds.



(a) February 2022

(b) July 2023

Fig. 14. Electricity procurement costs of one week for different SOC^{min} and charging threshold combinations.

With regard to our cost sensitivity analysis, we would like to define three cases for the SOC^{min} values to guide the discussion. We distinguish these three cases in terms of their flexibility and convenience to the users. First, we define 0 % SOC^{min} as the case offering full flexibility but low convenience. This case gives energy providers full control over charging during the plugin duration, but it can be inconvenient for users as they are unsure when their energy needs will be met. Second, we define 100 % SOC^{min} as the case offering no flexibility but high convenience. Here, users retain full control over their charging, ensuring their energy requirements are met immediately but providing no flexibility to energy providers. Third, we define 80 % SOC^{min} as offering low flexibility and maximum convenience. Energy providers can control charging only after EV reaches 80 % of the total battery, but users are assured that 80 % of their battery will be charged immediately. For most EV users, an 80 % SOC^{min} is nearly as effective as 100 %, as 80 % of the battery is sufficient for most trips, even in emergencies such as a nighttime trip to a nearby hospital. Therefore, this case also does not affect the user's convenience to a large extent.

Energy providers are concerned that users might set a high SOC^{min} to preserve their convenience, which would reduce flexibility and increase the EPC. However, our cost sensitivity analysis illustrates that even with low flexibility, energy providers can reduce their EPC up to

33.9 %, compared to no flexibility case. The EPC reduction at full flexibility is only slightly higher, at around 49.6 %. These results indicate that energy providers could achieve a similar magnitude of reduction as full flexibility, even with low flexibility, without causing much inconvenience to the users.

Our cost sensitivity analysis suggests that considerable cost reductions in low flexibility cases can be achieved when EVs connect more frequently to the charging point. The cost reductions for low flexibility are notably higher for higher charging thresholds (60 %–100 %). Many EV owners tend to plug in their vehicles less frequently, i.e., at lower battery thresholds, fearing potential battery degradation. However, the preferable operating range is typically between 20 % and 80 % [22]. Hence, energy providers could incentivize users to plug in their vehicles when their battery is between 60 % and 80 % (which is still within the preferable operating range), benefiting both users and energy providers.

6.2. Limitations and Outlook

There are several limitations in our study that we intend to address in future research.

We assumed linear charging when calculating EV flexibilities. In reality, charging power decreases as the battery's SOC approaches full capacity, which may extend charging times and slightly reduce flexibility. Additionally, battery degradation over time may affect charging efficiency and usable capacity, further influencing available flexibility. However, when flexibility is aggregated across multiple EVs, these individual discrepancies are minimized, resulting in a relatively small impact on the monetary value of EV flexibility in spot market trading. Future research could incorporate more realistic charging profiles to improve the accuracy of the flexibility modelling.

Beyond charging dynamics, our flexibility estimations rely on synthetic mobility data based on German driving patterns. While this approach provides a structured dataset, it does not fully capture real-world uncertainties, such as seasonal variations. For example, holiday mobility patterns often differ significantly from typical workdays, influencing driving and charging behaviours. Additionally, our estimations do not account for variability in vehicle specifications, such as battery size. Since battery capacity can influence user charging preferences—particularly their SOC^{min} thresholds—it may affect both the flexibility provided by EVs and overall user behaviour. Future studies could integrate real-world data to enhance modelling accuracy, refining scenarios and adapting them to specific periods.

Moreover, while we provide general recommendations to energy providers on incentivizing users to adapt their charging preferences for greater flexibility at an aggregated level, we did not differentiate between demographic factors such as income, urban versus rural location, or access to home charging. Different demographic groups may respond differently to incentives for flexible EV charging. Future research could explore how various user segments react to different levels of monetary incentives, enabling more tailored strategies that optimise flexibility provision across diverse demographic profiles.

When estimating the monetary value of flexibility, our model assumes perfect foresight for electricity prices for simplicity. However, in reality, energy providers face price uncertainty. Future research could address this limitation by incorporating uncertain price scenarios or integrating price forecasting techniques into the optimisation process, making the model more reflective of real-world market conditions.

The role of bidirectional charging (V2G) also warrants further exploration. With V2G, providers could arbitrage price differences across markets, potentially increasing revenue compared to unidirectional charging, as demonstrated in [25,31]. However, revenue potential depends on users' willingness to allow battery discharge, which varies and should be considered in future assessments. Integrating these behavioural aspects into flexibility modelling could provide a more realistic assessment of V2G's benefits.

Beyond economic optimisation, aligning EV charging with periods of high renewable energy availability enhances sustainability by reducing reliance on fossil-based electricity. While our approach indirectly captures this effect—since lower electricity prices often coincide with higher renewable generation—future studies could explicitly integrate renewable energy forecasts into optimisation models. A multi-objective approach that balances cost-efficiency with sustainability considerations could provide deeper insights into effectively managing EV charging under real-world conditions.

Our study focuses on energy providers who leverage aggregated EV flexibility to minimize costs while trading in the market and procuring power for the entire fleet. Yet, when allocating power to individual EVs, grid constraints may restrict the ability to shift all charging to lower-cost periods, potentially leading to additional redispatch costs, thereby diminishing the financial benefits of flexible charging. Future research could integrate these constraints into optimisation models to better assess their impact on cost savings and the feasibility of flexible charging strategies in real-world applications.

Despite these limitations, they do not diminish the key conclusion of our study: EVs possess significant flexibility that energy providers can utilise to reduce their EPC, even under the uncertainties considered in this work.

7. Conclusion

Our paper evaluated the impact of uncertain user behaviour on the EV flexibility potential and its monetary value in both day-ahead and intraday markets. We consider uncertainties arising from variable driving patterns and charging preferences. We introduced 52 distinct scenarios to model uncertainties in driving patterns effectively. Regarding charging preferences, our paper considered variations in both the SOC^{min} requirement and the frequency with which users connect their EVs to charging points. By assuming four use cases that reflect different possibilities of these charging preferences, we computed flexibility for each scenario using a dedicated flexibility model. We then used these flexibility scenarios as input to our scenario-based robust optimisation model to calculate the EPC for each use case. We calculated the EPC for each use case for one week across all months for 2022 and 2023.

Our findings indicate that a decrease in the frequency of EV connections to the charging point and an increase in the SOC^{min} requirement resulted in reduced EV flexibility, subsequently leading to increased EPC. The cases' EPC were much higher in 2022 than in 2023 due to high market prices. Nevertheless, we still observed a notable reduction in the EPC for the cases offering higher flexibility in 2022.

We also performed a cost sensitivity analysis, where we varied the charging thresholds- below which users plugin their EVs and SOC^{min} values and calculated the corresponding EPC for all months in the years 2022 and 2023. We observed the highest reductions in EPC for the months of February and July in 2022 and 2023, respectively, when EVs offer flexibility as opposed to uncontrolled charging where EVs offer no flexibility.

The reductions in EPC when EVs offer high flexibility (0 % SOC^{min} and 100 % charging threshold) were up to 43.6 % for February 2022 and 49.6 % for July 2023. Furthermore, we found that the EPC reduces up to 33.5 % for February 2022 and 36.9 % for July 2023 even when SOC^{min} values are as high as 80 % when compared to 100 % SOC^{min} values. These results indicate that an 80 % SOC^{min} achieves nearly the same EPC reduction as when 0 % SOC^{min} values. Our findings outline that flexible EVs charging thus possesses high economic value, allowing energy providers to achieve substantial monetary gains with minimal impact on user convenience.

CRediT authorship contribution statement

Raviteja Chemudupaty: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Ramin Bahmani:** Writing – original draft, Validation, Methodology, Conceptualization. **Gilbert Fridgen:** Writing – review & editing, Supervision, Funding acquisition. **Hanna Marxen:** Writing – review & editing, Writing – original draft, Conceptualization. **Ivan Pavić:** Writing – review & editing, Validation, Supervision, Conceptualization.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used Grammarly and ChatGPT in order to improve readability and language. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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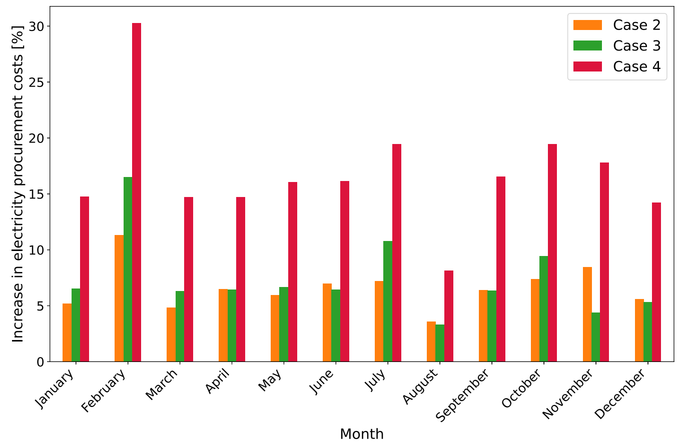
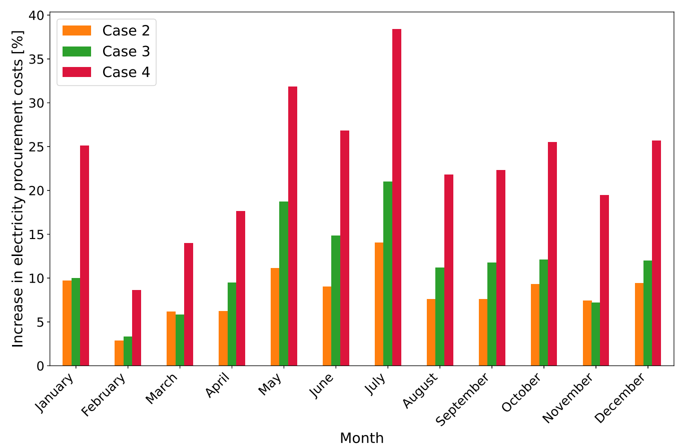
Appendix A. Relative values of increase in EPC for different use cases

See Fig. A.16(a) and (b).



(a) 2022

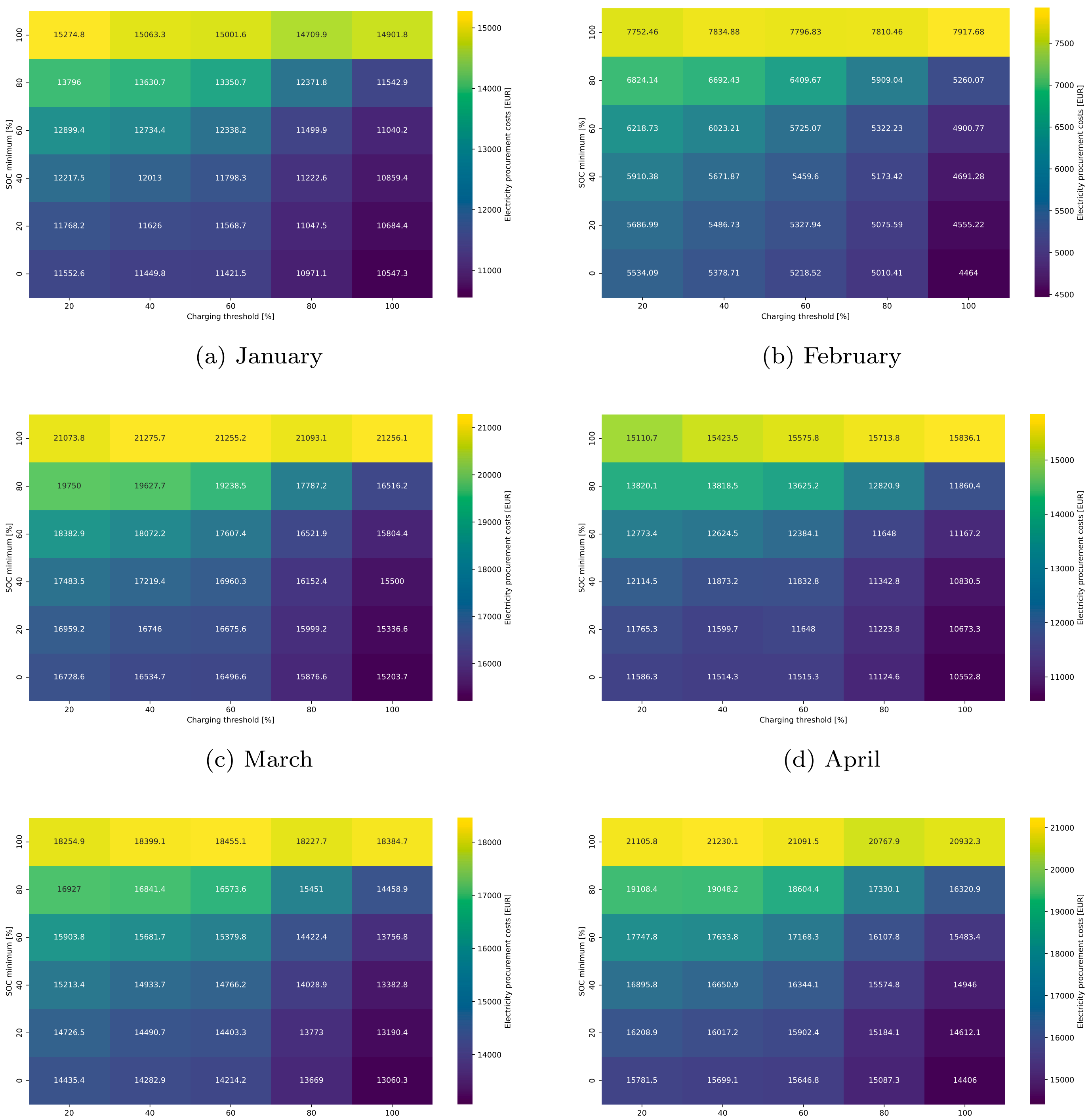


(b) 2023

Fig. A.16. Electricity procurement cost reduction for different cases when compared to Case 1 for one week across all months.

Appendix B. Cost sensitivity analysis for all months across the years 2022 and 2023

See Figs. B.17 and B.18.

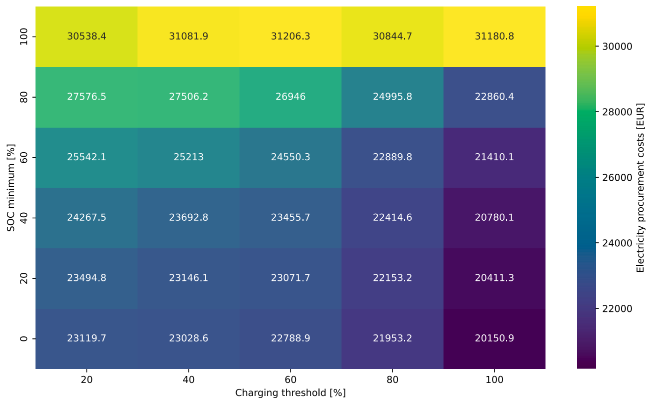


(a) January (b) February

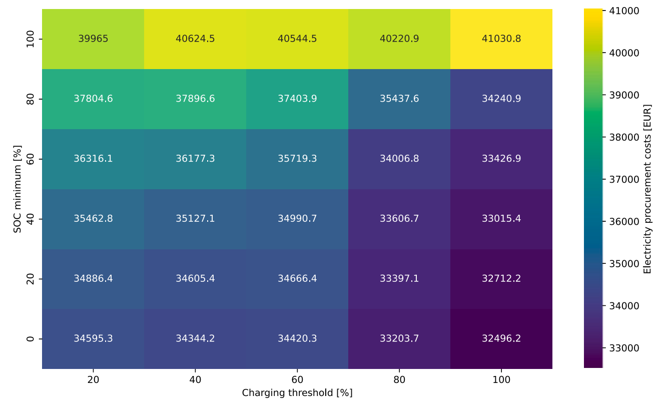
(c) March (d) April

(e) May (f) June

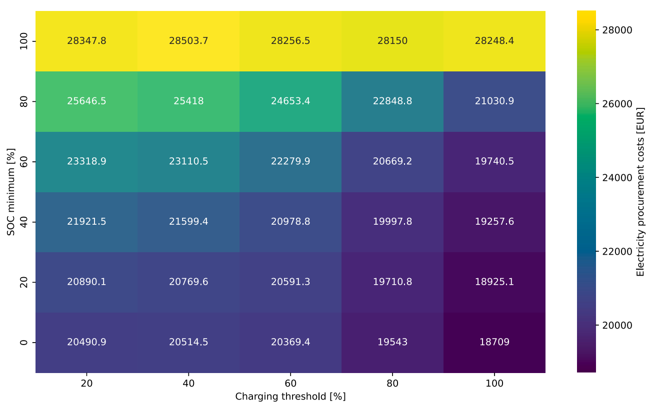
Fig. B.17. Electricity procurement costs of one week for different SOC^{min} and charging threshold combinations for each month in 2022.



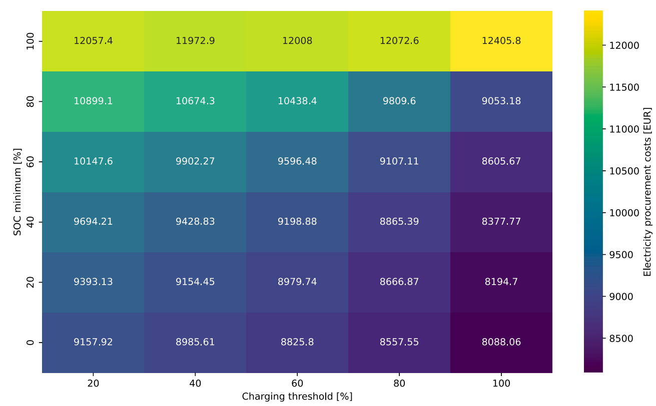
(g) July



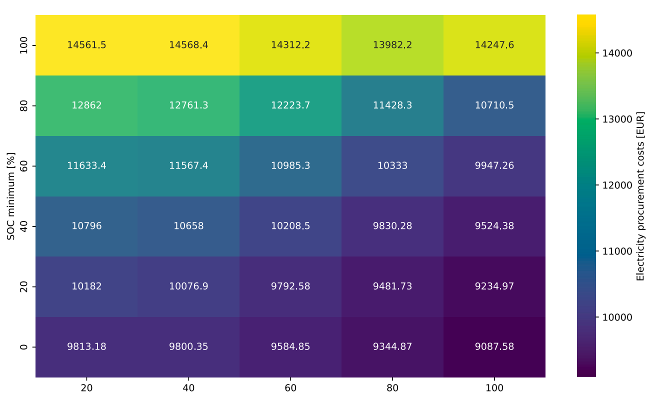
(h) August



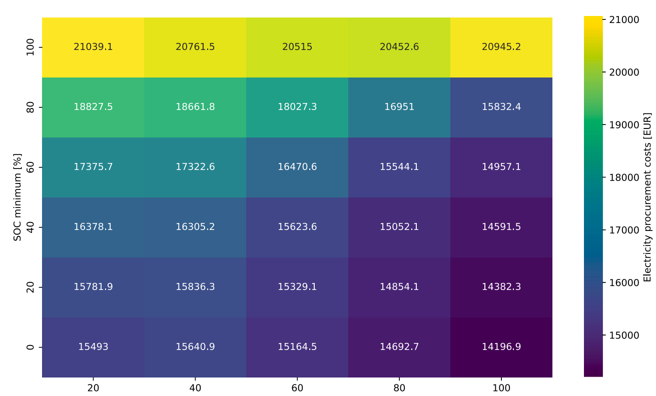
(i) September



(j) October

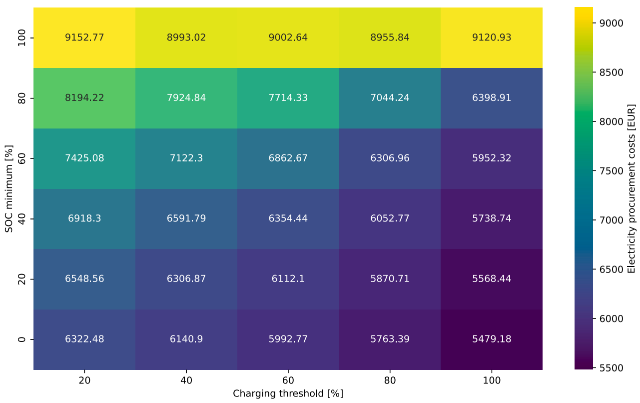


(k) November

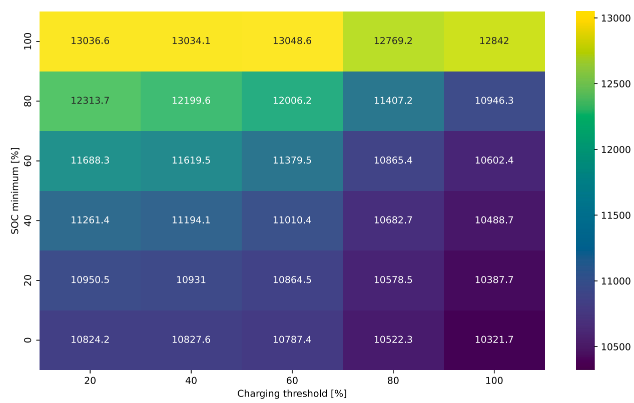


(l) December

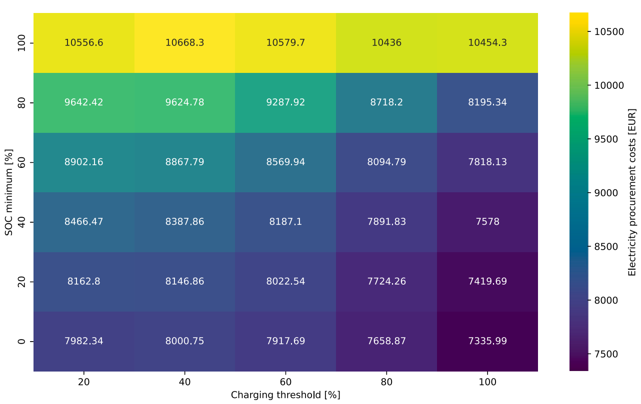
Fig. B.17. (*Continued*)



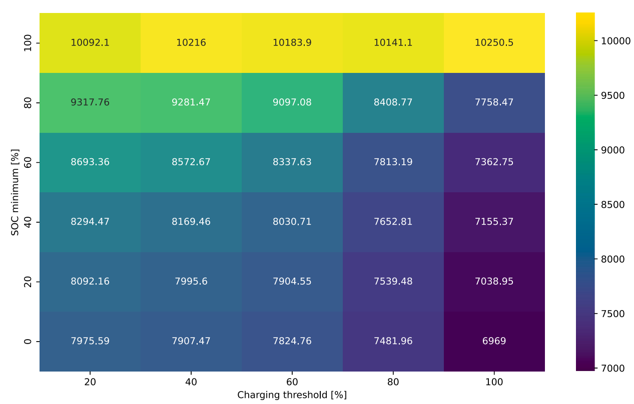
(a) January



(b) February



(c) March



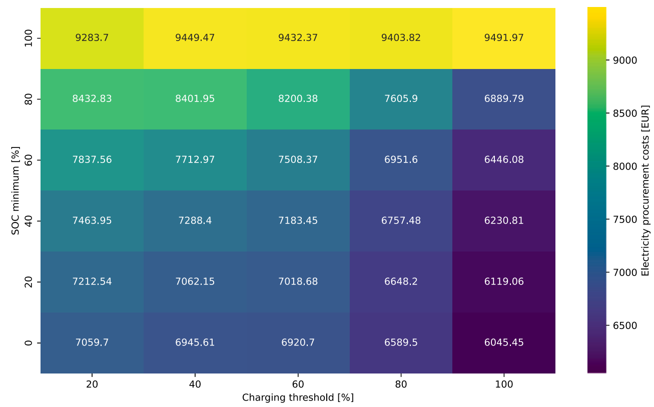
(d) April

(e) May

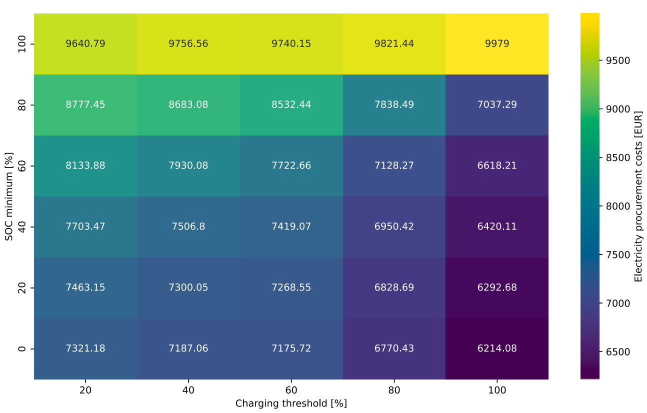
(f) June

Fig. B.18. Electricity procurement costs of one week for different SOC^{min} and charging threshold combinations for each month in 2023.

(g) July



(h) August



(i) September

(j) October

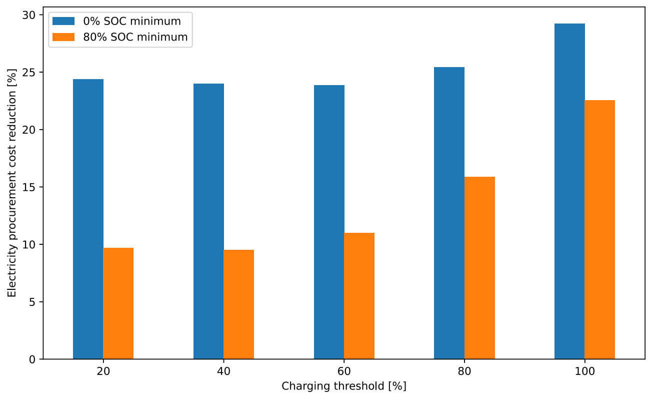
(k) November

(l) December

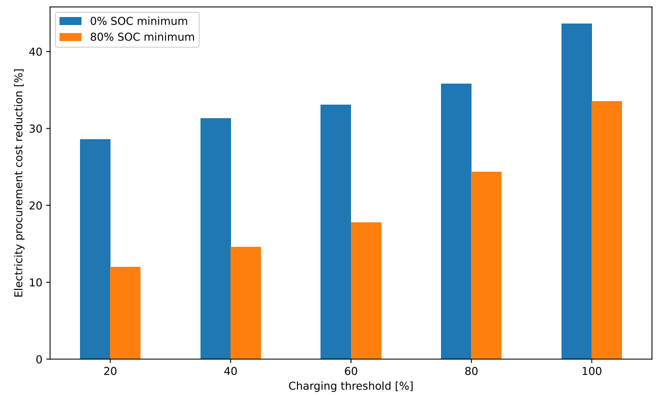
Fig. B.18. (*Continued*)

Appendix C. Relative reduction of EPC for different SOC^{min} for all months across the years 2022 and 2023

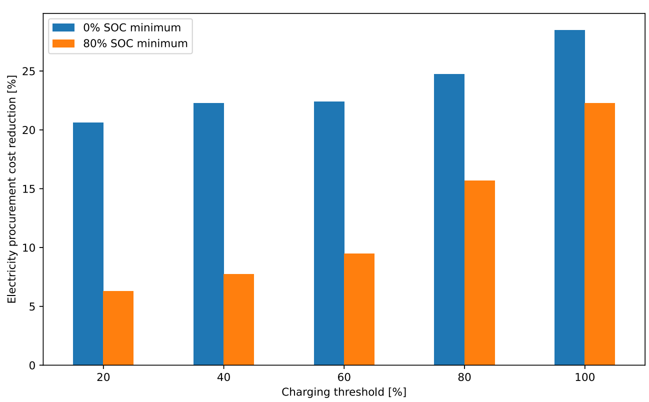
See Figs. C.19 and C.20.



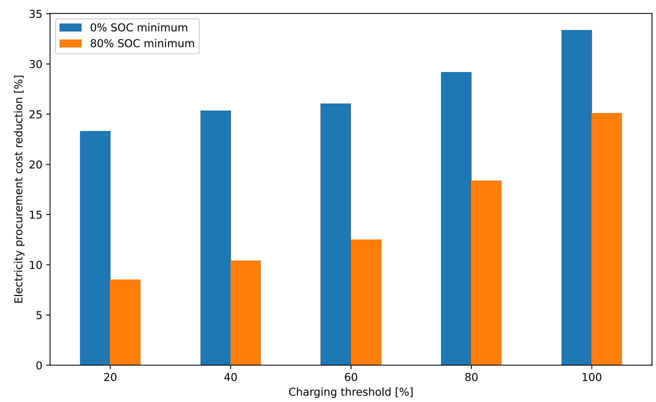
(a) January



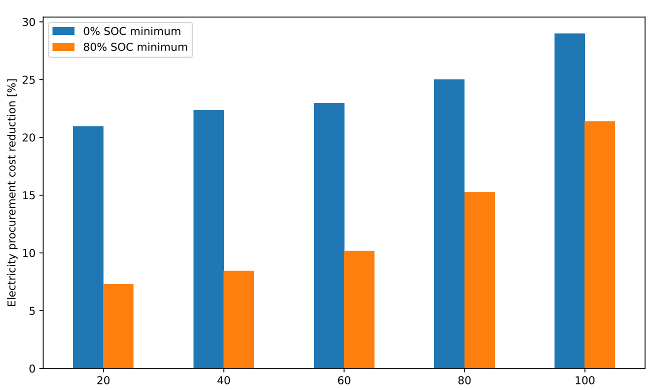
(b) February



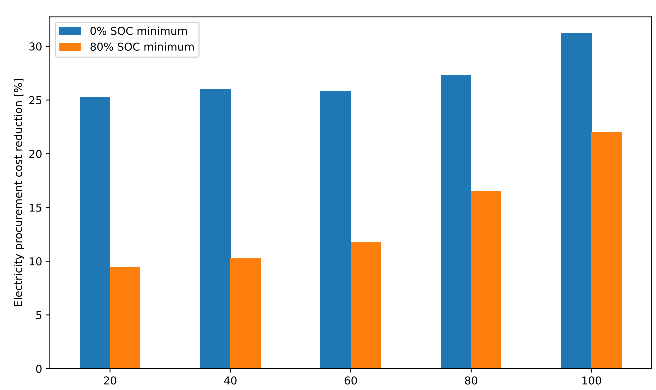
(c) March



(d) April

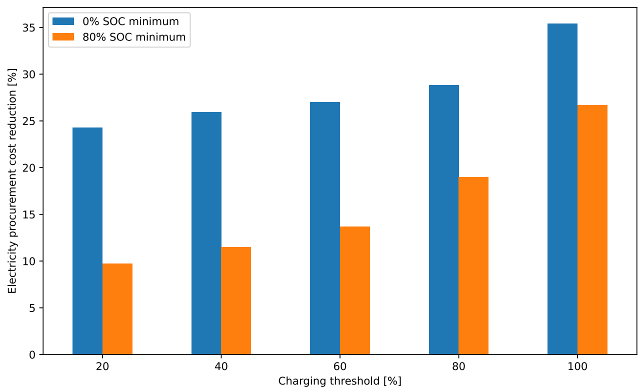


(e) May

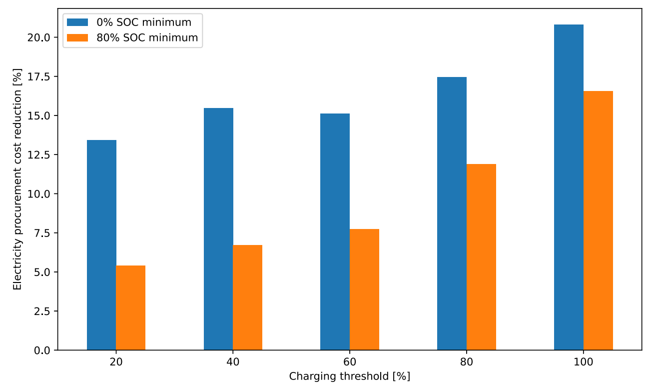


(f) June

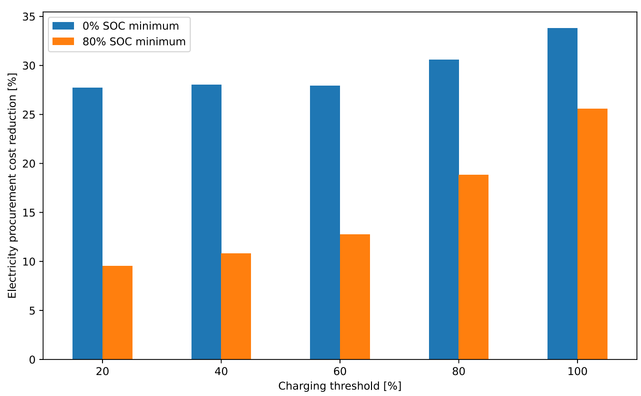
Fig. C.19. Relative cost reduction of different SOC^{min} values compared to 100 % SOC^{min} values across different charging threshold for each month in 2022.



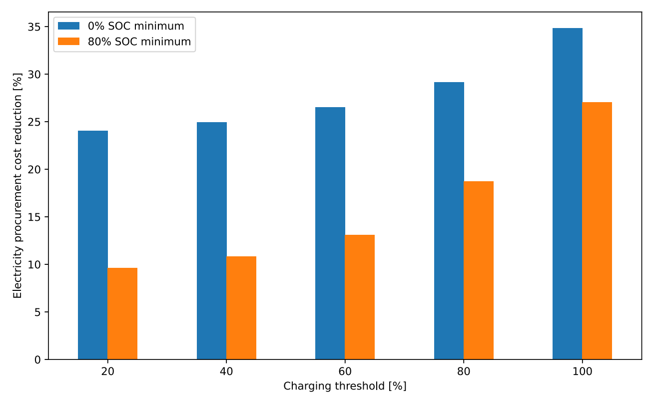
(g) July



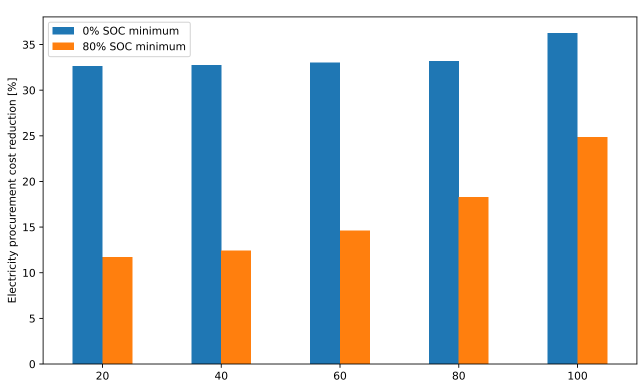
(h) August



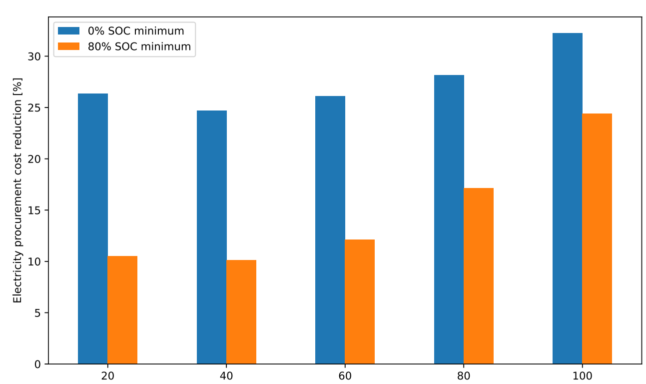
(i) September



(j) October

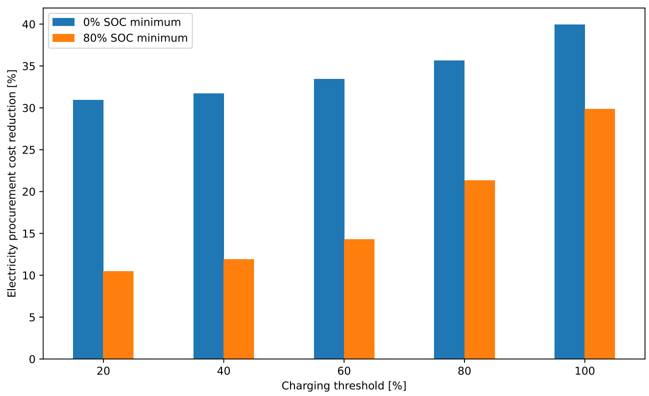


(k) November

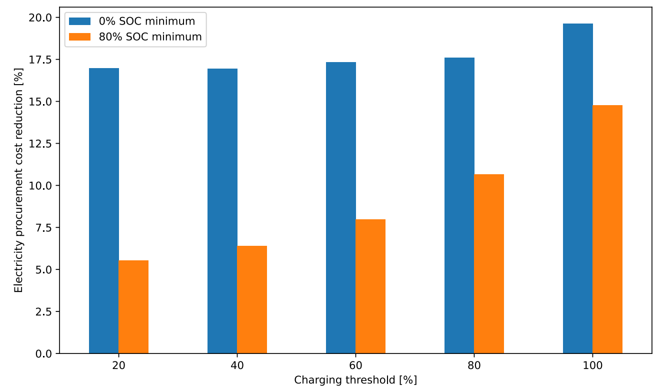


(l) December

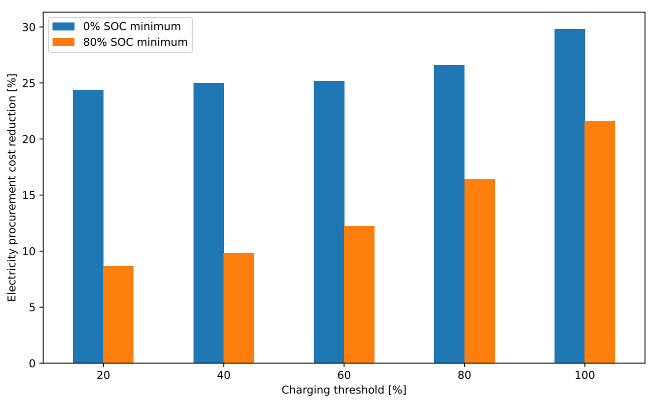
Fig. C.19. (*Continued*)



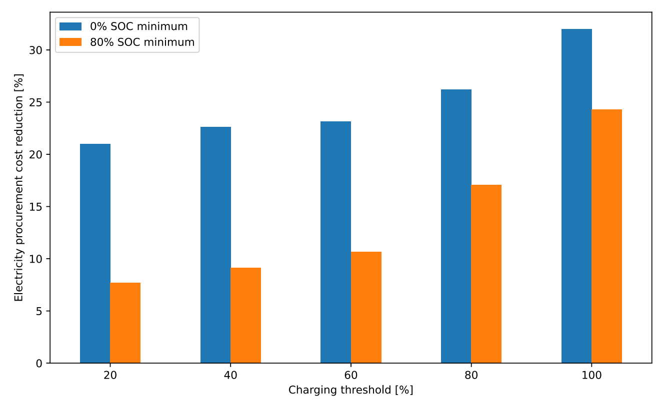
(a) January



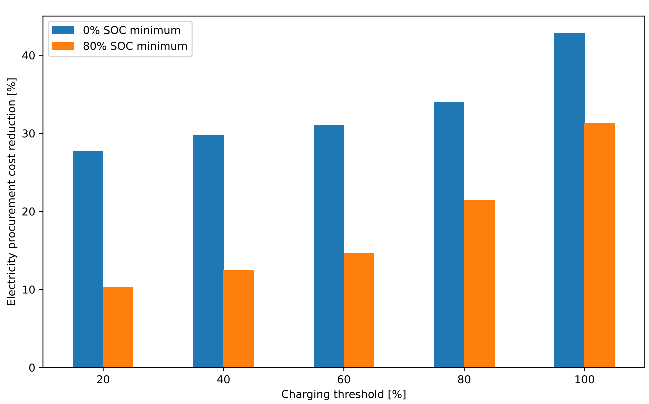
(b) February



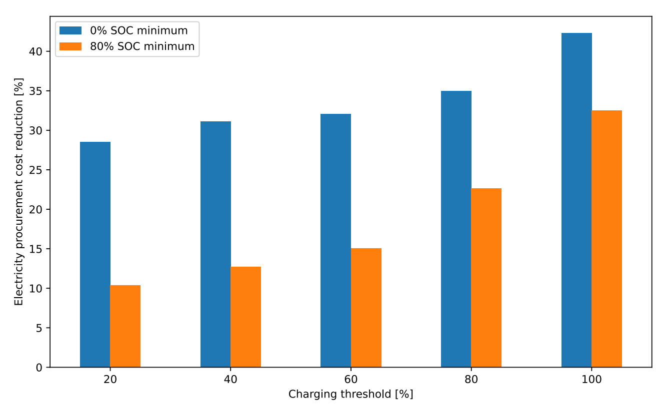
(c) March



(d) April

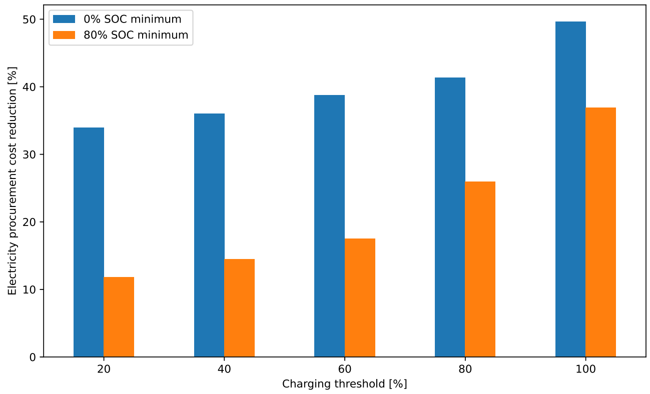


(e) May

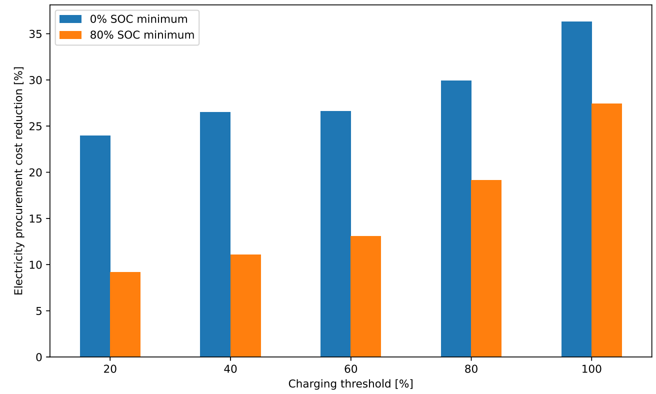


(f) June

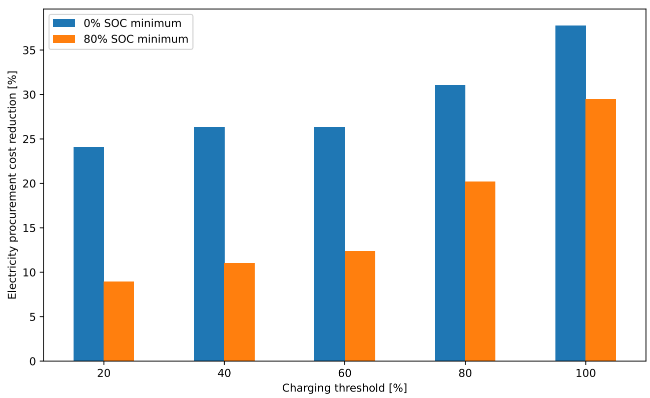
Fig. C.20. Relative cost reduction of different SOC^{min} values compared to 100 % SOC^{min} values across different charging threshold for each month in 2023.



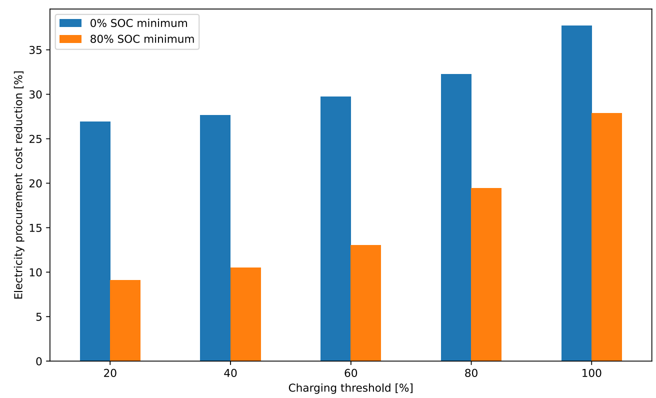
(g) July



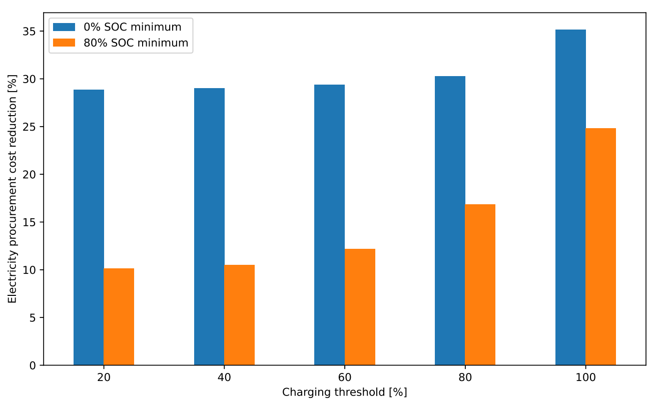
(h) August



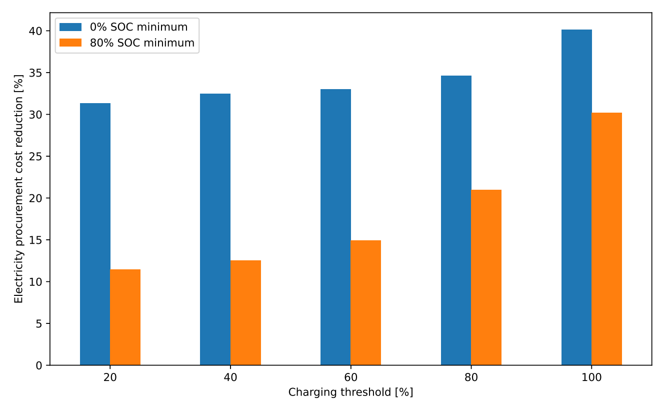
(i) September



(j) October



(k) November



(l) December

Fig. C.20. (*Continued*)

Data availability

Data will be made available on request.

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A.3.6 Research Paper 6 - Optimizing Trading of Electric Vehicle Charging Flexibility in the Continuous Intraday Market under User and Market Uncertainties

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Optimizing trading of electric vehicle charging flexibility in the continuous intraday market under user and market uncertainties

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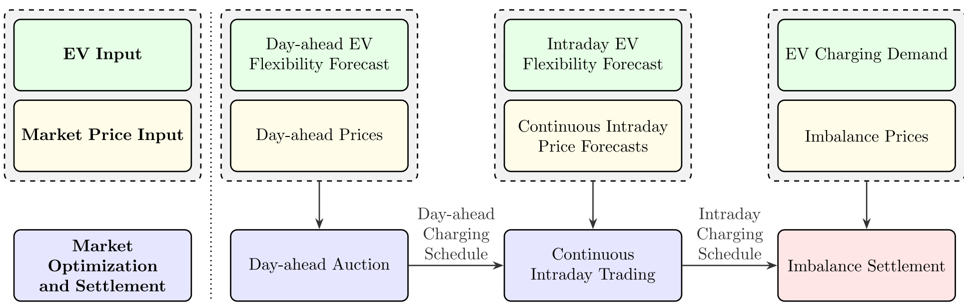
GRAPHICAL ABSTRACT



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ABSTRACT

The rise in electric vehicles (EVs) challenges energy suppliers with unpredictable charging behavior, making demand forecasts less accurate and increasing financial risks from power imbalances. In Europe, retailers can trade these imbalances in short-term markets like the continuous intraday (CID) market. By controlling EV charging times, suppliers can shift charging to periods with lower prices, potentially benefiting financially. However, the financial gains from trading this flexibility in the CID market remain uncertain due to EV user behavior and price fluctuations. In this study, we develop and test trading strategies designed to manage the power needs of a fleet of 1000 EVs across different segments of short-term electricity markets, focusing on the day-ahead (DA) auction, and the CID market. To address EV-use uncertainty, we take an initial EV charging flexibility forecast for the DA auction, and an updated forecast for the CID market. We find that trading in the CID market reduces the overall cost of making power purchases by capitalizing on the flexibilities of EV charging times. Our results suggest that energy suppliers trading in the CID market significantly reduce their financial risk, even when there are high margins of error in EV flexibility forecasts. In our scenario with the highest deviation between the DA and intraday (ID) flexibility metrics, applying the best CID strategies yielded an average yearly profit of €37.52 and €4,840.63 in 2019 and 2022 respectively. In comparison to the baseline strategy, which clears volumes as imbalances, the corresponding financial savings amounted to €1978.52 and €16,632.25, respectively.

1. Introduction

There has been significant growth in the use of EVs in recent years, boosted by regulation and the provision of state-financed incentives. As this growth is expected to continue in the coming years [1], energy suppliers will need to meet growing power demands for EV charging [2].

Energy suppliers use EV demand forecasts to help them plan, with these often based on historical driving and charging patterns [3].

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However, due to the variable nature of EV users' driving behaviors and their evolving charging preferences, discrepancies arise between forecast and actual charging demand [4]. These discrepancies might pose financial risks for energy suppliers, particularly in European markets where market participants pay penalties if there are "imbalances" between expected and actual demand [5].

Energy suppliers in Europe can mitigate power imbalance penalties by participating in short-term electricity markets, such as the DA market and the CID market. In Europe, the main difference between these markets is their gate closure times. In the DA market, gate closure is typically around noon on the day prior to the product's due delivery date. In the CID market, trading occurs up to a few minutes before delivery, thus enabling energy suppliers to adjust schedules to real-time demand [5]. Furthermore, when charging EVs in a controlled manner (i.e. using "smart charging" techniques), EVs can serve as a flexible asset [6,7]. Energy suppliers can leverage the flexibility provided by EVs to charge the vehicles when prices are lower, enabling the energy supplier to reduce procurement costs [8,9]. However, there remains a lack of clarity regarding the potential financial gains and risks for energy suppliers regarding the trading of EV charging flexibility in the CID market. This is due to uncertainties in EV usage and electricity market price fluctuations.

In the interests of facilitating EV flexibility trading in the CID market, rolling window (RW) horizon optimization methods have been proposed [10,11]. RW horizon optimization models allow energy suppliers to adapt dynamically to CID market conditions. By using a sequential trading strategy, energy suppliers can first acquire most of the power required to satisfy charging needs from the DA market while minimizing costs, and then also realize arbitrage gains by trading on the CID market [11,12]. Modeling price uncertainties in the CID market is achieved by modeling different price scenarios with their associated probabilities [12,13]. When modeling EVs flexibility, many authors [11,12,14] assumed that the forecast demand from EVs would remain constant when trading in the DA and CID markets.

Relying solely on the same DA EV demand forecasts when trading in the CID market could be impractical. DA demand forecasts (including EV power requirements) are typically generated at least 36 h before delivery, hence increasing the likelihood of inaccuracies due to changed circumstances. The closer a forecast is made to delivery time, the more accurate it will be thanks to the integration of the latest user data, such as on-going plug-in and plug-out times. Also, using the same forecast for both DA and CID markets risks overlooking potential additional imbalance costs stemming from changes in demand for EV charging capacity. Furthermore, including price uncertainty in modeled scenarios requires prior knowledge of market prices, as these scenarios often fit the whole modeling interval [12]. However, future market prices are difficult to predict, leading to unrealistic forecast scenarios which are poorly suited for practical applications. These require dynamic adaptation to changes in market prices. In our paper, we propose a novel optimization model that takes account of the uncertainties arising from (1) EV charging flexibility, and (2) price volatility in the CID market.

To effectively model the uncertainties implicit in the provision of EV charging flexibility, we quantify the flexibility of an EV fleet by stochastically combining individual flexibility metrics derived from a synthetic mobility dataset [15]. In our paper, we focus solely on the demands of EV charging at home, specifically unidirectional charging. Accordingly, we calculate the flexibility metrics for EVs connected to home charging stations. These flexibility metrics include measurements of power and energy over time. These metrics provide insights into the extent to which charging power can be adjusted at each time step of the process, while still ensuring that the EV battery receives sufficient charge to meet the user's needs when they are ready to depart. We generate two sets of flexibility metrics: one that serves as a forecast for the DA period, and a subsequent ID set updates the former, which then serves as a forecast for all ID trading activities.

To realistically capture price uncertainty in the CID market, we create a price forecasting model that features the average of the four most recent transactions in the current product. We thereby incorporate the latest market price information into the model [16]. This approach allows for optimized decisions to be made, given the difficulty of anticipating future CID market price movements. In contrast, we use realized market price data to evaluate the results of the optimization process, thus measuring performance against real-world conditions.

Consequently, in this paper, we examine three different trading strategies. In all three strategies, we first seek to procure most of the power needs required for EV charging from the DA market using the DA EV flexibility forecast. This is done while also seeking to minimize costs. During the subsequent ID period, market positions must be updated to account for the updated ID EV flexibility forecast. The three strategies feature different approaches to rescheduling during the ID period:

1. **Baseline Strategy**: This strategy settles power volumes necessary to fulfill the ID schedule for the imbalance price, known as "regelzonen bergreifender einheitlicher Bilanzausgleichsenergiepreis" (cross-control area uniform balancing energy price) (reBAP) in Germany [17]. The strategy minimizes the difference between DA and ID power needs, thereby reducing imbalances and the associated costs.
2. **Static CID Strategy**: Similar to the *baseline strategy*, this approach makes the same power volume adjustments but settles them in the CID market instead of treating them as imbalances. For simplicity, the strategy uses the ID_1, a price index published by the European Power Exchange (EPEX), which reflects the price during the final trading hour of each product in the CID market [18].
3. **Dynamic CID Strategy**: This strategy continuously adjusts positions in the CID market using a RW approach. The RW method allows multiple re-optimizations during the CID trading window, leveraging EV charging flexibility to arbitrage from changing prices between products trading in parallel.

We evaluate all strategies on German EPEX market data for two separate years, 2019 and 2022, thereby providing an understanding of the strategies' efficacy in different market conditions. Specifically, we quantify the benefit of adjusting positions taken in the DA market by trading in the CID market, as opposed to settling deviations as imbalances [5].

The remainder of the paper is structured as follows. Section 2 contains an introduction to the European wholesale power markets, particularly to CID markets, using Germany as an example. Furthermore, we discuss the literature on EV power flexibility modeling and trading. Section 3 introduces our sequential optimization model and CID trading strategies. Section 4 gives an overview of the data used in our paper. Section 5 covers the scenarios used for our simulations. Section 6 presents and discusses our simulation results. Section 7 concludes the paper.

2. Background and related work

Section 2.1 provides a brief overview of European electricity markets to facilitate understanding of the rest of the paper. Subsequently, Section 2.2 reviews related work and situates our study within the existing literature.

2.1. Background: Electricity spot markets

In Europe, power market participants such as energy suppliers can trade in short-term markets to reduce their demand and supply imbalances until just a few minutes before delivery. Although these markets are technically futures markets that feature a lag between trading and physical delivery, they are commonly referred to as spot markets [5]. Germany serves as an instructive case, as it is one of Europe's largest power markets by traded volume [19]. The German spot market includes a DA auction and an ID market. The ID market is divided into two parts: an auction market, known as the intraday auction (IDA) market, and a continuous market, referred to as the CID market. Products traded in the spot market are characterized by their different delivery time intervals, which can be one hour, thirty minutes, or fifteen minutes in length [20]. Within the German market, hourly products exhibit the highest liquidity, followed by quarter-hourly products [19,21]. Market participants such as energy suppliers can meet their short-term power needs by participating in the different parts of the spot market.

To participate in the European DA market, participants submit hourly orders to the DA auction, which clears through an auction mechanism. Orders can contain two types of offers: (1) bids, i.e., prices participants are willing to pay to buy power, and (2) asks, i.e., prices they are willing to accept to sell power. In Germany the DA auction takes place every day at noon for all hours of the following day [22]. Upon reaching the gate closure time (after which no more offers can be posted), a clearing algorithm matches these orders to establish a single product-specific clearing price for each market area, such as the German-Luxembourgish market area, adhering to the merit order principle [23].

While it is only possible to trade hourly products in the European DA market, the European ID market also allows trading in thirty minute and fifteen minute products [24]. The IDA works similarly to the DA auction and takes place every day at 3 PM for the products with delivery during the following day [22]. Unlike auctions, where all orders are cleared simultaneously based on the merit order principle, continuous trading in the CID market enables bids to be cleared continuously throughout the trading period. At 3 PM, trading in the European CID market starts [25]. In the CID market, the trading system instantaneously clears bids and asks whenever an ask price undercuts a bid [26]. In Germany, the CID market closes five minutes before delivery, i.e., before the start of the respective product.

After ID market closure ex-post imbalances are handled by transmission system operators (TSOs) [27]. All wholesale market participants belong to a balance responsible party (BRP), which compensates the TSOs for activating the balancing services required to minimize the imbalances caused by the activity of market players. It is important to note that the compensation can be negative, indicating a reversal in the direction of payment. In Germany, the compensation, (i.e., the imbalance price) is called the reBAP [17].

2.2. Related work: EV smart charging algorithms

Smart charging enables energy suppliers to manage EV charging, thereby reducing procurement costs by charging EVs when electricity prices are lower [28,29]. Properly estimating EV flexibility is crucial in developing smart charging algorithms. By accurately estimating the flexibility provided by EVs, energy suppliers could determine the potential for shifting the charging patterns while meeting EV users' energy requirements. This flexibility, derived from historical mobility patterns and charging preferences, requires accurate modeling of EV usage [3].

EV usage is subject to several uncertainties due to variable driving patterns and charging preferences. EV uncertainties could be related to the number of vehicles connected to charging points at any moment, the arrival and departure times of the vehicles, and the energy required for powering EVs [30,31]. To capture EV uncertainty, the likelihood of various parameters, such as trip distance, trip duration, trip start/end times, and others, are characterized by probability distribution functions (PDFs) [32].

These PDFs then serve as an input to Monte Carlo simulations, where stochastic EV usage patterns are modeled by drawing various EV parameters from the PDFs [33,34]. Another approach to model the stochastic EV usage patterns is by using a Markov chain. In a Markov chain, the transition between driving, parking/charging at different locations (e.g. workplace, home, commercial areas), and other states are determined by using transition probabilities [35,36]. The transition probabilities give the likelihood of the EV moving from one state to another in the next time step, with this based solely on the current state. These aid in developing a discrete-time state Markov chain which captures the spatio-temporal dynamics of EV usage over defined intervals (15 min, 30 min, 1 h) for a specific period (week, month, year) [15,37].

With these usage patterns as inputs, the charging demand is estimated by implementing an uncontrolled charging regime in which an EV is charged at full power until its requested energy need is fulfilled [38]. The energy required for a charging session is assumed to be equal to the estimated energy consumption of the EV for its next trip, or the energy required to reach maximum battery capacity. The necessary charging time can be calculated from the maximum charging power and the required energy. The load profile, which gives an electricity consumption pattern of each EV, is calculated and superimposed, representing the overall demand of EVs at each time step for a given time period [39,40].

To smart charge EVs, EV charging scheduling can be formulated as a mathematical optimization problem. This is because smart charging typically involves allocating resources (i.e., charging power) to maximize the objectives (such as minimizing energy supplier costs) while satisfying constraints (e.g. user requirements). In this notion, smart charging algorithms can employ stochastic optimization models to optimally schedule EV charging whilst dealing with uncertainties [41]. A stochastic optimization model utilizes probability distributions to represent uncertainties, allowing the model to account for a spectrum of potential scenarios [42]. When formulating objective functions to minimize costs for an energy supplier, various approaches are used. For instance, the objective function might focus on maximizing the expected profits in the DA market by calculating the average performance across different EV demand scenarios, based on their respective probabilities [43]. Additionally, some stochastic optimization models incorporate risk measures such as conditional value at risk (CVaR) [41,44,45] or variance [42] into the objective function, which could be to minimize the costs in the DA market [44] or maximize the energy suppliers profits [45]. Authors in [46] propose a hybrid stochastic and Information Gap Decision Theory (IGDT) optimization to maximize the EV aggregator profits. EV uncertainties are modeled with scenarios, while price risk is handled through IGDT.

Authors in [41,43,44,46] focused on the trading of EV flexibility primarily in DA markets. This is because these markets often exhibit more stable and predictable price patterns compared to ID markets, thus making it easier to model and optimize EV charging schedules.

However, by participating in DA and ID markets, energy suppliers can spread their risk exposure and hedge against the uncertainties created by fluctuating EV usage and market prices. Day-ahead markets offer energy suppliers foresight to help them plan strategically for the manifestation of anticipated patterns, while ID markets provide the flexibility to respond quickly to unforeseen changes in EV demand. The ID markets are also referred to as real-time (RT) markets in some electricity markets, such as the Iberian market [47], the Nordic RT market [48], and the PJM (US based) RT market [34,49].

Two-stage optimization models enable energy suppliers to optimize EV charging in both DA and RT/ID markets. The first-stage decisions usually correspond to DA market scheduling with the objective of minimizing the costs of the energy supplier. The second-stage decisions usually correspond to RT/ID markets where authors in [34,47] model the objective function in order to reduce the power imbalances and minimize the energy supplier's costs. Liu et al. [48] formulated the objective function to maximize the revenues of the energy supplier while considering bidirectional charging. Many authors [34,48,49] assumed perfect foresight, while in reality, market prices are uncertain and not known in advance, as explained in Section 2.1. To model the uncertainty in market prices, the authors in Sánchez-Martín et al. [47]

Table 1
Literature overview — Electricity markets
† non-German market.

Research paper	Electricity markets		
	DA	IDA	CID
Al-Awami and Sortomme [44]	✓	✗	✗
Aliasghari et al. [46]	✓	✗	✗
Balram et al. [45]	✓	✗	✗
Xu et al. [41]	✓	✗	✗
Zheng et al. [43]	✓	✗	✗
Liu et al. [48]	✓	✓†	✗
Jin et al. [34]	✓	✓†	✗
Silva et al. [49]	✓	✓†	✗
Sánchez-Martín et al. [47]	✓	✓†	✗
Naharudinsyah and Limmer [10]	✗	✗	✓
Chemudupaty et al. [51]	✓	✗	✓
Tepe et al. [11]	✓	✗	✓
Corinaldesi et al. [52]	✓	✗	✓
Shinde et al. [13]	✓	✗	✓
Vardanyan and Madsen [12]	✓	✓	✓
Meese et al. [50]	✓	✓	✓
Our paper	✓	✗	✓

Table 2
Literature overview — CID Modeling.

Research paper	CID price modeling		Multistage EV modeling
	Multi-price	Price input	
Naharudinsyah and Limmer [10]	✓	perfect foresight	✗
Chemudupaty et al. [51]	✗	scenarios	✗
Tepe et al. [11]	✗	perfect foresight	✗
Corinaldesi et al. [52]	✓	perfect foresight	✗
Shinde et al. [13]	✓	scenarios	✗
Vardanyan and Madsen [12]	✓	scenarios	✗
Meese et al. [50]	✗	perfect foresight	✗
Our paper	✓	**price forecast**	✓

employed forecasting models which predict price movements in ID markets. Meanwhile, the authors in [34,47–49] focused on modeling RT/ID markets which are similar to the IDA, where products are not traded continuously, as we explained in Section 2.1.

To capture the dynamics of the CID markets where trading occurs continuously, authors in [10,11] proposed an RW horizon optimization method to optimize the EV charging schedule. The RW method divides the problem into several windows over a specific time frame, allowing continuous adaptation of evolving constraints and data. Consequently, in the context of EV charging, the RW optimization model facilitates the recurrent updating of EV scheduling decisions within each window, while still minimizing the energy supplier's costs when trading in CID markets [10,13]. To represent the CID prices, authors implemented two approaches. In the first approach, authors in [11,50,51] consider single prices for each product. While in the second approach, authors in [10,14] consider multiple prices along the trading period. Multi-price modeling considers the price evolution within the trading sessions of CID products by reoptimizing positions repeatedly throughout the trading period [12,52]. At every repetition, the optimizations require price inputs to calculate the energy supplier's costs, since the optimization objectives rely on minimizing costs. Most authors [10,11,50, 52] assumed perfect foresight of CID prices. Other authors in [12,13, 51] model the prices by assuming different scenarios, with associated probabilities to account for uncertainty in CID prices.

In sequential trading across DA and ID markets, authors in [11,50] procured most of the power required for EV charging from the DA market while still minimizing costs. Subsequently, the authors in [11, 50] only traded power in the ID markets if this produces additional revenues. However, while modeling EV flexibility, most authors in [11–13,50–52] assumed the same EV demand forecast for both DA and ID markets. Thus, they also did not account for the potential imbalances and additional costs that could be incurred due to changes in EV demand while trading in CID markets.

To draw attention to the contributions of our paper, we summarize our literature review and compare existing literature with our paper in Tables 1 and 2.

In Table 1, we present the electricity markets considered by various papers for trading EV flexibility. Our paper focuses on trading EV flexibility in DA and CID markets. We do not investigate the IDA due to it having a similar clearing mechanism to the DA auction and lower liquidity in the German market compared to the DA auction [19].

In Table 2, we compile the papers that explore the trading of EV flexibility in CID markets, given our primary focus on modeling the CID market. We differentiate papers based on their approaches to CID price modeling and EV flexibility modeling. Table 2 lists all the papers focused on EV trading strategies within CID markets. We included all relevant studies from our initial search that addressed CID trading alongside EV flexibility. To the best of our knowledge, none of these papers integrated CID market price forecasts into their EV trading models. Our paper employs multiple prices for price modeling and utilizes price forecasts. By using price forecasts, we eliminate the need for prior knowledge of future prices during optimization. The price forecasting approach better reflects real-world trading scenarios, where decisions are made within trading sessions without prior knowledge of future price developments. We also consider the variation in EV demand between DA and CID markets. Therefore, we use an initial DA forecast for DA optimization, and update it with an ID forecast for CID trading. Using an updated ID forecast for CID trading enhances the accuracy of EV charging schedule optimization because the forecasts become more reliable over time. Additionally, we test different trading frequencies within the CID market and compare CID trading with settlement as an imbalance.

3. Methods

To enable the energy supplier to trade EV flexibility, we quantify the EV flexibility in terms of power and energy as functions of time. This will convey the information on the amount of power that can be varied in a controllable fashion during each time step, while maintaining the energy levels required to meet the users' requirements, and keeping charging power below charger limits. We then use this aggregated flexibility as an input to our optimization models to facilitate EV flexibility trading in both the DA and the CID markets. Fig. 1 illustrates the sequence of the different trading and optimization steps to obtain the final EV charging schedule.

Consistent with prevalent hedging strategies in short-term power markets, the objective is to meet all the power needs resulting from the DA EV flexibility forecast in the DA market while minimizing the procurement costs in line with [52]. Securing all volumes in the DA market is advantageous for hedging, offering higher liquidity than the CID [19] and a single clearing price per product. Conversely, continuous trading in the CID market increases risk due to fluctuating and volatile prices [53]. The model tries to find the cheapest periods in the DA timeframe to charge EVs without factoring in the ID markets or any possible imbalances. The DA optimization runs with the assumption of having perfect foresight of DA prices and an initial EV flexibility forecast, resulting in a preliminary DA charging schedule.

During the ID period, a more accurate EV flexibility forecast becomes available. For simplicity's sake, we assume that this forecast matches actual EV flexibility at the time of charging. To adjust the charging schedule to the updated flexibility forecast, we propose three strategies. The first strategy, the baseline strategy, aims to reschedule EV charging to minimize imbalances, specifically changes in the power of the EV charging schedule. Afterwards, the strategy settles remaining

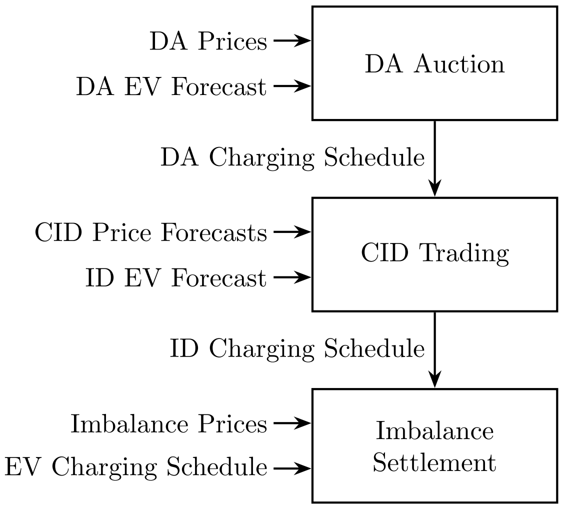


Fig. 1. Overview of trading steps.

imbalances for the reBAP. The second strategy, the static CID strategy, is similar, since it uses the same ID charging schedule. However, instead of settling power volumes for the reBAP, it settles power volumes in the CID market at the ID_1 price. The third strategy, the dynamic CID strategy, trades in the CID market, where the optimization model takes account of CID price forecasts. The strategy uses an RW approach, involving successive rounds of optimization and trading for the same product. Note, that opting to trade in the CID market eliminates imbalances, as all open volumes are traded in the CID market. All three strategies result in a final ID charging schedule, according to which EVs can be charged.

Section 3.1 quantifies the flexibility provided by an aggregated fleet of EVs. Sections 3.2 and 3.3 illustrate how our optimization models trade EV flexibility in the DA and CID markets, respectively. Section 3.4 summarizes the sequential optimization process.

3.1. EV flexibility model

3.1.1. Input parameters to quantify EV flexibility

In this Section, we outline the parameters of different user inputs, EV batteries, and EV chargers that are relevant for quantifying EV flexibility. The level of flexibility offered by an EV varies with each charging session; influenced by the user's driving and charging habits, as well as the EV battery and charger specification.

To quantify the EV flexibility, we need the maximum charging power of an EV charger, the plugin duration, and the energy that should be transferred within a charging session. The maximum charging power is the maximum power at which an EV can be charged ($P_v^{\max}$). The plugin duration is the time between EV arrival time (t^{arr}) and departure time (t^{dep}). The energy that should be transferred to satisfy the user's state of energy at departure ($\mathrm{SOE}^{\mathrm{dep}}$) requirement is denoted by E_v^{dep}.

In Fig. 2, we illustrate the typical EV battery with different energy values. $E_v^{\max}$ is the total battery capacity of the EV, E_v^{arr} is the EV battery capacity at the time of arrival (t^{arr}), and E_v^{dep} is the energy that should be transferred to satisfy the $\mathrm{SOE}^{\mathrm{dep}}$ requirement.

As we only consider unidirectional charging, the overall energy capacity of the battery can never drop below E_v^{arr}. Furthermore, the user might not always request maximum $\mathrm{SOE}^{\mathrm{dep}}$. This would mean that the sum of E_v^{arr} and E_v^{dep} would not always be equal to $E_v^{\max}$. Therefore, we only consider the part of the battery that can be charged i.e., E_v^{dep} while estimating EV flexibility.

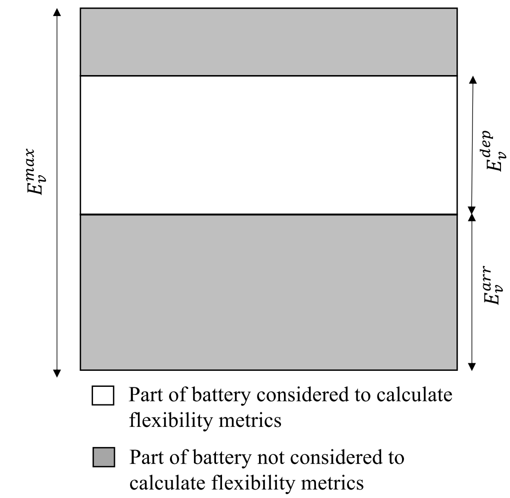


Fig. 2. Typical EV battery and different energy values.

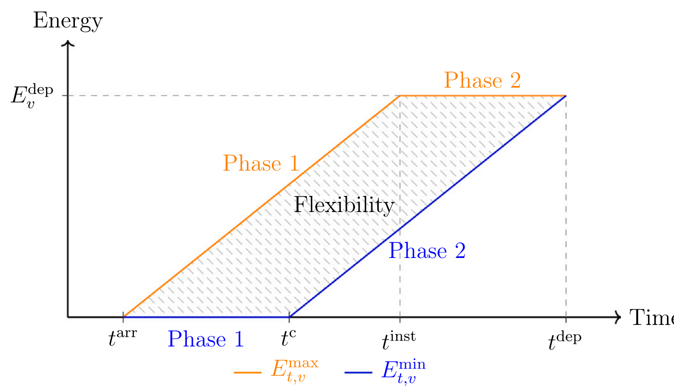


Fig. 3. Representation of EV flexibility in energy vs. time graph.

3.1.2. Quantification of individual EV flexibility

To estimate the flexibility provided by an EV, we quantify EV flexibility during its plugin duration using time-dependent energy and power metrics which are derived by using the parameters introduced in Section 3.1.1. The energy metrics are minimum energy ($E_{t,v}^{\min}$) and maximum energy ($E_{t,v}^{\max}$) at time t. The power metrics are minimum power ($P_{t,v}^{\min}$) and maximum power ($P_{t,v}^{\max}$) at time t. These metrics will convey the amount of power with which an EV can be charged while maintaining upper and lower limits of cumulative energy transfer.

$E_{t,v}^{\min}$ represents the minimum cumulative energy that must be transferred to the EV at time t to satisfy the user's energy requirement i.e., E_v^{dep}. The process to determine $E_{t,v}^{\min}$ is divided into two phases within its plugin duration as illustrated in Fig. 3.

The first phase is the idle state where there is no energy transfer to the EV until critical time (t^{c}). t^{c} marks the moment when the EV must begin charging at full power to meet the required energy level by departure time (E_v^{dep}). Therefore, the first phase to determine $E_{t,v}^{\min}$ extends from the t^{arr} to the t^{c}. The second phase covers the time between t^{c} and the time of departure (t^{dep}). During this phase, the EV is charged at full power to ensure that E_v^{dep} is achieved by the departure time. We present the mathematical formulation to determine $E_{t,v}^{\min}$ in Eqs. (1) and (2).

$$E_{t,v}^{\min} = E_{t-1,v}^{\min} + P_{t,v} \times \eta \times \Delta t \tag{1}$$

$$P_{t,v} = \begin{cases} 0 & t^{\mathrm{arr}} < t \leq t^{c} \quad \text{(Phase 1)} \\ P_v^{\max} & t^{c} < t \leq t^{\mathrm{dep}} \quad \text{(Phase 2)} \end{cases} \tag{2}$$

In reality, EV charging is not linear and involves different stages (such as constant current and constant voltage) to optimize the charging process for safety and battery health [54]. However, for simplicity, we assume linear charging of the EV where the charging power takes continuous values. Therefore, we calculate $E^{\min}_{t,v}$ by using Eq. (1), where $P_{t,v}$ is the charging power at time t, η is the charging efficiency to account for power losses while charging, and Δt is the time interval during which the charging power is delivered. The value of $P_{t,v}$ to calculate $E^{\min}_{t,v}$ in the first phase and the second phase are 0 and $P^{\max}_{v}$ respectively, as depicted in Eq. (2).

$E^{\max}_{t,v}$ represents the maximum cumulative energy that can be transferred to the EV at time t. Similar to $E^{\min}_{t,v}$, the process for determining $E^{\max}_{t,v}$ is divided into two distinct phases (as illustrated in Fig. 3).

In the first phase, the EV is charged instantaneously at maximum power until the energy required for departure, E^{dep}_{v}, is met. The duration of this phase is from t^{arr} (arrival time) to t^{inst}, where t^{inst} is the time needed to transfer E^{dep}_{v} instantaneously at full power. The second phase starts at t^{inst} and lasts until t^{dep} (departure time), during which no energy transfer occurs.

We present the mathematical formulation for calculating $E^{\max}_{t,v}$ in Eqs. (3) and (4). As we assume the linear charging of the EV, the maximum energy level at time t, $E^{\max}_{t,v}$ is calculated by Eq. (3). The $P_{t,v}$ value to calculate $E^{\max}_{t,v}$ in the first phase and second phase is $P^{\max}_{v}$ and 0 respectively, as depicted in Eq. (4).

$$E^{\max}_{t,v} = E^{\max}_{t-1,v} + P_{t,v} \times \eta \times \Delta t \tag{3}$$

$$P_{t,v} = \begin{cases} P^{\max}_{v} & t^{\text{arr}} < t \leq t^{\text{inst}} \quad \text{(Phase 1)} \\ 0 & t^{\text{inst}} < t \leq t^{\text{dep}} \quad \text{(Phase 2)} \end{cases} \tag{4}$$

When plotting $E^{\max}_{t,v}$ and $E^{\min}_{t,v}$ on the energy vs. time graph, the region bounded by these two energy metrics represents the degree of flexibility (see Fig. 3). As depicted in Fig. 3, the EV offers flexibility throughout the plugin duration, allowing the charging power to fluctuate between maximum and minimum possible values. This variation in charging power is possible as long as the cumulative energy transfer remains within the defined flexibility region. Therefore, the value of the minimum power flexibility metric - $P^{\min}_{t,v}$, which represents the minimum allowable power at which the EV must be charged at time t, is equal to 0 for the whole plugin duration.

The maximum power flexibility metric - $P^{\max}_{t,v}$, represents the maximum allowable power at which the EV can be charged at time t. Therefore, $P^{\max}_{t,v}$ for the whole plugin duration is equal to $P^{\max}_{v}$.

3.1.3. Quantification of EV fleet flexibility

As we manage a portfolio of an energy supplier, (which includes an EV fleet) aggregating their flexibilities becomes essential to facilitating trading in electricity markets. To obtain the aggregated flexibility of an EVs fleet, we sum up the flexibilities of individual EVs. We represent the resulting aggregated energy and power flexibility metrics as $E^{\min}_{t}$, $E^{\max}_{t}$ and $P^{\min}_{t}$, $P^{\max}_{t}$. These metrics characterize a virtual battery model, defined by its minimum and maximum thresholds for both power and energy levels. To account for uncertainties in EV flexibility forecasts, we generate different flexibility metrics for the DA and ID period by applying different weights to individual EV flexibility metrics during summation. Section 4.2 provides more details on the generation of the EV flexibility metrics. Consequently, we adapt the notation of the flexibility metrics to distinguish between both periods. Taking the minimum energy flexibility metric ($E^{\min}_{t}$) as an example, we denote the DA metric as $E^{\min,\text{DA}}_{t}$ and the ID metric as $E^{\min,\text{ID}}_{t}$.

3.2. DA optimization

We develop a linear optimization model with the objective of minimizing procurement costs incurred for charging the EV fleet. The input data for our optimization model are DA market prices and EV flexibility forecasts. The EV flexibility forecasts for the DA market are calculated using the flexibility model, detailed in Section 3.1. We assume perfect foresight of DA prices in line with [43]. This assumption allows us to isolate price uncertainty specifically within the CID market, aligning with our study's focus. Importantly, this assumption's impact is limited, as the DA schedule serves only as an initial reference for subsequent ID rescheduling, with our analysis centered on schedule changes made during the ID phase.

Our objective function aims to minimize the energy supplier's DA procurement costs (see Eq. (5)). The objective function considers the variable P^{DA}_{t} and parameter $C^{\text{DA,true}}_{t}$, which are the power purchased from DA market and the DA price at time t, respectively. As we assume perfect foresight of the DA price, $C^{\text{DA,true}}_{t}$ is the same as the clearing price of the DA market at time t.

$$\min_{P^{\text{DA}}_{t}, E^{\text{DA}}_{t}} \sum_{t} C^{\text{DA,true}}_{t} \times P^{\text{DA}}_{t} \times \Delta t \tag{5}$$

As we trade the aggregated flexibility of the EV fleet, we assume that all the EVs connected to their respective charging points at residential level create a large virtual battery [55]. In this regard, the power and energy flexibility metrics represent the minimum and maximum power and energy thresholds of the virtual battery (see Section 3.1.3). Therefore, $P^{\min,\text{DA}}_{t}$ and $P^{\max,\text{DA}}_{t}$ represent the minimum and maximum charging power of the virtual battery for the DA market at time t. While, $E^{\min,\text{DA}}_{t}$ and $E^{\max,\text{DA}}_{t}$ represent the minimum and maximum energy that could be transferred to the virtual battery at time t, for the DA market.

In the context of the virtual battery, P^{DA}_{t} represents the power procured from the DA market to charge the virtual battery. Thus, the P^{DA}_{t} value should always be between $P^{\min,\text{DA}}_{t}$ and $P^{\max,\text{DA}}_{t}$, ensured by the constraint formulated in Eq. (6):

$$P^{\min,\text{DA}}_{t} \leq P^{\text{DA}}_{t} \leq P^{\max,\text{DA}}_{t} \quad \forall\, t \in T. \tag{6}$$

The variable E^{DA}_{t} represents the cumulative energy transferred to this virtual battery at time t in the DA market. The value of variable E^{DA}_{t} should always be within $E^{\min,\text{DA}}_{t}$ and $E^{\max,\text{DA}}_{t}$, ensured by the constraint formulated in Eq. (7):

$$0 \leq E^{\min,\text{DA}}_{t} \leq E^{\text{DA}}_{t} \leq E^{\max,\text{DA}}_{t} \quad \forall\, t \in T. \tag{7}$$

The following Eq. (8) depicts the energy balance of the virtual battery:

$$E^{\text{DA}}_{t} = E^{\text{DA}}_{t-1} + P^{\text{DA}}_{t} \times \Delta t - E^{\text{left,DA}}_{t} \qquad \forall\, t \in T. \tag{8}$$

E^{DA}_{t} is the variable illustrating the cumulative energy transferred to the virtual battery at the time step t. Its value is affected by E^{DA}_{t-1}, P^{DA}_{t}, and $E^{\text{left,DA}}_{t}$. E^{DA}_{t-1} is the cumulative energy transferred to the virtual battery in the previous time step. P^{DA}_{t} is the power procured to charge the virtual battery at the current time step t. $E^{\text{left,DA}}_{t}$ is the cumulative energy transferred to the EVs that disconnect from the chargers at the current time step t, i.e., they no longer contribute to the virtual battery.

3.3. CID optimization

While we assume perfect foresight of DA market prices during DA optimization (see Section 3.2), we perform the CID optimization process using price forecasts of hourly CID products. Using price forecasts for CID optimization aligns with a realistic scenario in which trading decisions are made given uncertain knowledge of future prices. Given that the CID market is typically only highly liquid during the last few hours before delivery, we start optimization four hours before delivery [56].

Fig. 4 illustrates the simultaneous trading process for multiple hourly products, each represented by a distinct timeline. Each product is defined by two characteristics: the delivery start and the delivery period. The delivery start (indicated by the red dot) marks the exact

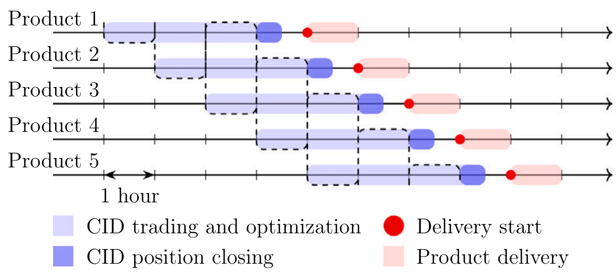


Fig. 4. Parallel trading of several hourly CID products.

moment when power delivery begins, while the delivery period (represented by the shaded area following the red dot) specifies the duration over which the power is supplied. For every product, the trading period opens four hours before delivery starts and closes half an hour before delivery starts. A timeline for a single product contains the following subintervals (from left to right): The chronological breakdown of a single product's timeline contains the following three segments:

1. The first segment spans three hours and covers the CID trading window of the respective product (light blue interval). This phase permits the re-optimization of the power schedule following updates in CID price forecasts.
2. The second segment, lasting 30 min, is a transition period where re-optimization ceases, yet the trading of remaining open positions continues (dark blue interval). Trading activity then stops 30 min before the start of delivery, which aligns with the decoupling of German control areas [25].
3. The third segment, which extends for one hour, denotes the product delivery period (light red interval). The start of this period is indicated by a red dot.

At any point in time, three hourly products can be traded in parallel, as highlighted by the dashed rectangles in Fig. 4.

We enter the CID market with an updated set of EV flexibility metrics, which may differ from the DA metrics (see Section 3.1.3). The updated flexibility metrics lead to updated ID constraints for the ID charging schedules depicted by the Eqs. (9), (10), and (11):

$$P_t^{\text{min,ID}} \leq P_t^{\text{ID}} \leq P_t^{\text{max,ID}} \quad \forall t \in T, \tag{9}$$

$$0 \leq \; E_t^{\text{min,ID}} \leq \; E_t^{\text{ID}} \leq \; E_t^{\text{max,ID}} \quad \forall t \in T, \tag{10}$$

$$E_t^{\text{ID}} = E_{t-1}^{\text{ID}} + P_t^{\text{ID}} \times \Delta t - E_t^{\text{left,ID}} \quad \forall t \in T. \tag{11}$$

The corresponding DA constraints are depicted by the Eqs. (6), (7), and (8). These constraint alterations could cause the DA solution (i.e., the planned EV charging schedule comprising E_t^{DA} and P_t^{DA}), to violate the new ID constraints. As a result, it becomes necessary to reoptimize the charging schedule to comply with the updated constraints, yielding an ID charging schedule comprising E_t^{ID} and P_t^{ID}.

We present three strategies for ID rescheduling. First, Section 3.3.1 discusses a baseline strategy aimed at minimizing deviations from the DA power schedule. The strategy settles power volumes as imbalances for the reBAP. Second, Section 3.3.2 introduces our static CID trading strategy, that relies on the market index ID_1 for power volume settlement. Third, Section 3.3.3 presents our dynamic CID trading strategy that takes advantage of parallel trading across different products. Parallel trading allows for arbitrage between the different CID products within the limits of the constraints for the ID schedule.

3.3.1. Baseline strategy

Our baseline strategy ignores market prices while rescheduling. Instead, it focuses solely on minimizing deviations from the DA schedule. Not considering market prices significantly reduces rescheduling complexity, since it allows for a single optimization run for every product. This method starkly contrasts with strategies aiming to capitalize on the CID market's continuous dynamics, which requires repeated optimization runs in a RW fashion (see Section 3.3.3). The baseline optimization serves as a benchmark for evaluating the continuous optimization strategy. The optimization approach is also valuable for market participants such as EV aggregators who aim to minimize imbalances without delving into the complexities of forecasting CID prices.

To express this strategy formally, for each product with a delivery start time of t, we reoptimize the power and energy schedules one hour before delivery, specifically at $t - 1h$, using the objective function corresponding to Eq. (12):

$$\min_{P_k^{\text{ID}}, E_k^{\text{ID}}} \sum_{k=t,t+1h,t+2h} |P_k^{\text{DA}} - P_k^{\text{ID}}|. \tag{12}$$

We apply the ID constraints given by the Eqs. (9), (10), and (11). The optimization aims to minimize the gap between the DA and ID EV power schedules, since any deviation requires market settlement. Although the formulation of the objective function (Eq. (12)) is nonlinear, the objective function can be rendered linear (see Appendix A). Note that the optimization takes account of three products simultaneously. Also note that a single optimization iteration only fixes P_k^{ID} and E_k^{ID} for $k = t$, as the decision variables for products with a later delivery start (i.e., with larger k), might still undergo changes in subsequent rounds of optimization.

After calculating the new schedules, we contemplate two options for balancing the discrepancy between the DA power schedule P_t^{DA} and the ID power schedule P_t^{ID}. The first option involves settling open volumes as imbalances, effectively bypassing the CID market to settle the difference and invoice the imbalance price (reBAP). The corresponding formula for the ex-post evaluation of this approach is Eq. (13):

$$\sum_t C_t^{\text{reBAP}} \times (P_t^{\text{DA}} - P_t^{\text{ID}}) \times \Delta t. \tag{13}$$

Settling for the imbalance price eliminates the need to trade in the CID market. This market can be complex due to its continuous nature.

3.3.2. Static CID strategy

Our second strategy reschedules power volumes in the same manner as the baseline strategy (see Section 3.3.1). However the strategy settles the power volumes financially in the CID market. According to the baseline optimization schedule, the final schedule for any product becomes known one hour before delivery, providing a half-hour trading window before the decoupling of the German control areas [25]. The ID_1 price index, a volume-weighted average published by the EPEX, reflects all transaction prices during this specific half-hour interval [18]. We employ the ID_1 price for settlement as it encompasses the relevant trading period. Moreover, the ID_1 serves as an indicator of the expected transaction price within the given interval — a price that can be expected in the long term. The corresponding formula for the ex-post evaluation is Eq. (14):

$$\sum_t C_t \times (P_t^{\text{DA}} - P_t^{\text{ID}}) \times \Delta t$$
$$-C^{\text{CID,fee}} \times |P_t^{\text{DA}} - P_t^{\text{ID}}| \times \Delta t, \tag{14}$$

where $C^{\text{CID,fee}}$ is a CID trading fee in €/MWh.

A limitation of this optimization strategy is that rescheduling is price agnostic, penalizing any deviation from the DA power schedule uniformly, regardless of variations in price signals. The subsequent section will present an approach that incorporates CID price dynamics and forecasts.

3.3.3. Dynamic CID strategy

This section explains our CID trading strategy, tailored to adapt to CID market trends. The foundation of our trading strategy lies in the DA schedule, available for all considered products during ID reoptimization. As Fig. 4 illustrates (see Section 3.3), at any time the CID strategy focuses on three hourly products at once in a RW fashion.

Limiting the optimization interval to a three-hour window, starting four hours before delivery, neglects charging needs beyond the three products considered in parallel at any time. In practice, this means that when prices are positive, the optimization may sell off any excess power not required within that window, neglecting future charging needs.

To address this issue, our CID optimization consists of two stages. The first stage identifies a "feasible energy target" based on the DA energy schedule. We use the DA schedule as a reference since it reflects power needs beyond the immediate CID optimization window, while still maintaining flexibility for trading within the current window. A "feasible energy target" is the minimum amount of energy that must be stored in the virtual battery at the defined product delivery time. Following this, the second stage trades in the CID market. The "feasible energy target" is the result of the first stage of our CID optimization.

The first stage runs two hours before the delivery start t of every product, i.e., at $t - 2h$. Eq. (15) depicts the objective function used to find a viable energy target for the product scheduled for delivery at $t + 2h$:

$$\min_{P_k^{\mathrm{ID,target}}, E_k^{\mathrm{ID,target}}} |E_{t+2h}^{\mathrm{DA}} - E_{t+2h}^{\mathrm{ID,target}}|, \tag{15}$$

where k represents the set of times $\{t, t+1h, t+2h\}$, covering the three hourly products that are traded simultaneously in the subsequent hour. Note, that the optimization adheres to the ID constraints (see Eqs. (9), (10), and (11)). The objective function (Eq. (15)) minimizes the difference between the scheduled DA and a feasible ID energy target ($E_{t+2h}^{\mathrm{ID,target}}$). When the DA schedule is feasible under the ID constraints, the energy target defaults to the DA schedule. The objective function (Eq. (15)) only considers the product with the latest delivery start ($t+2h$), as the goal is to align with the DA energy forecast in a longer-term perspective, thus providing flexibility in the preceding hours. The remaining flexibility can then be leveraged to trade in the CID market.

The second stage covers the CID trading approach. To model continuous trading, we introduce the additional index ℓ, representing continuous decision making during a specific hour. For every product with delivery start t, the optimization runs at $t - 2h + \frac{1h}{|L|} \times \ell$ for $\ell \in L$. For instance, when trading at quarter-hourly frequency, we obtain $L = \{0, 1, 2, 3\}$, given that $\frac{1h}{|L|} = 15min$. For every delivery start t and every index ℓ, we repeat the profit maximization optimization process with the objective function given by Eq. (16) to obtain the ID schedules for EV charging, which is composed of the power and energy schedules ($P_{k,\ell}^{\mathrm{ID}}$ and $E_{k,\ell}^{\mathrm{ID}}$ respectively):

$$\max_{P_{k,\ell}^{\mathrm{ID}}, E_{k,\ell}^{\mathrm{ID}}} \sum_{k=t,t+1h,t+2h} C_{k,\ell}^{\mathrm{CID,fcst}} \times (P_{k,\ell-1}^{\mathrm{ID}} - P_{k,\ell}^{\mathrm{ID}}) \times \Delta t$$
$$- C^{\mathrm{CID,fee}} \times |P_{k,\ell-1}^{\mathrm{ID}} - P_{k,\ell}^{\mathrm{ID}}| \times \Delta t. \tag{16}$$

This operates under the ID constraints (see Eqs. (9), (10), and (11)) and under the additional energy level constraint (Eq. (17)):

$$E_{t+2,\ell}^{\mathrm{ID}} \geq E_{t+2}^{\mathrm{ID,target}}. \tag{17}$$

This forces the energy schedule to meet or exceed the energy target $E_{t+2}^{\mathrm{ID,target}}$. The first term in the objective function estimates the value of trades which consider price forecasts $C_{k,\ell}^{\mathrm{CID,fcst}}$. Here, $P_{k,\ell-1}^{\mathrm{ID}} = P_t^{\mathrm{DA}}$ in the first iteration of ℓ. The second term considers volume-dependent trading fees $C^{\mathrm{CID,fee}}$.

From this optimization, we obtain $P_{k,\ell}^{\mathrm{ID}}$ and $E_{k,\ell}^{\mathrm{ID}}$ as the results, which enable the calculation of the trading profit for the current ℓ with the true future market prices $C_{k,\ell}^{\mathrm{CID,true}}$ using Eq. (18):

$$\sum_{k=t,t+1h,t+2h} C_{k,\ell}^{\mathrm{CID,true}} \times (P_{k,\ell-1}^{\mathrm{ID}} - P_{k,\ell}^{\mathrm{ID}}) \times \Delta t$$
$$- C^{\mathrm{CID,fee}} \times |P_{k,\ell-1}^{\mathrm{ID}} - P_{k,\ell}^{\mathrm{ID}}| \times \Delta t, \tag{18}$$

We repeat this procedure for all iterations of ℓ within a specific trading hour. Thus, the presented method aims to follow the DA energy schedule closely while executing a continuous optimization strategy in the CID market. This allows adaptation to ID constraints and offers a degree of freedom to facilitate a shift of power volumes between products.

Table 3
Overview of optimization processes.

DA	Stage 1	Objective	(5)	
		Constraints	(6), (7), (8)	
		Result	DA Schedule	
ID			Approach 1	Approach 2
	Stage 2	Objective	(12)	(15)
		Constraints	(9), (10), (11)	(9), (10), (11)
		Result	ID Schedule	Energy target
	Stage 3	Objective	N/A	(16)
		Constraints	N/A	(9), (10), (11), (17)
		Result	N/A	ID Schedule

3.4. Optimization process summary

To summarize the optimization processes discussed in this paper, Table 3 presents an overview. It lists the optimization stages along with references to the objective and constraints of the respective optimization problems. The first stage (Stage 1) contains the DA optimization procedure and yields a DA charging schedule. During the ID period, we propose two possible optimization approaches. First, the baseline strategy and the static CID strategy requires only one additional stage (Stage 2) to compute an ID charging schedule. Second, the dynamic CID strategy requires two additional optimization stages (Stage 2 and Stage 3). Stage 2 yields an energy target, i.e., a lower bound for the battery energy level. Afterwards, Stage 3 optimizes the CID schedule, taking into account the energy level bound from the previous stage. Regardless of the approach chosen, both approaches result in a final ID schedule for EV charging.

4. Data

The following section introduces the data we use in this paper. Section 4.1 outlines the mobility data. Section 4.2 describes the computation of flexibilities for both the DA and ID periods, based on the mobility data. Finally, Section 4.3 details the price data used in our study.

4.1. Mobility data

We use existing synthetic mobility data to derive the inputs required to calculate the flexibility metrics for each EV [15]. The synthetic mobility data stems from a German mobility survey [57]. The mobility data consists of 200 unique mobility profiles of residential EVs. The mobility profile is time series data that gives the location of the vehicle, the distance traveled, and the energy consumed every 15 min over a one year period. We analyze only the home charging case since majority of the vehicles currently charge at home [58], with the following assumptions:

- All vehicles charge at home as our focus is on home charging.
- To simplify our model, we assume that all vehicles are plugged in whenever parked at home. We consider that plugging in the vehicle daily might not be a significant burden for users, especially if they could derive tangible benefits from participating in smart charging programs.
- All vehicles are charged until maximum state of energy (SOE) is reached, or the highest possible SOE that can be reached during the time the vehicle is plugged in.
- The battery capacity of all vehicles is 75 kWh, which is similar to that of the Tesla Model S [59].
- As per IEC 61851-1:2017 standard, we consider a Level 2 charger with a mean power rating of 7.4 kW, typically used for home charging [60].
- The charging efficiency η is 95% which is within the efficiency range of a Level 2 charger [61].

4.2. EV flexibility data

As input for the optimization process, we generate multiple flexibility forecasts for the EV fleet, distinguishing between forecasts for the DA period and the ID period. These forecasts depend on individual EV flexibility metrics (see Section 4.1). Specifically, we construct linear combinations of the 200 individual EV flexibility metrics (see Section 4.1). Each aggregated flexibility metric incorporates variables $E_t^{\min}$, $E_t^{\max}$, $P_t^{\min}$, $P_t^{\max}$, and E_t^{left}. The computational approach remains consistent across all variables, thus we present equations only for $E_t^{\min}$. For the DA period, we use a single aggregated flexibility metric computed using Eq. (19):

$$E_t^{\min,\text{DA}} = \sum_{v=1}^{200} w_v \times E_{t,v}^{\min} \quad \forall t \in T, \tag{19}$$

Here, the individual vehicle weight $w_v = 5$ holds for all vehicles (v), leading to an aggregated flexibility metric for 1000 EVs (200 × 5). In other words, we assume that the fleet of 1000 EVs has five types of EV, of which there are 200 each. For the ID period, we introduce variations by altering the weights associated with individual EV flexibility metrics, following Eq. (20):

$$E_t^{\min,\text{ID}} = \sum_{v=1}^{200} \text{round}(\tilde{w}_v) \times E_{t,v}^{\min} \quad \forall t \in T, \tag{20}$$

with $\tilde{w}_v \sim \mathcal{N}(\mu = 5, \sigma^2)$ truncated to $[-0.4\bar{9}, 10.4\bar{9}]$ for $\forall v$. Since individual EV metrics represent discrete users, we round the weights to integers. Truncation guarantees that the values of the final weights ($\tilde{w}$) are non-negative and less than or equal to ten, thus obtaining a symmetrical distribution of weights. The degree of divergence from the DA schedule increases with higher variance σ^2 in the truncated normal distribution.

After drawing weights from the distribution, we correct them to achieve unbiased power consumption estimates in the specific ID and DA schedules. Mathematically, we minimize the difference between the energy consumption in the DA and ID periods (see Eq. (21)):

$$\min_{\tilde{w}_v} \left| \sum_t E_t^{\text{left,ID}} - \sum_t E_t^{\text{left,DA}} \right|, \tag{21}$$

where, $\sum_t E_t^{\text{left,ID}}$ and $\sum_t E_t^{\text{left,DA}}$ represent the total energy consumption in the ID and DA schedules, respectively. Long-term lack of bias requires there to be no overestimation nor underestimation of power consumption occurring throughout the simulation. This is an important factor for schedules which are used as forecasts for power procurement.

4.3. Price data

Our study uses various historical price datasets, using the German market as a reference: DA auction prices, CID market transactions, and reBAPs. We obtain all DA and CID market data from EPEX [24] and focus solely on hourly product price data. For the DA market, we directly use auction clearing prices. However, handling CID market data is more complex due to the large number and random timing of trades. As a solution, we calculate volume-weighted average prices (VWAPs) at different intervals.

We generate two types of VWAPs for calculating the price forecasts and transaction prices during CID optimization. For forecasting, we calculate backward-looking price averages aligning with the efficient market hypothesis, which states that current asset prices reflect available information at any given time [62]. More specifically, we use the average price of the four most recent completed trades, as this method has demonstrated strong forecasting accuracy across various forecasting horizons [16]. Within the CID market context, this implies that the latest transaction prices are indicative of the most up-to-date information available. For ex-post price calculation, we employ forward-looking quarter-hourly VWAPs. Although market liquidity is generally high, there is no guarantee that trades occur for a product during every considered interval, potentially leading to situations where orders remain uncleared. To address this, we use a backfilling approach, relying on future prices to fill these gaps. While this method introduces a delay in the timing of specific transactions, the trades are still executed, ensuring that the simulation results remain valid. Meanwhile, for CID prices, we also use a VWAP, considering trades between one hour and half an hour before delivery, known as ID_1 and available from EPEX since 2021 [18]. For periods predating 2021, we compute our own ID_1 index. For trades in the CID market, we assume a volume trading fee of 0.1€/MWh [63].

Lastly, we obtain reBAP prices from TransnetBW [64] up to 2022 and Netztransparentz.de [65] starting from 2023. Since reBAP prices are quarter-hourly [17] and our study focuses on hourly products, we average the quarter-hourly prices to derive hourly prices.

5. Scenarios

We run our optimization across different scenarios defined by several dimensions. Section 5.1 presents the time frames, specifically the time period used for testing. Section 5.2 contains the parameterizations for the uncertainty modeling of EV flexibility. Section 5.3 covers the parameterization of the different trading strategies.

5.1. Timeframe

The study focuses on two specific time frames: the years 2019 and 2022. The year 2019 is chosen as it precedes both the Covid-19 pandemic and the Ukraine war, events that significantly impacted electricity markets [66]. In contrast, we include 2022 due to the heightened market price volatility in this year [66]. Examining periods of high price volatility contributes to the evaluation of the resilience of trading strategies under atypical market conditions. In our study, the EV schedules follow weekly patterns, requiring us to adjust the time intervals to start on the first Monday of the relevant year. For scenarios set in 2019, the specific dates range from January 2, 2019, to January 1, 2020. Similarly, for the 2022 scenarios, the time frame extends from January 5, 2022, to January 4, 2023.

5.2. EV uncertainty parameterization

We examine multiple forecasting scenarios for EVs. We employ the same DA flexibility metrics across all scenarios and generate a collection of ID flexibility metrics, each varying to a certain degree from the DA schedule. Section 4.2 elaborates on the method we use to create these flexibility metrics, based on individual EV profiles. We consider four different scenarios with increasing deviation between the DA and ID metrics, each characterized by a distinct standard deviation σ used for the distribution of the weights of individual EV metrics $\tilde{w}_v$:

1. Perfect forecast: $\sigma = 0$
2. Low deviation: $\sigma = 1$
3. Medium deviation: $\sigma = 2$
4. High deviation: $\sigma = 3$

Appendix B contains a more detailed evaluation of EV flexibility metrics. To obtain robust results, we repeat the calculations 128 times. The reason to do this is that we generate the aggregated ID flexibility metrics randomly. We selected 128 repetitions to match the hardware on which we carry out the computations: a high performance computing (HPC) node with two physical sockets, each containing an AMD Epyc ROME 7H12 processor with 64 cores, resulting in a total of 128 cores per node [67]. This hardware configuration enables the parallel execution of all scenarios.

Table 4
Trading strategies.

Strategy	Description	Section	Parameters
BL_P^{reBAP}	Baseline strategy with settlement of volumes for reBAP	3.3.1	N/A
$BL_P^{\mathrm{ID}_1}$	Static CID strategy with settlement of volumes for ID_1	3.3.2	N/A
CID_E^x	Dynamic CID strategy with continuous settlement of volumes in CID market	3.3.3	x∈{2 min, 5 min, 10 min, 15 min, 20 min, 30 min, 60 min}

5.3. Trading strategies

We investigate various trading strategies for power settlement in the ID period. While the volumes acquired in the DA market stay constant across all trading strategies, we assess three unique trading strategies for rescheduling in response to the ID updates to EV schedules. Table 4 contains an overview of these strategies. The first two strategies (BL_P^{reBAP} and $BL_P^{\mathrm{ID}_1}$) aim to closely align the ID schedule (P_t^{ID}) with the DA power schedule (P_t^{DA})(see Sections 3.3.1 and 3.3.2). However, these two strategies settle the discrepancies in the power schedules differently. The first strategy (BL_P^{reBAP}) settles power volumes as imbalances for the reBAP and the second strategy ($BL_P^{\mathrm{ID}_1}$) settles power volumes in the CID market for the ID_1 price, which is a VWAP covering the period from one hour to half an hour before the start of delivery. Our third trading strategy (CID_E^x), operates continuously in the CID market and has different parametrizations (see Section 3.3.3). More specifically, these parameters define the hourly frequency at which the strategy runs, as defined by the period length (x) between single runs. We consider seven different such period lengths (x): 2 min, 5 min, 10 min, 15 min, 20 min, 30 min, and 60 min, which means that the optimization runs between thirty times and once per hour.

Our analysis evaluates the three trading strategies across two distinct periods, specifically the years 2019 and 2022 (see Section 5.1). Furthermore, we assess each strategy under a range of different EV flexibility uncertainties (see Section 5.2). We structure the analysis of our optimization strategies around the different trading strategies.

6. Results and discussion

This study introduces optimization models for EV scheduling in both DA and ID markets. In particular, our study focuses on the rescheduling of DA schedules during the ID period, taking account of price and EV user uncertainties. Section 6.1 illustrates the rescheduling process across the DA and ID time periods by discussing an exemplary period. Section 6.2, compares the different trading strategies, calculating the annual profit derived from trading EV flexibility in ID markets. Section 6.3 broadens the scope of comparison by evaluating the different trading strategies.

6.1. Rescheduling example

To illustrate the rescheduling process, we present results for an exemplary period of three days: June 6 to June 8, 2022. Each step contains flexibility metrics and schedules for power and energy respectively. The power schedule corresponds to the power purchased from the respective power markets. The energy schedule is the cumulative energy of all EVs connected to the grid. At any time, the power and energy schedules must stay between the bounds determined by the flexibility metrics, i.e., P_t^{min} and P_t^{max} for the power procured from market and E_t^{min} and E_t^{max} for the cumulative energy.

Fig. 5 contains the results of the DA optimization step (see Section 3.2). The DA energy and power schedules (E_t^{DA} and P_t^{DA}) are

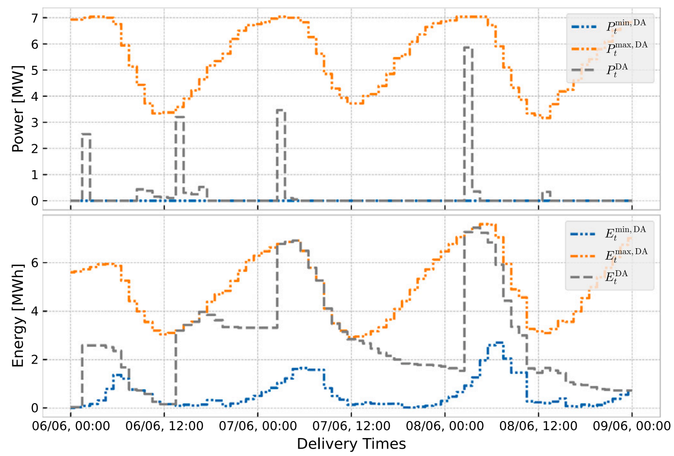


Fig. 5. Exemplary DA schedule for EV fleet from June 6 to June 8, 2022.

depicted as dashed lines (in gray), whereas the flexibility metrics are in the form of lower ($E_t^{\mathrm{min,DA}}$, $P_t^{\mathrm{min,DA}}$) and upper bounds ($E_t^{\mathrm{max,DA}}$, $P_t^{\mathrm{max,DA}}$) are shown as dashed lines with double dots (blue and orange respectively). The DA schedule (P_t^{DA}, E_t^{DA}) always stays between the limits defined by the flexibility metrics. The power schedule (P_t^{DA}) never reaches the upper limit and often takes the value of its lower limit ($P_t^{\mathrm{min,DA}}$) which is zero. In contrast, the energy schedule (E_t^{DA}) reaches both the bottom and the top limit, for example on June 6 during the intervals of 8:00–13:00 and 14:00–17:00 respectively. The DA schedule (E_t^{DA}, P_t^{DA}) serve as the starting points for the subsequent ID optimizations, for which the paper covers three options: a baseline strategy (see Section 3.3.1), a static CID strategy (see Section 3.3.2), and a dynamic CID strategy (see Section 3.3.3). Note that both the baseline strategy and the static CID strategy produce identical power and energy schedules, as neither incorporates price signals during rescheduling.

Fig. 6 illustrates the rescheduling in the ID period by the baseline strategy (or the static CID strategy), extending Fig. 5. In addition to the DA flexibility metrics and schedules, it additionally contains the ID flexibility metrics and the baseline ID schedule. The lower ($E_t^{\mathrm{min,ID}}$, $P_t^{\mathrm{min,ID}}$) and upper bounds ($E_t^{\mathrm{max,ID}}$, $P_t^{\mathrm{max,ID}}$) are dashed lines with double dots (green and red respectively); and the ID baseline schedule (P_t^{BL}, E_t^{BL}) is the dashdot line (black). Similar to the DA case, the baseline ID schedule remains within the boundaries defined by the ID flexibility metrics. More specifically, the power schedule (P_t^{BL}) never reaches its upper limit, while the energy schedule (E_t^{BL}) reaches both the upper and the lower limits.

Fig. 7 exemplifies the dynamic CID rescheduling by extending Fig. 5. Just as for the baseline rescheduling, the figure contains the ID bounds. In addition, it also contains the final ID schedule for a CID optimization (E_t^{CID}, P_t^{CID}) with 15 min trading frequency as dashdot line (cyan). Similarly to the DA and baseline cases, the CID schedule (E_t^{CID}, P_t^{CID}) stays within the bounds set by the ID flexibility metrics, where the power schedule (P_t^{CID}) mostly follows the lower bound ($P_t^{\mathrm{min,ID}}$) and the energy schedule reaches both the lower and the higher energy bounds ($E_t^{\mathrm{min,ID}}$ and $E_t^{\mathrm{max,ID}}$).

Taking a closer look at Fig. 6 or Fig. 7, we observe that the DA schedule violates the ID bounds. Note that the ID flexibility metrics are the same in both figures. For example, on June 6 at 14:00–18:00 the DA energy schedule (E_t^{DA}) violates the ID upper energy boundary ($E_t^{\mathrm{max,ID}}$). This violation highlights the need for rescheduling the DA schedule to comply with the ID boundaries.

We discuss two distinct rescheduling approaches: the baseline (or static CID) rescheduling (see Fig. 6) and the CID trading strategy (see Fig. 7). The core difference between these approaches lies in their power schedules. The baseline strategy and static CID strategy (see

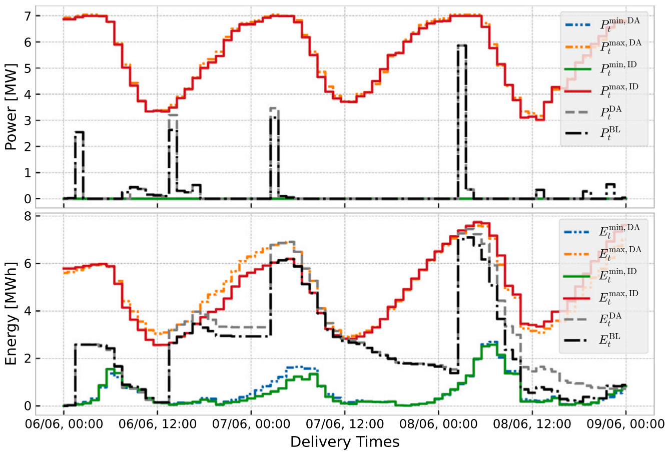


Fig. 6. Exemplary baseline schedule for EV fleet from June 6 to June 8, 2022.

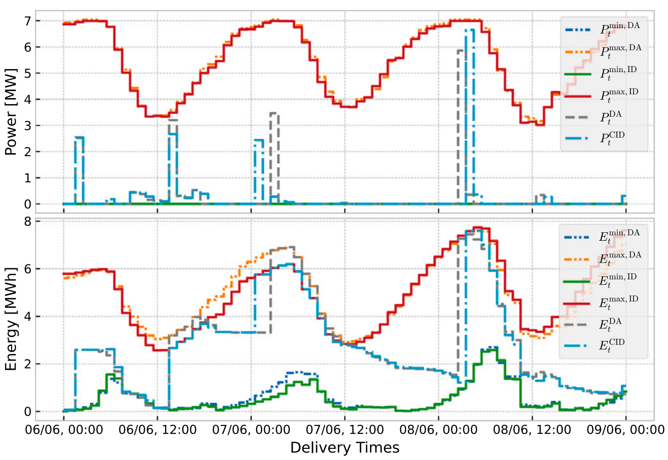


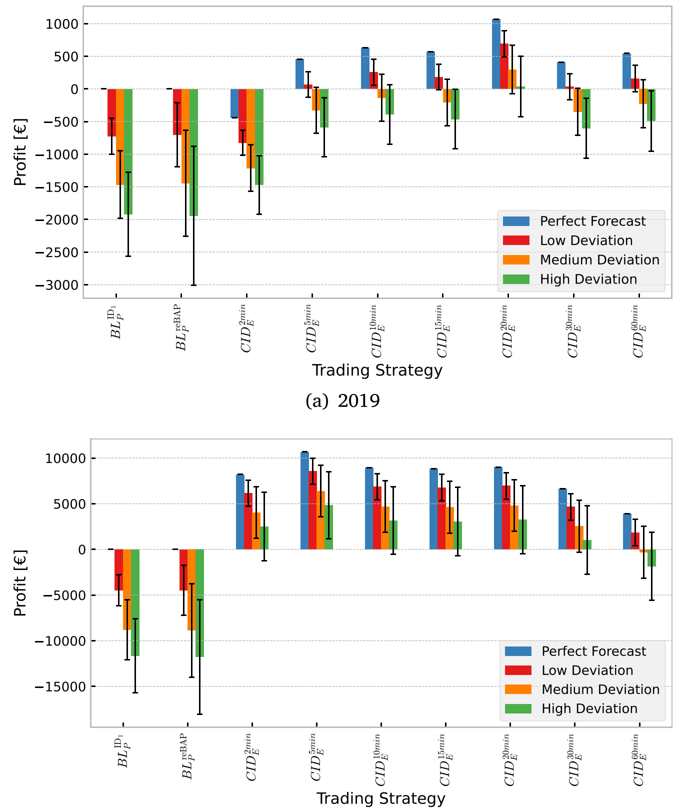
Fig. 7. Exemplary CID final schedule for EV fleet from June 6 to June 8, 2022.

Fig. 6) aim to minimize trading volumes. Therefore, they selects a power schedule that tracks closely the DA schedule (E_t^{DA}). As a result, the resulting power schedule (P_t^{BL}) predominantly adjusts the power magnitude, while maintaining the original timing of the DA power schedule (P_t^{DA}). An instance of such an adjustment occurs on June 7 at 3:00. In contrast, the power schedule of the dynamic CID strategy (P_t^{CID}) deviates significantly from the DA power schedule (P_t^{DA}) in both timing and magnitude (see Fig. 7). For example, this deviation can be seen on June 7 where the optimization shifts power from 3:00 in DA to 1:00 in CID. The different rescheduling results are a consequence of the strategy's dual objectives: to adhere to ID constraints and to capitalize on price arbitrage opportunities. Consequently, the times when charging power is scheduled differ between the DA and ID schedules. This leads to situations where EVs end up being charged at different times under the ID schedule compared to what was originally planned in the DA period.

To sum up, all strategies successfully adjust their schedules to stay within the ID energy and power constraints. However, the differences in their power schedules highlight their different optimization targets.

6.2. Trading profit

The financial evaluation of the rescheduling strategies involves calculating the expected yearly profits for 1000 EVs under each strategy. For each strategy, we compute the annual profits during the ID period by aggregating the value of all transactions occurring within



(a) 2019

(b) 2022

Fig. 8. Comparison of yearly profits for different trading strategies in 2019 and 2022.

this period. This includes all trades in the CID including CID fees and imbalance settlement costs. More precisely, under the assumption of positive prices, profit rises when selling power volumes and declines when acquiring power volumes. Conversely, when prices are negative, the profit directions invert. The optimization algorithms behind the strategies operate without knowledge of future prices. They rely on price forecasts. However, the computation of profit uses actual prices for both the CID and imbalances, namely the reBAP. We analyze the two years 2019 and 2022 separately due to different market conditions, yielding two sets of profits.

The bar charts in Fig. 8 illustrates the mean annual profits generated by the various trading strategies. The chart contains four bars for each strategy, with each bar representing a different level of discrepancy between the DA and ID EV flexibility forecasts. From left to right the bars represent a perfect forecast (in blue), low deviation (in orange), a medium deviation (in green), and high deviation (in red) (see Sections 4.2 and 5.2 for more details on EV flexibility forecasts). To provide information on the variability of profit, each bar includes whiskers that extend to show a range of two standard deviations above and below the average profit. The strategies BL_P^{reBAP} and $BL_P^{\mathrm{ID}_1}$ only vary in their power volume clearing approach. The strategy BL_P^{reBAP} takes power volumes to the imbalance market, clearing for the reBAP, and $BL_P^{\mathrm{ID}_1}$ trades in the CID market clearing for the ID_1 price. The range of strategies from CID_E^{2min} to CID_E^{60min} represent different parametrizations of the dynamic CID strategy, distinguished by their decision frequency intervals, specifically 2 min and 60 min in the mentioned strategies, as described in Sections 3.3.3 and 5.3.

Analyzing the strategies employed during these two years, we observe a consistent trend across all strategies. Profit declines noticeably as the deviation between the DA and ID EV flexibility forecasts increases. Further, the decline of profit correlates with an increase in profit variability, as indicated by the expanding whisker intervals. This trend occurs since larger deviations between the DA and ID EV flexibility forecasts necessitate more involuntary rescheduling. The term "involuntary rescheduling" refers to rescheduling due to violations of ID flexibility metrics, in contrast to "voluntary rescheduling", which occurs exclusively to enhance profit through arbitrage. The occurrence of involuntary rescheduling reduces the flexibility available for voluntary rescheduling, thereby reducing the potential and increasing the volatility of profits.

Focusing on the baseline strategy and the static CID strategy, namely $BL_P^{\mathrm{ID}_1}$ and BL_P^{reBAP}, the strategies yield zero profit in the perfect forecast scenario. This outcome is a consequence of their design, which minimizes traded volumes. In other words, when forecasts are perfect, these strategies do not engage in trading, leading to the generation of neutral profits. However, the profits from these strategies become increasingly negative in the scenarios with higher deviation between the DA and ID EV flexibility forecasts. These negative profits are a consequence of involuntary rescheduling and limited exploitation of EV flexibility inherent to these strategies, as they only adapt schedules to ID flexibility metrics.

In contrast, the outcomes for the dynamic CID strategies are more favorable. These strategies (ranging from CID_E^{2min} to CID_E^{60min}), do not only adjust positions to comply with the ID flexibility constraints, but they also exploit arbitrage opportunities when trading across different products. In the year 2019, only the CID_E^{20min} strategy yields positive profits across all levels of deviation, reaching up to €1,067.98. The year 2022 has different characteristics, with all CID strategies except CID_E^{60min} generating positive profits at all deviation levels. Notably, the overall profit in 2022 is significantly higher. The top-performing strategy CID_E^{5min} reaches profit of up to €10,670.59.

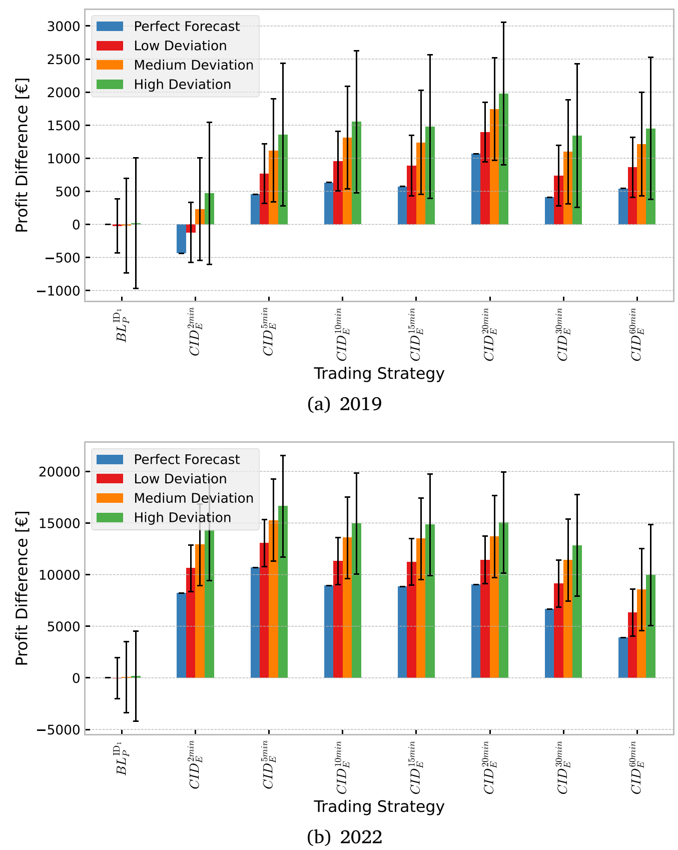
The comparison of the results from 2019 and 2022 reveals two differences. First, profit margins vary significantly between the two years, being significantly higher in 2022. This rise reflects the differing market conditions, particularly the higher prices in 2022 and the ensuing rise in volatility. Secondly, the optimal dynamic CID strategy differed between the years. In 2019, the CID_E^{20min} strategy performs best, whereas in 2022, the CID_E^{5min} strategy performs best. The strategies differ in their trading frequency (every 5 min as opposed to every 20 min). This difference indicates that a higher trading frequency was beneficial in 2022, contrary to 2019. This finding contradicts the expectation that higher frequency trading should yield more profit by revealing a greater arbitrage opportunities. However, market liquidity is limited and changes over time. Markets in 2019 were less liquid than those in 2022. The increase in CID market liquidity from 2019 to 2022 provides a plausible explanation for the shift towards a higher optimal trading frequency.

In summary, the analysis over two years reveals that trading profit decreases with downgrades of EV flexibility forecasts. The baseline strategy and the static CID strategy minimize traded volumes, and therefore yield no profits under perfect forecasts, and lead to losses with greater forecast deviations. In contrast, dynamic CID strategies can incur profits, with higher frequency CID trading strategies being more profitable in 2022 than in 2019. Overall margins are significantly higher in 2022 than in 2019. Additionally, the results underscore the importance of accurate EV flexibility forecasts, and the need for trading to adapt to market conditions.

6.3. Trading profits over imbalance baseline

Expanding our analysis, we evaluate the relative profitability of strategies trading in the CID market against the baseline strategy (BL_P^{reBAP}) that takes volumes to the imbalance market and incurs the reBAP. Consideration of relative profits enables us to illustrate the financial implications of participating in the CID market, as opposed to settling volumes as imbalances which incur the reBAP price.

Fig. 9 displays differences in profits of the 1000 EVs for all strategies trading in the CID ($BL_P^{\mathrm{ID}_1}$, and CID_E^{2min} to CID_E^{60min}) over the baseline strategy BL_P^{reBAP}. To represent uncertainty, each bar has whiskers that extend two standard deviations above and below the mean profit differences. Echoing the approach in Fig. 8, Fig. 9 also displays results for different levels of deviation between the DA and ID flexibility forecasts. It also features two plots, one for each of the years 2019 and 2022.



(a) 2019

(b) 2022

Fig. 9. Comparison of yearly improvement over BL_P^{reBAP} as a share of DA costs in 2019 and 2022.

Comparing the various strategies, the static CID strategy $BL_P^{\mathrm{ID}_1}$, which settles volumes at the ID_1 price, performs similarly to the baseline strategy (BL_P^{reBAP}), as indicated by the approximate zero values in the figure. Within the dynamic CID strategies, the most yield an improvement over the static CID strategy $BL_P^{\mathrm{ID}_1}$ in both 2019 and 2022. A singular exception is the CID_E^{2min} strategy under the perfect forecast scenario in 2019, which under-performs relative to the baseline strategy, a fact underscored by the negative values on the graph. Conversely, all other dynamic CID strategies show gains over the baseline strategy, suggesting that energy suppliers would benefit from adopting these strategies rather than depending on the baseline strategy and settling additional power needs in imbalance markets. The extent of these improvements increases with the level of deviation between the DA and ID schedules.

The increased benefit of participating in the CID market under conditions of higher uncertainty in EV schedules arises from the dynamic CID strategy being able to facilitate the exploitation of EV charging flexibility for arbitrage across products with different delivery intervals. Our dynamic CID trading strategy capitalizes efficiently on these arbitrage opportunities. EV charging is particularly suitable for such optimization. Given the constraints set by user requirements, the charging intervals can be optimized not only to reduce imbalances, but also to generate profit.

6.4. Limitations and outlook

We acknowledge limitations in our study that open avenues for future research. Although we focused on the German market, our methodology could be adapted to other European markets due to the harmonization of power market designs [68]. Incorporating additional market segments like the IDA could provide more trading opportunities. Applying cross-market optimization instead of sequential optimization might increase profits and allow for the selection of the most favorable prices. Future research could explore the optimal distribution of purchase volumes across various markets in a multi-market optimization framework, though this requires advanced price forecasts beyond our current scope.

Enhancing CID price forecasting models and increasing the temporal resolution of products to 15-minute intervals could improve profitability and provide more granular insights. Our assumption that ID EV flexibility forecasts equal realized flexibility stems from the fact that the ID forecasting time is very close to the actual realization and that we are considering a fleet of EVs. However, this assumption requires further investigation, as there may still be discrepancies between forecasts and actual flexibility.

To quantify EV flexibility in our paper, we use synthetic data generated from the German mobility patterns. While this approach is effective, it may overlook certain uncertainties in driving and charging behaviors. For instance, mobility patterns in Germany could shift during the holiday season—a detail that synthetic data may not fully capture. Future research could use real-world data to quantify EV flexibility, allowing for a more precise modeling of such seasonal variations and behavioral uncertainties. Additionally, we assume linear charging for simplicity. In reality, charging power decreases when the state of charge (SOC) of the battery is getting closer to full battery capacity, which can extend charging times and might reduce flexibility. Despite this, aggregating multiple EVs helps minimize the individual discrepancies, so the impact on overall profits from trading EV flexibility in the CID market remains relatively small. Finally, while our current model assumes full flexibility provision by EV users, exploring scenarios with partial flexibility provision is essential for understanding the strategies' applicability.

7. Conclusion

In this paper we explored the potential of EV charging flexibility trading in the CID market. Our focus was twofold: examining market price dynamics in the CID market, and the uncertainties caused by unpredictable EV user behavior. To address CID price uncertainties, we used a forecasting model to inform trading decisions. When considering the uncertainties of EV charging requirements, we took account of a DA forecast, which later underwent an update with a new forecast made during the ID period.

Our method involved a two-step optimization process. First, we optimized power acquisition in the DA market according to the DA EV charging flexibility forecast. Second, based on an updated ID EV flexibility forecast, we reoptimized the charging schedules. We introduced several trading strategies for this readjustment. The baseline strategy avoids completely any trading in the CID market, opting instead to always settle imbalances through the reBAP. In contrast, our alternative strategies settle power volumes directly in the CID market. We paid special attention to strategies that exploit EV charging flexibility, as these feature arbitrage opportunities within the CID market. We also explored rolling windows with their different trading frequencies.

The empirical results suggest that higher differences in EV charging flexibility metrics between the DA and ID coincide with decreased profits across all examined strategies. Nonetheless, the advantage of trading in the CID market increases with greater EV charging schedule uncertainty. Active trading in CID markets improves profit margins, as this creates market arbitrage opportunities by exploiting EVs' charging flexibility. Adhering to a baseline strategy and clearing the remaining power differences through imbalance markets incurs considerable costs. Our optimization method can facilitate more successful trading in the CID market, thus helping to manage forecast discrepancies in EV schedules and potentially generating profits. In our scenario with the highest deviation between the DA and ID flexibility metrics, applying the best CID strategies yielded an average yearly profit of €37.52 and €4,840.63 for 1000 EVs in 2019 and 2022 respectively. In comparison to the baseline strategy, which clears volumes as imbalances, the corresponding financial savings amounted to €1,978.52 and €16,632.25 respectively.

Our findings suggest that with an appropriate trading strategy, energy suppliers serving EV users can mitigate financial risks arising from inaccuracies in the forecasts of EV power requirements. The efficacy of such a strategy relies on two key components: First, it requires EV users to facilitate flexibility, specifically through the adoption of smart charging practices. Second, it requires strategic trading in the CID market. A profitable trading strategy should not only take account of the flexibility offered by EVs, but should also feature arbitrage between products that are traded in parallel.

CRediT authorship contribution statement

Raviteja Chemudupaty: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Data curation, Conceptualization. **Timothée Hornek:** Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Data curation, Conceptualization. **Ivan Pavić:** Writing – review & editing, Conceptualization. **Sergio Potenciano Menci:** Writing – review & editing.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used ChatGPT and Writefull in order to improve readability and language. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Raviteja Chemudupaty reports financial support was provided by Fondation Enovos. Timothee Hornek reports financial support was provided by Enovos Luxembourg S.A. Ivan Pavic reports financial support was provided by Enovos Luxembourg S.A. Sergio Potenciano Menci reports financial support was provided by Luxembourg National Research Fund. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Absolute values in LP objective functions

Objective functions containing absolute values are not inherently solvable by a linear programming (LP) solvers. However, in specific scenarios, these objective functions can be linearized. Consider the objective function expressed in Eq. (A.1):

$$\min \sum_i |a_i - b_i|, \tag{A.1}$$

where a_i and b_i represent variables, potentially subject to linear constraints. Linearizing this objective function involves introducing auxiliary variables ($z_i \forall i$) alongside additional constraints (see Eqs. (A.3) and (A.4)). The modified optimization problem is defined by the objective function in Eq. (A.2):

$$\min \sum_i z_i, \tag{A.2}$$

subject to the new constraints:

$$z_i \geq a_i - b_i \quad \forall i, \tag{A.3}$$

$$z_i \geq b_i - a_i \quad \forall i, \tag{A.4}$$

in addition to the original problem's constraints. This reformulation aligns with an LP formulation. Note that this transformation is applicable exclusively to minimization problems.

Appendix B. Aggregated EV flexibility evaluation

To validate the parameterization of the resulting schedules, we quantify the deviation between the DA and ID schedules using two established error metrics: the root mean squared error (RMSE) and the mean absolute error (MAE). For instance, the respective metric definitions for $E_t^{\min}$ are given by:

$$MAE(E_t^{\min}) = \frac{1}{|T|} \sum_{t \in T} \left| E_t^{\min,\mathrm{ID}} - E_t^{\min,\mathrm{DA}} \right| \tag{B.1}$$

$$RMSE(E_t^{\min}) = \sqrt{\frac{1}{|T|} \sum_{t \in T} \left(E_t^{\min,\mathrm{ID}} - E_t^{\min,\mathrm{DA}} \right)^2}, \tag{B.2}$$

where $E_t^{\min,\mathrm{ID}}$ denotes the ID bound for $E_t^{\min}$, while $E_t^{\min,\mathrm{DA}}$ denotes the DA bound for $E_t^{\min}$. The same definition applies to: $E_t^{\min}$, $E_t^{\max}$, $P_t^{\max}$, and E_t^{left}. We omit $P_t^{\min}$ from further consideration as we assume that $P_t^{\min,\mathrm{DA}} = P_t^{\min,\mathrm{ID}} = 0$, implying that both RMSE and MAE yield errors of zero.

Fig. B.10 depicts the resulting error metric values for the low, medium, and high deviations between the DA and ID flexibility metrics (see Section 3.1.3). Table B.5 contains the exact values depicted in Fig. B.10. We omit the results for the perfect forecast scenario in the figure, since all errors are zero. In the figure, the whiskers span two standard deviations both above and below the mean, meaning that, if we assume normality of the errors, the whiskers cover over 95% of the target population.

Comparing the different variables, both the RMSE and MAE errors for the maximum energy level $E_t^{\max}$ exceed the errors of the other variables. This implies, that the maximum energy level $E_t^{\max}$ is most sensitive to forecast errors in EV user behavior. Comparing the different scenarios yields a consistent pattern across variables. The errors for the variables increase in line with the deviation level between the DA and ID schedules, validating our generation approach for the schedule bounds.

Data availability

The authors do not have permission to share data.

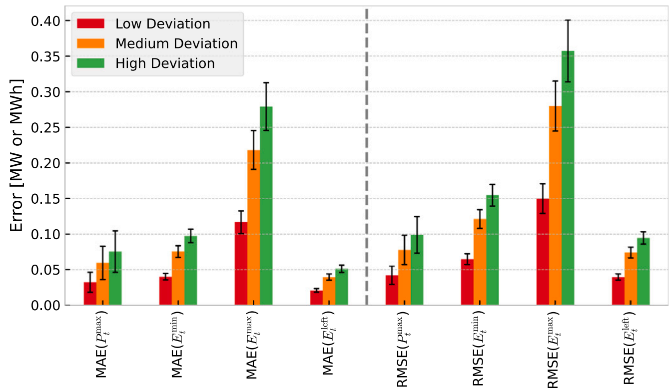

Fig. B.10. Mean absolute percentage error (MAPE) and root mean squared percentage error (RMSPE) for the different flexibility metrics.

Table B.5
Means and standard deviations of relative errors of EV schedule variables for different levels of deviations EV flexibility forecast deviations in %.

(a) 2019

Strategy	Mean			Std.		
	Low	Medium	High	Low	Medium	High
MAE($P_t^{\max}$)	3.23	5.94	7.54	0.71	1.16	1.45
MAE($E_t^{\min}$)	4.0	7.54	9.73	0.23	0.41	0.48
MAE($E_t^{\max}$)	11.67	21.8	27.91	0.8	1.37	1.68
MAE(E_t^{left})	2.08	3.95	5.12	0.12	0.22	0.25
RMSE($P_t^{\max}$)	4.22	7.78	9.9	0.64	1.03	1.29
RMSE($E_t^{\min}$)	6.47	12.11	15.46	0.38	0.66	0.76
RMSE($E_t^{\max}$)	14.98	27.99	35.73	1.04	1.76	2.17
RMSE(E_t^{left})	3.96	7.41	9.45	0.22	0.38	0.43

(b) 2022

Strategy	Mean			Std.		
	Low	Medium	High	Low	Medium	High
MAE($P_t^{\max}$)	3.22	5.92	7.57	0.67	1.18	1.48
MAE($E_t^{\min}$)	4.01	7.52	9.71	0.22	0.41	0.45
MAE($E_t^{\max}$)	11.66	21.77	27.89	0.74	1.4	1.58
MAE(E_t^{left})	2.08	3.94	5.11	0.12	0.22	0.25
RMSE($P_t^{\max}$)	4.2	7.76	9.92	0.6	1.05	1.3
RMSE($E_t^{\min}$)	6.48	12.08	15.43	0.36	0.68	0.73
RMSE($E_t^{\max}$)	14.98	27.95	35.7	0.98	1.81	2.06
RMSE(E_t^{left})	3.96	7.39	9.44	0.21	0.39	0.42

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A.3.7 Research Paper 7 - Electric Vehicle Scheduling Strategies to Reduce the Imbalances due to User Uncertainties

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Electric Vehicle Scheduling Strategies to Reduce the Imbalances due to User Uncertainties

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ABSTRACT

There has been an increase in the adoption of electric vehicles (EVs) due to growing environmental concerns, technological advancements, and supportive government policies. This rapid increase in EVs necessitates energy providers to procure sufficient power to meet the charging demands. However, uncertainties in EV usage due to variable driving patterns and charging preferences make it challenging for energy providers to predict the charging demand. To address these uncertainties, energy providers can use stochastic models and trade in multiple short-term electricity markets. Moreover, when smart charging, energy providers can use the EV flexibility to charge the vehicles during lower market price periods, reducing procurement costs. Despite these strategies, there is a time lag between trading and delivery during which users could change their EV usage patterns, leading to new user requirements during delivery. This update in the user requirements creates discrepancies between procured and updated power needs, causing imbalances. Our study analyzes whether EVs possess enough flexibility to overcome their uncertainties, satisfy user energy requirements, and reduce imbalance costs. We develop a two-step approach: 1) procuring energy in the day-ahead market and 2) rescheduling across each EV to meet updated requirements. We test three rescheduling strategies across 51 scenarios, reflecting the updated user requirements. Our findings reveal that, despite uncertainties, EVs have enough flexibility to meet user needs and reduce imbalance costs, with the potential for additional revenues.

Keywords: Smart charging, Electric vehicle flexibility, Optimization, Day-ahead market, Imbalance costs

NOMENCLATURE

Abbreviations

DA	day-ahead
EV	electric vehicle
reBAP	imbalance price

1. INTRODUCTION

In recent years, there has been a surge in the adoption of electric vehicles (EVs) [1]. This growth is expected to continue, compelling energy providers to meet the escalating power demands of EV charging. Typically, energy providers can use EV demand forecasts based on historical driving and charging patterns to help them better predict the demand and procure the power required to satisfy the charging demand [2].

However, diverse driving patterns and charging preferences create uncertainties in EV usage, posing challenges to energy providers [3]. Factors such as EV user trip distances, parking durations, arrival and departure times, and energy requirements contribute to these uncertainties, making accurate prediction difficult for the energy providers [4, 5]. To address these challenges, energy providers can utilize Monte Carlo simulation models based on probability functions [6, 7] or Markov chain models [8]. These modelling techniques enable the representation of stochastic EV usage patterns and facilitate better estimation of charging demand.

Furthermore, the actual charging duration of EVs is often less than their plugin duration, especially in the case of residential charging, which is the focus of this paper. This makes EV charging temporally flexible [9]. This temporal flexibility allows the energy providers to control and adjust the EV charging schedule within a specific period [10, 11]. Thus, when smart charging energy providers can leverage the flexibility provided by EVs to minimize their procurement costs by scheduling the EV charging when the market prices are lower [12, 13].

To handle the EV uncertainties while trading in day-ahead (DA) market, energy providers can use stochastic optimization models [14]. These models aim to minimize the expected costs while satisfying user requirements. Authors in [15] developed a stochastic optimization model with the objective to minimize the energy provider's expected cost in DA market. Within the optimization model, they considered the EV uncertainties by modelling different demand scenarios. Additionally, authors in [16, 14] include risk measures such as conditional value at risk (CVar) in their stochastic models. The inclusion of risk measures to mitigate the financial risks incurred due EV uncertainty while trading in DA market.

Two-stage optimization models enable energy providers to optimize the EV charging in both DA and intraday markets [17]. The first-stage decisions usually correspond to DA market scheduling to minimize the costs of the energy provider. The second-stage decisions usually correspond to intraday markets where the objective function is to reduce the power imbalances and minimize the energy provider's costs [18]. Furthermore, authors in [19] developed a sequential trading strategy to trade in both DA and intraday markets. They developed a rolling window optimization model to deal with uncertainties while trading in the intraday market.

While the above studies effectively handle uncertainties by integrating them into their models and trading in multiple markets, a time lag exists between trading and the delivery period. During this interval, the initial user requirements predicted during the trading time may change; for instance, users may update their plugin duration and energy requests. This update in user requirements would lead to discrepancies between the procured power while trading and the updated power demand during delivery time, causing imbalances. In Europe, energy providers must settle these imbalances in the imbalance market and pay additional costs. However, if EVs possess sufficient flexibility, energy providers can reschedule the allocated power to each EV to meet the updated EV requirements and reduce imbalance costs. Therefore, our research paper aims to answer the following research questions:

- RQ 1) To what extent can energy providers use the EV flexibility to satisfy the updated energy requirements at delivery time?
- RQ 2) Do EVs possess enough flexibility to reduce the energy provider's overall imbalance costs?

To answer the above research questions, we develop a two-step optimization approach. In the first step, we procure the aggregated power required for EV charging from the DA market using the initial user requirements. We develop a linear optimization model to facilitate trading in DA market to minimize the procurement costs. In the second step, we update the user requirements and reschedule the power allocated to each EV. We use three rescheduling strategies and evaluate the imbalance costs for each strategy. In the first strategy, we assume that the energy provider tries to satisfy the updated energy requirements by reallocating the power to each EV using the aggregated power from DA market. In this strategy, the energy provider settles in the imbalance market only if they have excess power. In the second strategy, the energy provider settles all the imbalances in the imbalance market to satisfy the updated energy requirements while minimizing the overall imbalance volume. The third strategy is similar to the second, but we minimize the energy provider's overall imbalance costs in this strategy.

2. METHODS

Figure 1 gives an overview of our two-step optimization approach. The first step is related to the DA scheduling based on initial user requirements, where the energy provider procures the aggregated power required for EV charging while trading in DA market. Section 2.1 presents our optimization model and relevant data required for trading in DA market. The second part

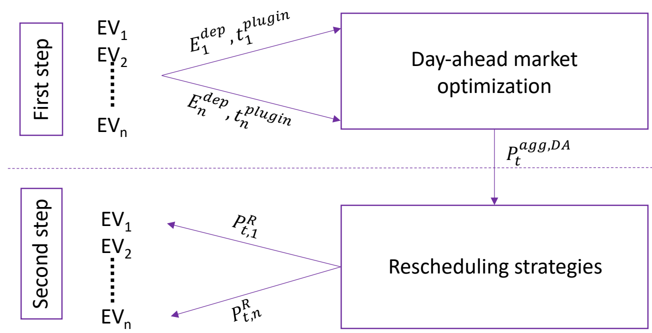

Fig. 1 Overview of our two-step optimization approach.

relates to rescheduling, where the energy provider allocates the power to each EV based on the updated user requirements using three strategies for which we develop three optimization models. Section 2.2 presents the optimization models and relevant data required to reschedule the power allocated to each EV.

2.1 Day-ahead market optimization model

We develop a linear optimization model to minimize energy provider's procurement costs incurred for charging the EV fleet while trading in DA market. The input data for our optimization model are DA market prices (C_t^{DA}), EV specifications and user requirements. The EV specifications include the maximum charging power of each EV ($P_v^{\max}$) and maximum battery capacity ($E_v^{\max}$). The user requirements include plugin duration (t_v^{plugin}) and energy level requested at departure ($E_v^{\text{dep,DA}}$). We assume perfect foresight of DA prices in line with [20].

Our objective function aims to minimize the energy provider's DA procurement costs (see Equation 1). The objective function considers the variable $P_t^{\text{agg,DA}}$ and parameter C_t^{DA}, which are the aggregated power procured from DA market for charging the EVs and the DA price at time t, respectively.

$$\min \sum_t C_t^{\text{DA}} \times P_t^{\text{agg,DA}} \times \Delta t \tag{1}$$

The aggregated power procured from DA market ($P_t^{\text{agg,DA}}$) should be equal to the power allocated to each EV while trading in DA market ($P_{t,v}^{\text{DA}}$) and this is ensured by Equation (2).

$$\sum_v \left(P_{t,v}^{\mathsf{DA}}\right) = P_t^{\mathsf{agg,DA}} \quad \forall t \tag{2}$$

Since $P_{t,v}^{\mathsf{DA}}$ is the power with which each vehicle is charged, its value should always be within the limits of the maximum charging capacity of the EV. Thus, the constraint in Equation (3) ensures that $P_{t,v}^{\mathsf{DA}}$ value is between 0 and P_v^{max} during the plugin duration.

$$0 \leq P_{t,v}^{\mathsf{DA}} \leq P_v^{\mathsf{max}} \quad \text{for } t \in t_v^{\mathsf{plugin}} \quad \forall v \tag{3}$$

$E_{t,v}^{\mathsf{DA}}$ is the energy level of the vehicle at time t, and it should be within the battery capacity limits, which is ensured by Equation (4).

$$0 \leq E_{t,v}^{\mathsf{DA}} \leq E_v^{\mathsf{max}} \quad \text{for } t \in t_v^{\mathsf{plugin}} \quad \forall v \tag{4}$$

The constraints in Equations (5), (6), and (7) ensure the energy balance of EVs at the time of arrival (t_v^{arr}), throughout the plugin duration (t_v^{plugin}) and at the time of departure (t_v^{dep}).

$E_{t,v}^{\mathsf{DA}}$ gives the energy level of an EV at timestep t, $E_v^{\mathsf{arr,DA}}$ is the energy level of an EV at t_v^{arr} which we obtain from user input, $E_{t-1,v}^{\mathsf{DA}}$ gives the energy level of an EV at previous timestep, η_{ch} is the charging efficiency, $E_v^{\mathsf{dep,DA}}$ is the energy level of EV at t_v^{dep}.

$$E_{t,v}^{\mathsf{DA}} = E_v^{\mathsf{arr,DA}} \qquad \text{for } t = t_v^{\mathsf{arr}} \quad \forall v \tag{5}$$

$$E_{t,v}^{\mathsf{DA}} = E_{t-1,v}^{\mathsf{DA}} + \eta_{\mathsf{ch}} \cdot P_{t,v}^{\mathsf{DA}} \cdot \Delta t \quad \text{for } t \in t_v^{\mathsf{plugin}} \quad \forall v \tag{6}$$

$$E_{t,v}^{\mathsf{DA}} = E_v^{\mathsf{dep,DA}} \qquad \text{for } t = t_v^{\mathsf{dep}} \quad \forall v \tag{7}$$

2.2 *Rescheduling optimization model*

Trading in the DA market occurs up to 36 hours before energy delivery, in our case, before EV charging. During the time between trading and delivery, the users might change their arrival time, departure time and energy level requested at departure. This update in the user requirements would mean that there might be a mismatch between the procured power from DA markets (aggregated DA power schedule) and updated power needs for charging, causing imbalances. The energy providers can reschedule the power allocated to each EV to address these imbalances. In our paper, we propose three rescheduling strategies for energy providers:

- First strategy: uses the same aggregated DA schedule to satisfy the updated user requirements without settling in the imbalance market. We reallocate the power to each EV to minimize the deviation between their updated energy level requirement at departure and the actual energy level resulting from the updated power we allocate to each EV.

- Second strategy: settling the imbalances in the imbalance market to satisfy the updated user requirements while minimizing the imbalance volume. By doing this, we change the aggregated power schedule at delivery (updated power schedule), ensuring we meet the updated energy requirements.

- Third strategy: settling the imbalances in the imbalance market to satisfy the updated user requirements while minimizing the imbalance costs. By doing this, we change the aggregated power schedule at delivery time (updated power schedule), ensuring we meet the updated energy requirement.

The following subsections will describe each of the strategies in more detail.

2.2.1 First strategy: Minimizing energy deviation

In the first strategy, we assume that energy providers reschedule the power allocated to each EV using the same aggregated power procured from DA market. Instead of procuring additional power from the imbalance market, the energy provider reallocates the power to each EV to reduce the deviation of the energy level requested by EV users at departures. Thus, the objective of the energy provider is to minimize the sum of the difference between the updated energy level request of the user at the departure ($E_v^{\mathsf{dep,R}}$) and the actual energy level of the user at departure time after the delivery ($\tilde{E}_v^{\mathsf{dep,R}}$) for all vehicles. Equation (8) represents the mathematical formulation of the objective function.

$$\min \sum_v \left(E_v^{\mathsf{dep,R}} - \tilde{E}_v^{\mathsf{dep,R}}\right) \tag{8}$$

The constraint in the Equation (9) ensures that the sum of the updated power allocated to each EV ($P_{t,v}^{\mathsf{R}}$) is equal to the updated aggregated power schedule ($P_t^{\mathsf{agg,R}}$).

$$\sum_v \left(P_{t,v}^{\mathsf{R}}\right) = P_t^{\mathsf{agg,R}} \quad \forall t \tag{9}$$

In this strategy, energy providers use the same DA aggregated power schedule to meet users updated energy requirements by utilizing the flexibility provided by EVs. Ideally, if all the updated energy requirements are satisfied, $P_t^{\mathsf{agg,R}}$ should equal $P_t^{\mathsf{agg,DA}}$. However, with updated requirements, $P_t^{\mathsf{agg,R}}$ might be higher or lower than $P_t^{\mathsf{agg,DA}}$. Since we assume that the energy provider does not procure additional power from the imbalance market, $P_t^{\mathsf{agg,R}}$ can never exceed $P_t^{\mathsf{agg,DA}}$. Instead, $P_t^{\mathsf{agg,R}}$ can be less than $P_t^{\mathsf{agg,DA}}$ to ensure feasibility if the overall $P_t^{\mathsf{agg,R}}$ needed is less than the overall $P_t^{\mathsf{agg,DA}}$. When $P_t^{\mathsf{agg,R}}$ is less than $P_t^{\mathsf{agg,DA}}$, the energy provider settles the excess power in the imbalance market. Equation (10) ensures the power balance between $P_t^{\mathsf{agg,R}}$ and $P_t^{\mathsf{agg,DA}}$.

$$P_t^{\text{agg,R}} \leq P_t^{\text{agg,DA}} \quad \forall t \tag{10}$$

Furthermore, the objective function is subject to updated constraints given by (11), (12), (13), (14), and (15).

$$0 \leq P_{t,v}^{\text{R}} \leq P_v^{\text{max}} \quad \text{for } t \in t_v^{\text{plugin}} \quad \forall v \tag{11}$$

$$0 \leq E_{t,v}^{\text{R}} \leq E_v^{\text{max}} \quad \text{for } t \in t_v^{\text{plugin}} \quad \forall v \tag{12}$$

$$E_{t,v}^{\text{R}} = E_v^{\text{arr,DA}} \qquad \text{for } t = t_v^{\text{arr}} \quad \forall v \tag{13}$$

$$E_{t,v}^{\text{R}} = E_{t-1,v}^{\text{R}} + \eta_{\text{ch}} \cdot P_{t,v}^{\text{DA}} \cdot \Delta t \quad \text{for } t \in t_v^{\text{plugin}} \quad \forall v \tag{14}$$

$$E_{t,v}^{\text{R}} \leq E_v^{\text{dep,R}} \qquad \text{for } t = t_v^{\text{dep}} \quad \forall v \tag{15}$$

The only major difference compared to DA optimization model is the energy balance equation at t_v^{dep} that is relaxed. We depict this using Equation (15). This constraint ensures that the actual energy level at departure can be less than the requested one.

$$E_{t,v}^{\text{R}} = \tilde{E}_v^{\text{dep,R}} \quad \text{for } t = t_v^{\text{dep}} \quad \forall v \tag{16}$$

The Equation (16) gives the mathematical representation of how we calculate the actual energy level at departure ($\tilde{E}_v^{\text{dep,R}}$), which is also the decision variable of the objective function (see Equation 8)

2.2.2 Second strategy: Minimize power deviation

In this strategy, we assume that the energy provider settles all the imbalances in the imbalance market and reallocates the power to each EV. While doing so, the energy provider tries to reduce the imbalance volumes whilst satisfying the user requirements. Accordingly, we formulate our objective function in Equation (17), which is to minimize the sum of the absolute power difference between the updated aggregated power schedule ($P_t^{\text{agg,R}}$) and aggregated DA power schedule ($P_t^{\text{agg,DA}}$).

$$\min \sum_t \left| P_t^{\text{agg,R}} - P_t^{\text{agg,DA}} \right| \tag{17}$$

We can observe that the objective function (Equation (17)) is non-linear as we are minimizing an absolute value. To make the objective function linear, we introduce an auxiliary variable for each time t denoted by z_t and additional constraints formulated in Equations (19) and (20). Accordingly, we present the modified optimization problem with an updated objective function in Equation (18) to minimize the sum of variable z_t.

$$\min \sum_t z_t \tag{18}$$

The constraints (refer to Equations (19) and (20)) ensure that z_t is at least as large as the absolute value of the expression inside.

$$z_t \geq \left(P_t^{\text{agg,R}} - P_t^{\text{agg,DA}} \right) \quad \forall t \tag{19}$$

$$z_t \geq -\left(P_t^{\text{agg,R}} - P_t^{\text{agg,DA}} \right) \quad \forall t \tag{20}$$

The objective function is subject to the same constraints as the first strategy (refer to Section 2.2.1) given by Equations (9), (11), (12), (13), and (14). However, the constraint in Equation (21) is different compared to the first strategy as the energy provider must ensure that they satisfy the EV user's energy requirements.

$$E_{t,v}^{\text{R}} = E_v^{\text{dep,R}} \quad \text{for } t = t_v^{\text{dep}} \quad \forall v \tag{21}$$

2.2.3 Third strategy: Minimizing imbalance costs

In the third strategy, we assume that the energy provider has perfect foresight of imbalance prices and aims to reduce the imbalance costs. Accordingly, our objective function (refer to Equation 22) is to minimize the energy provider's imbalance costs when settling in the imbalance market.

$$\min \sum_t \left(P_t^{\text{agg,R}} - P_t^{\text{agg,DA}} \right) \times C_t^{\text{reBAP}} \times \Delta t \tag{22}$$

The objective function is subject to the same constraints as in the second strategy (refer to Section 2.2.2), given by Equations (9), (11), (12), (13), (14), and (21).

3. DATA AND SIMULATION SETUP

3.1 Mobility data

We use existing synthetic mobility data to derive the user requirements for each EV [21]. The synthetic mobility data stems from a German mobility survey [22]. The mobility data consists of 200 unique mobility profiles of residential EVs. We analyze only the home charging case with the following assumptions:

- All vehicles are always plugged in when parked at home.
- All vehicles are charged until they reach E_v^{max}, or the maximum energy level they can reach when the users plugin their vehicle.
- The battery capacity of all vehicles is 75 kWh
- We consider a Level 2 charger with a mean power rating of 7.4 kW and charging efficiency (η) of 95%, typically used for home charging [23].

We divide the mobility dataset, containing individual profiles for the entire fleet of 200 EVs over one year, into weekly datasets. This results in 52 datasets comprising the individual mobility profiles for the entire EV fleet over one week each. Out of the 52 new datasets, we use one dataset to reflect the predicted (initial) user requirements while trading in DA market, and we use the other 51 datasets to reflect the change in user requirements and to test our rescheduling strategies for each of the 51 datasets separately.

3.2 Market data

We use the German DA market's one week's price data from January 2024 for trading in DA [24]. The resulting price data is from 15th January 2024 to 21st January 2024. We obtain imbalance price (reBAP) prices from ENTSOE-E Transparency Platform [25] for the same period as that of DA market data. We calculate the imbalance costs for all strategies ex-post using the reBAP price data. Equation (23) gives the formula we use to calculate the total imbalance costs for each rescheduling trading strategy.

$$\sum_t \left(P_t^{\text{agg,R}} - P_t^{\text{agg,DA}} \right) \times C_t^{\text{reBAP}} \times \Delta t \qquad (23)$$

4. RESULTS AND DISCUSSION

In this section, we present the results to answer our research questions. Section 4.1 presents the aggregated power schedule resulting from the DA optimization and updated aggregated power schedules resulting from the three rescheduling strategies. In Section 4.2, we compare the three strategies by calculating the energy deviation incurred for the EVs across all the charging sessions. Section 4.3 compares the three strategies, calculating the imbalance costs incurred while settling in the imbalance market.

4.1 Aggregated EV schedules

We first present the aggregated power schedule from the DA optimization. To illustrate our rescheduling process, we plot the updated aggregated power schedules from our three strategies and compare them with the DA aggregated power schedule. We present the aggregated power schedules for a single day: January 18, 2024.

Figure 2 presents the aggregated DA power schedule ($P_t^{\text{agg,DA}}$) based on DA market optimization (refer to Section 2.1) and DA market prices (C_t^{DA}). As the objective of the DA market optimization model is to minimize the overall costs, it tries to procure the power when prices are lower. Therefore, we can observe that most of the power procured for EV is between 02:00 and 04:00 when the prices are lower.

Figure 3 presents two aggregated power schedules - $P_t^{\text{agg,DA}}$ and $P_t^{\text{agg,R1}}$. $P_t^{\text{agg,R1}}$ is the updated aggregated power schedule based on the first strategy (refer to Section 2.2.1). We can observe that both power schedules are overlapping each other, indicating that $P_t^{\text{agg,R1}}$ is the same as that of $P_t^{\text{agg,DA}}$. This is because, in the first strategy, the model tries to allocate the power to each EV while still using the $P_t^{\text{agg,DA}}$.

Figure 4 presents two aggregated power schedules -

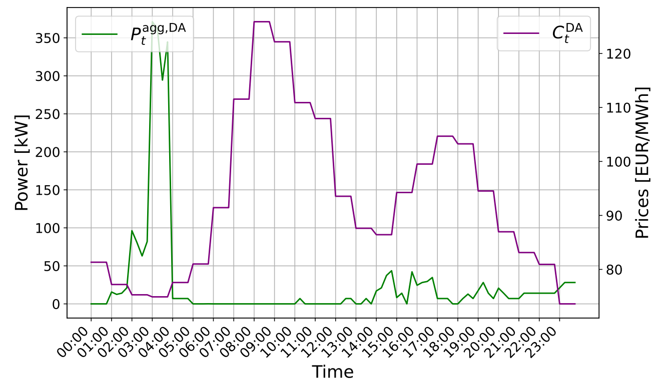

Fig. 2 Day-ahead schedule on 18th Jan 2024.

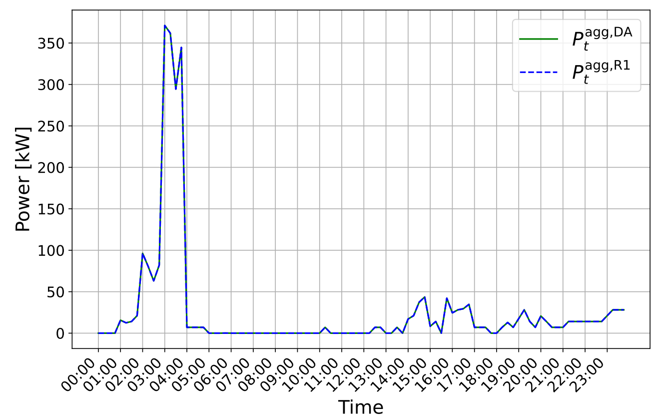

Fig. 3 Updated schedule based on first strategy on 18th Jan 2024.

$P_t^{\text{agg,DA}}$ and $P_t^{\text{agg,R2}}$. $P_t^{\text{agg,R2}}$ is the updated aggregated power schedule based on the second strategy (refer to Section 2.2.2). The objective of the second strategy is to minimize the power deviation. Therefore, we can observe that $P_t^{\text{agg,R2}}$ profile is very similar to $P_t^{\text{agg,DA}}$ albeit, there are few instances where the magnitude of $P_t^{\text{agg,R2}}$ is different to that of $P_t^{\text{agg,DA}}$ to account for imbalances caused due to the change in user requirements. One instance where the imbalance occurs is around 05:00. This is a negative imbalance since the $P_t^{\text{agg,R2}}$ value is higher than that of $P_t^{\text{agg,DA}}$ during this instance (at 05:00), which means the energy provider has to procure more power to satisfy the users' updated energy requirements.

Figure 5 presents the results for the third strategy (refer to Section 2.2.3). In the figure, we present $P_t^{\text{agg,DA}}$, $P^{\text{agg,R3}}$ - the updated aggregated power schedule based on the third rescheduling strategy, and imbalance prices (C_t^{reBAP}). We can observe that $P^{\text{agg,R3}}$ is quite different from $P^{\text{agg,DA}}$. The difference is because the third rescheduling strategy aims to minimize the imbalance costs. Therefore, the model utilizes the EV flexibility to create a negative imbalance when the imbalance prices are lower and procure the power from the imbalance market, and create a positive imbalance when the im-

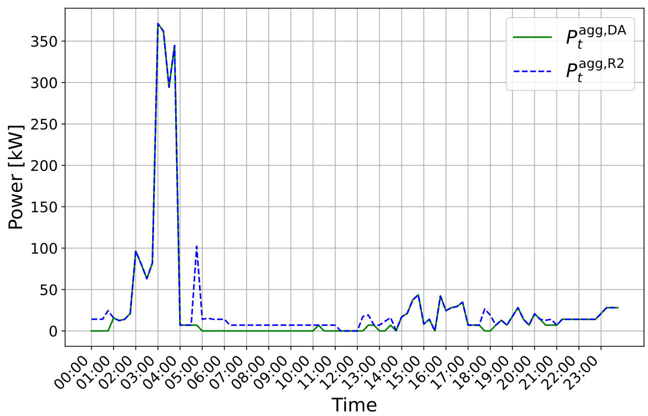

Fig. 4 Updated schedule based on second strategy on 18th Jan 2024.

balance prices are high and sell the imbalance power to the market. A few instances where we can observe instances of negative imbalance are around 02:00, 04:00 and 23:00. One instance of positive imbalance is around 03:00.

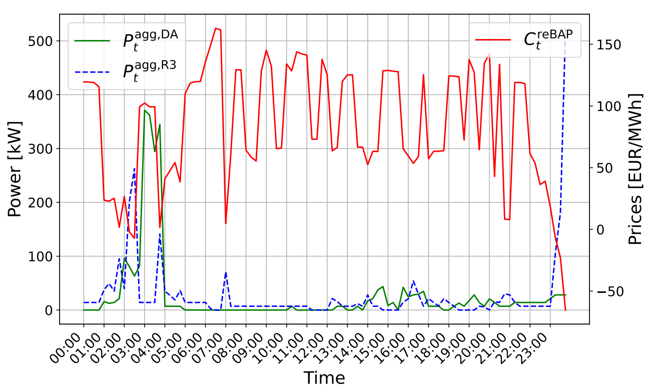

Fig. 5 Updated schedule based on third strategy on 18th Jan 2024.

4.2 Deviation in requested energy

The energy level deviation gives the difference between the updated energy level requested by users and the actual energy level that EVs have at the departure time after the rescheduling. Figure 6 shows the histogram of energy level deviations for all EVs at departure time in all 51 scenarios over one week for the first trading strategy. The x-axis represents the energy level deviation of each EV in kWh, and the y-axis represents the percentage of occurrences. We limit the x-axis data to 25 kWh to better illustrate the distribution of values. From the figure, we observe that in about 85% of cases, the energy level deviation is zero; for the remaining 15%, the deviation is spread from 1 kWh to 60 kWh, most of which are under 15 kWh. These results indicate that using the first strategy, the energy providers could satisfy the energy requirements of users for about 85% of the cases.

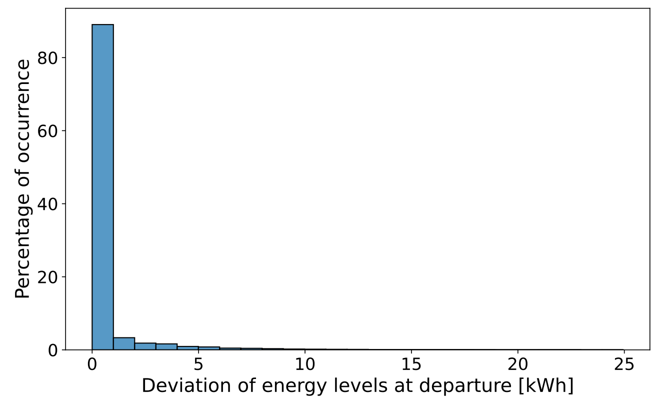

Fig. 6 Energy level deviation across all scenarios.

The energy level deviation for all EVs across all scenarios in the second and third strategies is equal to zero. The value is zero because the model allocates the power to each EV in a way that satisfies the user requirements, which means that the actual energy level is equal to the updated energy level requested by the user.

In the first strategy, energy deviations primarily occur in scenarios where overall energy requirements significantly exceed the anticipated levels during DA trading, resulting in insufficient power to meet the demand. In our study, we assume that all EVs would be charged until they reach their maximum battery capacity, which translates to EV users requesting 100% battery capacity at the time of departure. Often, EV users do not need 100% of their battery for their daily driving needs. For example, the average daily distance in Germany is around 33 km, which requires approximately 9% of the total battery capacity for a vehicle with a 75 kWh battery. In the 15% of instances where the updated energy requirements were not satisfied, the energy deviation is less than 15 kWh for most instances. The 15 kWh deviation implies that their battery percentage is at least 80%, which is sufficient for most of the trips and thus might not hinder user comfort in terms of their driving needs.

4.3 Imbalance costs

Figure 7 depicts the distribution of imbalance costs incurred across all scenarios for each rescheduling strategy. In the first strategy, the imbalance costs vary from around -71 to 0 EUR for a week across all scenarios. The imbalance costs are negative because, in the first strategy, the model uses EV flexibility and tries to reallocate the power to each EV based on DA. In case of potential imbalance, the energy provider only settles in the imbalance when there is a positive imbalance, i.e., aggregated DA power is higher than updated aggregated power. As most imbalance prices are positive, the overall imbalance cost is negative (refer to the formula in Equation 23).

In the second strategy, the imbalance costs vary from around -50 EUR to 200 EUR for one week across all sce-

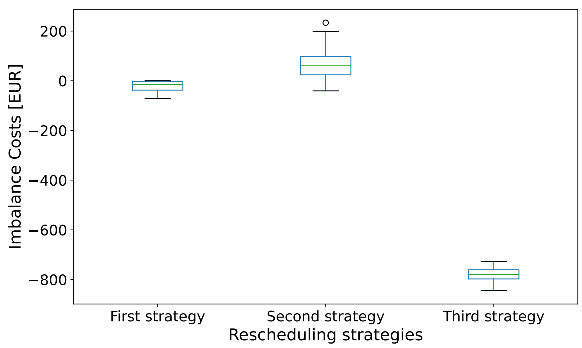

Fig. 7 Distribution of imbalance costs for each strategy.

narios, with a median value of around 60 EUR. Though the model tries to use the EV flexibility to minimize the power deviation from the aggregated DA power schedule while rescheduling, there could be several instances where there is a positive or negative imbalance. The positive imbalance occurs when the aggregated rescheduled power is less than the aggregated DA power. During the positive imbalance period, the energy provider settles (sells) the excess power in the imbalance market. If the price during the positive imbalance period is positive, the imbalance cost is negative (the provider makes revenue); else, the imbalance cost is positive (refer to the formula in Equation (23)).

The negative imbalance occurs if the aggregated rescheduled power exceeds the aggregated DA power. During the negative imbalance period, the energy provider settles (buys) the excess power in the imbalance market. If the price during the negative imbalance period is positive, the imbalance cost is positive; else, the imbalance cost is negative (the provider makes revenue) (refer to the formula in Equation (23)).

Therefore, overall imbalance costs are negative in some scenarios because there are more periods with a combination of positive imbalance and negative price and/or negative imbalance and positive price. Similarly, overall imbalance costs are negative in some scenarios because there are more periods with a combination of positive imbalance and positive price and/or negative imbalance and negative price. Therefore, creating a positive imbalance by procuring more power in DA does not always create revenues.

In the third strategy, the imbalance costs are negative, ranging from -850 EUR to -750 EUR, with a median value of -780 EUR. This strategy assumes perfect foresight of imbalance prices, allowing the model to utilize the flexibility provided by EVs to create positive and negative imbalances during periods that minimize costs. Consequently, the imbalance costs are negative in all scenarios.

However, the third strategy is purely theoretical since providers cannot predict imbalance prices upfront and thus cannot reschedule power to EVs to generate such revenues. These results highlight that advanced knowledge of imbalance prices could help minimize overall imbalance costs. However, this strategy illustrates that energy providers can harness EV flexibility to provide balancing energy services to system operators, helping to minimize overall system imbalances and generate additional revenues for suppliers or EV owners. This is because balancing energy prices is used to establish imbalance prices in the first place.

4.4 Discussion

Using the first strategy, energy providers could meet most users' energy needs. There is a risk that they might not fully satisfy the user's energy requirement, reducing the charging reliability and impacting user comfort regarding their driving needs. Suppose users offer more flexibility by reducing their energy requirements. In that case, energy providers can allocate power in a way that ensures all EVs have enough energy to complete their next trip without significantly impacting user comfort. In cases where there is still a high deviation between the energy levels at departure for the EVs, causing substantial discomfort and preventing users from meeting their driving needs, the energy provider can then resort to the second strategy. The second strategy involves settling the imbalances through the imbalance markets to meet the user's energy requirements. Thus, using the second strategy would not impact the user's comfort and charging reliability as they would have the requested energy by the end of the charging session. Furthermore, though the third strategy is impractical to implement directly, it illustrates that EVs possess enough flexibility to provide balancing energy services to system operators, helping to minimize overall system imbalances and generate additional revenues for energy providers or EV owners.

In our study, we recognize several limitations that highlight opportunities for future research. We used price data for one week to test our strategies and calculate the imbalance costs. We could extend our study for longer periods, allowing us to capture the seasonal effects. From the wholesale market model perspective, we only considered DA market because it is more liquid than the intraday market. However, for future work, we can also consider trading in the intraday market, where trading goes on until a few minutes before delivery, and analyze if trading multiple markets would reduce the imbalance costs. However, these limitations will not significantly impact our overall result, which is that despite uncertainties, EVs possess enough flexibility to meet user requirements and reduce imbalance costs.

5. CONCLUSION

Our paper analyzed if EVs possess enough flexibility to overcome the uncertainties arising due to variable EV usage, satisfy the user requirements, and reduce the energy provider's imbalance costs. We proposed a two-step scheduling approach. The first step relates to DA scheduling, where we developed a linear optimization model to procure the power required for EV charging based on the predicted initial user requirements while minimizing the energy provider's procurement costs. The second step relates to rescheduling, where we proposed three strategies to reallocate the power allocated to each EV to satisfy their updated user requirements. The first strategy reallocated power to EVs without settling in the imbalance market, minimizing deviation from updated energy requirements. The second strategy minimized imbalance volume by adjusting the aggregated power schedule at delivery. The third strategy focused on minimizing imbalance costs and adjusting the power schedule to meet updated energy requirements.

Our analysis demonstrated that energy providers could meet most of the users' energy needs by leveraging EV flexibility. Additionally, we found that providers could minimize user impact and imbalance costs by adjusting power allocation and utilizing the imbalance markets. Although the third strategy assumed perfect foresight of imbalance prices and was impractical for direct use, it illustrated that EVs possessed enough flexibility to provide balancing energy services, minimize system imbalances, and generate additional revenue. These findings highlighted the potential of EV flexibility to overcome their own uncertainties and use this flexibility to satisfy user energy requirements and reduce imbalance costs - potentially generating additional revenues.

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