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Assessment of the Added Value of Bidirectionally Chargeable Electric Vehicles for the User and the Energy System

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Abstract

To limit the anthropogenic greenhouse gas effect, a variety of adjustments are required in the final energy sectors in addition to transforming the energy sector toward a climate-neutral energy supply. For example, the integration of electric vehicles (EVs) enables the displacement of fossil fuels in the transport sector and leads to a stronger coupling of the transport and supply sectors. EVs can potentially provide flexibility as storage in this process through the new technology of bidirectional charging and discharging. Therefore, the objective of this cumulative dissertation is to quantify the added value of bidirectional EVs for both the user and the energy system. The developed modeling of bidirectional EVs has specificities depending on the point of view (system or user view) and the use case.

To evaluate the added value of bidirectional EVs from the user perspective, the optimization model eFlame is further developed to evaluate the use cases of photovoltaic (PV) self-consumption optimization and arbitrage trading via the spot markets. Due to the small power flows in the household, there is a requirement to model PV self-consumption optimization with variable charging and discharging efficiencies of the EV. Without this, revenue potentials are overestimated by 30%. For optimized trading in the spot market, consecutive trading in the day-ahead and intraday markets is modeled so that countertrading between the markets is possible. The modeled use cases show a high variability of revenue potentials depending on EV characteristics, user behavior, level and volatility of electricity prices, PV feed-in tariff, and numerous other influencing factors. Even taking into account the additional costs of bidirectional charging, however, both use cases become economical for an average user when investing in 2025.

For the evaluation of the added value of bidirectional charging from an energy system perspective, the energy system model ISAaR is further developed in order to be able to analyze two systemically oriented vehicle-to-grid use cases: Arbitrage trading via the spot markets, and congestion management provision. For this purpose, bidirectional EVs are modeled via aggregated profiles per market area or per grid node in the transmission grid in order to keep the complexity as low as possible. Despite the additional investment costs, numerous bidirectional EVs are integrated in the modeled, cost-optimal future energy system. These, in turn, lead to improved integration of PV energy and reduce the necessary capacities of both stationary storage and thermal power plants, significantly lowering the overall costs of the energy system in turn. The provision of congestion management in the transmission grid can also be partially provided by bidirectional EVs, reducing energy system costs and greenhouse gas emissions by displacing thermal power plants.

The use case of arbitrage trading via the spot markets can lead to added economic value for both the user and the energy system. Therefore, the regulatory framework should enable this use case. The other use cases considered can also be economical for either the users or the energy system, leading to the conclusion that the technology of bidirectional charging can be classified as an important part in the energy system of the future.

Kurzfassung

Zur Einschränkung des anthropogenen Treibhausgaseffekts bedarf es zusätzlich zur Transformation des Energiesektors hin zu einer klimaneutralen Energieversorgung auch in den Endenergiesektoren vielfältiger Anpassungen. So ermöglicht die Integration von Elektrofahrzeugen (EVs) die Verdrängung von fossilen Brennstoffen im Verkehrssektor und führt zu einer stärkeren Kopplung zwischen Verkehrs- und Bereitstellungssektor. EVs können durch die neue Technologie des bidirektionalen Ladens und Entladens dabei potenziell als Speicher Flexibilität bereitstellen. Ziel dieser kumulativen Dissertation ist daher die Quantifizierung des Mehrwerts bidirektionaler EVs sowohl für den Nutzer als auch das Energiesystem. Die entwickelten Modellierungen bidirektionaler EVs weisen Spezifika in Abhängigkeit der Betrachtungsweise (System oder Akteurssicht) und des Use Cases auf.

Zur Bewertung des Mehrwerts bidirektionaler EVs aus Nutzersicht wird das Optimierungsmodell eFlame weiterentwickelt, um die Use Cases der Photovoltaik (PV)-Eigenverbrauchsoptimierung und des zeitlichen Arbitrage-Handels am Spotmarkt bewerten zu können. Aufgrund der kleinen Leistungsflüsse im Haushalt ergibt sich die Anforderung, die PV-Eigenverbrauchsoptimierung mit variablen Lade- und Entladewirkungsgrad des EVs zu modellieren, da sich ansonsten um 30 % überschätzte Erlöspotenziale ergeben. Für den optimierten Handel am Spotmarkt wird das konsekutive Handeln am Day-Ahead- und am Intraday-Markt modelliert, so dass ein Countertrading zwischen den Märkten möglich ist. Die modellierten Use Cases weisen eine hohe Variabilität der Erlöspotenziale in Abhängigkeit der EV-Charakteristik, des Nutzerverhaltens, des Niveaus und der Volatilität der Strompreise, der PV-Einspeisevergütung, sowie zahlreicher weiterer Einflussfaktoren auf. Auch unter Beachtung der zusätzlichen Kosten durch das bidirektionale Laden werden beide Use Cases aber für einen durchschnittlichen Nutzer bei einer Investition im Jahr 2025 wirtschaftlich.

Für die Bewertung des systemischen Mehrwerts des bidirektionalen Ladens wird das Energiesystemmodell ISAaR weiterentwickelt, um die Vehicle-to-Grid Use Cases zeitliche Arbitrage durch den Handel am Spotmarkt und Engpassmanagement- Bereitstellung aus Energiesystemsicht analysieren zu können. Bidirektionale EVs werden dafür über aggregierte Profile je Marktgebiet bzw. je Netzknoten im Übertragungsnetz modelliert, um die Komplexität möglichst gering zu halten. Trotz der zusätzlichen Investitionskosten werden im modellierten, kostenoptimalen zukünftigen Energiesystem zahlreiche bidirektionale EVs integriert. Diese führen wiederum zu einer verbesserten Integration der PV-Energie und zu verringerten notwendigen Kapazitäten von stationären Speichern sowie thermischen Kraftwerken, so dass die Gesamtkosten des Energiesystems signifikant sinken. Auch die Bereitstellung des Engpassmanagements im Übertragungsnetz kann teilweise durch bidirektionale EVs erbracht werden, wodurch Kosten und Treibhausgasemissionen des Energiesystems durch Verdrängung von thermischen Kraftwerken verringert werden.

Der Use Case zeitliche Arbitrage durch Handel am Spotmarkt kann sowohl auf Nutzer- als auch auf Energiesystemseite zu einem ökonomischen Mehrwert führen, so dass der regulatorische Rahmen diesen Use Case ermöglichen sollte. Aber auch die anderen betrachteten Use Cases können für die Nutzer oder das Energiesystem wirtschaftlich sein, so dass die Technologie des bidirektionalen Ladens als ein wichtiger Baustein im Energiesystem der Zukunft einzustufen ist.

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Abbreviations

BCM	Bidirectional Charging Management
Bidirectional EV	Bidirectionally Chargeable EV
EFC	Equivalent Full Cycles
eFlame	Electric Flexibility Assessment Modeling Environment
EV	Electric Vehicle
EVSE	Electric Vehicle Supply Equipment
GCP	Grid Connection Point
HP	Heat Pump
ISAaR	Integrated Simulation Model for Unit Dispatch and Expansion with Regionalization
LP	Linear Programming
MID	Mobility in Germany (Survey on Mobility)
MILP	Mixed Integer Linear Programming
NPV	Net Present Value
NUTS	Nomenclature of Territorial Units for Statistics
OH	Operating Hours
PTDF	Power Transfer Distribution Factors
PV	Photovoltaic
ResOpt	Residential Optimizer
RQ	Research Question
SBS	Stationary Battery Storage
Smart EV	Smart unidirectional charging EVs
SoC	State of Charge
V2B	Vehicle-to-Business
V2G	Vehicle-to-Grid
V2H	Vehicle-to-Home

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List of Publications

In this cumulative dissertation, based on four publications, the added value of bidirectionally chargeable electric vehicles for the user and the energy system is assessed. The four publications are briefly summarized on the following pages. The complete publications can be found in the appendix of this dissertation. In the main part of this dissertation (Chapters 2 to 5), the publications are linked together and supplemented with further analysis, methodology, and elaboration.

In science, and thus also at the Research Center for Energy Economics (FfE), publications by only one author are the exception, since work is often done on complex models with a wide variety of interfaces. Therefore, all persons involved in the implementation of the described model and the processing of the input data used are listed as authors on publications. However, in all publications listed below, the first author developed the basic concept as well as the methodological approach to answer the respective research questions, and the first author was responsible for the interpretation of the model results.

This cumulative dissertation is based on the following publications:

- **Kern, T.,** Dossow, P., von Roon, S. Integrating Bidirectionally Chargeable Electric Vehicles into the Electricity Markets. Energies 2020, 13, 5812. https://doi.org/10.3390/en13215812
- **Kern, T.,** Dossow, P., & Morlock, E. (2022). Revenue opportunities by integrating combined vehicle-to-home and vehicle-to-grid applications in smart homes. Applied Energy, 307. https://doi.org/10.1016/j.apenergy.2021.118187
- **Kern, T.,** Kigle, S. (2022). Modeling and Evaluating Bidirectionally Chargeable Electric Vehicles in the Future European Energy System. Energy Reports. (Accepted, not yet published)
- **Kern, T.,** Wendlinger, C. (2022). Added Value of Providing Transmission Grid Congestion Management via Bidirectionally Chargeable Electric Vehicles. 2022 18th International Conference on the European Energy Market (EEM), 2022. (Accepted, not yet published)

The following four pages present a summary of the publications. In Chapter 8 the complete publications are attached. The detailed contributions of the first author are listed in the Section ‘Own contribution’. The citation keys [Pub1] to [Pub4] refer to the publications.

Publication 1 (Pub1): Integrating Bidirectionally Chargeable Electric Vehicles into the Electricity Markets

Summary: The energy system transformation entails structural changes in all sectors. While the electricity supply sector in Germany has already been subjected to massive adjustments due to the expansion of renewable energies, the final energy sector of transport has been very slow to switch to more climate-friendly technologies. Replacing traditional internal combustion engine vehicles with electric vehicles (EVs) proves to be challenging for the transport sector, particularly due to the higher initial investment costs. Since EVs could be more profitable by participating in the electricity markets, the aim of this paper is to investigate revenue potentials when marketing bidirectionally chargeable EVs in the spot market.

To simulate a realistic marketing behavior of electric vehicles, a mixed integer linear, rolling horizon optimization model is formulated considering real trading times in the day-ahead and intraday market. The objective of the optimization problem is the charging at minimum costs while discharging at maximum costs. A single day is separated into eight time steps, in each of which an optimization of the following 48-72 hours is performed to enable an optimal adjustment of the schedule based on the current traded electricity market prices. By considering consecutive trading possibilities in the day-ahead market and the intraday trading, trades can be counter traded to generate revenues by price differences in the day-ahead and intraday markets. In addition to the in-depth modeling of the trading in electricity markets, a detailed modeling of the electric vehicle and vehicle user is also introduced. The state of charge (SoC) of the EV is constrained by a minimum SoC of the battery and a minimum SoC at departure of the EV that can be parameterized by the EV user. The developed optimization model allows a flexible adjustment of the scenarios, whereby a change of important influencing factors can be analyzed.

Results suggest that revenue potentials are strongly dependent on the EV pool, the user behavior, and the regulatory framework. Modeled potential revenues of EVs of current average size marketed with 2019 German day-ahead prices are found to be at around 200 €/EV/a, which is comparable to other findings in literature, and go up to 500 €/EV/a for consecutive trading in German day-ahead and intraday markets. For future EVs with larger batteries and higher efficiencies, potential revenues for current market prices can reach up to 1300 €/EV/a. This study finds that revenues differ widely for different European countries and future perspectives. The identified revenues give EV owners a clear incentive to participate in vehicle-to-grid use cases, thereby increasing much needed flexibility for the energy system of the future.

Own contribution: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Visualization, Writing - original draft and review & editing.

Citation: Kern, T.; Dossow, P.; von Roon, S. Integrating Bidirectionally Chargeable Electric Vehicles into the Electricity Markets. Energies 2020, 13, 5812. https://doi.org/10.3390/en13215812

This publication can be found in the Appendix.

Publication 2 (Pub2): Revenue opportunities by integrating combined vehicle-to-home and vehicle-to-grid applications in smart homes

Summary: A smart integration of electric vehicles (EVs) in the future energy system will be crucial in decarbonizing the energy sector. A survey by the German Association of Energy and Water Industries found that the high investment costs for an EV are the main argument against switching to electromobility. If the economic viability of EVs could be increased, it would provide an additional incentive for users to purchase an EV. Bidirectional EVs can provide flexibility for the system and generate revenues for the user through multiple use cases. Vehicle-to-home (V2H) use cases offer the benefit of optimized use of locally generated renewable energy while also providing revenue opportunities. In vehicle-to-grid (V2G) applications, bidirectionally chargeable EVs can contribute to grid stability and market liquidity in a system serving manner while offering economic benefits for EV owners.

V2H use cases are modeled with and without varying charging and discharging efficiencies. This novel evaluation of more realistic modeling of V2H as mixed-integer linear programming (MILP) with varying efficiencies versus modeling of V2H as linear programming (LP) with fixed efficiencies is necessary to assess whether MILP with varying efficiencies is beneficial or even necessary for V2H analyses. For this purpose, an optimization model is developed that optimizes the electric power flows of a household with the objective of minimizing electricity costs while taking technical restrictions into account. Three different charging strategies are compared regarding household energy flows: an unmanaged charging strategy, a smart charging strategy and a bidirectional charging strategy. Finally, a combined application of V2H and V2G arbitrage trading is modeled to show differences and benefits on the electricity costs of a household. This combined, novel modeling of V2H and V2G can realistically combine the seasonally different revenue opportunities of the use cases and shows that a separate modeling of a V2H or V2G use case can underestimate the revenue opportunities.

For a typical German household using a bidirectional EV for optimizing PV self-consumption, revenues for V2H exclusively are about 310 €/a, mostly generated during the summer. The revenue potentials are highly dependent on the influencing factors of PV size and PV feed-in tariff, household size, as well as household components, like heat pumps or stationary storages. Arbitrage trading well complements this V2H use case in the winter months, resulting in revenues up to 530 €/a. These significant revenue potentials can lead to more profitable and interactive EVs incentivizing users to change from internal combustion vehicles to electric mobility.

Own contribution: Conceptualization, Methodology, Investigation, Formal analysis, Software, Validation, Data curation, Writing – original draft, Writing – review & editing, Supervision.

Citation: Kern, T., Dossow, P., & Morlock, E. (2022). Revenue opportunities by integrating combined vehicle-to-home and vehicle-to-grid applications in smart homes. Applied Energy, 307. https://doi.org/10.1016/j.apenergy.2021.118187.

This publication can be found in the Appendix.

Publication 3 (Pub3): Modeling and Evaluating Bidirectionally Chargeable Electric Vehicles in the Future European Energy System

Summary: In addition to a massive expansion of renewable energies, a successful change towards a decarbonized energy system requires the flexibilization of consumers and the integration of storage and sector coupling technologies. Bidirectionally chargeable electric vehicles (EVs) represent such a consumer flexibility. They are able to charge when there is an electricity generation surplus and to discharge when there is a shortage in electricity generation. Therefore, they can act as a storage from the perspective of the energy system. This paper analyzes different modeling approaches of bidirectionally chargeable EVs in large-scale energy systems and evaluates the impact of bidirectionally chargeable EVs on the future European energy system.

The modeling of discrete EV profiles as a reference is compared to the modeling of clustered EV profiles as well as an aggregated EV profile with simplified constraints for bidirectionally chargeable EVs. The approach of clustered EV profiles limits the number of discrete EV profiles to lower the computation times. This approach results in EV profiles that do not represent the EV characteristics well. Aggregation of EV profiles per country leads to significantly lower computation times, while still representing EV behavior well. This approach also leads to energy system results, e.g., power plant investment and operation, that are close to the reference case, although the EV constraints are simplified.

The number of bidirectionally chargeable EVs in a cost optimal future European energy system increases from 6 million EVs in 2025 to over 60 million EVs in 2050. We show that bidirectionally chargeable EVs support the integration of Photovoltaic generation. This is of great importance for the future energy system, since wind generation, especially onshore wind generation, deals with various acceptance issues across Europe. Furthermore, bidirectionally chargeable EVs lower installed capacities of gas- and hydrogen-fired power plants as well as stationary battery storages. Replacing the need for power plant capacities that operate with very few full load hours through bidirectionally chargeable EVs means contributing to covering the peak load in the energy system. Bidirectionally chargeable EVs also lead to decreasing electricity prices and total European energy system costs that are up to 9 billion €/a lower compared to the reference scenario.

Own contribution: Conceptualization, Methodology, Investigation, Formal analysis, Software, Validation, Data curation, Writing – original draft, Writing – review & editing, Supervision.

Citation: Kern, T., Kigle, S. (2022). Modeling and Evaluating Bidirectionally Chargeable Electric Vehicles in the Future European Energy System. Energy Reports. (Accepted, not yet published)

This publication can be found in the Appendix.

Publication 4 (Pub4): Added Value of Providing Transmission Grid Congestion Management via Bidirectionally Chargeable Electric Vehicles

Summary: Congestion management in the European transmission grid is currently mostly provided by conventional power plants. As electricity generation in the future will be increasingly characterized by volatile renewable energies, new technologies need to be integrated into congestion management provision. This paper develops a methodology for modeling storages in congestion management and investigates the potential for bidirectionally chargeable electric vehicles (bidirectional EVs) in 2030.

Congestion management in the energy system model ISAaR (Integrated Simulation Model for Unit Dispatch and Expansion with Regionalization) is modeled in a two-step approach. First, a multi-energy market optimization run is conducted, in which one market area is represented by one node. Energy transfers between market areas are allowed up to maximum net transfer capacities. In the following step, the resulting dispatch of generation, load and storage instances is taken as a base for the transmission grid optimization run, in which the costs of congestion management (curtailment of renewable energies and provision of redispatch services) are minimized. A direct current load flow via Power Transfer Distribution Factors (PTDF) is used to model the load flow in the transmission grid. Since the modeling involves great complexity due to time-coupling constraints of storages, different modeling approaches are investigated. The length of the time slice that is optimized coupled is set to 168 hours so as not to overly constrain the flexibility of bidirectional EVs while maintaining computability.

The results show that bidirectional EVs can take over a significant part of the congestion management due to their decentralized distribution. A total of 26 TWh of positive congestion management of conventional power plants in 2030 can be replaced by the optimized use of bidirectional EVs. This leads to a reduction of emissions of 12 million tons CO_2. The high absolute volumes of congestion management that appear in the simulations are classified and possible reasons for the deviation from current volumes are elaborated.

Own contribution: Conceptualization, Methodology, Investigation, Formal analysis, Validation, Data curation, Writing – original draft, Writing – review & editing, Supervision.

Citation: Kern, T., Wendlinger, C. (2022). Added Value of Providing Transmission Grid Congestion Management via Bidirectionally Chargeable Electric Vehicles. 2022 18th International Conference on the European Energy Market (EEM), 2022. (Accepted, not yet published)

This publication can be found in the Appendix.

1 Introduction

To minimize the anthropogenic greenhouse effect and thus mitigate climate change, the EU and Germany have set themselves ambitious climate targets. At the European level, the energy system is to be completely climate-neutral by 2050 [1]; in Germany, the aim is to decarbonize the energy system by 2045 [2]. The turnaround in energy policy that has been initiated is leading to challenges at a wide variety of levels. In the final energy sectors of private households, the tertiary sector, industry and transport, applications and processes are being adapted through efficiency measures, fuel substitutions, flexibilization and electrification [3]. The transport sector in particular has been slow to reduce greenhouse gases in recent years. In Germany, in 2021 the emissions of just under 150 million t CO_2 increased compared to in 2020 and were above the emissions permitted by the Climate Action Law [4]. However, with various subsidies for electric vehicles (EVs) [5] and the increase in fuel and CO_2 prices as a result of the Covid-19 crisis [6], 2020 and 2021 saw a dynamic increase in EV registrations [7].

In the energy sector, the massive expansion of variable renewable energies and the associated substitution of conventional nuclear, coal and gas-fired power plants will lead to a completely new characteristic of electricity supply. Due to the volatility of the supply from wind and sun, electricity from these renewable energies will not be generated in line with the static demand from the final energy sectors in the future. Flexibilities in the energy system are therefore needed to ensure that the balance between electricity generation and consumption is maintained [3].

Currently, almost all EVs in Germany are charged unmanaged, although there are numerous projects working on smart charging of EVs based on grid status, electricity prices or electricity generation of renewable energies [8]. Bidirectionally chargeable electric vehicles (bidirectional EVs) represent a new technology that can address major challenges in the transportation final energy sector and the energy sector alike by a stronger coupling of these sectors. Bidirectional EVs can not only charge electricity, but also discharge via bidirectional electric vehicle supply equipment (EVSE) [9]. This enables a variety of use cases that can bring potential added value for the user and the energy system. If the user receives an ecological or economic added value, this also promotes the integration of EVs, as these then become more profitable in terms of overall costs.

This cumulative dissertation therefore evaluates the added value of bidirectional EVs for the user and the energy system. In this introduction, Section 1.1 first identifies the current state of research and existing research gaps. From this, the research questions of this dissertation are derived in Section 1.2. Based on this, Section 1.3 presents the methodology to answer these research questions. Finally, the structure of this cumulative dissertation and classification of the publications is added in Section 1.4.

1.1 Literature Review and Research Gaps

Bidirectional EVs can execute a wide variety of energy-related use cases, leading to increased coupling of the transportation sector with the energy sector [10]. In the 'Bidirectional Charging Management' (BCM) project, numerous use cases of bidirectional EVs were defined, which were divided into the groups Vehicle-to-Home (V2H), Vehicle-to-Grid (V2G) and Vehicle-to-Business (V2B) [11]. V2H includes the photovoltaic (PV) self-consumption optimization and the electricity tariff optimized charging and discharging. V2G implies arbitrage trading in the day-ahead and intraday market, CO_2-optimized charging and discharging as well as different distribution and transmission grid-oriented use cases. V2B mainly deals with peak load shaving in companies in order to save grid fees. This dissertation focuses on the use cases PV self-consumption optimization, arbitrage trading and the provision of the ancillary service congestion management as a transmission grid-oriented use case. These selected use cases are prioritized in the BCM project, implemented in the field test, and show promising values from a user and system perspective. The main region of analysis from the user perspective is Germany, whereas the systemic analysis focuses on the European coupled energy system. However, the developed models can also be applied to other regions worldwide by adapting the parameters. In this section, this dissertation is classified within the existing research based on relevant studies, upon which the research questions are posed in the following section.

The economic and ecological added values from the user's perspective on bidirectional EVs are of great relevance because ultimately the user makes the investment decision in a bidirectional EV and EVSE. Numerous studies model smart unidirectional charging EVs (smart EVs) and bidirectional EVs dealing with their revenue potentials for arbitrage trading. While investigations in studies of Illing et al. [12] and Shafiullah et al. [13] are still limited to unidirectional smart charging, the work of Bessa et al. [14], Rominger et al. [15], Schmidt et al. [16], Peterson et al. [17], and Pelzer et al. [18] model bidirectional EVs participating in the electricity spot markets. These studies show revenue potentials for bidirectional EVs in different spot markets worldwide, but do not focus on the modeling of a realistic user behavior and its impact on the revenues, and furthermore only model the trading on single electricity markets in a simplified way without the possibility of consecutive trading in different spot markets. PV self-consumption optimization has also been the subject of numerous studies. Publications of Salpakari et al. [19], Chen et al. [20], Erdinc et al. [21], Kataoka et al. [22], Wickert et al. [23] and Keiner et al. [24] model V2H with bidirectional EVs in a household and examine their revenue potentials in the countries Sweden, China, Portugal, Japan, and Germany. When comparing the studies, it becomes clear that the regulatory framework, such as the composition of the household electricity price, is a key influencing factor. Again, in these studies, user behavior is only inaccurately modeled, so that the effects of different parameterizations cannot be highlighted. In addition, a fixed charging and discharging efficiency of the EV is always assumed in order to keep the optimization problem linear. Englberger et al. [25] also already deal with a combination of different use cases for bidirectional EVs by segmenting the battery for front-of-the-meter and behind-the-meter applications. Behind-the-meter applications refer to use cases that happen on the energy user's side of the meter. Front-of-the-meter applications represent use cases that interact with the electricity grid off the energy user's side of the meter. However, this interesting modeling approach of Englberger et al. seems hardly feasible in terms of measurement technology, so that the need for more practice-oriented modeling arises here.

While V2B and V2H optimize energy flows behind the meter to enable, for example, savings in electricity costs, V2G applications are designed to meet the needs of the energy system. By integrating bidirectional EVs into the electricity market, studies of Hanemann et al. [26], Rodríguez et al. [27], and Huang et al. [28] describe a smoothing effect on electricity demand that also smoothes resulting electricity prices [26]. The publication of Wie et al. [10] also shows a positive ecological and economic effect of bidirectional EVs on integrated multi-energy systems. However, these demonstrated positive effects of bidirectional EVs refer to small- and medium-scale energy systems and are shown with a highly simplified modeling of the EVs. Furthermore, hardly any effects on other flexibilities, such as stationary battery storages and sector-coupling elements, are investigated. The work of Child et al. [29] analyzes this feedback of bidirectional EVs on the energy system, by indicating that reduced capacities of generation and storage are needed, but again only for a small-scale energy system, the Åland Islands near Finland. The integration of bidirectional EVs into a large European energy system model implies the challenge of no longer modeling each EV discretely, but rather performing such simplifications as clustering or aggregation of EV profiles.

This challenge of realistic simplifications arises even more when modeling the provision of congestion management (curtailment of renewable energies and redispatch services). Redispatch services refer to short-term adjustments of the schedule of generation or consumption assets to lower congestions in the transmission grid [30]. The integration of bidirectional EVs or other storage assets leads to much more complex simulations of the European transmission grid. For example, the work of Böing [31] excludes storages in the congestion management run because of their time-coupled constraints, which introduces great complexity and considerable modeling challenges. Kotzur et. al analyze possibilities to handle the complexity of time coupling in energy system models, like temporal decomposition of the optimization problem, but point out that these possibilities are usually associated with complex implementations and numerous assumptions [66]. However, in the literature, some studies already deal with the integration of storages in the provision of ancillary services. The publications of Meyer-Huebner et al. [32], Xiong et al. [33], Eickmann et al. [34], Müller et al. [35] and Gutermuth et al. [36] model stationary storages or other time-coupling elements, such as power-to-gas units with virtual gas storages, providing redispatch services. These studies focus only on stationary and not mobile storages and limit the optimization to small-scale test systems, only few timesteps or to very simplified EV modeling. The integration of bidirectional EVs into the redispatch process is modeled in the work of Staudt et al. [37] and Thormann et al. [38] but with simplified heuristic modeling or without considering the operation of EVs and the system needs of redispatch services. None of the existing approaches in the literature explore the transferability of their modeling approaches to a large-scale European energy system, which causes a very different complexity. Thus, the added values of bidirectional EVs can only be determined inadequately from a system perspective.

In general, none of the studies mentioned in the previous two paragraphs address the question of how high the share of bidirectional EVs in the total EVs is optimal in a future multi energy system. This requires the more complex modeling of bidirectional EVs as an element that can be added endogenously optimized by the energy system model. However, answering this question is of great importance so that stakeholders in the field of energy can design their business models, policy makers their support mechanisms, and scientists their energy system models accordingly. Furthermore, the question arises to what extent bidirectional EVs can bring a combined added value from the user and energy system perspective, which this dissertation aims to answer.

1.2 Research Questions

The previously analyzed research gaps are transferred into the research questions of this dissertation. The definition of the research questions (RQ) is divided into three sections as shown in Figure 1-1.

The first section of the research questions refers to the added value of bidirectional EVs for the user:

1. What modeling specifications are required for the evaluation of revenue potentials of vehicle-to-home and vehicle-to-grid use cases?

2. What are the revenue potentials and their most important influencing factors for vehicle-to-home and vehicle-to-grid use cases?

3. What is the economic profitability of vehicle-to-home and vehicle-to-grid use cases considering the additional investment costs?

The second section of the research questions deals with the added value of bidirectional EVs for the energy system:

4. How do modeling specifications of bidirectional EVs need to be adapted to evaluate the European energy system perspective compared to modeling discrete EVs?

5. How high is the optimal share of bidirectional EVs in the total EVs from a system cost perspective?

6. What is the added value of bidirectional EVs integrated in the electricity markets and in congestion management in the transmission grid from an energy system perspective?

The third section of the research questions brings together the previous sections and discusses the possibility of a combined added value for the user and the energy system.

7. How can use cases of bidirectional EVs create combined added value from the user and the energy system perspective?

Figure 1-1 depicts the relationships between the research questions in the three sections and shows the sequential structure of this dissertation. It can be observed that the research questions within the sections are not considered completely separately but build on each other. The analysis of the revenue potentials and profitability of vehicle-to-grid and vehicle-to-home use cases from the user perspective in RQ2 and RQ3 depend on the approach to modeling bidirectional EVs in RQ1. The assessment of the systemic cost-optimal share of bidirectional EVs in total EVs and its impact on the energy system in RQ5 and RQ6 depend on the developed modeling in RQ4. RQ7, in turn, builds on all the previously named RQs. There are also interdependencies between the analyses from the user perspective and from the system perspective. The detailed modeling to answer the research questions is described in the following section.

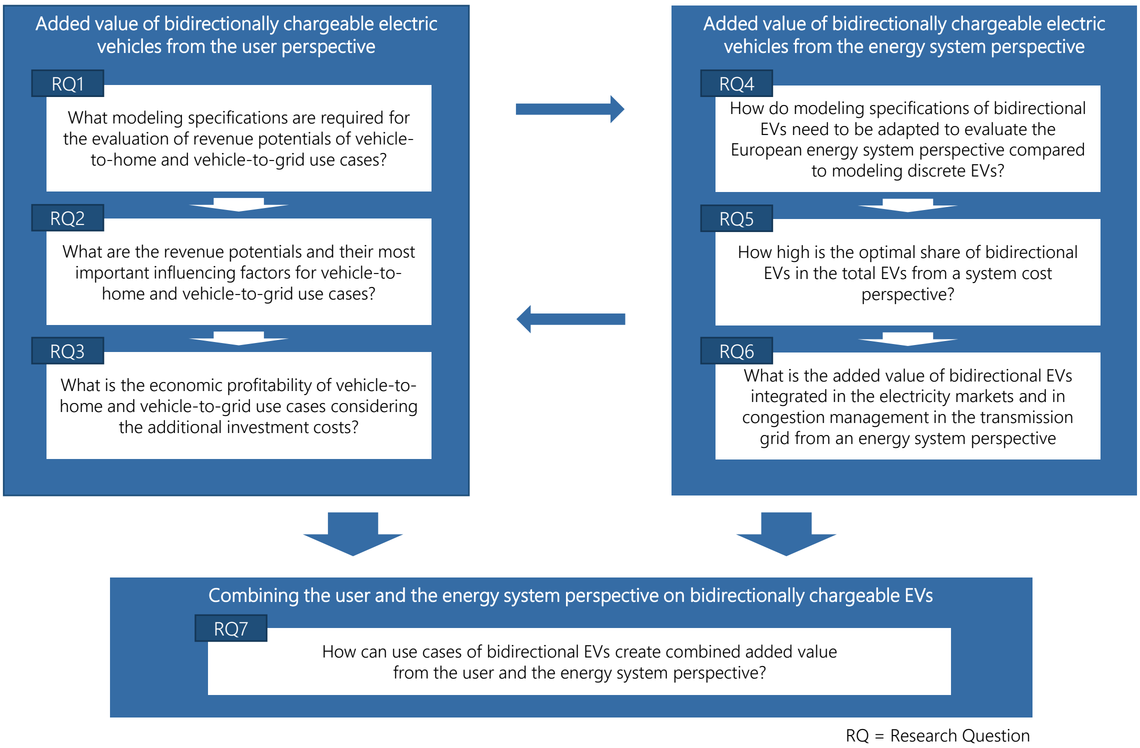


Figure 1-1: Research questions (RQ) at user, energy system and combined perspective

1.3 Methodology

Based on the research questions established in the previous section, Figure 1-2 presents the methodology of this dissertation. The methodology is divided into the sub-areas of bidirectional charging from the user's point of view and from the energy system's point of view.

First, the eFlame model (electric Flexibility Assessment Modeling Environment) with the optimization module ResOpt (Residential Optimizer) [Pub2] is further developed by a methodology for modeling V2H PV self-consumption optimization and V2G arbitrage trading from the user's perspective. For V2H, minimization of household electricity costs is modeled to allow evaluation of the revenue potentials of bidirectional EVs. The charging and discharging efficiencies are modeled to be variable, so that the revenue potentials of bidirectional EVs are not overestimated. For V2G arbitrage trading, minimizing the charging costs while maximizing the revenue from discharging an EV is implemented. For this purpose, a rolling optimization is developed that allows trading in all consecutive spot markets. Countertrades can be used to take advantage of price differences in the consecutive spot markets. The next step merges V2H and V2G modeling to evaluate a combination option. Based on various sensitivity calculations, the revenue potentials and their most important influencing factors of the use cases are then analyzed. By evaluating the additional investment costs of bidirectional charging, the economic profitability of the different use cases can be assessed in a final step.

Second, the energy system model ISAaR (Integrated Simulation Model for Unit Dispatch and Expansion with Regionalization) [39] is further developed by a methodology for modeling bidirectional EVs in the energy system and in congestion management provision in the transmission grid. To evaluate V2G arbitrage trading from an energy system perspective, a minimization of the total economic costs of the European energy system is performed. Different approaches to model bidirectional EVs are investigated in order to keep the complexity of the model as low as possible while representing bidirectional EVs realistically. Based on a scenario for the future European energy system, cost-optimal shares of bidirectional EVs in the total EVs are then determined for future years in the different European countries. For the evaluation of V2G congestion management provision, a minimization of congestion management costs in the European energy system is performed considering bidirectional EVs. For this purpose, different time slice lengths of the rolling optimization are analyzed, since the optimization problem has a very high complexity due to the time coupling constraints of bidirectional EVs. Finally, the impact of bidirectional EVs on the future energy system and the provision of congestion management in the transmission grid is assessed. This includes, for example, the impact of bidirectional EVs on the capacities of thermal power plants, renewable energies, and stationary battery storages as well as the impact on the total system costs.

The methodology considers the interdependencies between the user and the energy system side through user behavior constraints for discrete EVs, mean investment costs for bidirectional charging, and future electricity prices. User behavior constraints are first analyzed for discrete EVs in use case arbitrage trading and then, in a simplified way, also modeled in the system perspective. The future mean investment costs of bidirectional EVs are passed to the energy system model ISAaR. ISAaR decides endogenously within the optimization, considering the additional costs of bidirectional charging, how high the cost-optimal share of bidirectional EVs is for the future European energy system. Future electricity prices are in turn fed back to eFlame from the ISAaR energy system model to determine future revenue potentials for various users.

In a consolidating step, the modeling approaches of bidirectional EVs from the user and energy system perspective are compared and evaluated. Finally, the highlighted added values of bidirectional EVs are summarized and a combination of added values from user and energy system perspectives is discussed.

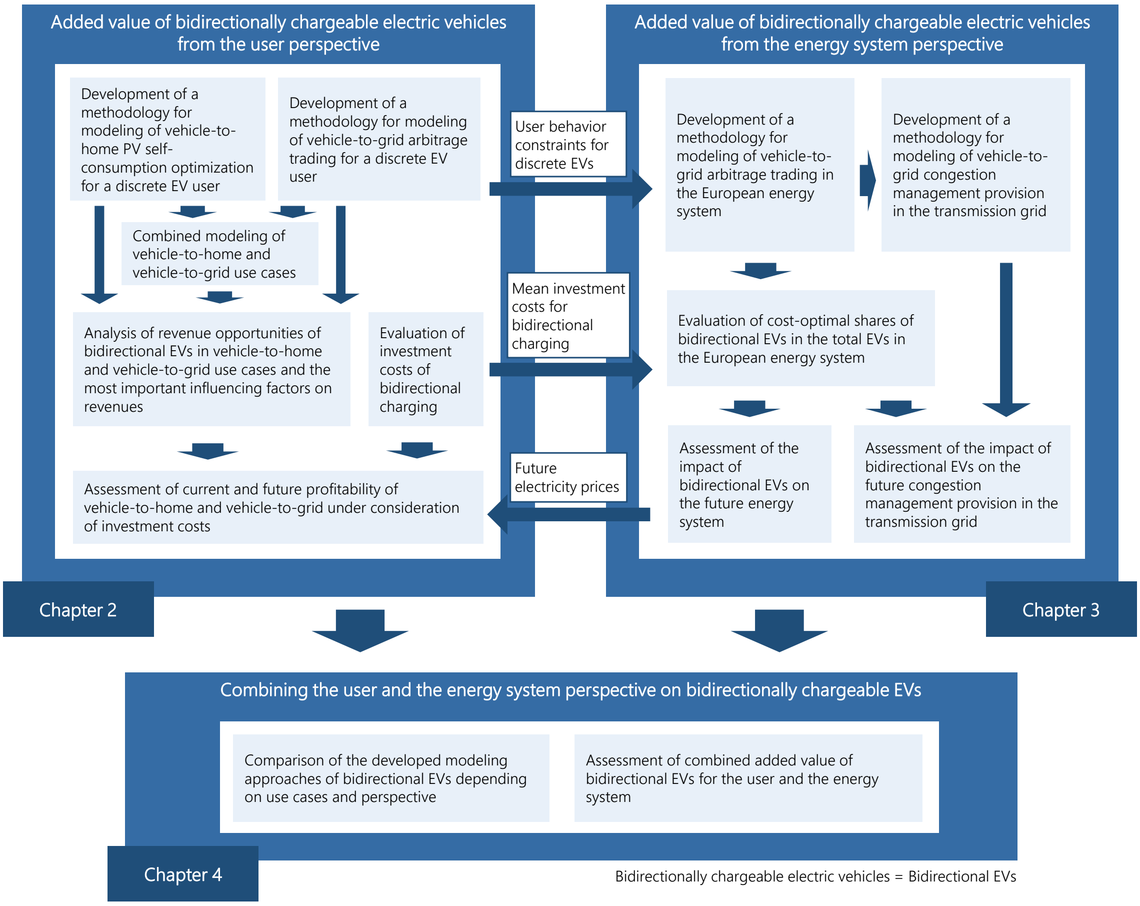


Figure 1-2: Methodology for assessing the added value of bidirectional EVs for the user and the energy system

1.4 Dissertation and Publication Structure

The structure of this dissertation builds on the previous sections. Chapter 2 evaluates bidirectional charging from the user's perspective with regard to various influencing factors. Section 2.1 starts with the modeling developed for V2H and V2G use cases. Based on this, revenue potentials are determined for different user types in Section 2.2 with the highlighting of the revenues' most important influencing factors. Section 2.3 compares the revenue potentials to the additional investment costs for the technology of bidirectional charging in order to ultimately be able to evaluate the economic profitability for the user.

Chapter 3 switches the perspective on bidirectional EVs from the user to the energy system. Consequently, the focus here is on V2G use cases that interact with the energy system. Section 3.1 presents the approaches to model bidirectional EVs integrated in the electricity markets and providing congestion management. Following the scenario definition in Section 3.2, Section 3.3 assesses the cost-optimal penetration rates of bidirectional EVs in the future energy system. Finally, Section 3.4 analyzes the impact of bidirectional EVs on the costs and characteristics of the future energy system.

Chapter 4 then brings together the findings of the previous chapters and assesses bidirectional EVs combined from a user perspective and from an energy system perspective. To this end, Section 4.1 first compares the different modeling approaches and highlights

the differences in modeling the user and system views. Section 4.2 analyzes which use cases combine well and when to obtain added value for the EV user and the energy system.
Finally, Chapter 5 concludes by answering the research questions raised, discussing the key findings, and summarizing them. Based on this, an Outlook identifies the need for further research.
Figure 1-3 summarizes the structure of this dissertation and assigns the research questions to the publications carried out. Each publication addresses several research questions. Publications 1 and 2 investigate bidirectional EVs from the user's perspective and answer the research questions RQ1 and RQ2 on modeling, economic efficiency, and the most important influencing factors for V2H and V2G use cases, respectively. The main part of this dissertation, considering the investment costs of bidirectional charging, complements these analyses by evaluating the profitability of bidirectional EVs today and in the future. Publications 3 and 4 evaluate the energy system view on bidirectional EVs, answering RQ4 to RQ6. Publication 3 evaluates the effect of bidirectional EVs on the electricity market and other components in the future energy system. Publication 4 identifies the potential of bidirectional EVs to provide congestion management in the transmission grid and thus prevent renewable energy curtailment and reduce the operation of thermal power plants. The main part of this dissertation complements these publications by examining two sensitivities with greatly reduced investment costs of smart EVs to draw conclusions about the robustness of the results. Furthermore, additional investigations on the impact of bidirectional EVs on the regional residual load (load minus electricity generation of variable renewable energies) show indications for the grid loads in the electricity grid.
Further, the main part of this dissertation addresses and answers RQ7 by summarizing and comparing the findings of the Chapters 2 and 3.

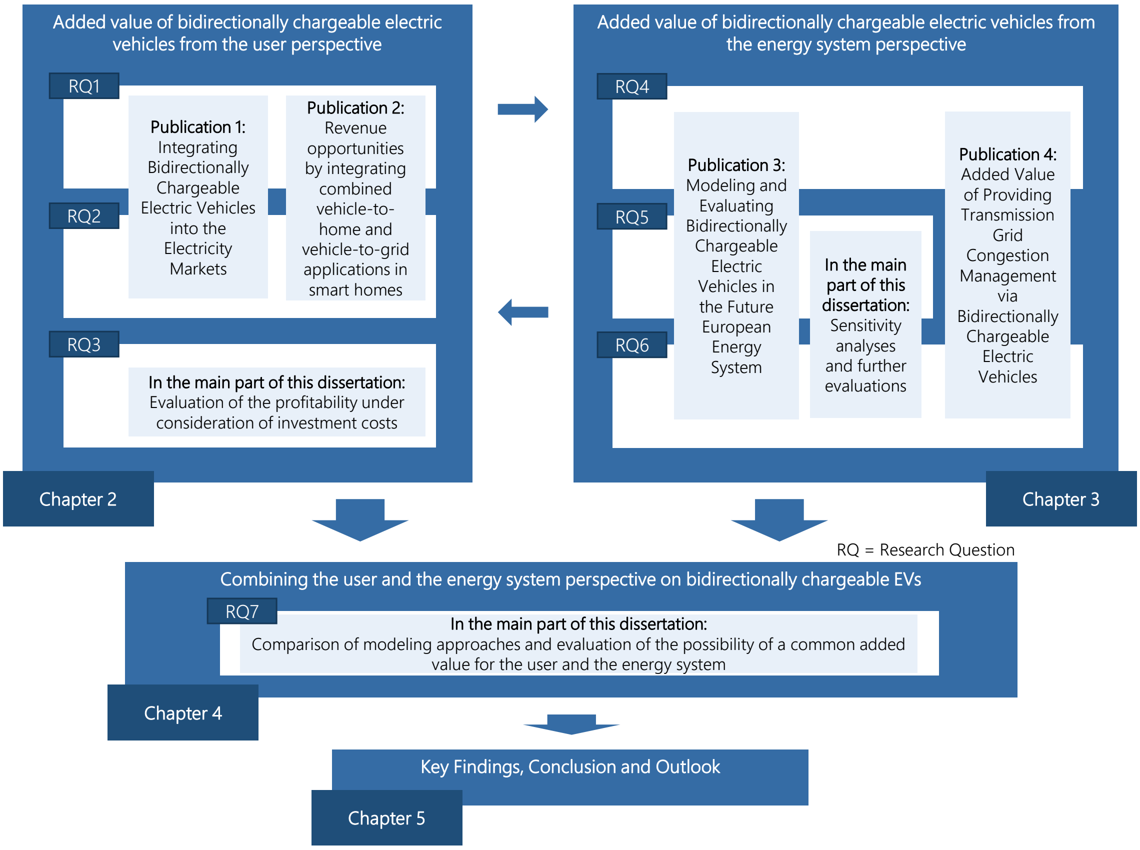


Figure 1-3: Structure and publications of this dissertation assigned to research questions at user, energy system and combined perspective

2 Bidirectionally Chargeable Electric Vehicles from the User Perspective

Based on the publications [Pub1] and [Pub2] and further research, this chapter analyzes the profitability of PV self-consumption optimization (V2H) and arbitrage trading (V2G) by bidirectional EVs. For this purpose, Section 2.1 first addresses the use case dependent requirements of the modeling, upon which the revenue potentials and most important influencing factors of the use cases are determined in Section 2.2. Section 2.3 then presents the economic profitability of bidirectional EVs by including the additional costs of bidirectional charging.

2.1 Methods

For the detailed evaluation of bidirectional EVs from the user's point of view, the model environment eFlame with the optimization module ResOpt has been further developed. The model environment eFlame allows a variable scenario creation for different use cases of bidirectional EVs or other energy assets, like stationary battery storages (SBS). In ResOpt, the mathematical optimization problem is formulated depending on the parameterization made in eFlame. The optimization problem can be formulated as linear programming (LP) or mixed integer linear programming (MILP). ResOpt is a module that is also integrated into other models, such as the distribution grid model GridSim of FfE Munich [40].

Figure 2-1 represents the structure of eFlame including ResOpt with the main decision and input variables. The model environment eFlame formulates scenarios in the database, which are read into Matlab and passed to ResOpt. The variable scenario definition in eFlame allows the calculation of numerous sensitivities, whereby the most important influencing factors of use cases can be determined. For each scenario created, the EV is modeled with three different charging strategies:

- **unmanaged charging:** the EV charges directly after arriving at a charging location.
- **smart charging:** the EV can postpone charging at a charging location within its flexibility limits.
- **bidirectional charging:** the EV can charge and discharge at a charging location at any time within its flexibility limits.

The differential electricity costs of the charging strategies can be used to determine revenues of a bidirectional or smart EV versus an unmanaged charging EV.

Depending on the energy assets modeled in a use case, ResOpt introduces different decision variables: EV charging $P_{EV,c}$, EV discharging $P_{EV,d}$ and potentially standby losses of the EV and EVSE $P_{EV,l,s}$, SBS charging $P_{SBS,c}$ and discharging $P_{SBS,d}$, PV curtailment $P_{PV,curt}$, heat pump (HP) demand $P_{HP,el}$, as well as power from grid $P_{GCP,in}$ and power to grid $P_{GCP,out}$. In addition, public charging energy $E_{EV,pub,c}$ and driving energy $E_{EV,drive}$ of the EV are considered as fixed input. For the combined modeling of V2H and V2G use cases, the decision variables $P_{GCP,in,v2g}$ and $P_{GCP,out,v2g}$ are integrated. A fixed thermal $P_{HH,th}$ and electrical $P_{HH,el}$ household demand, an electrical industry demand $P_{Ind,el}$ as well as a fixed PV generation P_{PV} can also be provided, whereas industrial demand is not used in this dissertation. For the modeling of trading in consecutive spot markets, the decision variables $P_{EV,cou,buy}$ and $P_{EV,cou,sell}$ that represent countertrades are integrated. $P_{sched,AC}$ represents scheduled powers from previous optimization runs. A more detailed description of eFlame and integrated model ResOpt can be found in [Pub1] and [Pub2].

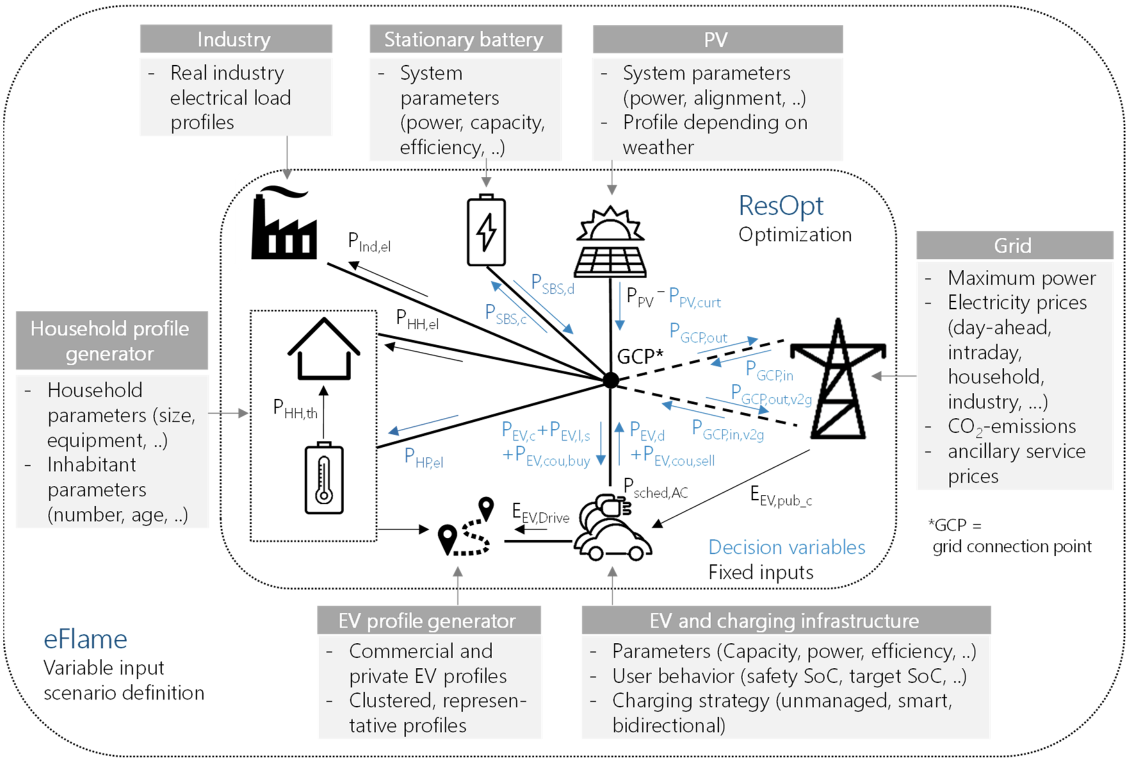


Figure 2-1: Schematic representation of eFlame and ResOpt for evaluation of use cases of bidirectional EVs based on [Pub2]

The use cases PV self-consumption optimization and arbitrage trading and a combined modeling of these use cases have different modeling requirements due to their fundamentally different functionality. Sections 2.1.1 and 2.1.2 address specifics in the modeling of the use cases, after which the basic mathematical formulation is derived in Section 2.1.3.

2.1.1 Modeling of Charging and Discharging Efficiencies

A very important aspect is the different modeling of the charging and discharging efficiency since this significantly influences the complexity of the optimization. [Pub2] shows that power losses of an inverter consist of a constant self-consumption, voltage losses at diodes and transistors that are proportional to the output power, and quadratic power-dependent losses caused by ohmic loss resistances. Figure 2-2 (a) shows the comparison of the real charging efficiency and different modeled charging efficiencies in a linear programming.

Modeling a fixed charging efficiency (line ‘fix’, red) leads to proportionally increasing charging losses to the AC charging power. A comparison with the real losses (yellow line) shows that the losses are greatly underestimated, especially for small charging powers. Modeling charging losses as a linear function (‘Interval 1’, light blue) or a piecewise linear function (‘Interval 2’, dark blue) results in a much better representation of the real losses. The modeling results in a mixed-integer linear programming with higher complexity, because in both cases constant losses depending on the Boolean operation variable (operating or not operating) are included [Pub2].

Since real losses during charging and discharging differ from modeled losses with a fixed efficiency, especially at low powers, the typical charging and discharging power of a use case is important for choosing the modeling approach. For this purpose, Figure 2-2 (b) classifies the EV charging and discharging powers for the PV self-consumption optimization use case by showing the annual duration curve of the residual load of five different medium households from [Pub2] with an annual electrical demand of 3,800 kWh and a 5.5 kWp PV system. The residual load for the household in this case is calculated by the load subtracted by the PV generation. For these exemplary medium households, the absolute residual load is less than 2 kW in 85% of the time. Due to these numerous time points with low power at the household connection point, a linear modeling would lead to a strong underestimation of the losses. Accordingly, [Pub2] reports revenues for V2H for linear modeling that are 30% higher than revenues with mixed-integer linear modeling.

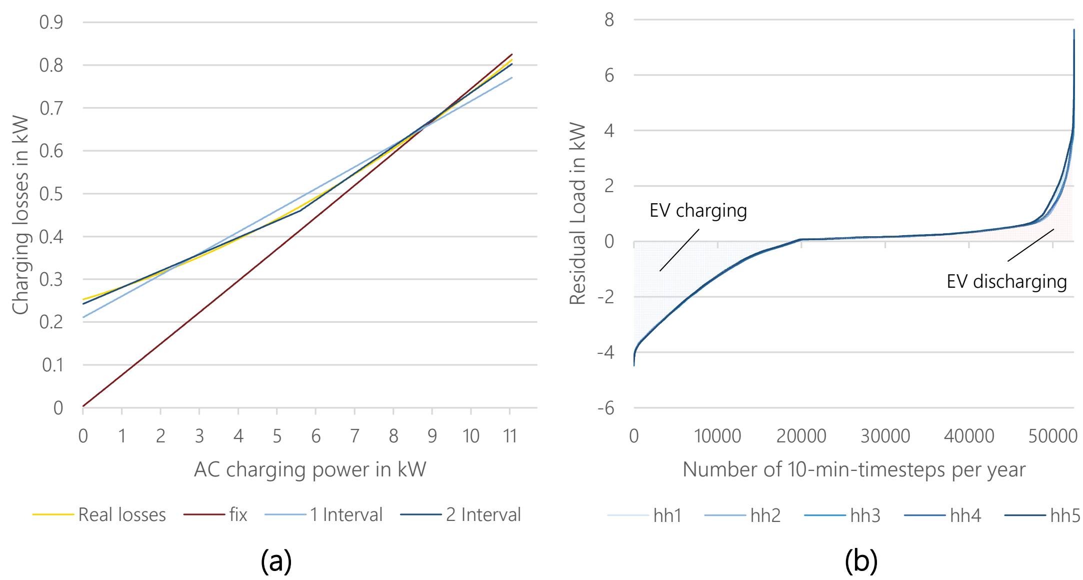


Figure 2-2: (a): Comparison of real and modeled charging losses depending on the AC charging power; (b): Annual duration curve of residual load of five households (hh1 to hh5)

In contrast, for exclusively marketing of EVs in the electricity market in [Pub1], the charging and discharging powers are usually high. Provided that the price spreads between sold and purchased electricity are adequate, the EV will discharge and charge at full power if it has sufficient flexibility to maximize revenues. Further, the marketing in the electricity market will be done through a pool of EVs in which the EVs can be intelligently managed so that only high charging and discharging powers are called for a single EV. For this reason, the modeling of the use case arbitrage trading with fixed charging and discharging efficiencies is valid and yields reliable results.

2.1.2 Modeled Optimization Horizons

Participating in European electricity markets can include consecutive day-ahead trading, trading in the intraday auction followed by continuous intraday trading. In Germany, bids for the day-ahead trading have to be submitted by 12 noon [41]. For the German intraday auction, bids must be submitted by 3 pm [41]. Thereupon, continuous intraday trading starts. The modeling of consecutive marketing on spot markets with real trading hours leads to the requirement to formulate the model as a rolling optimization model.

In [Pub1], the developed rolling optimization model is introduced. With each optimization step, the starting point of the optimization period is set three hours forward. A limited forecast of two to three days is modeled. Figure 2-3 illustrates that depending on the start time for the optimization period, different prices are set from the day-ahead and intraday market. For the start time 12 noon, for example, prices from continuous intraday trading are set for the first 12 hours, prices from the day-ahead market for the following day (d+1) and a day-ahead price forecast for one more following day (d+2).

Consecutive optimization runs lead to the possibility of countertrades for a considered period. Purchased or sold energy in the day-ahead market can be countertraded in the intraday auction or in the continuous intraday trading. A more detailed description of the consecutive rolling optimization can be found in [Pub1].

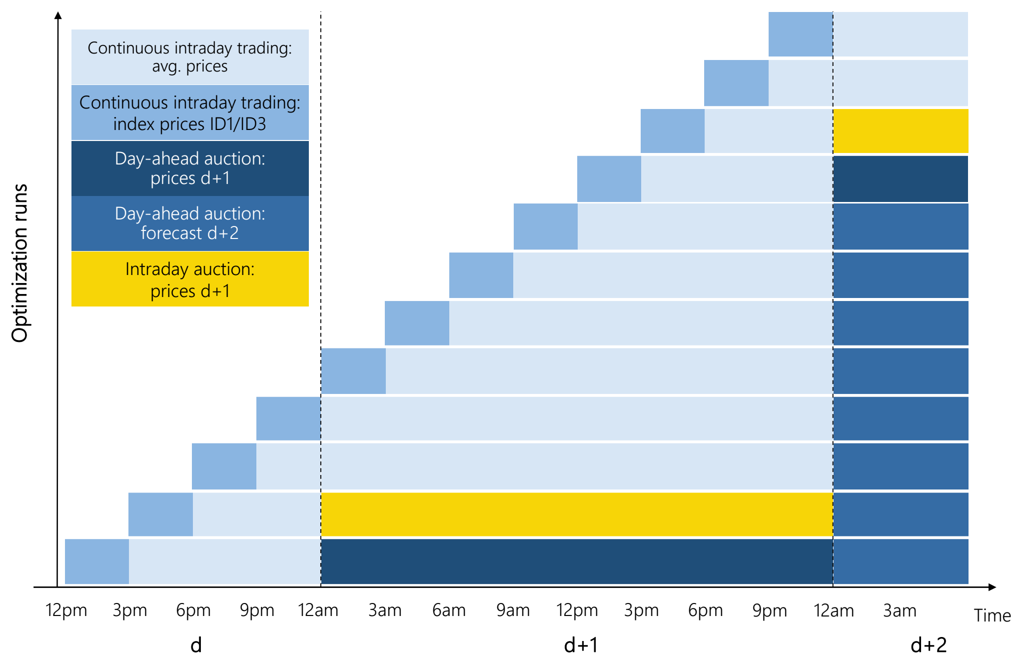


Figure 2-3: Schematic representation of the rolling optimization runs with limited foresight of different market prices based on [Pub1]

For the modeling of the PV self-consumption optimization, a perfect forecast for a whole year is set. Since there are no consecutive actions for a period, like countertrading in different electricity markets, and there is generally a good foresight for PV feed-in, this simplified perfect foresight is acceptable here [Pub2].

2.1.3 Use Case Dependent Mathematic Formulation

In publications [Pub1] and [Pub2], the mathematic formulation for arbitrage trading with consecutive spot markets [Pub1] and for PV self-consumption optimization [Pub2] is presented. Further, in [Pub2] the modeling of combined PV self-consumption optimization and arbitrage trading is shown. In this section, the most important constraints, as well as the objective function of the different use cases are compared. For a more detailed derivation of the equations, [Pub1] and [Pub2] can be consulted.

First, Equations (2-1), (2-2), and (2-3) show the different objective functions of the use case dependent optimization problem. Variables $p_{el,buy}$, $p_{el,buy,v2g}$, $p_{el,\mathrm{sell}}$, and $p_{el,\mathrm{sell},v2g}$ refer to electricity market prices, household prices or feed-in tariffs. These prices are multiplied by the power at the grid connection point $P_{GCP,in}$, $P_{GCP,out}$, $P_{GCP,in,v2g}$, and $P_{GCP,out,v2g}$ or, in the case of V2G, by the powers of the EVs $P_{EV,c}$, $P_{EV,d}$, $P_{EV,cou,buy}$, and $P_{EV,cou,sell}$. Minimization is performed over all time steps t of a period *T*. Equation (2-1) focuses on minimizing the household electricity costs $p_{el,buy}(t) \cdot P_{GCP,in}(t) \cdot \Delta t$ minus the feed-in revenues from PV electricity $p_{el,\mathrm{sell}}(t) \cdot P_{GCP,out}(t) \cdot \Delta t$ for the PV self-consumption optimization (V2H). Equation (2-2) minimizes the costs of purchasing electricity for the EV $p_{el,buy}(t) \cdot \left(P_{EV,c}(t) + P_{EV,cou,buy}\right) \cdot \Delta t$, while maximizing revenues of sold electricity $p_{el,\mathrm{sell}}(t) \cdot (P_{EV,d}(t) + P_{EV,cou,sell}) \cdot \Delta t$ in consideration of countertrades for purchasing $P_{EV,cou,buy}$ and selling $P_{EV,cou,sell}$ electricity in consecutive spot markets (V2G) independently of household electricity demand. For the combination of V2H and V2G (Comb), Equation (2-3) merges these optimizations without considering countertrades for complexity reasons. In Equation (2-3), V2G prices $p_{el,buy}$ and $p_{el,sell}$ are transferred to $p_{el,buy,v2g}$ and $p_{el,\mathrm{sell},v2g}$ to allow different pricing for arbitrage trading compared to household pricing. The charging and discharging powers of V2G $P_{EV,c}$ and $P_{EV,d}$ are transferred to $P_{GCP,in,v2g}$ and $P_{GCP,out,v2g}$ to separate the power flows for V2G from the household power flows. Since the prices in Equations (2-1) to (2-3) refer to energies, all power variables are multiplied by the corresponding timeframe Δt.

Objective functions

V2H
$$min\left(\sum_{t=1}^{T}\left[p_{el,buy}(t) \cdot P_{GCP,in}(t) \cdot \Delta t - p_{el,\mathrm{sell}}(t) \cdot P_{GCP,out}(t) \cdot \Delta t\right]\right) \quad (2\text{-}1)$$

V2G
$$\begin{aligned} min\Bigg(\sum_{t=1}^{T}\Big[&p_{el,buy}(t) \cdot \left(P_{EV,c}(t) + P_{EV,cou,buy}\right) \cdot \Delta t \\ &- p_{el,\mathrm{sell}}(t) \cdot (P_{EV,d}(t) + P_{EV,cou,sell}) \cdot \Delta t\Big]\Bigg) \end{aligned} \quad (2\text{-}2)$$

Comb
$$\begin{aligned} min\Bigg(\sum_{t=1}^{T}\Big[&p_{el,buy}(t) \cdot P_{GCP,in}(t) \cdot \Delta t - p_{el,\mathrm{sell}}(t) \cdot P_{GCP,out}(t) \cdot \Delta t \\ &+ p_{el,buy,v2g}(t) \cdot P_{GCP,in,v2g}(t) \cdot \Delta t \\ &- p_{el,\mathrm{sell},v2g}(t) \cdot P_{GCP,out,v2g}(t) \cdot \Delta t\Big]\Bigg) \end{aligned} \quad (2\text{-}3)$$

Second, Equations (2-4), (2-5), and (2-6) constrain the power flows at the grid connection point (GCP). Equation (2-4) includes the power flows of all modeled assets of a household for V2H. Equation (2-5) referring to the arbitrage trading constrains the power flows of the EV equal to the power flows of the GCP. Standby losses of the EV and EVSE $P_{EV,l,s}$ are neglected in [Pub1] for V2G, as the operating hours are significantly higher than for V2H. $P_{sched,AC}$ represents scheduled powers from previous optimization runs. $P_{EV,cou,buy}$ and $P_{EV,cou,sell}$ describe countertraded powers in current optimization run. For regulatory reasons, a separate grid connection point for the EV has initially been modeled here [Pub1]. Equation (2-6) combines V2H and V2G by adding to Equation (2-4) a separate modeled power consumption $P_{GCP,in,v2g}(t)$ and supply $P_{GCP,out,v2g}(t)$ for the V2G use case.

Power constraints GCP

V2H

$$\begin{gathered} P_{GCP,in}(t) - P_{GCP,out}(t) = P_{HH,el}(t) + P_{HP,el}(t) - P_{PV}(t) \\ + P_{PV,curt}(t) + P_{SBS,c}(t) - P_{SBS,d}(t) + P_{EV,c}(t) - P_{EV,d}(t) + P_{EV,l,s}(t) \end{gathered} \tag{2-4}$$

V2G

$$\begin{gathered} P_{GCP,in}(t) - P_{GCP,out}(t) = P_{EV,c}(t) - P_{EV,d}(t) \\ + P_{EV,cou,buy}(t) - P_{EV,cou,sell}(t) + P_{sched,AC}(t) \end{gathered} \tag{2-5}$$

Comb

$$\begin{aligned} P_{GCP,in}(t) - P_{GCP,out}(t) + P_{GCP,in,v2g}(t) - P_{GCP,out,v2g}(t) & \\ = P_{HH,el}(t) + P_{HP,el}(t) - P_{PV}(t) + P_{PV,curt}(t) & \\ + P_{SBS,c}(t) - P_{SBS,d}(t) + P_{EV,c}(t) - P_{EV,d}(t) + P_{EV,l,s}(t) & \end{aligned} \tag{2-6}$$

Another elementary constraint of the use cases is the energy conservation of the EV storage level E_{EV}. Equation (2-7) formulates this constraint for V2H and Comb under consideration of constant charging and discharging losses of the EV $P_{EV,l,const,c/d}$ depending on the charging and discharging decision $b_{EV,c/d}$ and linear charging and discharging losses of the EV and EVSE $P_{EV,l,c/d}$ depending on the charging and discharging power. Equation (2-8) constrains the EV storage energy conservation under consideration of countertrades $P_{EV,cou,sell}$ and $P_{EV,cou,buy}$, while modeling losses by a fixed charging and discharging efficiency $\mu_{EV,c/d}$ for V2G. The schedule of the previous marketed power including charging and discharging losses is stored in the variable P_{sched}. Public charging $E_{EV,pub,c}$ and driving energy $E_{EV,drive}$ also affect the storage level.

Storage energy conser-vation EV

V2H/ Comb

$$\begin{gathered} E_{EV}(t) = E_{EV}(t-1) + \left[P_{EV,c}(t) - P_{EV,l,c}(t)\right] \cdot \Delta t \\ - \left[P_{EV,d}(t) + P_{EV,l,d}(t)\right] \cdot \Delta t - P_{EV,l,const,c/d} \cdot \left[b_{EV,c}(t) + b_{EV,d}(t)\right] \cdot \Delta t \\ + E_{EV,pub,c}(t) - E_{EV,drive}(t) \end{gathered} \tag{2-7}$$

V2G

$$\begin{gathered} E_{EV}(t) = E_{EV}(t-1) + P_{EV,c}(t) \cdot \mu_{EV,c} \cdot \Delta t \\ - P_{EV,cou,sell}(t) \cdot \mu_{EV,c} \cdot \Delta t - \frac{P_{EV,d}(t)}{\mu_{EV,d}} \cdot \Delta t + \frac{P_{EV,cou,buy}(t)}{\mu_{EV,d}} \cdot \Delta t \\ + P_{sched} \cdot \Delta t + E_{EV,pub,c}(t) - E_{EV,drive}(t) \end{gathered} \tag{2-8}$$

For all use cases considered, Equations (2-9), and (2-10) further constrain the EV's battery storage level. Equation (2-9) sets the minimum battery storage level in dependance of the maximum EV battery capacity $E_{EV,max}$, and a parameterized safety state of charge (SoC) SoC_{safe} for all time steps $c_{EV,connected}$, in which the EV is connected to the EVSE. This limitation on storage capacity is introduced so that the user can make at least one trip to the hospital with the EV at any time for safety reasons. Equation (2-10) further constrains the minimum battery storage level depending on the user parameterization SoC_{dep} and the EV battery capacity $E_{EV,max}$ for all time steps $c_{EV,dep}$, in which the EV is scheduled to depart. This is again due to realistic modeling of the user, who can specify a desired minimum SoC when the EV departs.

Safety SoC	**V2H/ V2G/ Comb**	$E_{EV}(t) \geq SoC_{safe} \cdot E_{EV,max} \cdot c_{EV,connected}(\mathrm{t})$	(2-9)
Departure SoC		$E_{EV}(t) \geq SoC_{dep} \cdot E_{EV,max} \cdot c_{EV,dep}(t)$	(2-10)

The mathematical formulation of the use cases shown here reveals fundamental differences in modeling. In [Pub1] and [Pub2], numerous other constraints are introduced to model a realistic design of the use cases. For example, the simultaneous combination of V2G and V2H is restricted for regulatory reasons, and the modeling of countertrades is described in more detail for V2G. More details of the modeling can therefore be taken from the publications.

2.2 Revenue Potentials and Their Most Important Influencing Factors

In the following, Section 2.2.1 presents revenue potentials for PV self-consumption optimization as a V2H use case based on [Pub2]. Section 2.2.2 shows revenue potentials for arbitrage trading as a V2G use case on the basis of [Pub1]. Then, Section 2.2.3 combines these use cases for an evaluation of added revenues by a use case combination based on [Pub2]. More detailed descriptions of parameter assumptions and revenue assessments can be found in [Pub1] and [Pub2].

2.2.1 Photovoltaic Self-Consumption Optimization

For the evaluation of revenue potentials from PV self-consumption optimization, a medium household (average annual electricity demand of 3,800 kWh) and user type (not regularly commuting to work) is defined, for which 20 different instances are modeled. The average revenues for such a medium household are around 210 €/a for a smart EV compared to an unmanaged charging EV and around 310 €/a for a bidirectional EV compared to an unmanaged charging EV.

Based on this medium household and user, Figure 2-4 (a) analyzes numerous sensitivities to this basic configuration (scenario *Base*). First, as already mentioned in Section 2.1.1, linear programming with fixed charging and discharging efficiencies (*Base linear*) results in 30% overestimated revenues for a bidirectional EV. From this, it was concluded in [Pub2] that modeling of fixed charging and discharging efficiencies is not valid for V2H. Second, a user who regularly commutes to work (*COM*) has 30% decreased revenues for a bidirectional EV, but only 5% decreased revenues for a smart EV. Since commuting EVs on average have a higher annual consumption and thus greater potential for smart charging, this compensates for lower availability. Integrating other smart components into the home, such as heat pumps (*HP*), stationary battery storage (*SBS*), or a combination of those (*HP SBS*), reduces the revenues of a smart or bidirectional EV significantly. These other smart components also use the cheaper PV energy and thus compete with the EV.

The correlation of revenues to PV self-consumption is evident in Figure 2-4 (b). In the scenarios, where the PV self-consumption can be increased more, the revenues also increase more.

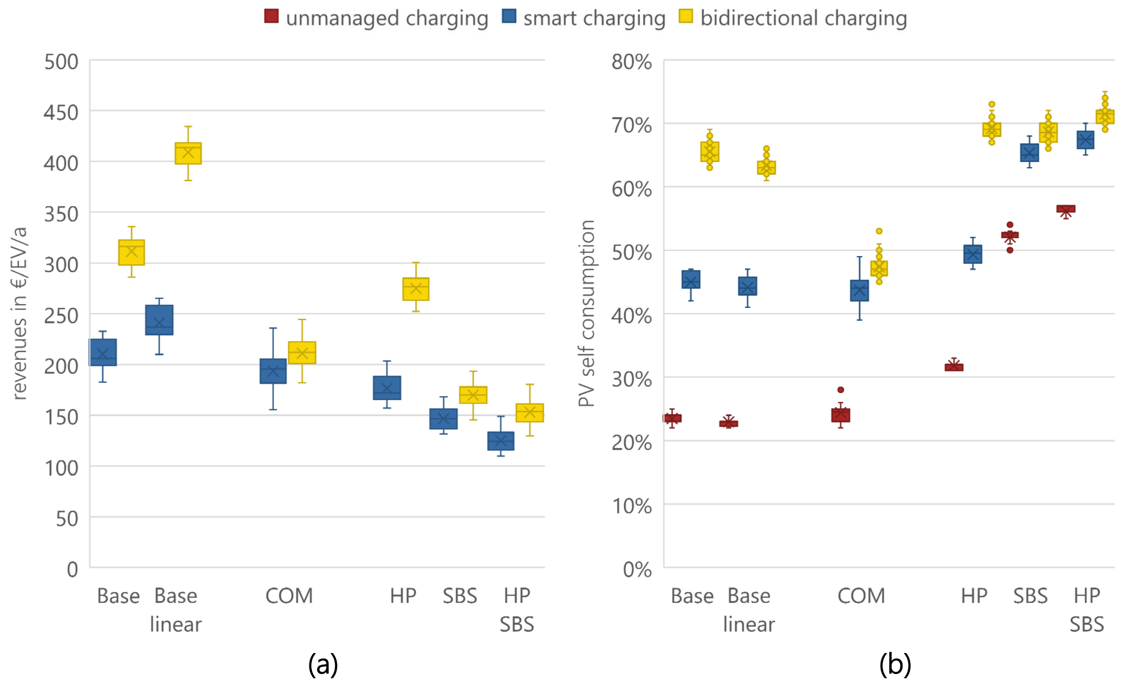


Figure 2-4: (a): Revenues through PV self-consumption optimization of smart and bidirectional EVs depending on household configuration and user type as presented in [Pub2]; (b): PV self-consumption depending on EV charging strategy, household configuration, and user type as presented in [Pub2]

There are numerous other quantitative influencing factors that affect the revenue potentials of smart and bidirectional EVs, as shown in Figure 2-5. Starting from the household and user scenario *Base* (represented by the central point in the chart), the figure shows how an increase or decrease of the influencing factors affect the revenues. The steeper the curve in the chart, the greater is the impact of the influencing factor. The PV parameters peak power and feed-in tariff affect the revenues significantly. A lower feed-in tariff leads to greater revenues since the spread between household electricity price and feed-in tariff increases and thus the self-consumption of PV energy becomes more profitable. In contrast, the parameters of the EV have only a minor impact on revenues. Since the power flows in a household are small, a smaller or larger power of the EVSE as well as a smaller or larger EV battery capacity has little impact on revenues. In the course of the fuel crisis and the strong increase of electricity prices in Europe since the end of 2021 [63], there was a sharp rise in electricity stock exchange prices in Europe and consequently also in household electricity prices. Therefore, the household electricity price was added to the influencing factors analyzed in [Pub2]. It is evident that the revenue changes for changes in the household electricity price show an even higher absolute gradient than for the PV feed-in tariff. This is because the absolute difference between the household electricity price and the PV feed-in tariff is decisive for the revenue potentials. A relative increase of the feed-in tariff by 70% and a relative reduction of the household electricity price by one third equally lead to a reduced spread between household electricity price and PV feed-in tariff of 10 ct/kWh. Revenues are reduced by 65% in both cases. In a *Max* scenario with the most attractive characteristics of the influencing factors in Figure 2-5, the revenues go up to 1,300 €/a for the bidirectional EV and 750 €/a for the smart EV, which shows the high revenue potential of the use case.

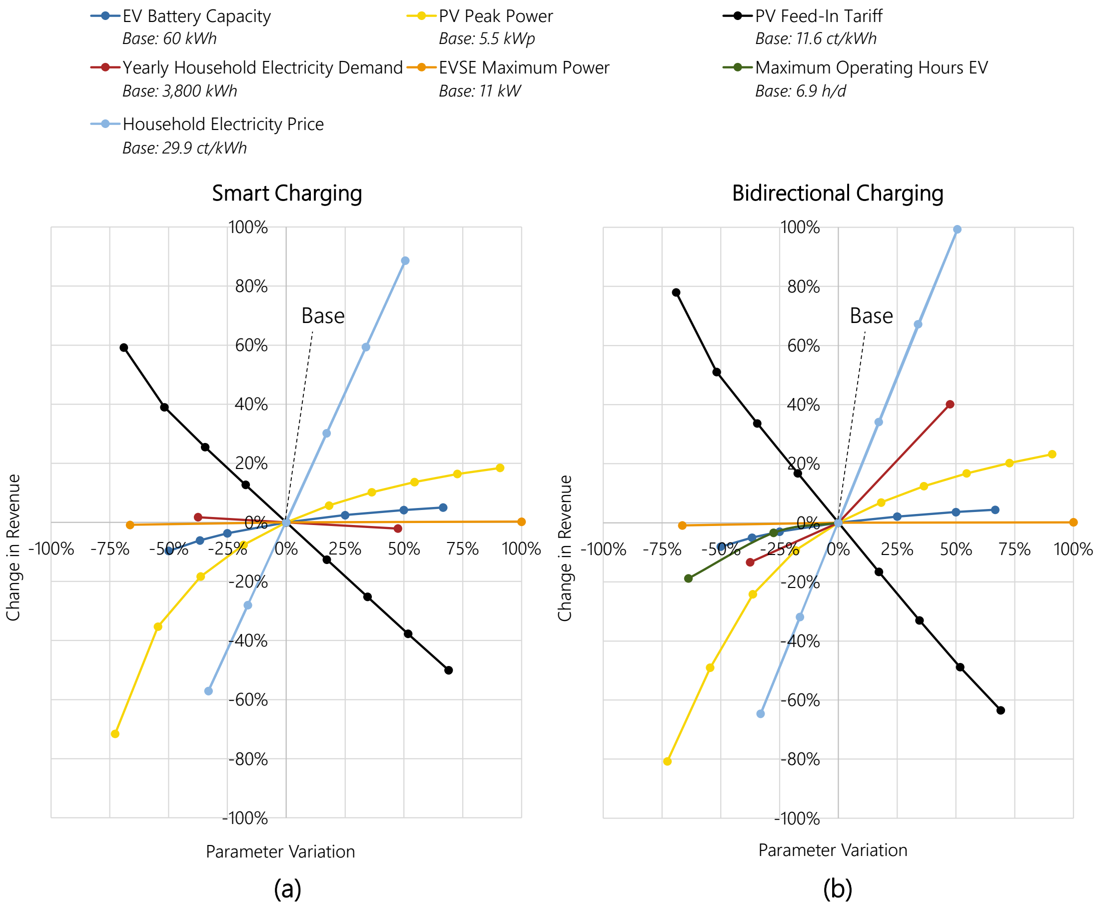


Figure 2-5: Impact of most important influencing factors on revenues of PV self-consumption optimization for smart EVs (left) and bidirectional EVs (right) based on [Pub2]

Overall, the use case of PV self-consumption optimization through smart or bidirectional EVs is very sensitive. To estimate revenues, it is necessary to know the exact configuration of the household and user. The most important factor influencing revenue potentials is the spread between household electricity prices and PV feed-in tariff. The higher is the spread, the higher are the revenue potentials.

2.2.2 Arbitrage Trading

For the evaluation of arbitrage trading in the German electricity markets in 2019, Figure 2-6 presents the revenues of smart and bidirectional EVs dependent on the EV and EVSE configuration, the user type, and the considered electricity market. Revenues again refer to the differential revenues of smart and bidirectional EVs compared to unmanaged charging EVs. For this initial revenue analysis, an exemption from taxes, levies and surcharges is assumed for charged electricity that is temporarily stored and thus discharged later.

Various influencing factors can be identified that have a strong impact on revenues of bidirectional EVs. Marketing in the intraday market can generate 50% to 100% higher revenues than marketing in the day-ahead market due to the higher price volatility in the intraday trading. Consecutive marketing on the day-ahead and intraday market can increase the revenue potential by another 10% compared to intraday trading. Furthermore, a higher battery capacity of the EV and a higher charging and discharging power of the EVSE have a strong revenue increasing effect. Non-commuters can generate on average about 15% higher revenues than commuters by participating in the electricity market. Smart charging leads to revenues that are only 5% to 25% of bidirectional EVs. These revenues depend only slightly on the EV and EVSE configuration, but more on the considered electricity market. However, revenue potentials of smart EVs are comparably low so that smart charging is far less relevant for the use case arbitrage trading than for the use case of PV self-consumption optimization.

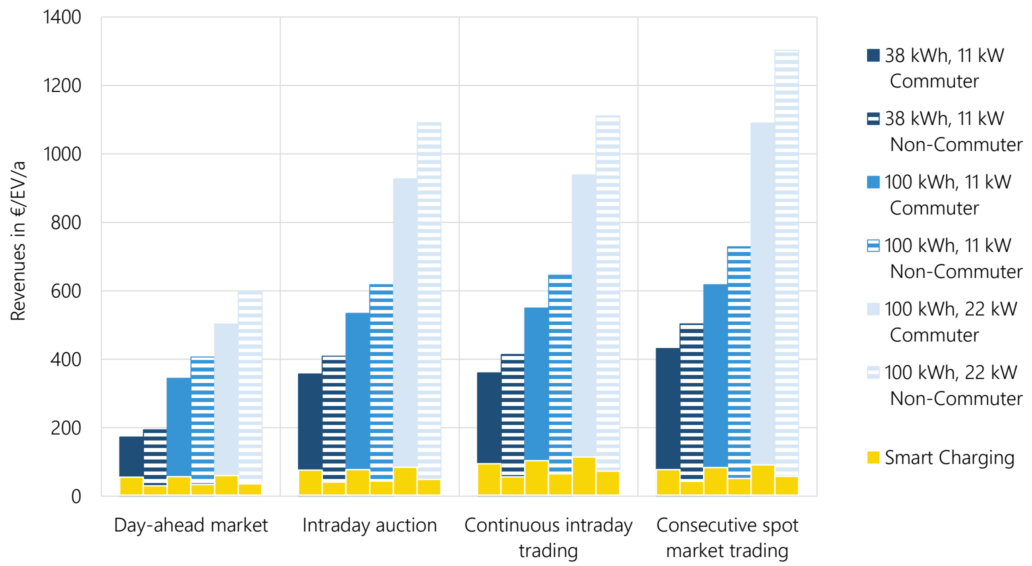


Figure 2-6: Revenue potentials of arbitrage trading in different electricity markets for different EV and user types in the year 2019 in Germany as presented in [Pub1]

Two other very important factors influencing revenue potentials are the regulation and thus the taxes, levies and surcharges that must be paid on charged electricity, and the electricity price volatility, as shown in Figure 2-7. For these studies, a non-commuting EV with battery capacity of 100 kWh and a charging and discharging power of 11 kW has been assumed.

Figure 2-7 (a) shows that the revenues (here exemplified in the intraday market) decrease sharply with increasing taxes, levies, and charges to be paid on charged electricity. In Germany, storage facilities are eligible for exemption from taxes, levies, and surcharges on charged electricity that is later discharged. The BCM project has published a policy paper on this subject that details the possibilities for exemption from taxes, levies, and surcharges [42]. In the case of a regulatory classification of bidirectional EVs as storage systems, reduced taxes, levies, and surcharges on temporarily stored electricity will be incurred. There is currently no exemption option for the ‘StromNEV’ levy (depending on the annual energy throughput in the storage facility) and the 'AbLaV' levy. A home storage system must also pay a concession fee to the city or municipality on charged electricity, which does not necessarily apply to a large battery storage system or a pumped storage system [42]. The exemptions from taxes, levies, and surcharges result in the reduced revenues shown in Figure 2-7 (a) for a regulatory classification as pumped storage hydropower, large-scale stationary battery storage, or home storage system. Since even with the intuitive regulatory classification of a bidirectional EV as a home storage system, the revenue potentials drop by almost 70%, further exemptions from taxes, levies, and surcharges should be created to make arbitrage trading economically more feasible.

Figure 2-7 (b) shows the dependence of the revenue potentials of bidirectional EVs on the characteristics of electricity prices, which changes significantly in the years 2020 to 2050. The underlying electricity prices are modeled prices using the energy system model ISAaR [39], which is described in more detail in Chapter 3, without taxes, levies, and surcharges. Electricity price volatility, shown in the figure by the average daily standard deviation of electricity prices over one year, increases sharply in the considered scenario in future years. Due to the strong expansion of variable renewable energies that have a high simultaneity in electricity generation, there are numerous times with very low electricity prices. Additionally, there are increasingly times with high electricity prices due to higher fuel costs and CO_2-prices, which increase the marginal costs of thermal power plants. Overall, this leads to a strongly increasing mean daily standard deviation of the electricity price. Revenue potentials correlate very strongly with the daily standard deviation of the electricity price, as bidirectional EVs often act as daily storage. The influence of the electricity price volatility is also shown in [Pub1] by modeling the revenue potentials of bidirectional EVs in 28 different European countries for the year 2019. Revenues for modeled non-commuting EVs trading in the day-ahead market vary from 50 €/EV/a in Norway to 700 €/EV/a in Hungary. In the course of the energy crisis in 2021, the electricity price volatility has increased a lot, so that in 2021 the average daily standard deviation of the day-ahead price of 24.5 €/MWh was almost 3 times as high as in 2019 [63]. Accordingly, the revenue potentials have also increased by about three times.

In summary, the revenue potentials of the arbitrage trading use case are also very sensitive, like those of the PV self-consumption optimization. In contrast to the PV self-consumption optimization, the influencing factors of electricity price volatility, regulatory framework, as well as the EV and EVSE characteristics are of great importance. Other influencing factors, including, for example, user behavior and liquidity of the electricity spot markets, are discussed in [Pub1].

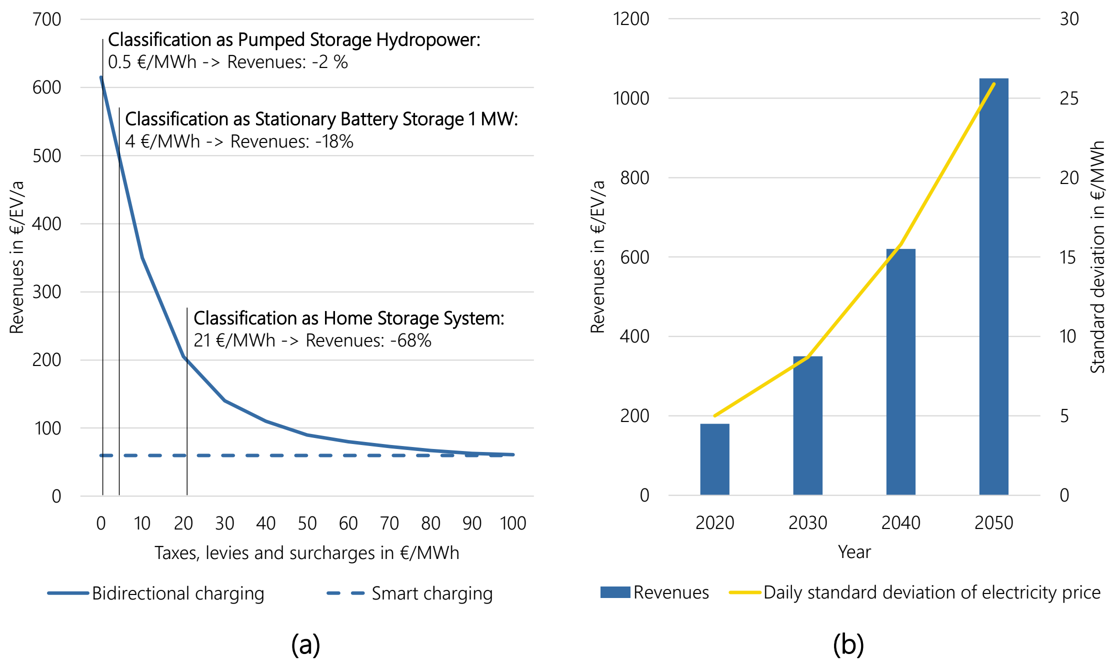


Figure 2-7: Revenue potentials depending on the regulatory framework (a) and on the electricity price volatility (b) based on [Pub1]

2.2.3 Combined Photovoltaic Self-Consumption Optimization and Arbitrage Trading

In the combined modeling of PV self-consumption optimization and arbitrage trading, arbitrage trading is limited to the day-ahead market for reasons of complexity. From a regulatory point of view, a simultaneous implementation of V2H and V2G is challenging, since the PV electricity could then be fed into the grid via the EV and thus possibly pay reduced taxes, levies and surcharges for electricity purchased later. Therefore, daily usage is limited to either V2H or V2G so that seasonal characteristics can also be analyzed. For trading in the electricity market, an exemption from taxes, levies and surcharges is assumed for this study.

Figure 2-8 shows in the upper diagram first the weekly standard deviation of electricity prices and the weekly PV generation of the medium household (see Section 2.2.1). In the lower part of Figure 2-8 the share of V2G and V2H used by the 20 modeled households is shown. It is evident that V2H PV self-consumption optimization is clearly preferred in the summer months from April to September. When comparing the diagrams, a correlation with the PV feed-in can be identified. In contrast, V2G is used more in the winter months, when there are slightly higher spreads of electricity prices in the spot market, expressed by the higher standard deviation. It can be deduced from this that V2H and V2G can in principle be combined very well due to their seasonally different revenue potentials.

From a revenue perspective, the combination of the use cases PV self-consumption optimization and arbitrage trading brings significant added value. Thus, the revenues of the medium household can be increased by 70% from 310 €/a to 530 €/a. Interestingly, the actual V2H revenues are only slightly reduced, since V2H is hardly carried out in the winter months due to small PV feed-in quantities. Even with a modeled limitation of the operating hours (OHs) and the equivalent full cycles of the battery (EFCs) to 5 OHs/d and 130 EFCs/a, respectively, significant additional revenues of 100 €/a can still be generated by this use case combination.

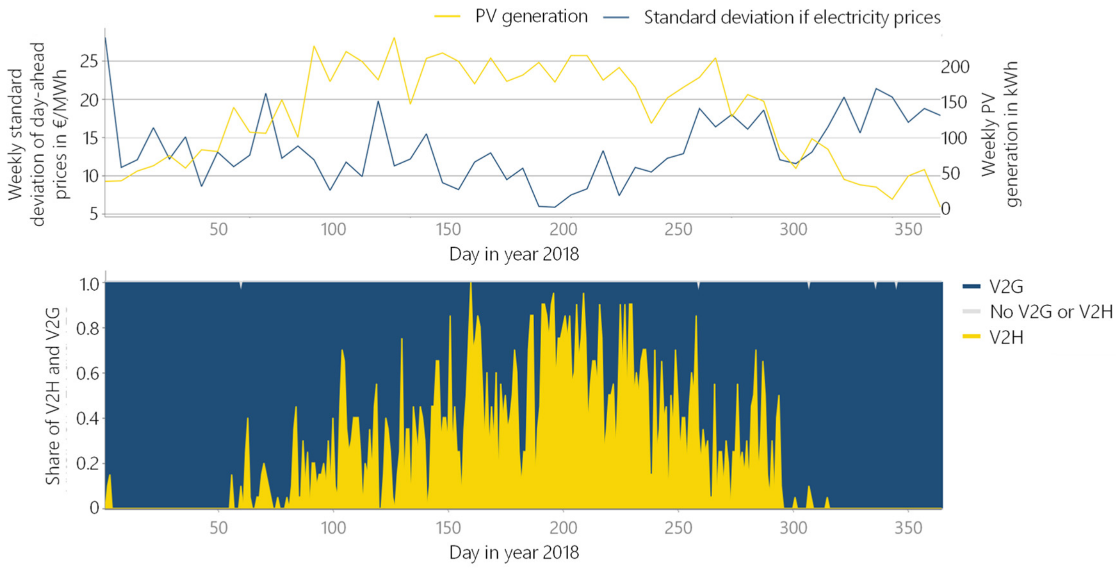


Figure 2-8: Daily share of households using V2H and V2G (bottom figure) depending on weekly standard deviation of electricity prices and weekly PV generation (upper figure) based on [Pub2]

2.3 Profitability of Bidirectional Charging

To evaluate the economic profitability of bidirectional EVs performing the PV self-consumption optimization or arbitrage trading use cases, the additional costs of bidirectional charging must be considered in addition to the revenues highlighted in Section 2.2.

2.3.1 Additional Costs of Bidirectional Charging

Based on research and discussions with experts in the BCM project, the following additional cost components for bidirectional charging of EVs were identified:

- purchase of bidirectional EVSE
- installation of bidirectional EVSE
- operation of bidirectional EVSE
- installation and operation of additional metering equipment
- additional hardware/software
- purchase of bidirectional EV
- operation of bidirectional EV
- additional processes of registration, permits and contracts

Detailed information on the additional costs can be found in [43]. For the purchase and installation of the bidirectional EVSE, the installation and operation of additional metering equipment and additional hardware, costs and cost predictions were determined within the BCM project. The operation costs of the bidirectional EVSE through additional losses are included in the revenue modeling. The additional purchase and operation costs of the bidirectional EV could not be determined. Since Volkswagen, as an example of an EV manufacturer, sees bidirectional charging as a standard in the future [44], there could also be no additional investment costs for a bidirectional EV, at least for upper-class models. The costs for additional processes of registration, permits and contracts are set to zero since it is uncertain whether there will be additional costs for it.

Table 2-1 shows the projected development of additional investment costs of bidirectional charging compared to unmanaged charging. It can be noticed that especially in 2020 the additional investment costs are driven by the purchase of the bidirectional EVSE, which will show a significant cost degression in the future. The bidirectional EVSE installation is more expensive than the installation of an unmanaged EVSE due to higher working time costs and potential laid empty conduits with wall openings for network connection. Additional hardware includes either an optocoupler or an additional smart energy meter. In future years, an existing smart energy meter might be sufficient, such that additional hardware costs could be reduced to zero."

Table 2-1: Additional investment cost range for V2H, and V2G in €$_{2021}$/EV compared to unmanaged charging based on [43]

	2020	2025	2030	2035	2040
EVSE purchase	5,300-5,700	2,000-2,100	1,400-1,500	1,100-1,200	800-900
EVSE installation	830-880	60-350	60-350	60-350	60-350
Additional hardware	100-450	100-450	0-450	0-450	0-450
Total	6,230-7,030	2,160-2,900	1,460-2,300	1,160-2,000	860-1,700

Table 2-2 shows the additional yearly costs due to additional modern measuring devices and smart meter gateways (SMGWs). SMGWs are mandatory in Germany under certain circumstances, e.g., for consumers with an electricity consumption of more than 6,000 kWh per year [45]. Since the modeled medium household with the EV electricity demand has a higher electricity consumption, the SMGW is mandatory regardless of whether it is an unmanaged charging EV or a bidirectional EV. Therefore, only one additional modern measuring device with costs of 20 €$_{2021}$/a is needed. These costs are assumed to be constant in real terms.

Table 2-2: Additional yearly cost range for V2H, and V2G in €$_{2021}$/EV/a compared to unmanaged charging based on [43]

	2020	2025	2030	2035	2040
Metering equipment	20	20	20	20	20
Total	20	20	20	20	20

2.3.2 Evaluation of Profitability

For final evaluation of the economic profitability, the findings on the revenue potentials of bidirectional EVs from Section 2.2 and the additional costs of bidirectional EVs versus unmanaged charging EVs from Section 2.3.1 are brought together in this section. The three investment dates 2020, 2025 and 2030 for a bidirectional EV are considered. The one-time and yearly additional costs for bidirectional charging compared to unmanaged charging are obtained from Table 2-1 and Table 2-2.

The revenues for the use case PV self-consumption optimization are calculated based on sensitivity analyses for a differing PV feed-in tariff for a medium household. Table 2-3 presents the revenues as well as the underlying parametrization for the years 2020 to 2030. The feed-in tariff of the PV electricity generation for 2020 is taken from [67] for a PV plant with a peak power smaller 10 kW constructed in July 2020. For the years 2025 (5.5 ct/kWh) and 2030 (4 ct/kWh) a further reduction of the fixed PV feed-in tariff has been assumed according to the trend of the last years. In April 2022, for example, the feed-in tariff had already been reduced to 6.5 ct/kWh [67]. All other parameters, such as PV peak power (5.5 kW), household electricity price (29.9 ct/kWh) and EV characteristics are left constant according to the baseline household scenario described in Section 2.2.1. The household electricity price is kept constant in nominal terms, which corresponds to a reduction in real terms. The actual future development of household electricity prices shows great uncertainties here, especially in the context of the current energy crisis. Increasing household electricity prices would mean increasing revenue potentials from PV self-consumption optimization, as shown in Section 2.2.1.

Table 2-3: V2H Revenues based on household type and PV feed-in tariff for the years 2020, 2025 and 2030

	2020	2025	2030
Household type	medium	medium	medium
PV feed-in tariff	9.0 ct/kWh	5.5 ct/kWh	4 ct/kWh
EV/EVSE parameterization	60 kWh battery capacity, 11 kW charging/discharging power, non-commuting user		
Revenues	380 €/a	470 €/a	530 €/a

For future years after the investment year, the revenues are generally assumed to be constant. The parameters of the household do not change, the fixed feed-in tariff is guaranteed to be paid for a period of 20 years [68], and the household electricity price is assumed to be constant. Since the reference year for costs is 2021, all revenues must consequently still be discounted. For this purpose, an average future inflation rate of 1.4% is used based on the average inflation rate in Germany from 2012 to 2021 [46]. In addition, a real interest rate of 1.6%, reflecting risk premium rate, is used, resulting in a nominal interest rate of 3%. This nominal interest rate i_n of 3% is used for discounting the revenues Rev_t of a time step t to the discounted revenues Rev_0 by following Equation (2-11). The discounting formula is based on [69].

$$Rev_0 = \frac{Rev_t}{(1+i_n)^t} \tag{2-11}$$

The net present value *NPV* is thus calculated as the sum of all revenues less the initial investment costs $costs_{initial}$ and the sum of the annual costs $costs_{yearly}$ in real terms based on [70] in Equation (2-12).

$$NPV = \sum_{0}^{t} \frac{Rev_t}{(1+i_n)^t} - costs_{initial} - \sum_{0}^{t} costs_{yearly} \tag{2-12}$$

The yearly cash flows as well as the NPV for the three scenarios with a V2H investment in 2020, 2025 and 2030 are shown in Figure 2-9. Due to the high investment costs of a bidirectional EVSE, an investment in V2H is not economical in 2020. However, with an investment in V2H in 2025, a positive NPV can already be achieved after seven years, which is 2,300 €$_{2021}$ at the end of the EVSE's lifetime of 15 years. An investment in 2030 achieves a positive NPV after a little more than five years, which rises to 2,800 €$_{2021}$ at the end of the EVSE's lifetime.

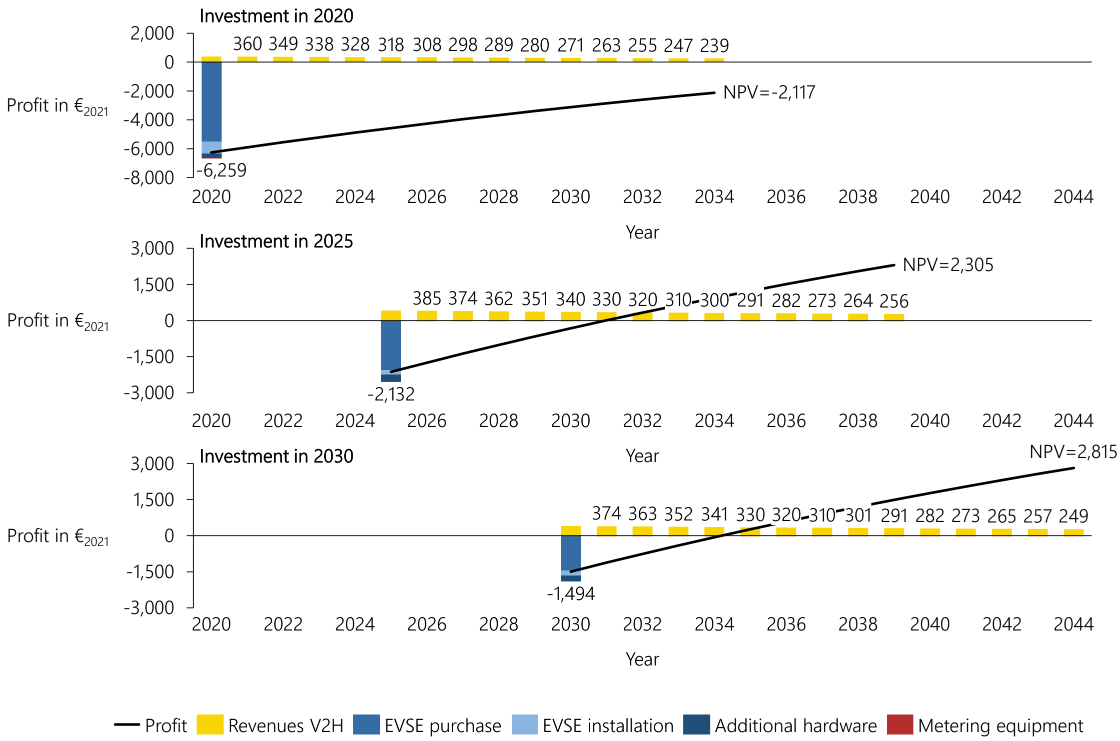


Figure 2-9: Profitability of V2H PV self-consumption optimization depending on the investment year of bidirectional EV and EVSE

The revenues for the profitability calculation of the arbitrage trading use case are determined using the parameterization of Table 2-4. For better comparability, the same EV and EVSE parameterization (including the same EV profiles) is assumed as in the profitability evaluation of the V2H use case, but with a fixed charging and discharging efficiency. For future years, a gradual exemption of the charged, temporarily stored electricity from taxes, levies and surcharges is assumed. In 2025, the bidirectional EV is classified as a home storage system (see Section 2.2.2), and from 2030 there is a complete exemption from taxes, levies, and surcharges.

Marketing is limited to trading in the day-ahead market. For the year 2020, historical day-ahead electricity prices are used [47]. For future years, modeled electricity prices are provided from the energy system model ISAaR based on simulations of the future European energy system in Section 3.4.2 with bidirectional EVs already integrated (*BCM* scenario). The electricity price time series have the mean daily standard deviations shown in Table 2-4. [Pub3] explains the future electricity price characteristics in more detail.

Table 2-4: V2G revenues based on regulatory framework, electricity price characteristic, as well as EV and EVSE parameterization for the years 2020 to 2040

	2020	2025	2030	2035	2040
Regulatory framework	All taxes, levies, and surcharges must be paid	Classification as home storage system: 2,1 ct/kWh	full exemption from taxes, levies, and surcharges	full exemption from taxes, levies, and surcharges	full exemption from taxes, levies, and surcharges
Daily standard deviation of electricity prices in €/MWh	9.4	15.8	18.0	17.6	16.8
EV/EVSE parameterization	60 kWh battery capacity, 11 kW charging/discharging power, 86% roundtrip efficiency, non-commuting user				
Revenues in €/a	60	120	360	340	280

Unlike V2H revenues, V2G revenues are not left constant after the investment decision of a bidirectional EV but are adjusted based on Table 2-4, since a regulatory change and a change of the electricity price characteristics also apply to earlier investments. The revenues are deliberately not interpolated here since the adjustment of the regulatory framework is a discrete decision. V2G revenues are only discounted by the risk premium rate of 1.6% since prices in the energy system model ISAaR are modeled in real terms (inflation-adjusted) and further related to the base year 2021.

Figure 2-10 shows the resulting profitability of V2G arbitrage trading depending on the investment year. For an investment in a bidirectional EV and EVSE in 2020, the NPV is strongly negative since revenues in the years 2020 to 2030 are low mainly due to regulatory issues. Investing in a bidirectional EV and EVSE in 2025 leads to a positive NPV after 12 years. Only a later investment in 2030 results in a short amortization period of around 7 years. Thus, with an investment in a bidirectional EV and EVSE in 2030, an NPV of around 1,650 $€_{2021}$ can be achieved after 15 years.

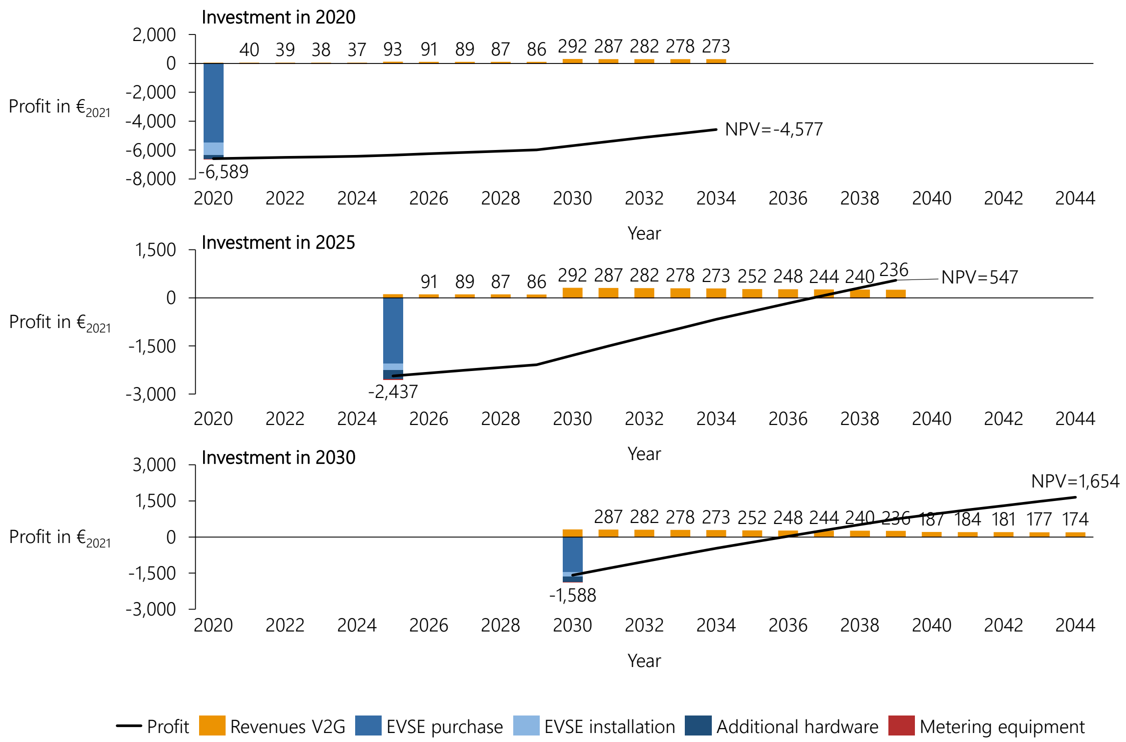


Figure 2-10: Profitability of V2G arbitrage trading depending on the investment year of bidirectional EV and EVSE

In summary, for the investigated parameterization of household, EV and EVSE, user behavior, regulatory framework, and electricity price characteristics, both use cases can become profitable in future years. V2H PV self-consumption optimization is the more secure economic use case, which depends less on the regulatory framework. However, the basic requirement for this use case is the ownership of a PV system, so that not all users can rely on it. In contrast, V2G arbitrage trading through, for example, participation in the intraday market, has similarly diverse opportunities to improve revenue potential. Finally, it is important to note that both use cases are extremely sensitive, as explained in Section 2.2, so that the final economic analysis must always be carried out with the real parameterization of a considered scenario.

3 Bidirectionally Chargeable Electric Vehicles from the Energy System Perspective

Due to ambitious European and national climate targets, the European energy system is facing major structural changes. Based on [Pub3] and [Pub4] and further research, this chapter analyzes the added value of bidirectional EVs for the European energy system. For this purpose, the focus is on systemically oriented V2G use cases. Section 3.1 analyzes the different modeling types of bidirectional EVs in a large-scale energy system model for the integration of EVs into the electricity market (use case arbitrage trading) and for the provision of system services by bidirectional EVs (use case congestion management). To evaluate the impact of bidirectional EVs on the energy system, Section 3.2 first defines scenarios. Based on the scenario definition and the modeling approaches, Section 3.3 analyzes the cost-optimal penetration rates of bidirectional EVs and their influencing factors. Finally, Section 3.4 examines the quantitative impact of bidirectional EVs on the European energy system.

3.1 Methods

For the consideration of the added value of bidirectional EVs from a system perspective, the energy system model ISAaR is further developed. Detailed information on ISAaR can be found in [31] and [39]. Section 3.1.1 focuses on modeling the integration of bidirectional EVs in the electricity market. Section 3.1.2 builds on the market integration and extends the subsequent transmission grid run by bidirectional EVs that can provide congestion management. In addition to the mathematical formulation in this section, the underlying data model, which contains a detailed description of the techno-economic parameters of all components of the European energy system, is also of great significance. The parameterization of the components is described in the following Section 3.2.

3.1.1 Modeling of Electricity Market Integration

The energy system model ISAaR forms a linear optimization problem with the objective function to minimize the European energy system costs. The linearized equations describe techno-economic relations within an energy system. The objective function is formulated in Equation (3-1). The costs C result from operation and investment costs. The operation costs are formed by specific costs $f_{t,n,i}$ and the utilization of the optimization variables $x_{t,n,i}$ for all time steps t, nodes n and instances i. Variables $x_{t,n,i}$ include generation, consumption, import and exports of all modeled energy carriers. Investment costs and other not time-dependent costs are calculated using specific costs $f_{n,i}$ and the utilization of the optimization variables $x_{n,i}$ for all nodes n and instances i. The utilization of the optimization variables $x_{n,i}$ include various kind of assets, e.g. storages, renewable energies or hydrogen-fired power plants. In the market optimization run, nodes n refer to market areas in the European energy system.

$$C = \min \left(\sum_{t\epsilon T}\sum_{n\epsilon N}\sum_{i\epsilon I}(f_{t,n,i} \cdot x_{t,n,i}) + \sum_{\mathrm{n\epsilon N}}\sum_{\mathrm{i\epsilon I}}(f_{n,i} \cdot x_{n,i})\right) \tag{3-1}$$

From the perspective of the ISAaR energy system model, bidirectional EVs represent an expansion option that replace unmanaged charging EVs. This expansion option is accompanied by investment costs that depend on necessary additional infrastructure and software as well as additional operational costs. These costs are included in the objective function of ISAaR. In addition to bidirectional EVs, the model can also replace unmanaged charging EVs with smart EVs that only charge unidirectionally and have lower investment costs.

The charging and discharging powers of bidirectional EVs are included in the power balances. According to Equation (3-2), the final energy demand P_{demand} is equal to generation P_{gen} and imports P_{import} minus consumption P_{cons} and exports P_{export} for every timestep t, nodes n and energy carrier c over all instances i. The charging of an EV is included in the system power balance as consumption and the discharging as generation.

$$\begin{aligned} P_{demand}(t,n,c) = \sum_{i} P_{gen}(t,n,c) - \sum_{i} P_{cons}(t,n,c) + \\ \sum_{i} P_{import}(t,n,c) - \sum_{i} P_{export}(t,n,c) \end{aligned} \tag{3-2}$$

The modeling of bidirectional EVs integrated into the European electricity market and thus of an energy system-optimized use of the vehicles corresponds to the use case of arbitrage trading from the user's perspective. In a system-optimal operation, bidirectional EVs are charged at times of low electricity prices and discharged at times of expensive electricity prices. In this way, they can displace the use of thermal power plants, which produce at expensive marginal costs when fuel and CO_2 prices are high. Compared to the modeling of the use case of arbitrage trading from the user perspective discussed in Chapter 2, however, the focus is now on the integration of the EVs in the day-ahead markets, since large energy system models do not typically model the short-term intraday markets. Price formation on intraday markets is based primarily on shorter product duration (in Germany quarter-hourly, half-hourly and hourly products), lower market liquidity and short-term forecast errors [48], neither of which is represented in large energy system models. Further, through cost-optimal integration of bidirectional EVs, the impact on electricity day-ahead prices is endogenously included in ISAaR.

Based on Equation (2-8), the storage energy conservation equation of EVs is simplified so that no counter trades are represented in the intraday market in Equation (3-3). The EV's storage level E_{EV} in a timestep t is equal to the storage level of the previous time step added by the charged energy $P_{EV,c}(t) \cdot \mu_{EV,c} \cdot \Delta t$ and the charged energy in public $E_{EV,pub,c}(t)$ subtracted by the discharged energy $\frac{P_{EV,d}(t)}{\mu_{EV,d}} \cdot \Delta t$ and the consumed energy by driving $E_{EV,drive}(t)$. The charging and discharging efficiencies $\mu_{EV,c}$ and $\mu_{EV,d}$ again are modeled constant due to predominantly high charging and discharging powers (compare Section 2.1.1).

$$E_{EV}(t) = E_{EV}(t-1) + P_{EV,c}(t) \cdot \mu_{EV,c} \cdot \Delta t - \frac{P_{EV,d}(t)}{\mu_{EV,d}} \cdot \Delta t + E_{EV,pub,c}(t) - E_{EV,drive}(t) \tag{3-3}$$

By using Equations (2-9) and (2-10) for the modeling of a safety SoC and a departure SoC that constrain the battery storage level, a realistic user behavior is also provided.

Discrete modeling of all individual EVs in the European energy system would lead to a great number of modeled storage instances, which would introduce an enormous complexity. In [Pub3] three approaches for modeling bidirectional EVs in large-scale energy system models are presented to solve this problem. All approaches have the goal of modeling entire vehicle fleets in countries while keeping the complexity of the model as low as possible. Table 3-1 sums up the approaches and their advantages and disadvantages.

Table 3-1: Modeling approaches of bidirectional EVs in a large-scale energy system model and their advantages and disadvantages

	1,000 Discrete EV Profiles per Market Area	**Clustered, Discrete EV Profiles per Market Area**	**Aggregated EV Profile per Market Area**
Modeling Approach	• Modeling of 1,000 discrete EV instances to represent EV fleet	• Modeling of clusters with 5 to 50 discrete EV instances to represent EV fleet	• Modeling of one aggregated EV instance to represent EV fleet
Advantages	• Best representation of EV fleet and its impact on energy system	• Exact representation of EV constraints • Good representation of EV fleet and its impact on energy system	• Lowest modeling complexity • Good representation of EV fleet and its impact on energy system
Dis-advantages	• High complexity • Not computable for optimized expansion of bidirectional EVs	• High complexity	• No exact representation of EV constraints

The modeling approach via aggregation of all EV profiles softens the EV constraints that restrict the SoC. Figure 3-1 shows the aggregated availability of EVs at the location at home compared to a single EV's availability for an exemplary week. Discrete EV profiles have time dependencies that are neglected when modeling an aggregated EV profile. A single EV departing with a SoC resulting from the system-optimal operation of the vehicle will return with a SoC that depends on the SoC at departure. Modeling an aggregated EV profile neglects this dependency, but still accounts for the overall SoC constraints of the EV pool due to the aggregated minimum availability. Since the modeling approach via aggregation of all EV profiles still leads to a good representation of the EV fleet and its impact on the European energy system, while exhibiting the lowest modeling complexity, it is chosen for further investigation. A more detailed description of the comparison of the modeling approaches can be found in [Pub3]. Further, smart EVs that only charge unidirectional can also be modelled by the same method. The only difference is their discharge power that is set to zero [Pub3].

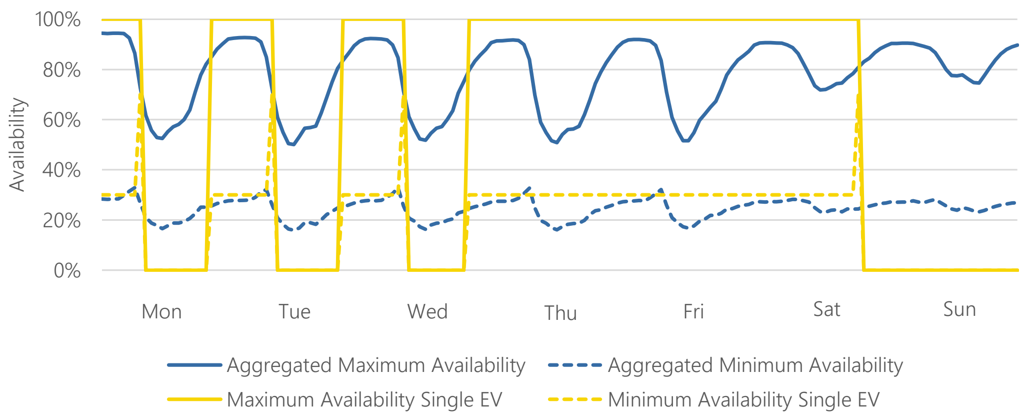


Figure 3-1: Different availability of aggregated and discrete EV profiles for an exemplary week as presented in [Pub3]

3.1.2 Modeling of Congestion Management Provision

Modeling of congestion management in ISAaR is based on a two-stage optimization:

- First run: multi-energy market optimization (described in Section 3.1.1)
- Second run: transmission grid optimization (described in this section)

The transmission grid optimization run fixes the investment in new assets based on the results of the multi-energy market optimization. Further, the dispatch of assets in the multi-energy market optimization represents the baseline for their operation in the transmission grid optimization, which can only deviate from the baseline with additional costs. For these reasons, the objective function of the transmission grid optimization differs from the market run according to Equation (3-4). It is limited to operation costs and costs incurred by the provision of congestion management for all time steps t, nodes n and instances i dependent on specific costs $f_{t,n,i}$ and the utilization of the optimization variables $x_{t,n,i}$. In the transmission grid optimization run, nodes n refer to transmission grid nodes in the European energy system. Generators, loads and flexibilities in the distribution grid are aggregated for complexity reasons and assigned to the nodes of the transmission grid.

$$C = \min \left(\sum_{t\epsilon T} \sum_{n\epsilon N} \sum_{i\epsilon I} (f_{t,n,i} \cdot x_{t,n,i})\right) \tag{3-4}$$

Congestion management costs (increase of dispatch) and revenues (decrease of dispatch) of thermal power plants are set dependent on their operational costs. Revenues for curtailment of renewable energies are set to zero to ensure their curtailment as a last option. Costs and revenues for storages that provide congestion management are set low. Their main costs arise from the subsequent compensation of schedule deviations. This energy compensation results in costs that are dependent on congestion management costs of other assets that provide the compensation.

The power balance in the transmission grid run is formulated per transmission grid node and thus has a significantly higher regional resolution than the market run. For the line flow, a DC (direct current) load flow based on PTDF (Power Transfer Distribution Factors) that represents a linearized approximation of the non-linear alternating current (AC) load flow is applied. This simplified modeling of the load flow is permissible under the assumption that there are no voltage drops (voltage amplitude is equal for all nodes), reactive power is neglected, line losses are neglected, and the voltage angle differences are small [49]. Modeling the DC load flow based on PTDF, the load flow of AC lines $P_{line,AC}$ is determined by the *PTDF* matrix multiplied by the injections and withdrawals in a grid node P_{node} according to Equation (3-5). The load flow of DC lines $P_{line,DC}$ can be fully controlled due to converter stations at the end and at the beginning of a DC line and are therefore modeled via a transport model from node *x* to *y* according to Equation (3-6).

$$P_{line,AC} = PTDF \cdot P_{node} \tag{3-5}$$

$$P_{line,DC} = P_{x \to y} \tag{3-6}$$

A detailed derivation of the PTDF equations has already been described numerous times and can be found for example in [50], [49], [31] as well as in [Pub4].

Injections and withdrawals in a grid node are the result of generation and consumption of all assets in the market run as well as their congestion management optimized in the transmission grid run. The output of power plants and renewable energies P_o is equal to the market result P_M added by the increased dispatch P_p and subtracted by the decreased dispatch P_n for all timesteps t according to Equation (3-7). Increasing dispatch represents positive congestion management and decreasing dispatch means negative congestion management. Variable renewable energies operate at their maximum output in the market run, considering a possible market-related curtailment. Therefore, their variable P_p is set to zero. Storages and thus also bidirectional EVs have the possibility to consume electricity P_i in addition to the possibility to generate electricity P_o from the system's perspective. For this reason, Equation (3-7) is expanded to Equation (3-8).

$$P_o(t) = P_M(t) + P_p(t) - P_n(t) \tag{3-7}$$

$$P_o(t) - P_i(t) = P_M(t) + P_p(t) - P_n(t) \tag{3-8}$$

Modeling of storages providing congestion management is more complex due to their time-coupling energy conservation constraint formulated in Equation (3-3) for bidirectional EVs. The temporal coupling further leads to the fact that time steps cannot be arbitrarily decomposed and parallelized in order to reduce complexity of the simulations. Figure 3-2 schematically illustrates the time-dependence of storages that compensate their adjusted schedule in the transmission grid run. Positive and negative congestion management is compensated by the opposite congestion management in a different time step. The storage level at the end of a time slice is fixed to the market run output and passed to the next time slice. Thus, the time slices are coupled only by the market run and can be simulated in parallel. The length of the self-contained optimized time slices can be selected variably. On the one hand, a longer time slice leads to greater flexibility to compensate for an adjusted schedule of a storage facility. On the other hand, it leads to a greater complexity of the optimization problem. [Pub4] analyzes the effect of different time slice lengths in detail. The results presented in Section 3.4.3 are based on a time slice length of one week.

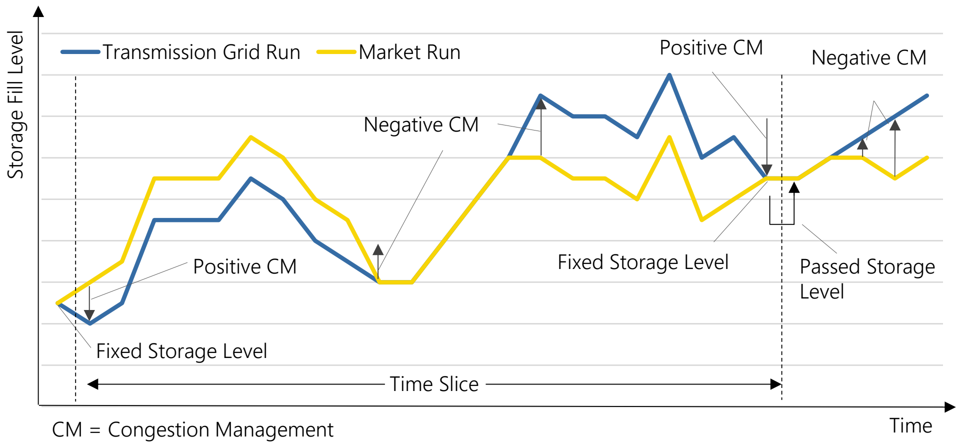


Figure 3-2: Schematic modeling of the restricted storage state of charge at the start and the end of a time slice as presented in [Pub4]

3.2 Scenario Definition

For an evaluation of the cost-optimal integration of bidirectional EVs into the future energy system, a scenario is set up that forms the framework for this study. This is based on the climate protection scenario solidEU from the eXtremOS project, which aims a 95% reduction in greenhouse gas emissions in Europe by 2050 with a strong electrification of the final energy sectors. Detailed information on the scenario and the techno-economic parameters can be found in [3]. For Germany, this scenario was updated to include targeted capacities for renewable energies and power plants in the year 2030 planned by the German government [51]:

- Installed capacity of PV plants: 200 GW
- Installed capacity of wind onshore plants: 100 GW
- Installed capacity of wind offshore plants: 30 GW
- Coal phase-out by 2030

The solidEU scenario did not provide the opportunity to integrate smart or bidirectional EVs in the future energy system. Therefore, the solidEU scenario with previously addressed adjustments serves as a reference scenario *Ref* to highlight the added value of an energy system with bidirectional EVs compared to a system without bidirectional EVs.

Based on the modeling with an aggregated EV profile per country (see Section 3.1.1), the model is endogenously allowed to integrate smart or bidirectional EVs into the system. For this purpose, Table 3-1 defines the parameterization of the EVs (including their EVSEs). The EVs are parameterized by a medium passenger car battery capacity of 50 kWh [52]. The other parameters are based on discussions within the research project BCM [Pub3].

Table 3-2: Technical parameters of bidirectional and smart EVs

Battery capacity	Charging/ discharging power	Charging/ discharging efficiency	Minimum safety SoC	Minimum SoC at departure	Location of bidirectional EVSE
50 kWh	11 kW	94%	30%	70%	At home

In addition to the technical parameters of the EVs shown in Table 3-2, the economic parameters are also relevant. Table 3-3 shows the additional investment costs for bidirectional and smart EVs compared to unmanaged charging EVs. The investment costs are based on the costs presented in Section 2.3.1 and are also discussed in [Pub3]. They include additional costs for hardware, software, and installation of EV and EVSE. In addition, sensitivities for lower costs of smart EVs (*Sen1* and *Sen2*) were added to assess the impact of smart EVs on bidirectional EVs more precisely. Investment costs are annualized by an expected lifetime of EV and EVSE of 15 years [53] and an interest rate from the energy system's perspective of 3.5% [54].

Table 3-3: Additional investment costs of bidirectional and smart EVs compared to unmanaged charging EVs for base and sensitivity (SenX) scenarios

		2025	2030	2035	2040	2045	2050
Additional investment costs for EV and EVSE in €	**Bidirectional EVs**	2840	2190	1890	1590	1590	1590
	Smart EVs Base	960	760	760	760	760	760
	Smart EVs Sen1	480	380	380	380	380	380
	Smart EVs Sen2	200	160	160	160	160	160

Since smart and bidirectional EVs are integrated as independent elements in the ISAaR energy system model, the maximum share of the absolute number of EVs is set to 50% in each case. This ensures that the number of smart and bidirectional EVs does not exceed the absolute number of EVs. Overall, the following study scenarios result:

- **Ref:** Reference scenario with no smart and bidirectional EVs
- **BCM:** Based on reference scenario with option to integrate bidirectional EVs and smart EVs with base investment costs in Table 3-3
- **Sen1:** Based on reference scenario with option to integrate bidirectional EVs and smart EVs with Sen1 investment costs in Table 3-3
- **Sen2:** Based on reference scenario with option to integrate bidirectional EVs and smart EVs with Sen2 investment costs in Table 3-3

3.3 Future Cost-Optimal Penetration Rates

Building on the scenarios established in Section 3.2, a cost optimization of the future European energy system is performed for the *BCM* scenario and the sensitivities *Sen1* and *Sen2* with reduced investment costs for smart EVs. An important finding in [Pub3] was that, given the investment costs in the *BCM* scenario, the option of smart EVs is hardly added endogenously by the model. The number of bidirectional EVs in the *BCM* scenario in Europe goes up from 19 million EVs in 2030 to 62 million EVs in 2050. This corresponds to a share of bidirectional EVs in total EVs of 25% in 2030 and of 30% in 2050. The share of bidirectional EVs in the total number of EVs is highest in 2040, at around 35%. The added value of bidirectional EVs for the European energy system compared to smart EVs is so much higher that their higher investment costs are compensated. On the one hand, this is due to the high availability of the EVs at home, so that the higher flexibility of bidirectional EVs through charging and discharging leads to added values for the energy system. On the other hand, smart EVs can only adapt their charging process, which limits their energy flexibility potential to their driving consumption.

With a reduction in investment costs for smart EVs in the *Sen1* and *Sen2* scenarios, significantly more smart EVs are endogenously integrated by the energy system model, as shown in Figure 3-3. Especially in scenario *Sen2*, the share of smart EVs in the absolute number of EVs is close to the maximum of 50% in 2030 and 2040. Consequently, the option of smart EVs leads to a sufficiently large added value for the energy system so that the additional investment costs can be compensated. However, compared to the BCM scenario, these additional smart EVs are used less to replace bidirectional EVs than previously unmanaged charging EVs. This shows that the flexibility option of smart EVs only slightly influences the integration of bidirectional EVs. Even in scenario *Sen2* with lowest costs for smart EVs, the number of bidirectional EV increases still robust, predicted to rise from 14 million EVs in 2030 to 54 million in 2050.

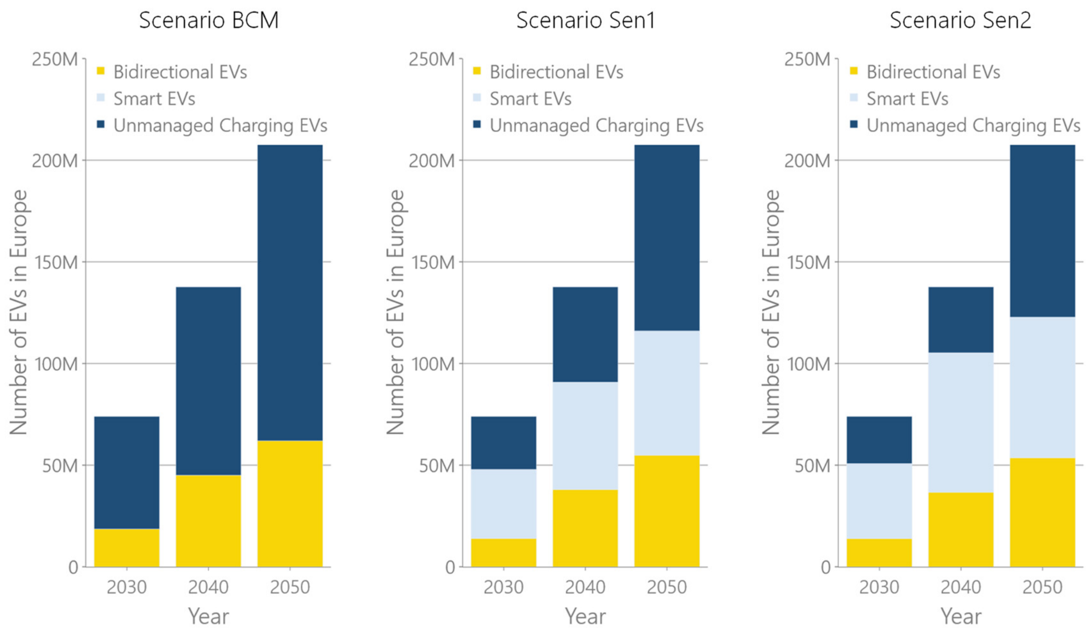


Figure 3-3: Number of EVs per charging strategy for scenarios BCM, Sen1 and Sen2 based on [Pub3] and on further evaluations

In addition to the absolute number of EVs per charging strategy, an analysis of the regional distribution of EVs is also informative in order to obtain indicators for factors influencing a high share of bidirectional EVs. For this purpose, Figure 3-4 presents the dependance of shares and numbers of EVs per charging strategy and country for the *BCM* and *Sen2* scenarios in 2050 on the full load hours of PV generation. This complements the analysis in [Pub3], which compares 2030 and 2050 for the *BCM* scenario. Various characteristics are recognizable. In Scandinavia, no bidirectional EVs are integrated in either scenario and only a quarter of smart EVs are integrated in the *Sen2* scenario. The shares of bidirectional EVs are higher in Southern Europe, especially in the *BCM* scenario, for example in Greece, Italy, Spain and Bulgaria. In the *Sen2* scenario, smart EVs displace a little part of the bidirectional EVs in almost all countries. Only France and Portugal stand out with a higher share of bidirectional EVs, although a large number of smart EVs are also integrated. This is due to a further significant increase in PV capacity. The European countries on the map are each colored based on the full load hours of PV systems. Here, a correlation can already be determined visually. A higher number of full load hours of PV plants tends to lead to a higher share of bidirectional EVs in total EVs.

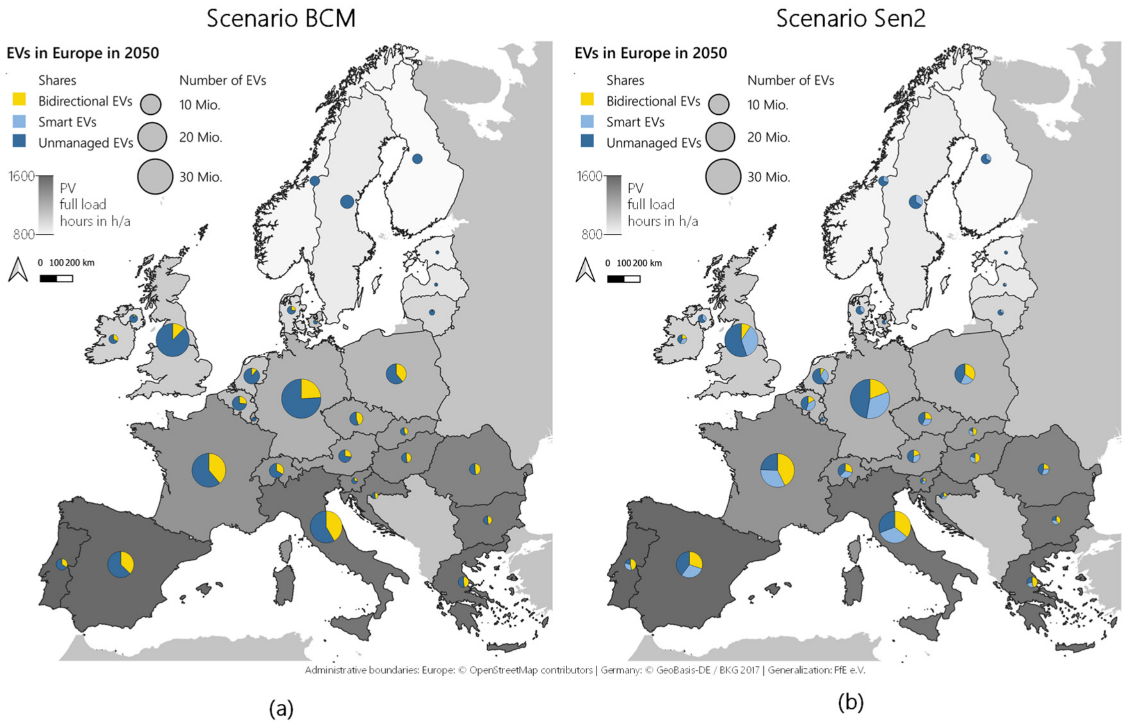


Figure 3-4: Dependance of shares and numbers of EVs per charging strategy and country for the BCM (a) and Sen2 (b) scenarios in 2050 on the full load hours of PV generation based on [Pub3] and on further evaluations

To further investigate the influencing factor of PV energy and other influencing factors, Figure 3-5 presents dependencies of the share of bidirectional EVs on various influencing factors for all countries with a total of more than one million EVs. This evaluation refers to the *BCM* scenario in 2050. Each point in the diagram represents one country. In addition, a linear regression curve and the coefficient of determination R^2 of the linear regression were determined. The coefficient of determination, which always lies in the interval between 0 and 1, indicates the quality of the regression. The closer the coefficient of determination is to 1, the better the fit of the determined regression line. With a coefficient of determination of 1, all residuals are 0 [55].

The upper left plot in Figure 3-5 shows the dependence of the share of bidirectional EVs on the average full load hours of PV systems in a country to reinforce or refute the visual indication from Figure 3-4. A coefficient of determination R^2 of 0.518 is obtained, which indicates a certain linear correlation of the share of bidirectional EVs with the average full load hours of PV plants. Since bidirectional EVs act as storage in the energy system, they will often use the PV peaks that are above the load peaks to integrate this otherwise curtailed energy into the system. Therefore, the upper right diagram in Figure 3-5 shows the dependance of the share of bidirectional EVs to the ratio of PV peak power to peak load. This results in a coefficient of determination R^2 of 0.718, which indicates a good linear relationship. Another possible assumption is that bidirectional EVs tend to be more integrated when peak wind power in a country is significantly above peak load. Therefore, the diagram in the lower left of Figure 3-5 shows the relationship between the share of bidirectional EVs and the ratio of peak wind power to peak load. Here, however, the coefficient of determination R^2 is close to 0, which means no linear correlation. The bottom right diagram in Figure 3-5 brings together wind energy and PV energy in a final study and plots the relationship of the share of bidirectional EVs to the ratio of the peak of the summed wind and PV power to the peak load. The coefficient of determination R^2 of 0.237 indicates only a slight linear correlation. It is also significantly lower here than when considering the ratio of peak PV power to peak load in the second plot.

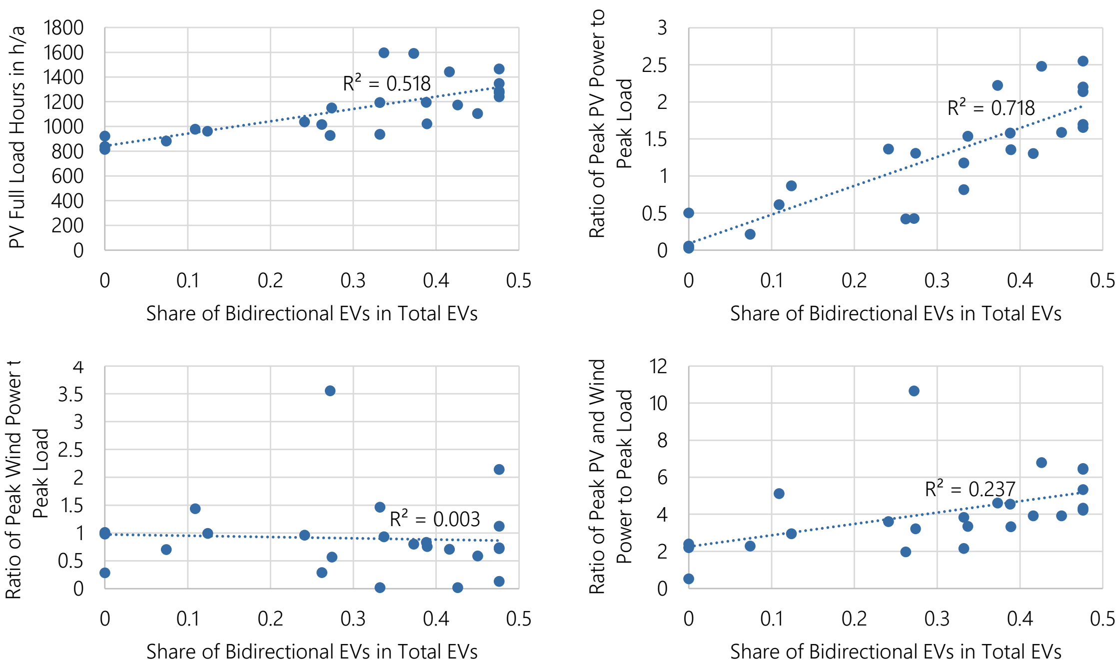


Figure 3-5: Dependance of shares of bidirectional EVs in total EVs on various influencing factors

Wind turbines have a less regular feed-in characteristic than PV systems, which always have their daily peak feed-in times around noon. This regular feed-in characteristic is well suited for daytime storages, which can charge during the day, store the energy and discharge at night. Even if the availability of bidirectional EVs is more limited during the day [56], at least 50% of all vehicles in a country are always at home. Bidirectional EVs therefore often act as daytime storage and are thus a very good complement to PV energy. This and other added values will be taken up and discussed in the following Section 3.4.

3.4 Impact on the Future Energy System

In the previous section, it was already shown that bidirectional EVs with underlying investment and operating costs are integrated in a cost-optimal future energy system. In this section, the added values and their impact on the energy system are evaluated more concretely based on [Pub3], [Pub4] and further evaluations.

3.4.1 Other Assets in the Energy System

The evaluations listed below complement the evaluations in [Pub3] by comparing the reference scenario *Ref* without smart and bidirectional EVs with the *BCM* scenario and the *Sen2* scenario defined in Section 3.2. In this way, the influences of smart and bidirectional EVs on the energy system and other elements in the energy system can be quantified.

Figure 3-6 shows the installed capacities of variable renewable energies and thermal power plants for the scenarios *Ref*, *BCM* and *Sen2* for the years 2030, 2040 and 2050 in Europe. As already pointed out in [Pub3], the installed capacity of PV increases significantly in the *BCM* scenario compared to the *Ref* scenario, whereas the capacities of onshore wind and offshore wind decrease. A comparison of the *BCM* and *Sen2* scenarios reveals only minor differences. The *Sen2* scenario tends to integrate slightly less PV and wind offshore capacity, while the installed capacity of wind onshore increases slightly. The relative curtailment of PV energy decreases by 2 to 3 percentage points from 9% to 6% in 2030 and 10% to 8% in 2050 in the *BCM* scenario compared to the *Ref* scenario. The relative wind energy curtailment, on the contrary, remains at a similar level at 2% in 2030 and 4% in 2050 in both scenarios.

The differences in the installed capacity of thermal power plants in the *BCM* and *Sen2* scenarios are similarly small. In *Sen2*, slightly lower capacities of gas-fired and hydrogen-fired power plants are required compared to *BCM*. Therefore, in both scenarios, the bidirectional EVs in particular lead to significantly lower capacities of gas- and hydrogen-fired power plants than in the *Ref* scenario.

The significant cost reduction of smart EVs and the associated high integration of these therefore only has a minor impact on the expansion of variable renewable energies and thermal power plants. As already discussed in Section 3.3, the share of bidirectional EVs in the *Sen2* scenario is similar to the *BCM* scenario resulting in the same characteristics of the energy system. Very cheap smart EVs cause slightly reduced required capacities of thermal power plants, but the impact compared to bidirectional EVs is small.

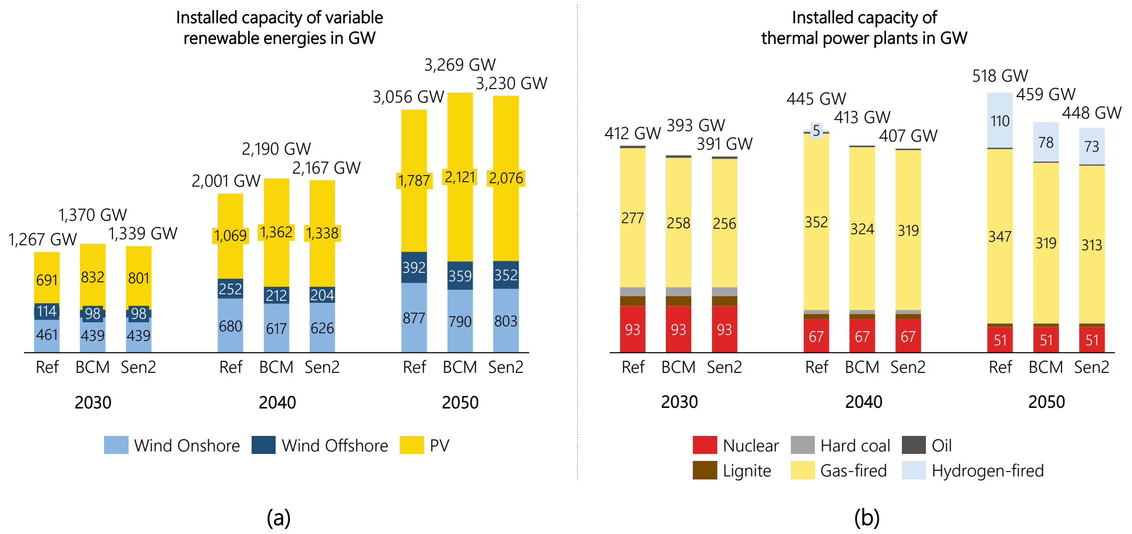


Figure 3-6: Installed capacities of variable renewable energies (a) and thermal power plants (b) for the scenarios Ref, BCM and Sen2 for the years 2030, 2040 and 2050 in Europe based on [Pub3] and on further evaluations

Going further, Figure 3-7 shows the installed capacities of mobile and stationary storages for the scenarios *Ref*, *BCM* and *Sen2* for the years 2030, 2040 and 2050 in Europe. The storage capacities of the smart and bidirectional EVs result directly from the number of EVs multiplied by a storage capacity of 50 kWh. Since the storage capacity cannot be fully utilized due to unavailability of the vehicles and limitations of the SoC, it represents a theoretical storage capacity. The storage capacities of stationary battery storages and pumped storage hydropower plants do not differ in the *BCM* and *Sen2* scenarios. Pumped storage hydropower plants are fixed and not modeled as endogenous expansion assets. Stationary battery storages are decreased to a minimum, exogenously specified capacity in both the *BCM* and *Sen2* scenarios. Therefore, the integration of very low-cost smart EVs in the *Sen2* scenario does not lead to any changes beyond the reduction of stationary battery storages in the *BCM* scenario.

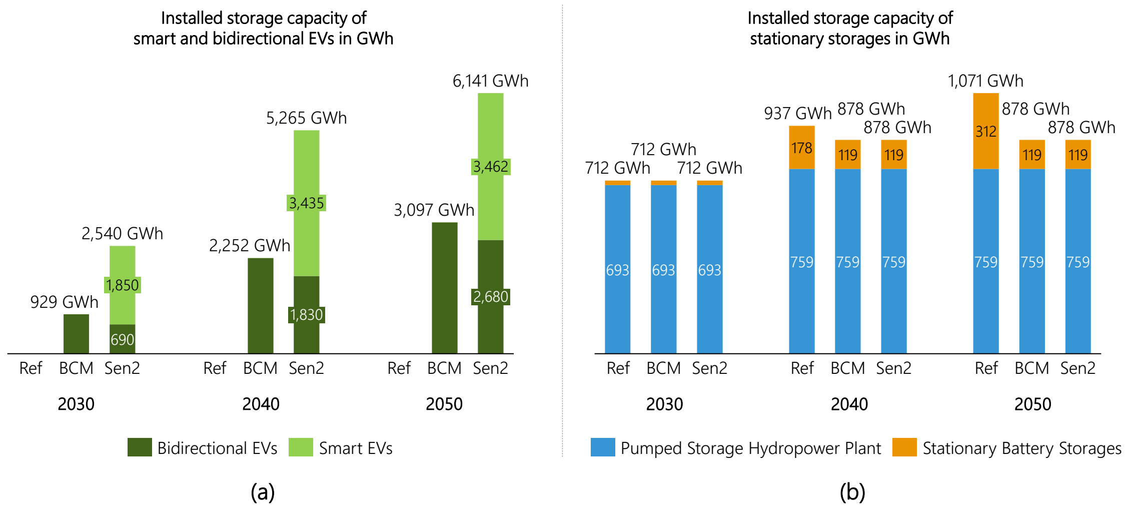


Figure 3-7: Installed capacities of mobile (a) and stationary (b) storages for the scenarios Ref, BCM and Sen2 for the years 2030, 2040 and 2050 in Europe based on [Pub3] and on further evaluations

3.4.2 Total System Costs and Electricity Prices

The structural changes in the energy system in the *BCM* and *Sen2* scenarios also result in different total system costs and mean European electricity prices, which are summarized in Table 3-4 for the years 2025 to 2050. The *Sen2* scenario is only modeled for the years 2030, 2040 and 2050. In the *BCM* scenario, total system costs decrease by €8 billion/a in 2050 compared to the *Ref* scenario, although the integration of bidirectional EVs is modeled by additional investment costs. In the *Sen2* scenario, total system costs can be reduced by a further €3 billion/a in 2050 compared with the *BCM* scenario, resulting in a total cost saving of €11 billion/a compared with the *Ref* scenario. More than €1 billion/a of the €3 billion/a cost reduction in the *Sen2* scenario compared to the *BCM* scenario can be attributed to the 8 million EVs reduction in bidirectional EVs. The average, consumption-weighted European electricity price on the wholesale market is 2-5 €/MWh lower in both scenarios *BCM* and *Sen2* than in the *Ref* scenario. The *Sen2* scenario does not cause any significant change in electricity prices compared to the *BCM* scenario. Since the total system costs consist of the infrastructure costs and the supply costs across all energy carriers, there is no direct correlation to the electricity prices.

As a complementary evaluation to the price analysis in [Pub3], Table 3-4 also presents the mean European daily standard deviation of the electricity prices in the three scenarios. It is calculated by the mean daily standard deviation of the electricity prices per country, which is then used to determine the consumption-weighted European mean. The impact of bidirectional EVs on the electricity price characteristics is evident. In the *BCM* scenario, the electricity price is significantly smoother, resulting in a daily standard deviation reduced by 6-11 €/MWh compared to the *Ref* scenario. In the *Sen2* scenario, the daily standard deviation of electricity prices no more changes significantly compared to the *BCM* scenario. In Section 2.3.2, electricity prices for the German market area from the *BCM* scenario are used as simulated future electricity prices to estimate revenue potentials of specific users of bidirectional EVs. For Germany in the *BCM* scenario, a slightly higher price volatility with a mean daily standard deviation of 15.8 €/MWh in 2025, 18 €/MWh in 2030, 17.6 €/MWh in 2035, and 16.8 €/MWh in 2040 is observed.

Table 3-4: Total energy system costs and mean European electricity price for the years 2025 to 2050 for scenarios Ref, BCM and Sen2

Year	Overall energy system costs in billion €/a			Mean European electricity price in €/MWh			Mean European daily standard deviation of electricity prices in €/MWh		
	Ref	BCM	Sen2	Ref	BCM	Sen2	Ref	BCM	Sen2
2025	432.4	431.7	-	44.6	42.6	-	21.2	15.3	-
2030	414.6	412.4	411.4	42.5	39.4	39.7	23.4	15.4	15
2035	354.9	350.1	-	43.1	39.1	-	26.8	16	-
2040	332.2	325.7	324.1	44.6	39.4	39.3	25.2	15.3	15.3
2045	323.5	314.4	-	44.4	41.1	-	25.5	17.7	-
2050	353.1	345.0	342.0	41.6	38.8	38.9	22.4	15.3	15.9

3.4.3 Regional Residual Load Characteristics

A much-discussed topic in the scientific community is the question of to what extent bidirectional EVs bring an additional load to the power grids, i.e., transmission grids and distribution grids [71], [57]. For the grid dimensioning of distribution grids in low voltage and medium voltage [58] as well as transmission grids in high and ultra-high voltage [72], both the peak load at low generation and the peak generation at low load can be relevant. Since the future energy system will be strongly characterized by variable renewable energies on the generation side, the maximum and minimum regional residual load, meaning the regional load minus the regional feed-in from renewable energies, is a meaningful indicator for the load of electricity grids in addition to detailed grid simulations. An increase of the maximum residual load peaks (peak load) or a decrease of the minimum negative residual loads (generation surpluses) thus signals a required higher grid utilization. This is only to be taken as an indicator, as the actual grid situation must be analyzed in each individual case. Nonetheless, smoothing the regional residual load and thus reducing load and generation peaks represents a reduction in the maximum loads and generation for which a grid must be designed. For this reason, this section supplements the evaluations in [Pub3] by an analysis of the impact of bidirectional EVs on regional residual load.

Figure 3-8 takes up the question of whether the residual load is smoothed by bidirectional EVs and first analyzes the Europe-wide residual load for the modeled years 2030, 2040, and 2050 for both scenarios *Ref* and *BCM* and the scenario *BCM without EVs*. The *BCM* scenario adds charging power and subtracts discharging power of bidirectional EVs to the residual load, which are excluded in the *BCM without EVs* scenario. The residual load is calculated by the static electricity load of the final energy sectors subtracted by the variable renewable energies generation. The European residual load is shown as an annual duration curve to better analyze the scenarios.

Over the years 2030 to 2050, the maximum residual load increases significantly, and the minimum residual load decreases considerably. On the one hand, this is due to increasing electrification in the final energy sectors, which increases the electrical load. On the other hand, variable renewable energies are increasingly being integrated on the generation side, which in some cases cause large generation surpluses due to high simultaneities. When comparing the *Ref* scenario with *BCM without EVs*, it becomes apparent that significantly higher generation surpluses occur in the *BCM without EVs* scenario. The bidirectional EVs bring more flexibility into the system, which means that in the *BCM without EVs* scenario, more PV power with a high feed-in simultaneity is integrated, so that the peaks of the generation surpluses increase. This effect is not only compensated by bidirectional EVs, but the residual load is also even smoother in the *BCM* scenario than in the *Ref* scenario. Cost-optimally operated bidirectional EVs charge at favorable electricity prices (often during generation surpluses) and discharge at high electricity prices (often during peak loads) and thus have a smoothing effect on the residual load.

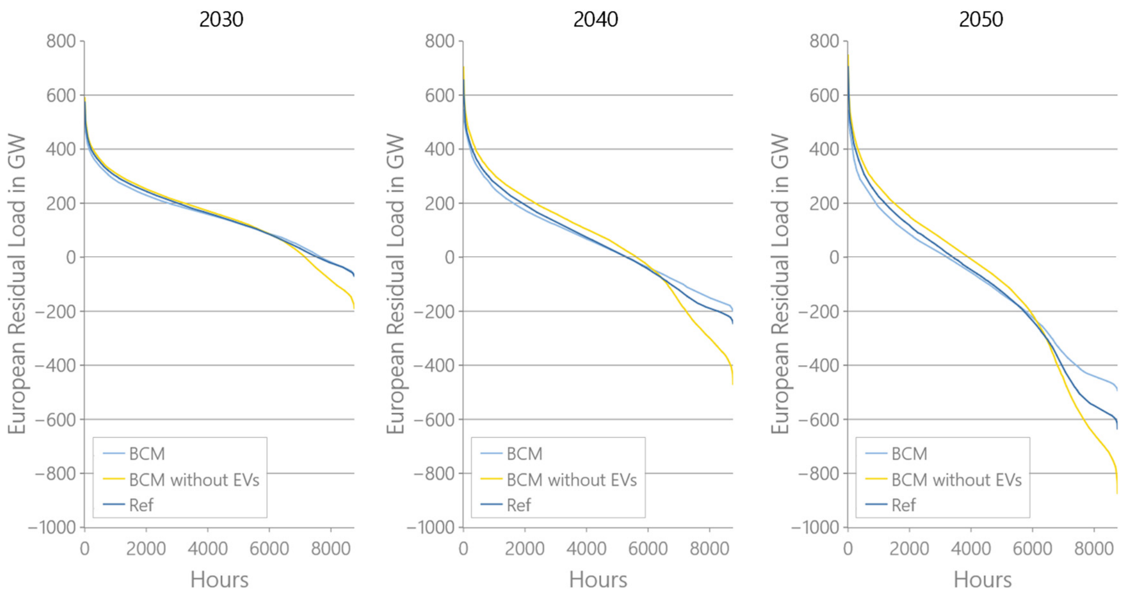


Figure 3-8: Annual hourly duration curves of European residual load for the years 2030, 2040 and 2050 for both scenarios Ref and BCM and the scenario BCM without bidirectional EVs

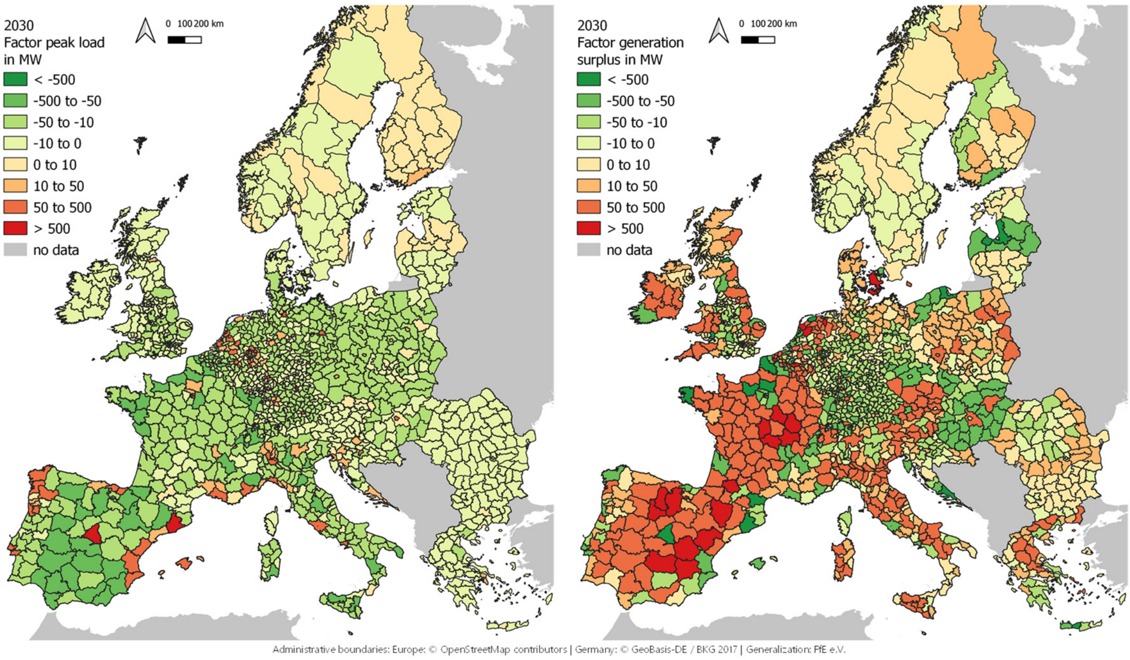
At the European level, the smoothing of the residual load is a fundamentally positive effect, as less flexibility is needed to keep load and generation in balance. However, analyzing the European residual load does not allow any conclusions on grid loads. To show the change of the regional residual load, all European market areas are regionalized into NUTS 3 (Nomenclature of territorial units for statistics) regions [59]. NUTS regions are a classification of territorial units for statistics. The regionalization of the final energy demand as well as the PV and wind power plants is based on research project eXtremOS. The regionalization of bidirectional EVs is consistently based on the distribution of passenger cars in the final energy sector of transport. Detailed information on the regionalization can be found in [60] and [3]. This regionalization into NUTS 3 regions divides Germany, for example, into about 400 regions. As of 2022, there are 569 substations in Germany for transforming electricity from the transmission grid level (380/220 kV) to the high voltage level (110 kV) based on data from 50Hertz (62 substations [73]), Amprion (234 substations [74]), TenneT (189 substations [75]), and TransnetBW (84 substations [76]). This means that a NUTS 3 region contains on average 1 to 1.5 substations. The analysis of the regional residual load under the implemented regionalization thus only allows for grid dimensioning indications on the transmission grid and partly on the high-voltage grid level since the high voltage grid is used for distribution as well as transmission [77]. Therefore, an indication for an evaluation of dimensioning lower voltage levels is not possible.

For each NUTS 3 region, the annual hourly residual load duration curve is created for both scenarios *Ref* and *BCM*. For an analysis of the change in peak load, the 100 hours with the maximum residual load of a region are extracted and the average of these values is calculated. In the same way, for an evaluation of the generation surpluses based on the 100 hours with the lowest residual load, the average value is calculated. Since the residual load can be negative or positive, but a grid load exists in both directions, the absolute value is taken in each case. To compare the peak load of both *BCM* and *Ref* scenarios, Equation (3-9) calculates a factor $factor_{peak\_load}$ by taking the average of the absolute maximum residual loads in the *BCM* scenario $\overline{|resload_{BCM,max100h}|}$ minus the absolute maximum residual loads in the *Ref* scenario $\overline{|resload_{Ref,max100h}|}$. In the same way, in Equation (3-10), a factor $factor_{gen\_surplus}$ is formed to evaluate the change in generation surpluses. It is important to note that there are also regions that have only positive residual loads throughout the year, e.g., urban regions. Consequently, these regions have no generation surpluses. In these cases, the minimum residual load refers to the minimum grid loads. However, due to the difference in the absolute values of the residual loads of the two scenarios, positive and negative minimum residual loads can also be compared. Consequently, if the factors are negative, it implies a reduction in grid loads due to peak loads or generation surpluses in the *BCM* scenario compared to the *Ref* scenario. If the factors are positive, the loads are lower in the *Ref* scenario.

$$\overline{|resload_{BCM,max100h}|} - \overline{|resload_{Ref,max100h}|} = factor_{peak\_load} \tag{3-9}$$

$$\overline{|resload_{BCM,min100h}|} - \overline{|resload_{Ref,min100h}|} = factor_{gen\_surplus} \tag{3-10}$$

The factors per NUTS 3 region are visualized in Figure 3-9. The left map plots the change in peak load per NUTS 3 region. Green tones indicate a decrease and red tones an increase of the peak load in the *BCM* scenario. It can be observed that the regional peak load in many regions in Europe is reduced by the integration of bidirectional EVs. However, especially in urban regions such as Madrid, Paris or Berlin, the peak load increases. This is because a high number of bidirectional EVs are integrated there due to the high population, which overlays the load characteristics of the regions in times of high charging power. The right map of Figure 3-9 shows the change in generation surpluses. Here, a much more heterogeneous picture emerges, which in some regions is exactly opposite to the evaluation of the peak loads. For urban regions, this can be explained by the fact that the residual load is often positive throughout the year. Bidirectional EVs overlay this load characteristic and cause a reduction of the absolute residual load in times with high discharge powers. In many other regions, e.g., in Spain and France, higher negative residual loads and thus generation surpluses occur. These are often regions where significantly more PV is integrated in the *BCM* scenario compared to the *Ref* Scenario, so that PV peak generation increases. In contrast, relatively few bidirectional EVs are integrated in these often-rural regions, so that a compensation of the higher PV generation by charging the bidirectional EVs cannot take place. In other regions, however, such as southern Germany, the highest generation surpluses correlate with high charging powers of bidirectional EVs, reducing generation surpluses. In Germany, it should also be noted that the PV expansion for the *Ref* and *BCM* scenarios in 2030 was fixed based on the targets of the German government.



(a) (b)

Figure 3-9: Factors indicating change in peak load (a) and generation surpluses (b) per NUTS 3 region in Europe in 2030 in scenario BCM compared to Ref

Since both generation peaks and load peaks are relevant for the design of electricity grids, the two factors are combined in Equation (3-11). The factor $factor_{grid\_dim}$ is calculated by the maximum of the absolute maximum and minimum residual loads in the *BCM* scenario minus the maximum of the absolute maximum and minimum residual loads in the *Ref* scenario. Consequently, the factor reflects the load on the distribution grids, regardless of whether they are generation or load peaks.

$$\begin{aligned} factor_{grid\_dim} = {} & \max\left(\overline{\left|resload_{BCM,max100h}\right|}, \overline{\left|resload_{BCM,min100h}\right|}\right) \\ & - \max\left(\overline{\left|resload_{Ref,max100h}\right|}, \overline{\left|resload_{Ref,min100h}\right|}\right) \end{aligned} \tag{3-11}$$

Figure 3-10 shows these factors indicating a change in grid dimensioning per NUTS 3 region in Europe in 2030 and 2050. When comparing the changes in generation surpluses and peak loads with the grid dimensioning factor for the year 2030, it is noticeable that in Southern Europe the change in generation surpluses accounts for the grid dimensioning in most regions. In Central and Northern Europe, the picture is heterogeneous with regions showing a reduced grid dimensioning factor and regions with higher grid loads. Overall, 770 regions have a negative grid dimensioning factor, and 610 regions have a positive grid dimensioning factor in 2030. It can be concluded that bidirectional EVs basically have a very different impact on regional residual load maxima and minima depending on regional conditions. There is no clear direction on whether integrating bidirectional EVs will increase or decrease the grid load in transmission and high voltage grids.

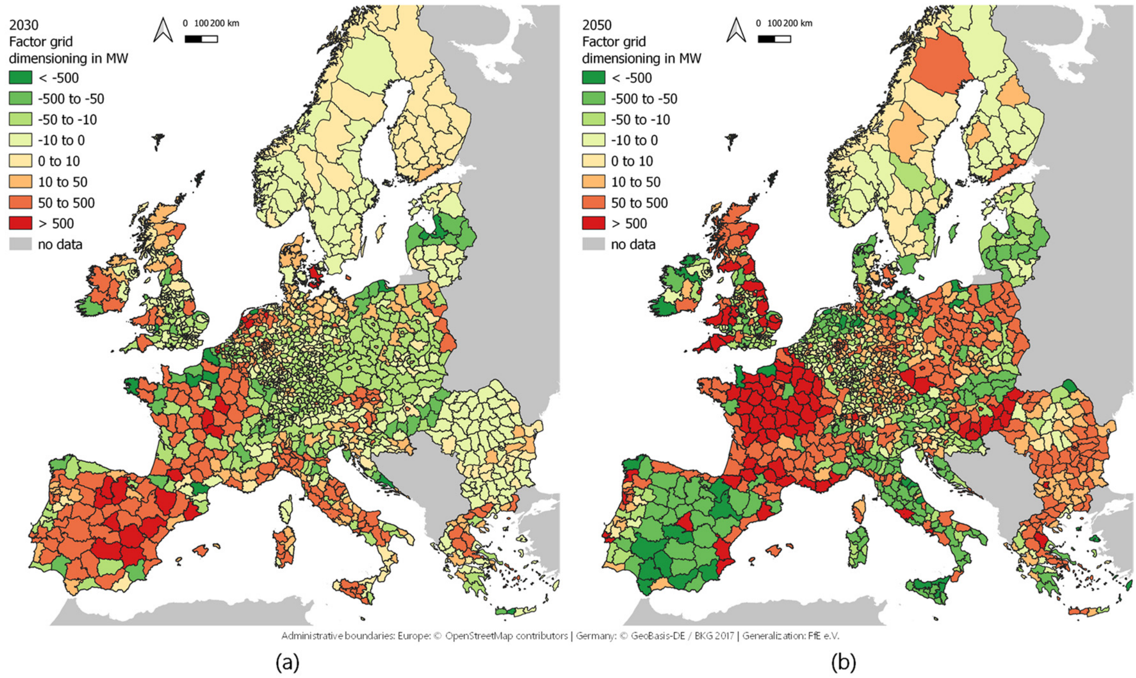


Figure 3-10: Factors indicating change in grid dimensioning per NUTS 3 region in Europe in 2030 (a) and 2050 (b) in scenario BCM compared to Ref

The comparison of the grid dimensioning factor for the years 2030 and 2050 also shows interesting changes. In most regions in Southern Europe, the grid dimensioning factor changes from positive values to negative values. This means that the integration of bidirectional EVs has a relieving effect on grid utilization there. This is due to the PV expansion there, which is at the maximum potential limit in both scenarios *BCM* and *Ref*. Since no additional PV capacity is added in the *BCM* scenario compared to the *Ref* scenario, the bidirectional EVs have a mostly positive smoothing effect on the residual load. This is different in Poland, the Czech Republic and France, for example. In France, the PV capacity in the *BCM* scenario in 2050 is 420 GW compared to 290 GW in the *Ref* scenario. The PV peaks are not completely smoothed by the bidirectional EVs, so that in most regions the generation surpluses are significantly higher regionally and thus the grid load increases. In Germany and Benelux, the level of grid dimensioning factors varies a lot. There, very high installed capacities of wind offshore and wind onshore have been integrated by 2050, which also leads to generation surpluses in the market areas in many hours. Since this stimulates the charging of bidirectional EVs in exactly these hours, the bidirectional EVs in northern Germany and Benelux often have a grid-relieving effect. In other regions, where PV and load are more relevant to grid dimensioning, the impact of bidirectional EVs is more heterogeneous. Overall, 590 regions have a negative grid dimensioning factor, and 780 regions have a positive grid dimensioning factor in 2050. Consequently, even in 2050, no clear statement can be made as to whether bidirectional EVs will reduce or increase grid loads when integrated into electricity markets. In individual cases, the regional load and generation conditions must be analyzed for each region or grid area.

3.4.4 Congestion Management

After the investigations of regional residual load described in the previous section indicate that bidirectional EVs have partly positive and partly negative impacts on the electricity grids, the extent to which they can provide congestion management in the transmission grid is now investigated in more detail. Since the grid simulations with optimization of congestion management as described in Section 3.1.2 are very complex, the study area is restricted to the year 2030. The studies presented here are based on [Pub4], which also describes the scenario framework of the European transmission grid in more detail. A comparison of two transmission grid simulations is performed:

- **Ref grid run:** Transmission grid run with optimization of congestion management without bidirectional EVs
- **BCM grid run:** Transmission grid run with optimization of congestion management with bidirectional EVs

Both transmission grid optimizations are based on the market run of the *BCM* scenario.

Congestion management volumes in both runs increase sharply from today's volumes. In the *Ref grid run*, the volumes of positive congestion management in Europe for the year 2030 are 600 TWh compared to a total electricity production of 5,000 TWh. The German positive congestion management volume of 160 TWh in the *Ref grid run* indicates high amounts of congestion management that do not fit to the volumes simulated in the German transmission grid expansion plan of around 7 TWh in 2035 in the base scenario. Reasons for this are discussed in [Pub4]. They include the lack of modeling of overhead line monitoring, uncertain regionalization of added assets, and simplified modeling of a linearized load flow. Furthermore, the endogenously cost-optimized scenario as well as the parameterization of the assets in the energy system is also not the same as the scenario used in grid expansion plans.

Nevertheless, by comparing the *BCM grid run* and *Ref grid run*, conclusions can be drawn about the added value of bidirectional EVs in congestion management. The use of bidirectional EVs in congestion management reduces 26 TWh positive redispatch of thermal power plants, 9 TWh negative redispatch of thermal power plants and 23 TWh curtailment of renewable energies. This results in 17 TWh less electricity generated by thermal power plants, saving 12 million tons of CO_2. Compared to total modeled emissions in the energy sector in 2030 of just under 500 million tons of CO_2, this is a 2.5% reduction in emissions.

Even though the absolute reduced numbers of congestion management by power plants and renewable energies are favored by the high total volumes of congestion management, the positive effect of bidirectional EVs is evident. Figure 3-11 shows the regional distribution of positive and negative congestion management per technology per transmission grid node. The decentralized distribution of bidirectional EVs proves to be an advantage.

Bidirectional EVs near nodes with high curtailments of renewable energies (for example in northern Germany) can reduce curtailments through negative congestion management. Positive congestion management then re-establishes their initial schedule within the time slice. In southern Germany, on the other hand, positive congestion management is often used first, thus displacing the use of thermal power plants. Here, the schedule must then be re-established at other times through negative congestion management.

In [Pub4], the regional distribution of congestion management per technology for the *Ref grid run* as well as the mean line usage of both runs are also shown and analyzed. Overall, many transmission grid lines have a very high utilization. However, especially in the case of wind offshore plants, the curtailment often takes place immediately after the grid connection point.

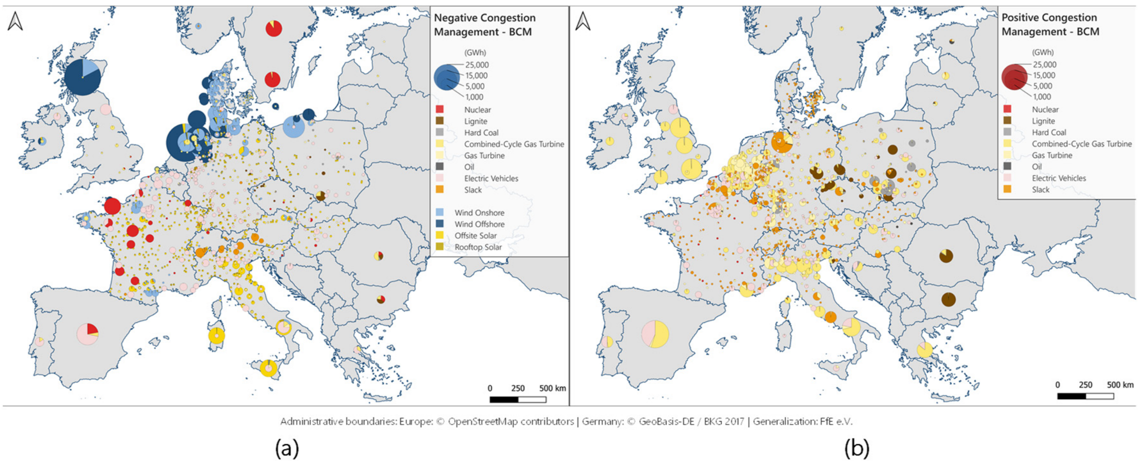


Figure 3-11: Negative (a) and positive (b) congestion management per grid node split up in different technologies for the BCM grid run

Overall, in addition to the added values of bidirectional EVs shown in the previous sections regarding the design of the future energy system, a potential added value for the provision of congestion management can also be shown. Ultimately, however, more in-depth analyses with a parameterization of the transmission grid that is suitable for the underlying market scenario are required.

4 Combining the User and the Energy System Perspective on Bidirectionally Chargeable Electric Vehicles

In a final step, the user and energy system views on bidirectional EVs are brought together. Section 4.1 compares the modeling approaches of bidirectional EVs developed in this dissertation. Section 4.2 discusses a common added value of bidirectional EVs from the user and the energy system perspective.

4.1 Comparison of Modeling Approaches Depending on Use Case and Perspective

As shown in the previous chapters, the modeling approaches of bidirectional EVs differ depending on the focus of investigation. For this purpose, Table 4-1 provides a clear comparison of the modeling approaches of bidirectional EVs presented in this dissertation.

All four presented types of modeling bidirectional EVs formulate an optimization problem. Depending on the perspective, the objective function focuses on minimizing the electricity costs of a user or the total systemic costs for energy provision or congestion management. For the user perspective, minimizing electricity costs could also be reformulated as maximizing revenues. The objective function values can become negative values and thus mean real revenues.

The basic modeling does not differ in all approaches. A bidirectional EV is modeled as a storage with limited availability and electrical consumption, which has typical storage constraints such as energy conservation, and EV user-specific constraints such as maintaining a minimum safety SoC and a departure SoC.

In addition, all modeling approaches presented have special features that are only relevant in the focus of investigation under consideration and thus lead to advantages and disadvantages of the respective approach:

- For the modeling of PV self-consumption optimization, variable charge and discharge efficiencies are modeled for a wide range of household types, since power flows in the household are small and losses would otherwise be greatly underestimated. The modeling approach leads to more realistic results but adds a higher complexity to the optimization problem, since it is no longer linear but mixed-integer linear.
- For the modeling of arbitrage trading from the user perspective, a rolling-horizon optimization with consideration of real trading hours is implemented to allow consecutive spot market trading in day-ahead and intraday markets. This consecutive market trading results in higher revenue potentials than single market trading and thus shows the potential revenues of the use case arbitrage trading.

The complexity of the optimization problem can be kept small by rolling optimization. However, no feedback effects on electricity prices are modeled, so that e.g., low liquidity of the intraday market indicates less robust revenue potentials.

- For the modeling of arbitrage trading from the energy system perspective, the aggregation of EV profiles and thus a non-discrete modeling of the constraints enables investigations on cost-optimal integration of bidirectional EVs with only a slight increase in the complexity of the optimization problem. The impact of the bidirectional EVs integrated into the electricity market on the day-ahead market prices result endogenously from the optimized operation of the EVs. The cost-optimal future penetration rates of bidirectional EVs can be used for policy recommendations.
- For the modeling of the provision of congestion management via bidirectional EVs, a rolling parallelized grid optimization run with simplified time-coupling of storage is performed based on a market run. In both runs, bidirectional EVs are modeled by aggregated EV profiles. Although the optimization problem of the transmission grid calculation is very complex, it is computable for a time slice length of one week by modeling of one aggregated instance per transmission grid node. This allows realistic potentials of congestion management to be determined.

Table 4-1 further shows the publications and sections associated with the modeling approaches in this cumulative dissertation. Overall, the various approaches to modeling bidirectional EVs have fundamental similarities, but also necessary differences. The specifics per use case and perspective can be transferred well to other use cases of bidirectional charging. Consequently, other modelers can benefit from the overview of the different approaches to modeling bidirectional EVs to adapt their modeling according to the use cases and perspective.

Table 4-1: Comparison of modeling approaches of bidirectional EVs presented in this dissertation

Use Case	**Vehicle-to-Home: PV self-consumption optimization**	**Vehicle-to-Grid: Arbitrage trading**	**Vehicle-to-Grid: Arbitrage trading**	**Vehicle-to-Grid: Provision of congestion management**
Perspective	**User**	**User**	**Energy system**	**Energy system**
Objective function	Minimization of household electricity costs	Minimization of EV's electricity costs	Minimization of total energy system costs	Minimization of congestion management costs
Base modeling approach of bidirectional EVs	• Modeling of bidirectional EVs as a storage with energy consumption and limited availability • Time-coupling via equation for storage energy conservation • Modeling of minimum safety SoC and minimum SoC at departure for realistic user behavior • Basic constraints, like maximum charging/discharging power and maximum absolute SoC • EV profiles of EV consumption and EV location			
Modeling specifics	• Modeling of varying charging and discharging efficiencies • Modeling of various household configurations	• Modeling of consecutive spot market trading • Rolling optimization with modeling of real trading hours	• Modeling of cost-optimized integration of bidirectional EVs • Aggregation of discrete EV profiles	• Aggregation of discrete EV profiles • Rolling grid optimization with simplified time-coupling of storage
Advantages of modeling specifics	• Realistic modeling of EV and EVSE losses leads to realistic estimation of revenue potentials	• Revenue optimization by multiple market trading • Limited complexity via rolling optimization	• Only slight increase of model complexity • Cost-optimal penetration rates of bidirectional EVs for policy recommendations	• Optimization problem still computable despite high complexity • Determination of realistic potentials of congestion management
Disadvantages of modeling specifics	• Increased complexity due to variable charging and discharging efficiencies	• No feedback of arbitrage trading on electricity prices modeled	• No exact representation of EV constraints • Limited on day-ahead market	• No exact representation of EV constraints • Highly complex optimization problem
Sections in Dissertation	2.1.1 2.1.3	2.1.2 2.1.3	3.1.1	3.1.2
Publication	[Pub1]	[Pub2]	[Pub3]	[Pub4]

4.2 Possibility of a Common Added Value

After multiple added values of bidirectional charging have been shown in this dissertation, the question arises as to what extent the added values for the user and the energy system can be combined.

The use case V2G arbitrage trading has been analyzed from a user and energy system perspective and shows promising added values for both perspectives. The user can generate significant revenues by participating in the day-ahead and intraday markets. These revenue potentials are above 1000 €/EV/a, but strongly depend on the EV and EVSE configuration, the user behavior and especially on the regulatory framework with regard to taxes, levies and grid charges to be paid. The energy system benefits from the integration of bidirectional EVs into the electricity markets on many levels. On the one hand, the flexibility of bidirectional EVs increases the market value of PV energy, allowing it to be better integrated. On the other hand, less capacity of thermal power plants and other storage technologies is needed. This ultimately decreases the total costs of the energy system even when considering the additional investment costs of bidirectional EVs. The energy system thus becomes more efficient. The significant systemic benefit also generates the added value for the user of contributing to a cost-optimal energy system based on renewable energies. This is only an indirect, qualitative added value, but it can be relevant for the acceptance of the use case V2G arbitrage trading.

The added value from both the energy system and the user perspective is not directly evident for the V2H PV self-consumption optimization use case. The economic added value for the user was shown in Sections 2.2.1 and 2.3.2. Further, Section 2.2.1 also points out that the self-consumption of renewable PV generation and thus the household self-sufficiency increases. The profitability of the use case gives users the incentive to invest in a bidirectional EV and EVSE. The added value from the system perspective is open to question since PV self-consumption optimization is a local optimization without considering the effects on the German or European energy system. Modeling of local prosumer cells in the energy system performing PV self-consumption optimization by bidirectional EVs poses another research need here. Nevertheless, analysis of renewable energy curtailment can provide conclusions about a systemic effect of PV self-consumption optimization. In total, by the market integration of bidirectional EVs in the energy system in 2030, the relative PV curtailment in Europe reduces by 2 to 3 percentage points. Since PV self-consumption optimization also incentivizes charging of EVs at daytime, on the one hand, a reduction in PV curtailment and thus a positive systemic effect can be expected in summer. In winter, on the contrary, when there is an increased curtailment of wind energy instead of PV energy, PV self-consumption optimization may even have a negative effect.

The provision of congestion management primarily has a systemic benefit: thermal power plants can be operated less and renewable energies less curtailed. The additional revenues for the user through participation in congestion management are very difficult to quantify under the current design in Germany, as there is a cost-based remuneration [42]. The costs of bidirectional EVs to participate in congestion management consist of battery aging costs, aggregator costs, and other cost components, while the user's behavior may be restricted.

In addition, cost-based remuneration does not result in any real added value for the user. The introduction of market-based congestion management, which is being discussed in various ways [61], would open up new revenue opportunities for the use case. Without such market-based revenue opportunities, it is very unlikely that EV users would voluntarily participate in congestion management.

Table 4-2 ultimately summarizes these pointed out added values of bidirectional charging from the user and energy system perspectives. Overall, V2G arbitrage trading in particular can generate a wide range of systemic and user-related added value.

Table 4-2: Main added values for the user and the energy system by considered use cases in this dissertation

Use Case	Added Value User		Added Value Energy System	
V2H PV self-consumption optimization	✓	• Revenues • Increase in household self-sufficiency • Increase in self-consumption of renewable PV generation	(?)	• Indirect positive effects by decreasing PV curtailment in summer possible • Unknown effect on renewable energy curtailment in winter
V2G arbitrage trading	✓	• Revenues • Contribution to cost-optimal energy system	✓	• Reduced capacities of power plants and battery storages • Reduced energy system costs • Improved market integration of PV
V2G congestion management provision	(×)	• In Germany only cost-based remuneration • Contribution to cost-optimal ancillary service provision	✓	• Less electricity generation of power plants needed • Less curtailment of renewable energies

The combination of different use cases of bidirectional EVs can also add combined value from the user and system perspective. The possibility of combining V2H PV self-consumption optimization and V2G arbitrage trading has already been discussed in [Pub2] and in Section 2.2.3. PV self-consumption optimization exhibits strong seasonality. In the summer months from April to September, the user can expect significantly higher revenue potentials than in the winter months. Here, a simple seasonal switch of the use cases suggests operating V2G arbitrage trading in the winter months and V2H PV self-consumption optimization in the summer months. In the long term, a highly dynamic change of use cases every minute or hour will also be of interest in order to optimize the revenue potentials for the user and the added values for the energy system. In [Pub2], however, the high requirements for metering data for use case switching are already discussed.

In Germany, the 'Law on Immediate Measures for Accelerated Expansion of Renewable Energies and Further Measures in the Electricity Sector' was passed in the summer of 2022 [62]. Here, a balancing of the charging and discharging via a charging point is specified to enable V2G. The volumes of electricity drawn from the grid and simultaneously charged by an EV via the charging point are considered as consumption at the charging point. The volumes of electricity discharged by EVs via the charging point and simultaneously fed into the grid are regarded as generation at the charging point. This generation and consumption from the point of view of the charging point are netted out on a calendar year basis. The levies and surcharges are reduced on the balanced charged electricity. Consequently, measured values must be collected both at the grid connection point and at the charging point. This robust approach of annual netting the input and output volumes at the charging point would mean that even the simultaneous implementation of V2H and V2G would be possible. However, this would still allow the potential misuse addressed in [Pub2]. During the summer months, a user could initially charge PV energy into the EV and later discharge this electricity from the EV into the grid. In the winter months, the user could charge electricity from the grid into the EV. Netting would exempt this charged energy from levies and surcharges. This could result in higher revenues than PV energy fed directly into the grid during the summer months. This example shows that there are still open regulatory questions for a V2H and V2G use case combination regarding the interaction between the household with its various components and the bidirectional EV.

Since provision of congestion management for the transmission grid is a short-term application that takes place after day-ahead market and intraday auction trading, the use cases arbitrage trading and provision of congestion management could be combined very well. However, compared to continuous intraday trading, which is also short-term, a competitive situation arises that can prevent simultaneous participation in both use cases. This must also be considered when combining V2H PV self-consumption optimization and V2G congestion management provision. A change in the operation of bidirectional EVs through the provision of congestion management directly affects the PV self-consumption of a household and thus the associated revenues.

5 Conclusion, Discussion and Outlook

In this cumulative dissertation, different approaches for modeling bidirectional EVs in different use cases and perspectives were developed and their advantages and disadvantages were discussed. Based on this, the added values for the user and the energy system were shown. This chapter is divided into two parts: Section 5.1 answers the research questions raised in the introduction. Section 5.2 then reflects on the modeling and results, provides concluding remarks, and identifies further research needs.

5.1 Answers to Research Questions

The following are concise answers to the research questions of this dissertation. Research questions 1 to 3 refer to the user perspective, whereas research questions 4 to 6 address the energy system perspective. Research question 7 deals with the combined perspective of the user and the energy system.

1. **What modeling specifications are required for the evaluation of revenue potentials of vehicle-to-home and vehicle-to-grid use cases?**

   The modeling of the analyzed V2H and V2G use cases shows fundamental similarities but also significant differences in order to realistically evaluate the revenue potentials. All developed modeling approaches are based on a modeling of the bidirectional EV as a storage element with electrical consumption and limited availability. By comparing the objective function values with the objective function values of an unmanaged charging EV, the revenues for a user can be quantified.

   For V2H PV self-consumption optimization, the condition of low-power load flows results in the requirement to set up the optimization problem as a MILP with variable charging and discharging efficiencies of the bidirectional EV. This leads to higher complexity but much more realistic revenues, which are otherwise overestimated by over 30%. Furthermore, the household is modeled with a wide variety of components, which leads to a large number of sensitivities. The modeling of V2G arbitrage trading is limited to the bidirectional EV and EVSE and their interaction with the electricity grid. Here, rolling optimization enables modeling of consecutive trading in the day-ahead and intraday markets with respect to real trading times.

2. **What are the revenue potentials and their most important influencing factors for vehicle-to-home and vehicle-to-grid use cases?**

   The revenue potentials of V2H and V2G use cases are very sensitive depending on a variety of influencing factors. For V2H PV self-consumption optimization, typical revenues for a bidirectional EV compared to an unmanaged charging EV are around 300 €/a for a medium household. Two thirds of this revenue can already be generated by smart charging. The most important influencing factor is the difference between the household electricity price and the PV feed-in tariff. The higher the spread, the higher the revenue potential. In a scenario with a parameterization for maximum revenues, the revenues go up to 1,300 €/a. Other important influencing factors on revenues include PV system size and electrical household demand characteristic and level.

The revenues from V2G arbitrage trading are highly dependent on the levies and charges on charged, temporarily stored electricity. Typical revenue potentials with today's regulation in Germany and participation in the day-ahead market are around 200 €/year for a bidirectional EV compared to an unmanaged charging EV. However, increased price volatilities as a consequence of the energy crisis [63], a consecutive marketing on the day-ahead and intraday market, as well as a change of the EV and EVSE characteristics can lead to much higher revenues.

3. **What is the economic profitability of vehicle-to-home and vehicle-to-grid use cases considering the additional investment costs?**

   The additional investment costs for bidirectional charging will see a strong cost degression in the coming years. Only then, V2H and V2G use cases can become profitable from the user's perspective. As with other new technologies, government subsidies may be necessary to support the ramp-up of the technology.

   V2H PV self-consumption optimization turns out to be the more robust use case, which in a medium base scenario with an investment in 2025 has already amortized after seven years. V2G arbitrage trading achieves payback only after 12 years for an investment in 2025. Both use cases become more profitable in later years, as costs fall and revenues tend to rise, so that later investments pay off more quickly. With an investment in 2030, V2H amortizes after 5 years with a net present value after 15 years of 2,800 €, whereas V2G amortizes after 7 years with a net present value after 15 years of 1,650 €.

4. **How do modeling specifications of bidirectional EVs need to be adapted to evaluate the European energy system perspective compared to modeling discrete EVs?**

   Complex European energy systems lead to the requirement of strongly clustering or aggregating bidirectional EVs rather than modeling them via discrete instances. The aggregation of all bidirectional EVs per country leads to a good representation of the vehicle fleet per country and its feedback on the energy system, while keeping complexity as low as possible. Here, the European market simulation with the objective function of minimizing the total costs leads to a similar operation of the bidirectional EVs, as in the V2G day-ahead market arbitrage trading use case from the user perspective.

   Congestion management modeling in the European transmission grid requires even more the aggregation of all bidirectional EVs per transmission grid node. The combination of the time-coupled constraints of bidirectional EVs and the complex load flow calculations in the transmission grid strongly increases the complexity of the optimization problem compared to the European market simulation. A partition of the hourly annual calculation into weekly time slices leads to a sufficiently large flexibility of the bidirectional EVs while ensuring computability.

5. **How high is the optimal share of bidirectional EVs in the total EVs from a system cost perspective?**

   Modeling the future energy system considering the additional investment costs of bidirectional EVs compared to unmanaged charging EVs results in system-cost-optimal penetration rates. The number of bidirectional EVs increases from just under 20 million EVs in 2030 to over 60 million EVs in 2050 in a baseline scenario. This corresponds to a share of bidirectional EVs in total EVs of 25% in 2030 and of 30% in 2050.

   Provided that the additional investment costs of smart EVs compared to unmanaged charging EVs fall very sharply, smart EVs will also be integrated into the energy system in high numbers. However, this additional flexibility in the energy system has only a minor impact on the number of bidirectional EVs. Through these sensitivity considerations, it was found that bidirectional EVs are very robustly integrated into the cost-optimal future energy system.

6. **What is the added value of bidirectional EVs integrated in the electricity markets and in congestion management in the transmission grid from an energy system perspective?**

   The integration of bidirectional EVs into the future energy system creates multiple added values:

   - The energy system requires less capacities of thermal power plants (especially gas-fired and hydrogen-fired power plants) and other storage technologies. Bidirectional EVs provide a contribution to cover the electrical peak loads in the system.
   - Bidirectional EVs often act as daytime storage, charging during the day and discharging at night. This increases the market value of PV and promotes PV integration. Since PV energy is more widely accepted and cheaper than wind energy in many countries, this encourages renewable energy expansion.
   - The previous points result in significantly lower European energy system costs, by up to €9 billion/a.
   - The provision of congestion management in the European transmission grid by bidirectional EVs leads to reduced use of thermal power plants and reduced curtailment of renewable energies. As a result, less CO_2 is emitted.

7. **How can use cases of bidirectional EVs create combined added value from the user and the energy system perspective?**

   Use cases of bidirectional charging can generate simultaneous added value for the user and the energy system. By investigating the use case arbitrage trading from the user's and the system's point of view, this dissertation was able to show that the added value here is given for the user and the energy system in the future. PV self-consumption optimization primarily gives monetary and environmental added value to the user. The impact of this use case on the energy system can be positive and negative. The provision of congestion management in the transmission grid, on the contrary, currently generates hardly any added value for the user in Germany, as remuneration is cost-based. Here, the focus is on the systemic added value of reducing costs and CO_2 emissions.

   Further, the combination of use cases can generate a combined added value for the user and the energy system. Especially V2H PV self-consumption optimization is very suitable for a combination with V2G use cases since it generates the revenues mainly in summer times and can be switched to other use cases in winter.

5.2 Critical Reflection, Concluding Comments and Further Research

The technology of bidirectional charging of EVs is still a new technology that is yet to experience its market take-off. Currently in 2022, for example, there is still only one bidirectional EVSE available on the German market, which has very high investment costs [78]. Few automotive manufacturers currently offer bidirectional EVs, even though many have clearly positioned themselves positively toward the technology [44]. In addition to the technological side of EVSE and EV manufacturers, the regulatory side also plays an important role. Although regulation in Germany has taken important steps, many regulatory issues are still open and will need to be addressed by policymakers in the coming years. Consequently, bidirectional charging technology is still in its early stages. The analyses of this work thus offer an important piece to support the ramp-up of the technology and thus to create added value for the user and system.

Over a time period of four years, this dissertation has been created. During this period, many energy-economic changes and regulatory adjustments have occurred that have been directly referred to or referenced in this dissertation. These changes and adjustments in Germany have a direct impact on bidirectional charging of EVs:

- The first to be mentioned is the **energy crisis**, which has caused fuel and electricity prices to rise sharply worldwide. Since the end of 2021, fuel prices and subsequently also electricity prices have risen very sharply in the wake of Covid-19. This effect was further intensified by the Ukraine invasion in February 2022. The energy crisis has multiple implications for bidirectional EVs. In addition to potentially higher investment costs for users for bidirectional EVs and EVSEs due to increases in a wide range of commodity prices, there may also be multiple impacts on the use cases of bidirectional charging.

The high electricity price level causes a sharp increase in household electricity prices. This effect was directly addressed in Section 2.2.1, highlighting that this has a very positive impact on the revenue potentials of the PV self-consumption optimization use case. In addition to the electricity price level, the volatility of electricity prices has also risen very sharply. This was also directly addressed in Section 2.2.2. The increase in electricity price volatility results in significantly higher revenue potentials for the arbitrage trading use case. The current energy crisis has thus significantly increased the attractiveness of these two use cases.

- As a result of the energy crisis, the medium-term **climate targets** for the year 2030 were tightened in Europe and Germany. For example, Germany has set targets of 215 GW of PV energy and 115 GW of onshore wind energy for the addition of variable renewable energies [62]. As a result, the systemic need for flexibilities such as bidirectional EVs is increasing as electricity generation becomes more fluctuating. Furthermore, this transformation of the energy system leads to further increased electricity price volatility, which is also attractive for the use case arbitrage trading from a user perspective.
- The **regulatory framework** regarding bidirectional EVs has also evolved in recent years. The highlighting of dependencies of the added values of bidirectional charging for the user on the regulatory framework in [Pub1] and [Pub2] has given important impulses for regulatory adjustments. The German 'Law on Immediate Measures for an Accelerated Expansion of Renewable Energies and Further Measures in the Electricity Sector' defines the bidirectional charging point of EVs as a storage facility to allow an exemption from levies and charges as for a stationary storage facility. This first step does not include the power losses during the charging and discharging process, nor does it include all levies, surcharges, and taxes. Further regulatory steps must therefore be taken here to make the use case of arbitrage trading more attractive from the user's point of view.

Due to the transformation process of the energy system towards a climate-neutral system as well as the current Ukraine crisis, there are various short-term adjustments of fundamental energy-economic conditions. For example, the sharp rise in fuel prices and, in particular, the price of gas led to higher electricity prices and higher electricity price volatility [63]. Therefore, some of the scenarios presented in this dissertation are no longer valid. However, the fundamental assessments of bidirectional EVs still hold through the numerous sensitivity calculations.

From a scientific point of view, this dissertation shows further need for research regarding the technology of bidirectional charging. In the BCM project, a total of 14 use cases were defined that could have revenue potentials from the user's perspective. The approaches developed in this dissertation for modeling bidirectional EVs can be transferred for modeling other use cases, although the specifics may have to be adapted. Only by modeling and combining all these use cases, bidirectional EVs can be evaluated comprehensively from the user's point of view. Furthermore, a comparison of current control strategies in field tests with the mode of operation in the developed optimization models can show to what extent the revenue potentials can be achieved. In addition, modeling the user-optimized behind-the-meter use cases endogenously in an energy system model could directly quantify the impact of these use cases on the energy system. However, this step may involve a high level of complexity. Finally, the studies of congestion management provision by bidirectional EVs have shown initial positive potential but should be detailed by further scenarios. In this way, recommendations for action in the direction of market-based congestion management can ultimately be supported in order to better integrate decentralized technologies into congestion management.

The added values of bidirectional charging of EVs, which were investigated by models in this dissertation, have also been tested in pilot operation since 2021 as part of the BCM research project. For this purpose, 50 BMW i3 were equipped with the technology of bidirectional charging [64]. A comparison of the realized revenues for the user with the simulated revenue potentials at the end of the project can show here the extent to which there is still potential for improvement in, for example, the control system or user behavior.

In summary, this dissertation has demonstrated added values of bidirectional charging of EVs from a user and system perspective and developed different approaches to modeling for this purpose. Some of the results have already been integrated into a policy paper [65]. This shows recommendations for policymakers, users of EVs, and energy entrepreneurs to make well-informed decisions regarding the technology of bidirectional charging of EVs.

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8 Publications of the Author

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Publication 1 (Pub1): Integrating Bidirectionally Chargeable Electric Vehicles into the Electricity Markets

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Abstract: Replacing traditional internal combustion engine vehicles with electric vehicles (EVs) proves to be challenging for the transport sector, particularly due to the higher initial investment. As EVs could be more profitable by participating in the electricity markets, the aim of this paper is to investigate revenue potentials when marketing bidirectionally chargeable electric vehicles in the spot market. To simulate a realistic marketing behavior of electric vehicles, a mixed integer linear, rolling horizon optimization model is formulated considering real trading times in the day-ahead and intraday market. Results suggest that revenue potentials are strongly dependent on the EV pool, the user behavior and the regulatory framework. Modeled potential revenues of EVs of current average size marketed with 2019 German day-ahead prices are found to be at around 200 €/EV/a, which is comparable to other findings in literature, and go up to 500 €/EV/a for consecutive trading in German day-ahead and intraday markets. For future EVs with larger batteries and higher efficiencies, potential revenues for current market prices can reach up to 1300 €/EV/a. This study finds that revenues differ widely for different European countries and future perspectives. The identified revenues give EV owners a clear incentive to participate in vehicle-to-grid use cases, thereby increasing much needed flexibility for the energy system of the future.

Keywords: V2G; bidirectionally chargeable electric vehicles; smart charging; unmanaged charging; spot markets; day-ahead market; intraday auction; continuous intraday trading; mixed integer linear optimization; revenues potentials of EVs

1. Introduction

The energy system transformation entails structural changes in all sectors. While the electricity supply sector in Germany has already been subjected to massive adjustments due to the expansion of renewable energies, the final energy sectors of private households, industry, transport, as well as small and medium enterprises have been very slow to switch to more climate-friendly technologies.

Emissions from the transport sector in Germany even increased since 1990 [1] and will, therefore, be unable to contribute to achieving the climate targets for 2020. Switching to electric vehicles (EVs) is one possible solution for lowering emissions. When comparing the carbon footprint of an EV to an internal combustion engine vehicle (ICEV), both the production of the battery as well as tailpipe emissions of the EV depend on the underlying energy system [2]. Due to a targeted reduction of CO_2-emission of the European energy sector by up to 95% [3], at least operational emissions of EVs resulting mainly from charging electricity will decrease. Consequently, EVs are promising for lowering CO2-emissions.

However, due to higher initial investment costs compared to ICEVs, the integration of EVs proves to be challenging. Investment in EVs could become more profitable by participating in the electricity markets by smart or bidirectional charging. In this respect, the "Bidirectional Charge Management" (BCM) project, which was launched in May 2019, focuses on the analysis of revenue potentials of bidirectionally chargeable EVs in the different electricity markets [4]. The main region of our investigations is Germany since it is the largest electricity market in Europe that is characterized by a heterogenic generation portfolio of renewable energy sources as well as conventional power plants [5]. Due to the German energy transition, volatility in electricity generation will continue to increase thereby enhancing the potential benefits of bidirectional chargeable EVs. German spot markets include the day-ahead market (auction at 12 noon one day before delivery), the intraday auction (at 3 pm one day before delivery) and the continuous intraday trading (starting at 3 pm one day before delivery) [6]. In addition, the results compare revenue potentials of bidirectionally chargeable EVs in 28 European countries, where findings of the parameter analysis can be generalized to other regions.

The BCM project defined 13 different use cases for bidirectional charging management separated into the three revenue creation groups: "Vehicle-to-Grid" (V2G), "Vehicle-to-Business" (V2B) and "Vehicle-to-Home" (V2H) [4]. Two use cases of the V2G use cases group are examined in this paper, which refer to arbitrage trading in the day-ahead market and the intraday market. Since bidirectionally chargeable EVs that participate in the spot markets increase the flexibility of the markets and energy system, these two use cases can have an impact on a cost-effective integration of renewable energies while providing revenues to the EV owners. The aim of this paper is to show these revenue potentials for the marketing of EVs in an aggregated pool in the spot markets at the same time ensuring faster integration of e-mobility into the energy system of the future.

Several scientific publications have discussed the revenue potentials by participation of EVs in the spot markets [7]. Using smart (but unidirectional) charging, an aggregator can considerably reduce the costs of charging electric vehicles [8,9]. Such costs can be further reduced and revenues can be generated by bidirectional charging according to [10]. The studies mentioned above are limited to marketing in the day-ahead and reserve market. Rominger et al. [11] point out revenues for intraday trading, but only restricted on flexibilities with constant availability such as stationery storage. Schmidt et al. [12] consider prices in the day-ahead market and the intraday auction for EV charging, but is limited to a smart charging process without discharging to the grid. We are thus extending existing research with a more detailed representation of bidirectionally chargeable EVs participating in the spot markets by considering day-ahead and intraday trading in a rolling optimization with a limited time horizon. Another limitation of most studies mentioned is the focus on revenues of EVs by a fixed EV parameterization. As revenue potentials of bidirectionally chargeable EVs are strongly dependent on many influencing parameters, this paper points out how a variation of user parameters like the minimum safety state of charge (SoC), minimum SoCs at departure, plug-in probabilities and location of charging infrastructure change revenue potentials.

Peterson et al. deal with profits of bidirectionally chargeable EVs using arbitrage trading in three different US local markets [13]. Pelzer et al. find out that revenue potentials of bidirectionally chargeable EVs in the US and Singapore markets are highly dependent on spatial and temporal resolution of market prices [14]. These studies regard battery degradation costs, but are limited to an EV participation in only one electricity market and modeling without consideration of user behavior parameters.

Furthermore, several studies investigate the effects of V2G on the electricity markets. The participation of bidirectional vehicles in the spot market has a smoothing effect on electricity prices. In times of surplus feed-in by renewable energies, V2G is able to reduce price drops resulting in higher market values of renewable energies [15]. Rodríguez et al. [16] show a flattening impact of V2G applications on the demand curve that results in a higher load factor. These findings showing promising effects on the energy system are expanded by our study to determine whether the vehicle owner can also benefit by participating in the electricity market. Since the regulatory framework is of significant importance for the evaluation of revenues, the influence of additional charges on purchased energy is pointed out.

2. Methods

To determine V2G revenue potentials, we developed an aggregated storage optimization model that covers the use cases of arbitrage trading in the spot markets. The holistic implementation of all V2G use cases facilitates the applicability and avoids building several parallel models.

A simplified representation of the modeling process is displayed in Figure 1, where the model consists of four different parts. Based on a model of the EV's battery, optimized charging strategies can be developed for different scenarios depending on charging and discharging restrictions. An uncoupled aggregated EV pool can be modeled to participate in different markets, where marketing strategies are optimized with a rolling forecast of market prices. The optimized strategy depends on electricity prices of the respective energy markets and is based on historical and simulated future market prices. In addition to bidirectionally chargeable EVs, two reference scenarios are considered that cover smart, unidirectionally chargeable EVs and simple, directly chargeable EVs. The entire model is implemented in Matlab, where a CPLEX solver (optimization software package) is used for optimization.

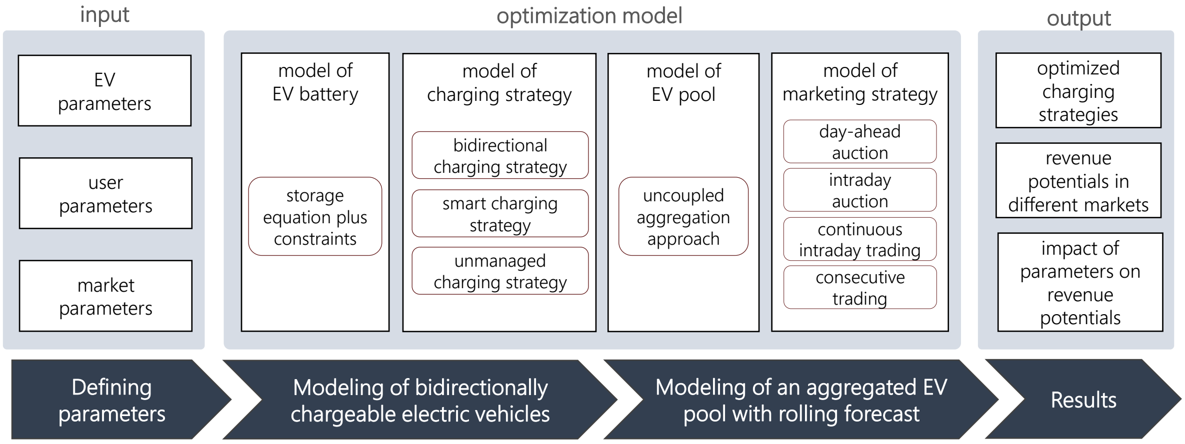


Figure 1. Schematic representation of the developed optimization model for Vehicle-to-Grid (V2G) use cases of bidirectional charging.

2.1. Modeling of Bidirectionally Chargeable Electric Vehicles

Modeling a bidirectionally chargeable EV consists mainly of a model of the electric battery of the vehicle similar to stationary electricity storage. The EV battery is modeled by the storage equation displayed below, which relates the state of charge (SoC) of the battery to the different amounts of electricity charged into or discharged out of the battery:

$$\begin{aligned} SoC(t) = {} & SoC(t-1) + P_{charge}(t) \cdot \eta_{charge} \cdot \Delta t - \frac{P_{discharge}(t)}{\eta_{discharge}} \cdot \Delta t \\ & + \frac{P_{counter-purchase}(t)}{\eta_{discharge}} \cdot \Delta t - P_{counter-sale}(t) \cdot \eta_{charge} \cdot \Delta t \\ & + P_{schedule}(t) \cdot \Delta t + P_{fastcharge}(t) \cdot \Delta t \cdot \eta_{charge} - E_{consumption}(t) \end{aligned} \quad (1)$$

here, t stands for the modeled point in time, Δt is the difference between two points in time and η represents efficiency, which differs for the charging and discharging process. $P_{charge}(t)$ is the charging power and $P_{discharge}(t)$ the discharging power at the modeled time t. The variables are considered on the alternating current side of the charging station and thus correspond to the amounts of energy traded in the market. $P_{schedule}$ is the sum of purchases and sales already made at the modeled time t. Accordingly,

$P_{counter-purchase}(t)$ and $P_{counter-sale}(t)$ represent the power which can be purchased or sold in the market to counteract transactions that have already taken place (countertrading). For example, purchased energy in the day-ahead market could be sold in the intraday markets resulting in a countertrade $P_{fastcharge}(t)$ is the power, that can be used to rapidly charge the vehicle if necessary and $E_{consumption}(t)$ is the EV's energy consumption by driving at time t. The limit values of all time-dependent variables are explained in the following section. Table A1 in the Appendix A provides an overview of all these variables and their limit values.

2.1.1. State of Charge

$SoC(t-1)$ represents the battery's storage level at the point in time prior to the modeled point in time. The change in capacity of the battery storage corresponds to the difference from $SoC(t)$ to $SoC(t-1)$. Due to the limited storage capacity of the electric vehicle and user requirements for a minimum storage level, the variable $SoC(t)$ can assume a limited range of values.

The maximum storage level of the battery storage is limited by SoC_{max}. If a value of 100% is set for this parameter, the entire storage capacity is available for the charging process. The minimum value SoC_{min} varies depending on the vehicle's location status, which is known for each point in time. Equation (2) summarizes the values that SoC_{min} can assume:

$$SoC_{min}(\mathrm{t}) = \begin{matrix} SoC_{min,safe} & \text{for status} = \text{connected} \\ SoC_{min,dep} & \text{for status} = \text{departure} \\ SoC_{min,disconnected} & \text{for status} = \text{not connected} \end{matrix} \tag{2}$$

If the vehicle is connected to the electric grid, SoC_{min} equals $SoC_{min,safe}$. The storage level must not fall below this value or must load onto it as quickly as possible. If the vehicle is connected to a charging station and is at the point of departure, SoC_{min} assumes the value $SoC_{min,dep}$. Before departure, the charging strategy is thus optimized in a manner such that the SoC at the time of departure at least corresponds to $SoC_{min,dep}$. If the vehicle is not connected to the electric grid, the value $SoC_{min,disconnected}$ results in the minimum SoC.

To ensure that $SoC(t)$ lies between the minimum and maximum possible storage level, Equation (3) is implemented:

$$SoC_{min}(t) \cdot C \leq SoC(t) + P_{supplement}(t) \cdot \Delta t \leq SoC_{max}(t) \cdot C, \tag{3}$$

where *C* describes the storage capacity of the electric vehicle and $P_{supplement}$ stands for additional, theoretical electric power to be charged. $P_{supplement}(t)$ is incorporated to meet the storage level restriction in Equation (2) at any time. The possibility that the value of the storage level is below SoC_{min} exists even if the EV is connected to the electric grid. This might occur if the storage level is lower than the minimum SoC when the vehicle arrives at a charging station or if it is not possible to charge to the minimum SoC before departure because the vehicle has not been connected for long enough. In the case that the minimum storage level cannot be reached with the charging strategy, $P_{supplement}(t)$ takes on a value greater than 0 to simulate a hypothetical charging process. The variable thus can be interpreted as penalty costs that arise from the driving behavior of a user who disregards the requirements for a minimal SoC. By introducing $P_{supplement}$(t), the model can optimize all driving profiles regardless of driving behavior or consumption, so that a selection of unsuitable driving profiles does not have to be made in advance. $P_{supplement}$(t) is not taken into account in the storage equation and does not change the actual storage level.

2.1.2. Charging/ Discharging Power and Already Traded Energy

In the storage Equation (1), $P_{charge}(t)$ and $P_{discharge}(t)$ describe the purchase and sale of power and determine the change in storage capacity for each time step. Due to the limited power of any EV charging station, the variables are limited to the maximum charging and discharging power $P_{charge,max}(t)$ and $P_{discharge,max}(t)$ and to the minimum charging and discharging power $P_{charge,min}(t)$ and $P_{discharge,min}(t)$. If the vehicle is connected to a charging station, the EV battery can be charged with $P_{charge,max}(t)$ or discharged with $P_{discharge,max}(t)$. If the vehicle is not connected to the electric grid, both maximum and minimum charging and discharging power become 0.

The boolean variables b_{charge} and $b_{discharge}$ describe the state of the battery during charging and discharging processes. If a charging process takes place, b_{charge} is *true*. Analogously, the variable $b_{discharge}$ becomes *true* during discharging. Due to the fact that it is not possible to purchase and feed electricity into the electric grid at the same time, only one of the boolean variables can assume the value 1 (= *true*) at the modeled point in time Equation (4). A simultaneous purchase and sale in the market is, therefore, excluded.

$$b_{charge}(\mathrm{t}) + b_{discharge}(\mathrm{t}) \leq 1 \tag{4}$$

The resulting constraints regarding these variables are shown in Equations (5) and (6):

$$P_{charge,min}(t) \cdot b_{charge}(\mathrm{t}) \leq P_{charge}(t) \leq \left(P_{charge,max}(t) - P_{schedule,purchase}(t)\right) \cdot b_{charge}(\mathrm{t}), \tag{5}$$

$$\begin{aligned} P_{discharge,min}(t) \cdot b_{discharge}(\mathrm{t}) &\leq P_{discharge}(t) \\ &\leq \left(P_{discharge,max}(t) - \mathrm{P}_{schedule,sale}(\mathrm{t})\right) \cdot b_{discharge}(\mathrm{t}). \end{aligned} \tag{6}$$

There is a possibility that the storage capacity of the electric vehicle has already been marketed through previous trading on the electricity markets, for example through consecutive trading on different spot markets. Such traded power must be taken into account in subsequent storage optimizations. In Equations (5) and (6), $P_{schedule,purchase}$ and $P_{schedule,sale}$ correspond to already made purchases or sales at the modeled time t. These amounts of electricity reduce the maximum charging or discharging power in such a way that only the capacity that has not yet been traded can be marketed. $P_{schedule}$ can be defined as the difference between $P_{schedule,purchase}$ and $P_{schedule,sale}$ Equation (7) and is included in the storage Equation (1).

$$P_{schedule}(\mathrm{t}) = P_{schedule,purchase}(t) \cdot \eta_{charge} - \frac{P_{schedule,sale}(t)}{\eta_{discharge}} \tag{7}$$

2.1.3. Countertrades

Electricity spot markets in Germany include consecutive day-ahead and intraday trading resulting in the opportunity to countertrade day-ahead purchases or sells in the intraday market. The model not only accounts for already marketed storage capacities, it also includes the possibility of compensation transactions (countertrades) that compensate for the previous trade in the opposite direction. In this regard, the variable $P_{counter-purchase}(t)$ corresponds to a buyback (counter purchase), the variable $P_{counter-sale}(t)$ to a sellback (counter sale) of already traded storage capacities. The volume of a countertrade can at most assume the previously inversely traded amount of energy. Countertrades do not describe a physical loading or unloading process. The resulting constraints are shown in Equations (8) and (9):

$$P_{counter-purchase}(t) \leq \mathrm{P}_{schedule,sale}(\mathrm{t}) \cdot b_{counter-purchase}, \tag{8}$$

$$P_{counter-sale}(t) \leq P_{schedule,purchase}(\mathrm{t}) \cdot b_{counter-sale}. \tag{9}$$

Similar to the charging and discharging processes, the boolean variables $b_{counter-purchase}$ and $b_{counter-sale}$ describe the state of countertrades. If a counter-purchase takes place at time t ($b_{counter-purchase} = 1$), the EV battery cannot be discharged at the same time. Conversely, no charging process can be conducted during a counter-sale ($b_{counter-sale} = 1$). Equations (10) and (11) show these constraints:

$$b_{counter-purchase}(\mathrm{t}) + b_{discharge}(\mathrm{t}) \leq 1, \tag{10}$$

$$b_{counter-sale}(\mathrm{t}) + b_{charge}(\mathrm{t}) \leq 1. \tag{11}$$

2.1.4. Electricity Consumption and Fast Charging

The battery of a vehicle has an electric energy consumption $E_{consumption}(t)$ at the modeled time t, which is considered in the storage equation. Due to the foresight of the driving profiles (explained in Section 2.4), EV consumption is known at all times. Each driving phase of the vehicle results in a capacity reduction.

Depending on the user's driving behavior, it might occur that the electricity consumption of an EV is so high at one point in time that the current storage level is not sufficient to meet the energy demand, for example if the EV has not been connected to a charging station for too long. In this case, the fast charging power $P_{fastcharge}(t)$ is utilized to comply with the restrictions of $SoC_{min}(t)$ and to avoid a supposed negative storage level. The employment of the fast charging process is accompanied by an increase in storage capacity. $P_{fastcharge}(t)$ represents the charging power at a public charging station rather than at a bidirectional charging station. The vehicle user is thus given the opportunity to charge the vehicle on the road.

2.2. Formulation of Optimization Model

The developed model of a bidirectionally chargeable EVs allows for the implementation of different optimized charging and discharging strategies, which differ in particular in the structure of the objective function. For the assessment of the use cases of arbitrage trading on the day-ahead market as well as on the intraday market, three different charging strategies are implemented: a strategy for bidirectional charging, a strategy for smart charging, and a strategy for unmanaged charging.

First, the bidirectional charging strategy, which allows for charging and discharging of the EV, is restricted to the storage equation and its aforementioned constraints. The objective of this charging strategy is to charge at minimum costs while discharging at maximum revenue. To do so, the objective function of the optimization model aims at minimizing all costs considered:

$$\begin{aligned} min\Bigg(& \sum_{t=1}^{T} p_{market,buy}(t) \cdot \left[P_{charge}(t) + P_{counter-purchase}(t)\right] \\ & - \sum_{t=1}^{T} p_{market,sell}(t) \cdot \left[P_{discharge}(t) + P_{counter-sale}(t)\right] \\ & + \sum_{t=1}^{T} p_{fastcharge}(t) \cdot P_{fastcharge}(t) + \sum_{t=1}^{T} p_{supplement}(t) \cdot P_{supplement}(t) \Bigg) \end{aligned} \tag{12}$$

where *T* corresponds to the number of time steps of the optimization. Depending on the respective market, traded energy quantities per time step as well as corresponding market prices $p_{market,i}(t)$ are considered. In this regard, $p_{market,buy}$ is the price at which electricity is bought and $p_{market,sell}$ is the price at which electricity is sold, where both prices can include respective transaction costs and possibly additional electricity price components. Charged power corresponds to a purchase transaction and is associated with costs as is each counter purchase of power. In contrast, discharged power and counter sales are traded with corresponding revenues, which is why $P_{discharge}$ and $P_{counter-sale}$ are subtracted.

Fast charging power and supplement power are also included in the objective function. Both fast charging costs $p_{fastcharge}(t)$ and penalty costs $p_{supplement}(t)$ are fixed to be a relatively high value, so that only the minimum necessary power is charged to meet the requirements for minimum storage level. As $P_{fastcharge}(t)$ should only be utilized to the extent that a negative *SoC* is avoided, $p_{fastcharge}(t)$ should be selected sufficiently larger than $p_{supplement}(t)$. Thus, the following condition must also be fulfilled to guarantee a functioning bidirectional charging strategy:

$$p_{market,i}(t) \ll p_{supplement}(t) \ll p_{fastcharge}(t). \tag{13}$$

Second, the smart charging strategy is implemented as a reference scenario to simulate already existing smart charging stations. The objective is to minimize electricity purchase costs by intelligent charging of the EV. Since discharging the EV battery is impossible in this scenario, Equation (14) is implemented. By eliminating the discharge power, the objective function already defined via Equation (12) for the bidirectional charging strategy can also be used for the smart charging strategy.

$$0 = P_{discharge,min} \le P_{discharge} \le P_{discharge,max} = 0 \tag{14}$$

Third, the unmanaged charging strategy accounts for today's most commonly installed simple charging stations as a second reference scenario, where the EV battery is charged as soon as the vehicle is connected without an optimized charging control. As with the smart charging strategy, discharging is not possible Equation (14). The aim of the unmanaged charging strategy is, therefore, to maximize the storage level that is equal to minimizing the negative value of $\mathrm{SoC(t)}$ at all times. The battery is accordingly charged at maximum charging power until the battery's storage level corresponds to $SoC_{max}(t)$ or until the EV leaves the location. In addition, as for the previously explained strategies, fast charging costs and penalty costs for an insufficient SoC with regard to the location-based limit values are included. The resulting objective function is expressed as follows:

$$min\left(\sum_{t=1}^{T} p_{fastcharge}(t) \cdot P_{fastcharge}(t) + \sum_{t=1}^{T} p_{supplement}(t) \cdot P_{supplement}(t) - \sum_{t=1}^{T} \mathrm{SoC(t)}\right) \quad (15)$$

2.3. Optimization with Limited Forecast in Consecutive Spot Markets

To investigate the influence of different characteristics and requirements of the considered markets on revenue potentials of bidirectional charging, optimized trading strategies based on price forecasts are simulated by a rolling optimization model, where realistic trading behavior results from a limited foresight of market prices.

Acting in the market under uncertainty is modeled in the same manner as described in [17], where each day is divided into 8 time slices of three hours each. The model regards real trading times in the spot markets. Figure 2 illustrates the methodical procedure of consecutive trading in the day-ahead and intraday markets with rolling price forecast horizons, where each horizontal bar displays the prices known in the respective optimization run of three hours. At 12 noon of day d, for instance, a market participant sees averaged continuous intraday prices of the following 12 quarter-hourly products. At the same time, less precise quarter-hourly prices of the continuous intraday are assumed for the interval from 3 pm to midnight. For day $d + 1$, day-ahead market prices are known and for $d + 2$ a forecast of the day-ahead market prices is presented. The participant's trading decision, which is the optimized marketing strategy, is based on this limited foresight.

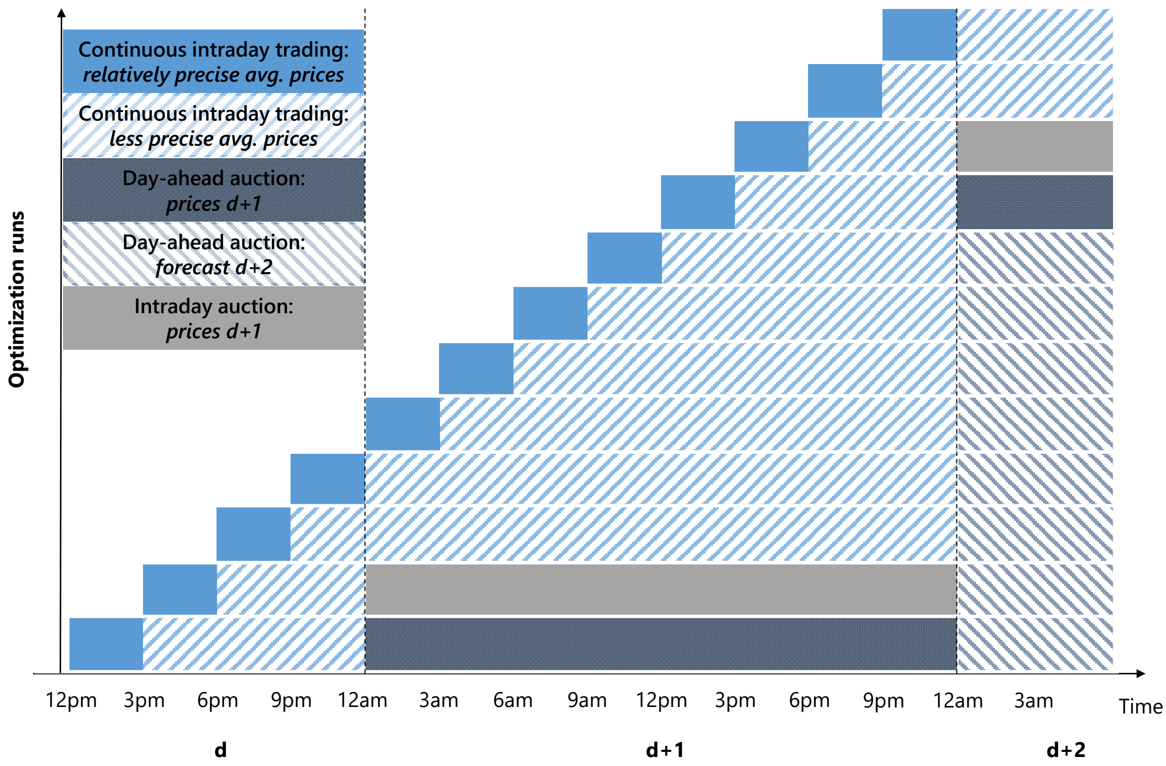


Figure 2. Schematic representation of the optimization steps with limited foresight of market prices.

As described by the example, foresight of market prices varies for the individual markets. Since the auction on the day-ahead market takes place daily at 12 noon for the respective following day $d+1$, precise prices forecasts for $d+1$ are known shortly before 12 noon on day d. To prevent unrealistic trading behavior at the end of day $d+1$, such as discharging all batteries to maximize revenues, estimated prices for day $d+2$ are included in the forecast horizon, where prices are also presented at 12 noon of day d. The forecast period $d+2$ can be one or more days representing a worse or better foresight and is evaluated in Appendix B. The length of the optimization time steps for day-ahead trading is 1h.

For the intraday auction, precise price forecasts of day $d+1$ are known shortly before 3 pm of day d, since the auction takes place at 3 pm. The length of the optimization time steps is 0.25 h.

Following the intraday auction, continuous intraday trading starts at 4 pm with quarter-hourly products, which defines the length of the optimization time steps. Here, a first forecast horizon of relatively precise prices is set to three hours covering the following 12 quarter-hourly products, where prices are based on trading transactions of these three hours. For the period following the three-hour time window, all continuous intraday transactions of this interval are used to calculate a second forecast price, thereby reflecting the uncertainty of market prices.

Hence, optimization runs before noon include market price information of the remaining day d and the following day $d+1$. The optimization runs from 12 noon on the trading day also include day $d+2$. The total revenue of the marketed EV battery corresponds to the summed costs and revenues of all traded products (filled areas). The cross-hatched areas in Figure 2 are not regarded as revenues, since these are only price forecasts serving as reference points for the trading strategy.

If consecutive trading takes place in several markets, storage capacities already marketed must be taken into account in subsequent optimization runs and can be countertraded as described before. The storage level at the end of real continuous intraday trading (filled blue area) of each optimization run determines the actual charging and discharging behavior of the vehicle. This storage level is applied as the starting value for the subsequent optimization run.

2.4. Input Data and Parameterization of Electric Vehicle (EV) Pool Scenarios

In the model, parameters related to the EV are the battery's storage capacity C, charging and discharging power $P_{charge/discharge}$, and different efficiency parameters. To investigate the range of revenue potentials in detail, three different sets of EV parameters are implemented: First, a currently common-sized EV is modeled (EV1), comparable to a 2018 BMW i3 [18] and a 2018 Renault Zoe [19], using realistic values regarding storage capacity, charging and discharging power and efficiencies. Second, a relatively large EV and a highly efficient charging station are defined representing a future EV (EV2). Third, a set of ambitious, yet plausible future values is selected to model maximum revenue potentials (EV3). These parameter sets were discussed and agreed upon within the research project BCM. Table 1 summarizes the chosen parameter values for the three sets of EV models.

Table 1. List of relevant electric vehicle (EV) parameters and chosen set of parameter values.

Parameter		EV1	EV2	EV 3
Storage capacity	C	38 kWh	100 kWh	100 kWh
Charging power	P_{charge}	11 kW	11 kW	22 kW
Discharging power	$P_{discharge}$	10 kW	11 kW	22 kW
Charging efficiency (AC-DC)	η_{charge}	92.5%	94.5%	95.0%
Discharging efficiency (DC-AC)	$\eta_{discharge}$	92.0%	94.5%	95.0%
Roundtrip efficiency (AC-AC)	$\eta_{roundtrip}$	85.1%	89.3%	90.3%

All losses and efficiencies considered in the model are based on discussions and on the consultation with experts from the BCM project. Other studies assume roundtrip efficiencies that are similar to EV1 [13] or slightly lower [14]. Constant values are set for the efficiencies in order to allow for a linear optimization problem, which results in much faster optimization times and thus enables many more optimization runs, i.e., more results. In real operation, however, efficiencies follow a declining, non-linear course for decreasing charging power. Hence, resulting revenue potentials of the presented model overestimate real revenues of bidirectional charging.

The user parameters result from characteristics, requirements and behavior of the vehicle user. In contrast to a large-scale stationary storage system, the battery of an EV is not continuously connected to the grid. The availability of an EV battery for V2G use cases largely depends on the individual driving profile of the user, the location of an appropriate charging station and the probability that the user has connected the vehicle to this charging station.

As a detailed representation of the driving behavior of the user, vehicle-specific driving profiles describe the EV's whereabouts as well as its energy consumption while driving in a chronological sequence. Based on data regarding household and route information as well as individual user logbooks from the "Mobility in Germany 2017" study [20] and a methodology first developed in the MOS 2030 [21] project, annual driving profiles of various EVs are created that are available as supplementary material (see Section 6). Each profile meets the following standards:

- A change of location is always accompanied by a driving phase.
- During each driving phase, the EV has discrete consumption, which leads to a reduction of the storage level.
- The EV can be located and connected either at the place of residence, the place of work or the public space

The temporal resolution of the driving profiles is quarter-hourly intervals. For each profile, the energy consumption is calculated based on information regarding driving speed, outside temperature and vehicle type.

The basic data is additionally used to cluster these driving profiles into user groups to further analyze the influence of user behavior on revenue potentials resulting in a set of commuter groups which display typical commuter behavior, and a set of non-commuter groups with homogeneous behavior different to commuter behavior. The commuter set consists of 12 commuter groups. These are defined by the time of arrival of the vehicle at the place of work and the distance traveled from the place of residence to the place of work. The non-commuter set is made up of three user groups, which are determined by age and number of persons in a household. The number of created commuter and non-commuter profiles per group reflects the real distribution within the German vehicle fleet [22]. Since revenue potentials are strongly related to driving behavior, these two different pools of driving profiles are defined as input for the model:

- a commuter pool consisting of representatives of all 12 commuter groups;
- a non-commuter pool consisting of representatives of all 3 non-commuter groups.

Table 2 summarizes the characteristics of the two pools of driving profiles including the probability of the EVs' whereabouts, which is the averaged probability of the EV's location at any given point in time. The sum of probability of all three locations apart from the driving phase is 94.5% for the commuter pool and 96.8% for the non-commuter pool, which represents the theoretical availability for bidirectional charging management if an appropriate charging station is installed at their location. To analyze the influence of possible charging station locations on revenue potentials of the discussed V2G use cases, the charging point location parameter can be flexibly selected in the model for each individual EV, where the distinguished three locations can be individually defined as available for bidirectional charging or not available.

Table 2. Characteristics of user pools.

Pools of Driving Profiles	Probability of Whereabouts				Averaged Consumption (kWh/100km)	Averaged Driving Distance (km/a)
	Place of Residence	Place of Work	Public Space	Driving Phase		
Commuter Pool	68.8%	22.1%	3.6%	5.5%	17.4	13,600
Non-commuter Pool	87.5%	1.4%	7.9%	3.2%	17.4	8300

The probability of each individual EV user to plug the vehicle into an available bidirectional charging station upon arrival determines the plug-in probability, where the expected value of a normally distributed probability is defined as a parameter. A higher plug-in probability results in a greater availability of the EV for V2G use cases. The parameter can be set flexibly to any value between 0% and 100%. As users will most likely be rewarded in some way for plugging in their EV, the plug-in probability is expected to be very high, up to a 100% certainty.

The parameter $SoC_{min,\mathrm{safe}}$ states the minimum storage level not to be undercut when the EV is connected to the electric grid, which guarantees a certain safety range in the event of an unscheduled departure. This parameter can be set flexibly to meet the requirements of users. The storage level that must be reached at the time of a scheduled departure, $SoC_{min,dep}$, should be adjustable by the user according to his/her preferences in a real implementation. In the model, the parameter can be set between 0% and 100%.

The charging and discharging behavior model is determined in particular by the time series of market prices. For the use cases of arbitrage trading, actual price time series of day-ahead and intraday markets from 2019 are used to represent price forecasts of a maximum of two and a half days [23,24]. For trading in the day-ahead and the intraday markets, corresponding auction prices of 2019 are used. Regarding the continuous intraday market, real prices are bilaterally determined for each transaction, where buy and sell orders are constantly matched. Thus, two representative forecast prices are determined. For the relatively precise forecast of the next three hours after modeling time t, ID3 is calculated, which is the volume-weighted quarter-hourly price of all transactions in the market for the last three hours, where market liquidity is sufficient to determine a representative market price. For the more uncertain time beyond three hours after modeling time, ID_{Avg} is used, which is the volume-weighted quarter-hourly price of all transactions for this forecasted time horizon.

The regulatory framework for bidirectional charging applications is not yet fully defined to the point that simulated revenue potentials might determine what kind of regulatory incentive or obstacle enables or respectively prevents the considered V2G use cases. A market design with a reduction of different electricity price components such as grid fees and taxes would decrease the marginal costs of the EV accordingly and thus lead to an increased discharging behavior. To incorporate this highly important role of the market design in the model, various values are assigned to the additional charges on purchased energy parameter and resulting differences in revenues are assessed. The applied additional charges on purchased energy range from 0 €/MWh, which corresponds to a complete exemption from all additional electricity price components, to 234 €/MWh, which reflects the amount of all electricity price components for households in Germany in 2019, excluding electricity purchase prices [25].

3. Results

For the following investigations, user and EV parameters that are introduced in Section 2.4 are combined to form six EV pool scenarios (EV1, EV2, EV3 each for commuters and non-commuters). Displayed revenues of bidirectional or smart charging EVs always refer to the difference of these revenues to revenues of the unmanaged charging scenario. As long as there is no presentation explicitly showing single profile revenues, displayed revenues always refer to mean revenues of the considered EV pool scenario. User, modeling and regulatory parameters are set to the values shown in Table 3. The process of determining suitable parameters is further discussed in Section 3.3 as well as Appendixes B and C.

Table 3. Fixed user, modeling and regulatory parameters for the investigation of revenue potentials.

Parameter	Value	Type	Further Discussion of Parameters' Influence on Revenue Potentials
Minimum SoC at departure	70%	User	Section 3.3.1
Minimum safety SoC	20% (EV1 and EV2) 30% (EV3)	User	Section 3.3.1
Plug-in probability	100%	User	Section 3.3.1
Charging point location	At place of residence	User	Section 3.3.1
Additional charges of purchased energy	0 €/MWh	Regulatory	Section 3.3.2
Forecast period	1 day	Model	Appendix B
EV pool size	Commuter: 50 Non-commuter: 75	Model	Appendix C

3.1. Revenue Potentials for Vehicle-to-Grid (V2G) Use Cases

All resulting datasets in Section 3.1, individual revenue potentials depending on EV pool scenario, and driving profiles, have been made freely available (see Section 6). The following analysis shows average revenue potentials and thus represents an aggregated extract of the provided result data.

3.1.1. Revenue Potential in the German Spot Market

The German spot market is divided into the day-ahead auction with hourly products, the intraday auction with quarter-hourly products, and the continuous intraday trading offering quarter-hourly and hourly products. Figure 3 shows the revenue potentials for the EV pool scenarios considered in the different markets with a separate participation in the markets compared to consecutive marketing. In comparison, the revenue potential of smart charging is shown in red bars. For commuters, smart charging is more attractive than for non-commuters because of the higher annual driving and thus the higher need for charging. However, for both commuters and non-commuters arbitrage trading with bidirectional charging leads to much higher revenues compared to smart charging. Revenues of non-commuters are slightly higher than revenues of commuters due to the higher availability at the place of residence.

For trading in the day-ahead market, revenues range from almost 200 €/EV/a (EV1) to 600 €/EV/a (EV3). Quarter-hourly intraday trading leads to higher revenues due to the higher volatility in prices. Consecutive trading in the day-ahead market, the intraday auction and continuous intraday trading results in best-case revenues of 400 €/EV/a (EV1) to 1300 €/EV/a (EV3). Comparing the EV1 to EV2 pool, the 2.6 times higher capacity of EV2 implicates higher flexibility for charging and discharging times. Therefore, revenues of EV2 are 200 €/EV/a higher than the revenues of EV1. EV3 almost doubles the revenues of EV2 due to doubled charging and discharging power. The increase of charging and discharging power is, thus, even more relevant for revenue potentials than the increase of battery capacity.

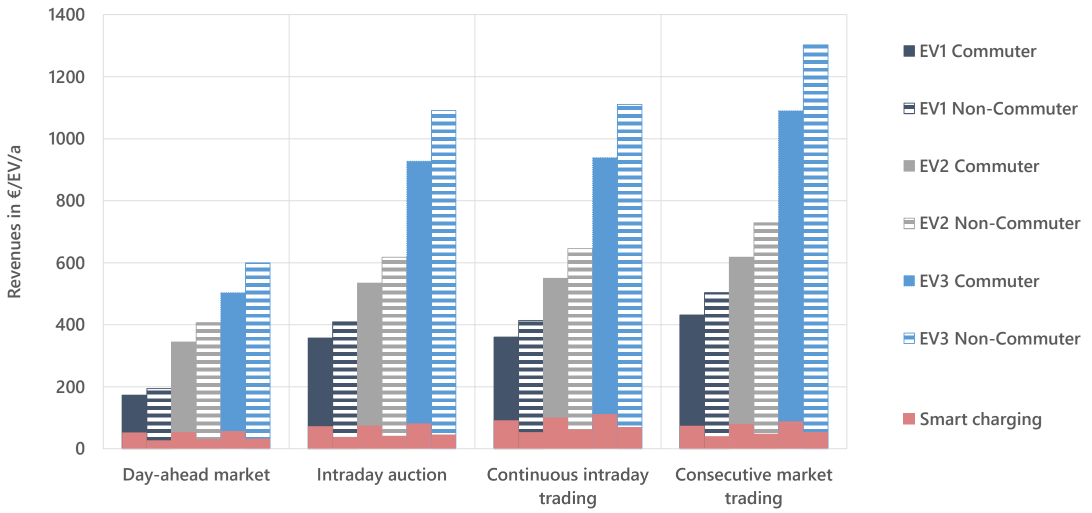


Figure 3. Revenues for bidirectionally chargeable and smart charging EVs participating in different spot markets in Germany.

3.1.2. Revenue Potential in European Markets

Since the energy systems change to a volatile and renewable production in most European countries, flexibility will be needed to cover the demand at any particular time. Therefore, bidirectionally chargeable EVs are a possible flexibility option in all European countries. To quantify revenue potentials in European countries other than Germany, we use entso-e data (European Network of Transmission System Operators for Electricity) of electricity day-ahead prices for 2019 as an input for the developed optimization model [24].

Figure 4 shows the resulting revenues for bidirectionally chargeable EVs compared to unmanaged charging for 28 European countries for commuters and non-commuters. Revenues are the highest in Ireland, Romania, Bulgaria and Hungary. These countries had scarcity prices of more than 100 €/MWh during approximately 200 hours to go along with a high standard deviation of electricity prices in 2019, giving bidirectionally chargeable EVs an opportunity to use arbitrage trading more profitably. On the other hand, the revenues are the lowest for Norway and Sweden. High capacities of hydropower and some nuclear power plants in Sweden characterize the energy system in those countries [26] with almost constant marginal costs, resulting in barely volatile electricity prices.

In other countries, like Germany, Austria and France, bidirectionally chargeable EVs generate medium revenues in arbitrage trading. These energy systems are more heterogenic with some volatile renewable production as well as gas-fired, coal-fired or nuclear electricity production. Revenues in this group of countries are still varying. For example, nuclear power plants with almost constant marginal costs dominate electricity production in France [27] resulting in narrow price spreads. As another example, Austria's energy system shows high capacities of pump storage facilities [26] resulting in flattened electricity prices. These structural characteristics lead to slightly lower revenues for bidirectionally chargeable EVs for the year 2019. On the other hand, Germany has a heterogenic production portfolio of volatile wind and solar generation as well as conventional power plants with widely varying marginal costs. Price spreads and the resulting revenues for bidirectionally chargeable EVs are thus higher there.

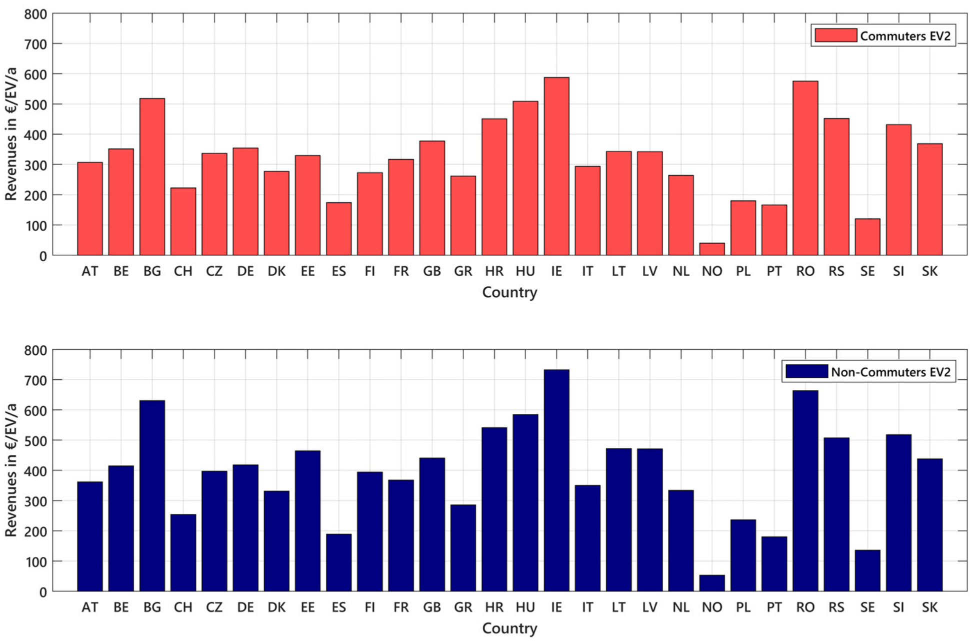


Figure 4. Revenues for bidirectionally chargeable EVs in different European day-ahead markets for market prices of 2019.

The structure of the energy system is consequently crucial for revenue potentials for bidirectionally chargeable EVs. In European countries, structural characteristics of electricity production differ a lot. In regard to energy transition in Europe accompanied by a shift to different volatile renewable production technologies, revenue potentials could vary even more in the future. For this reason, future revenue potentials in Germany are quantified and discussed in the following section.

3.1.3. Revenue Potential for Future Day-Ahead Market Prices

In addition to an assessment of current revenue potentials, future revenue potentials are also important for an investment in a bidirectionally chargeable EV and corresponding EV supply equipment (EVSE). For an estimation of the changed revenues, price time series for future years from the DYNAMIS project are used [28] (see Section 6). The DYNAMIS project performs a dynamic and intersectoral evaluation of measures for the cost-efficient decarbonization of the energy system. The multi-energy system model ISAaR (Integrated simulation model for unit dispatch and expansion with regionalization) determines the design of the future energy system in a model-based way to be able to evaluate the measures [29].

Based on the multi-stage, exploratory assessment of measures and packages of measures, a climate protection scenario has been developed that aims to reduce greenhouse gas emissions by 95% by 2050. This scenario is characterized on the supply side by a cost-optimized provision of energy sources and on the application side takes into account the technology- and sector-specific boundary conditions and restrictions. The expansion of renewable energies is the most important measure. Green fuels (including all solid, liquid and gaseous fuels produced from biomass, renewable electricity or a combination of both) will increasingly be used from 2040 onwards in applications that can only be electrified at considerable expense. Domestic power-to-x technologies increase the available flexibility in the electricity system due to the good storage capacity of green fuels. Bidirectionally chargeable electric vehicles are not yet modeled in this scenario path and, therefore, their effects on the energy system could not be investigated there either.

One output of the model are hourly marginal costs representing day-ahead electricity prices for the years 2020 to 2050. The mean annual day-ahead price and its daily standard deviation are shown in Table 4. It can be seen that the level and in particular the standard deviation of the electricity price increases sharply. This is mainly due to the severely changed energy system that includes high capacities of renewable energies resulting in production surpluses. This results in increasing times with electricity prices of 0 €/MWh. On the other hand, rising fuel and carbon prices many times lead to very high electricity prices due to the unavoidable use of power plants with expensive marginal costs.

Table 4. Modeled mean day-ahead prices and standard deviation of day-ahead prices for the years 2020 to 2050 in Germany [28] compared to empirical prices in 2019 [23].

Year	2020 (Modeled)	2030 (Modeled)	2040 (Modeled)	2050 (Modeled)	2019 (Real Prices)
Mean day-ahead price in €/MWh	46.3	61.2	63.8	80.4	37.7
Daily standard deviation of day-ahead price in €/MWh	5.0	8.7	15.8	25.9	9.0

The hourly price time series are transferred as input into the optimization model for bidirectionally chargeable EVs to estimate future revenue potentials in the day-ahead market. Figure 5 shows the revenues from 2020 to 2050 as a box plot. The black cross shows the mean revenues for the EVs considered. The top and bottom edges of the blue boxes indicate the 25th and 75th percentiles. The whiskers show the lowest and highest revenues, excluding outliers. Outliers that represent values that are 1.5 times bigger than the interquartile range are illustrated as red plus signs. Comparing the revenues of 2020 to those pointed out in Section 3.1.1 for 2019, mean revenues for the modeled prices are much lower than the mean revenues for the empirical data. Modeled electricity prices of energy system models often tend to be less volatile than real prices [30]. Consequently, lower price spreads lead to lower revenues.

Regarding modeled electricity prices for future years, mean revenues of bidirectionally chargeable EVs compared to unmanaged charging EVs increase by a factor of 5 to 6. This is mainly due to the future structural change of production units to renewable volatile production in combination with high carbon and fuel prices leading to many low electricity prices around 0 €/MWh and many high electricity prices. Bidirectionally chargeable EVs can harvest the resulting high price spreads to generate revenues. Another interesting aspect is the range of revenues within a user group that increases considerably in future years, showing higher uncertainty of revenue potentials. For non-commuters in particular, there is a heterogenic distribution of revenues.

The results for future electricity prices show a much higher revenue potential than for current electricity prices. Regarding these results, one has to keep in mind that there are many uncertainties about the design of the future energy system and the resulting electricity prices. Furthermore, bidirectionally chargeable EVs will have a retroactive effect on electricity prices, reducing price spreads and revenue potentials. Nevertheless, the use case of arbitrage trading for bidirectional EVs will most certainly get more attractive in future years.

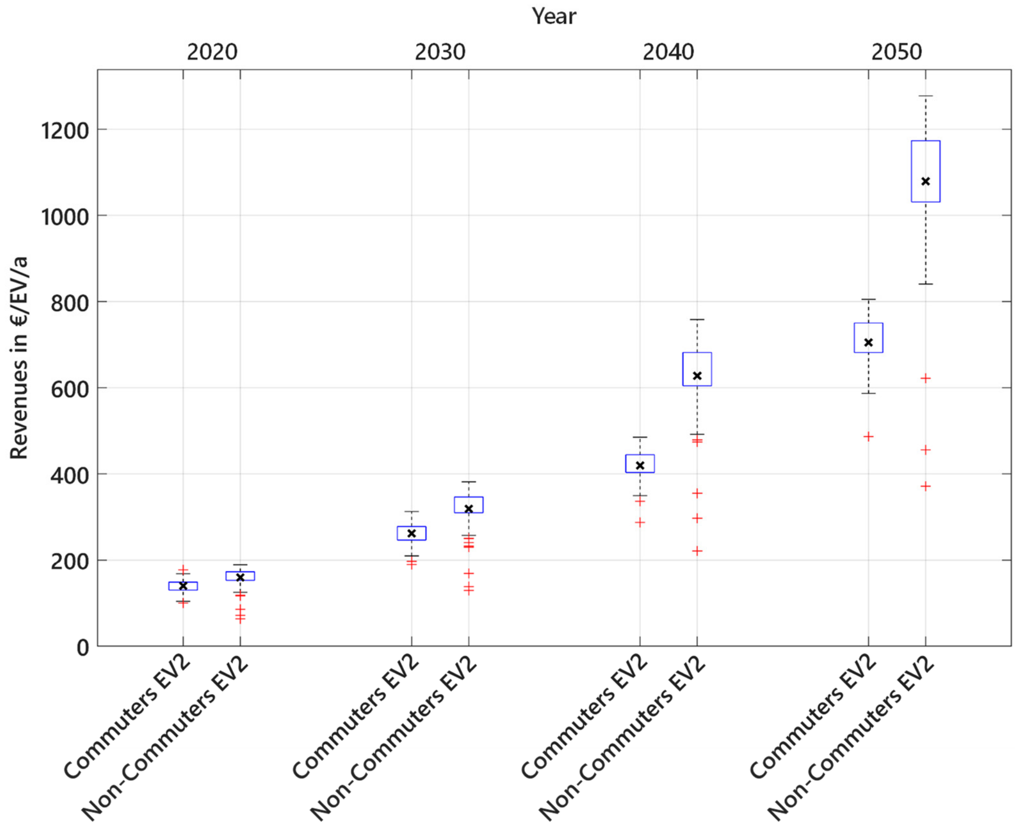


Figure 5. Revenues of bidirectionally chargeable EVs compared in accordance with future hourly day-ahead market prices.

3.2. Effect of V2G Use Cases on Full Cycles and Operating Hours

3.2.1. Effect of Unrestricted Trading in the Electricity Markets

The V2G use case of arbitrage trading leads to higher usage of the battery of the EVs and relevant supplying equipment as well as information and communication technology. Relevant parameters that show the additional charge of EVs are full battery cycles and total operating hours. High yearly full cycles and operating hours in particular mean a faster ageing of the battery. For the revenue modeling in Section 3.1, we deliberately applied no restrictions on cycles or operation hours. In the BCM project, a separate model will be used for evaluation of the impact of V2G use cases on EV components.

Table 5 shows the impact of the EV operation in Section 3.1.1 on the EV parameter full cycles, revenues per full cycle and operating hours. For arbitrage trading, a strong increase in full cycles by 100–500 full cycles/a and in operating hours by 1500–5000 hours/a is determined. Revenues per full cycle are around 1 to 3 €/full cycle for arbitrage trading.

If one sets the highlighted parameter values in relation to currently warrantied lifetime values of lithium-ion batteries (e.g., 5000 to 6000 full cycles for residential storage systems [31,32] and a typical 10,000 operating hours in automotive applications [33]), it becomes clear that strong, relevant, additional loads of the battery arise for the use cases of arbitrage trading. These additional loads are significant, yet the use cases can still become economic without overloading the battery. Since large battery systems (as in EV2 and EV3) do not have many full cycles from driving, an alternative usage of the battery is a logical addition.

Table 5. Impact of V2G use cases on EV's full cycles, revenues per full cycle and operating hours.

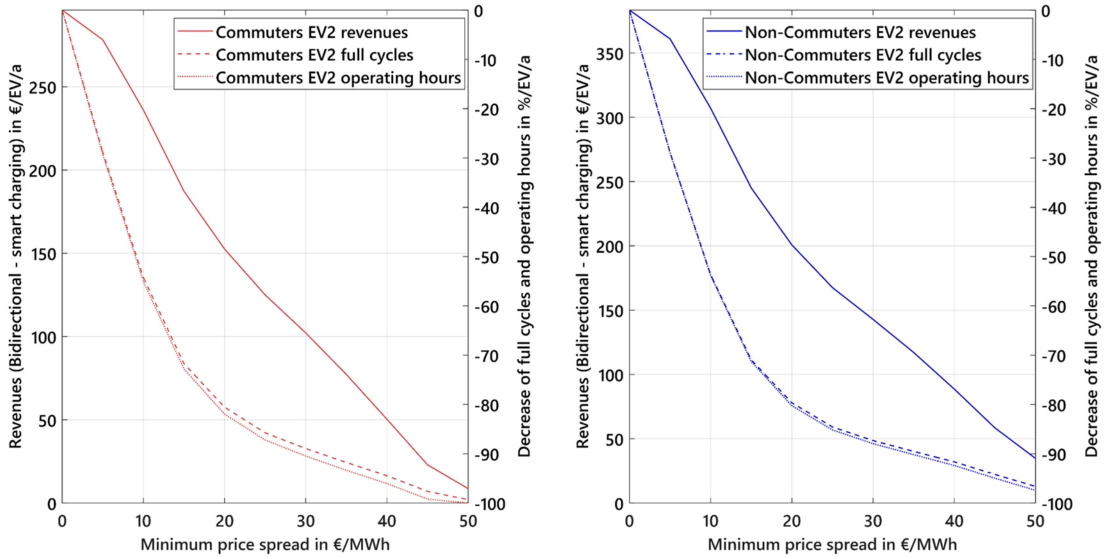
Market Modeling	Affected EV Parameter	Commuters			Non-Commuters		
		EV1	EV2	EV3	EV1	EV2	EV3
Reference Unmanaged charge	Full cycles	60	25	25	35	15	15
	Operating Hours	400	400	340	250	250	190
Arbitrage: Day-ahead market	Full cycles	230	210	300	320	270	400
	Revenues/ Full cycle	0.8	1.7	1.7	0.6	1.5	1.5
	Operating Hours	1860	3900	2920	2710	5070	3930
Arbitrage: Intraday auction	Full cycles	490	270	490	640	340	630
	Revenues/ Full cycle	0.7	2.0	1.9	0.7	1.9	1.7
	Operating Hours	3760	4880	4660	4890	6180	5970
Arbitrage: Continuous intraday trading	Full cycles	450	250	470	590	320	600
	Revenues/ Full cycle	0.8	2.2	2.0	0.7	2.0	1.9
	Operating Hours	3450	4670	4450	4490	5950	5680
Arbitrage: Consecutive trading	Full cycles	440	240	450	570	300	570
	Revenues/ Full cycle	1.0	2.6	2.5	0.9	2.4	2.3
	Operating Hours	3280	4350	4110	4340	5590	5310

3.2.2. Effect of Restricted Trading in the Electricity Markets

Since modeled full cycles and operating hours in the previous section could critically decrease the lifetime of the EV's battery and power electronics, a minimum spread of electricity prices as a limit value for arbitrage trading could lower the EV's operation while still generating high profits. The minimum spread refers to the spread of sold to purchased energy. Consequently, the selling price for these simulations has to be lowered by the minimum, modeled price spread divided by the roundtrip efficiency.

Figure 6 illustrates the effect of a minimum price spread of 0 to 50 €/MWh on full cycles and operating hours compared to revenues of EV2. Revenues refer to the difference of revenues of bidirectionally chargeable EVs to the revenues of smart charging EVs to show only the added benefit by bidirectional charging. The decrease of full cycles and operating hours is displayed in percentage referring to the simulation with no minimum price spread. The maximum decrease of full cycles and operating hours arises when increasing the minimum price spread from 0 to 5 €/MWh, whereas revenues do not decrease significantly for this change. For a minimum price spread of 10 €/MWh, additional full cycles for bidirectional charging of EV2 decrease by more than 50% to 95 full cycles per year for commuters and to 125 full cycles per year for non-commuters. For the same restriction, additional operating hours for bidirectional charging of EV2 also decrease by more than 50% to 1800 operating hours per year for commuters and to 2400 operating hours per year for non-commuters. For a minimum price spread of 10 €/MWh, revenues for both commuters and non-commuters decrease by only 20% to 240 €/EV/a and to 310 €/EV/a, respectively. By applying higher minimum price spreads, full cycles and operating hours further decrease and both the revenue per full cycle rate and revenue per operating hour rate increase. Full data for full cycles and operating hours of all EV scenarios is attached in Appendix D.

As a result, applying a minimum price spread is an effective method of limiting full cycles and operating hours while maintaining adequate profits. Even though revenues are generally decreased, this approach leads to an increase of the revenue per full cycle rate and revenue per operating hour rate and might thus represent a practicable approach for a future operation of bidirectionally chargeable EVs.



(a) (b)

Figure 6. Effect of restricted minimum price spread on revenues, full cycles and operating hours of EV2 for commuters (**a**) and non-commuters (**b**).

3.3. Analysis of User Parameters and Regulatory Framework on Revenue Potentials of V2G Use Cases

The revenues of bidirectional charging are determined by a multitude of input parameters. We use German day-ahead prices in 2019 (Section 3.3.1 and Section 3.3.2) as well as German intraday auction prices in 2019 (Section 3.3.2) to show the influence of user and regulatory parameters on the revenue potentials of bidirectionally chargeable EVs.

3.3.1. Influence of User Parameters

Minimum SoC at Departure

The user parameter $SoC_{min,dep}$ describes the minimum battery storage level that has to be reached at a scheduled departure. Considering this restriction, a higher minimum SoC at departure leads to a reduction of flexibility regarding the bidirectional charging strategy due to the smaller range between SoC_{max} and $SoC_{min,dep}$ in which the storage level can vary. This reduces the extent to which profitable price spreads and thus a revenue-maximizing discharge behavior can be used. The effects of different parameterization of $SoC_{min,dep}$ on the revenue potential in the day-ahead market are shown for the six different EV pool scenarios in Figure 7a. Potential revenues with $SoC_{min,dep}$ of 10% to 100% are compared to a reference of no minimum SoC at departure ($SoC_{min,dep} = 0\%$).

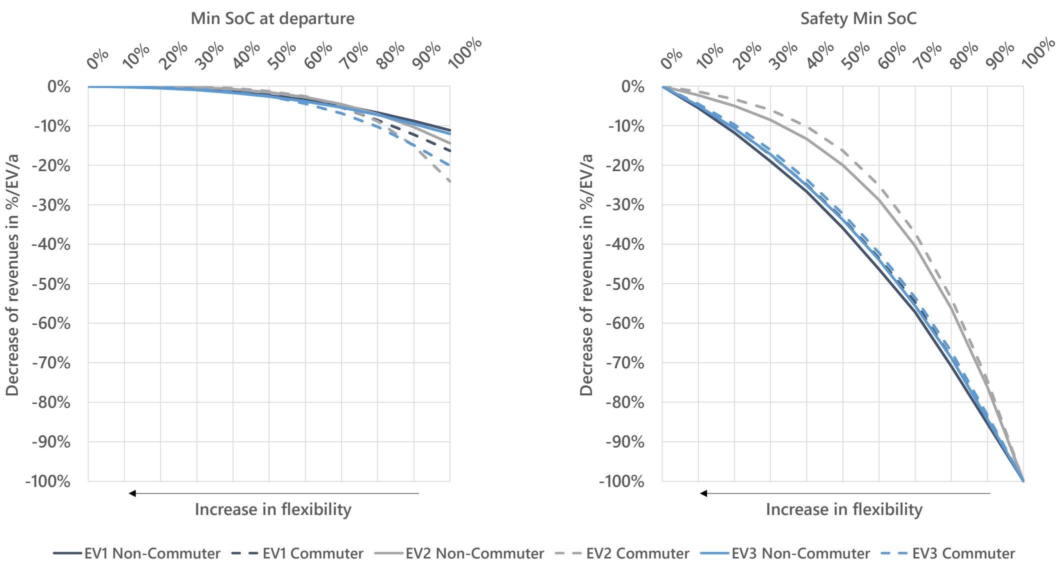
All scenarios show an exponential decrease in revenues with an increasing $SoC_{min,dep}$. If flexibility is gradually increased starting from a $SoC_{min,dep}$ of 100% up to a $SoC_{min,dep}$ of 0%, the impact on revenues is highest at the first adjustment from 100% to 90%. This is because with this first increase in flexibility, the highest electricity prices present at the considered time can be used to discharge at great profit. As low prices are used for charging, a great specific profit can be made. As flexibility is further increased due to a lower minimum SoC on departure, lower spot prices are also increasingly used for discharging. The price spread between charging and discharging decreases, which means that specific profits are reduced and revenues change less. Consequently, if an EV user can define the parameter himself, he/she should choose the lowest possible minimum SoC on departure to maximize revenues. In particular, users should avoid selecting an unnecessarily high $SoC_{min,dep}$. For investigations in this paper, a realistic minimum SoC of 70% at departure is assumed after consultation with the project BCM.

Minimum Safety SoC

The user parameter $SoC_{min,safe}$ describes the minimum battery storage level that an EV always should have when connected in order to guarantee a drive to the hospital or other relevant short-distance routes at any time. If an EV arrives at a charging station with a lower SoC than $SoC_{min,safe}$, it will start charging immediately until it reaches the minimum parameterized SoC. A higher minimum safety SoC alike a higher minimum SoC at departure leads to a reduction of flexibility, since the useable capacity for marketing in the spot markets of $SoC_{max} - SoC_{min,safe}$ decreases as the minimum safety SoC is increased. To quantify the impact of a minimum safety SoC, revenues with varied parameterization of $SoC_{min,safe}$ are compared in Figure 7b showing the relative decrease of revenues compared to a reference with no safety SoC.

There is an exponential decrease of revenues for all EV pool scenarios depending on the minimum safety SoC. EV1 and EV3 have similar functions, while EV2 has a much smaller gradient for low safety SoCs and a steeper gradient for higher safety SoCs. This is due to the large battery capacity of EV2 and the fact, that the capacity of the charging/discharging power ratio (E/P) is much higher for EV2 at around 9, compared to the ratios of EV1 and EV3 at 3.5 and 4.5, respectively. A large battery capacity of the EV in combination with a fixed SoC on departure makes it less likely that the vehicle comes back with a low SoC on arrival and thus it is less limited by a low safety SoC than an EV with a low capacity. A low E/P ratio, on the other hand, means that EV batteries can be charged and discharged quickly with a great cycle depth, which is limited even with a low safety *SOC*. EV2 rarely gets these low SoCs, so a low safety SoC has little effect.

Consequently, users with EVs that have a low E/P ratio should care more about a parameterization of a very low safety SoC than users that own an EV with a higher E/P ratio. In the investigations in this paper, a minimum safety SoC of 30% for EV1 representing the status quo for BMW electric vehicles and a lower safety SoC of 20% for EV2 and EV3 representing future electric vehicles are assumed.



(a) **(b)**

Figure 7. (a) Influence of a minimum SoC at departure on revenue potentials of bidirectionally chargeable EVs using arbitrage trading; (b) influence of a minimum SoC at the place of residence on revenue potentials of bidirectionally chargeable EVs using arbitrage trading.

Plug-in Probability

An EV user has the possibility to connect his vehicle to a charging station upon arrival at a location where a charging station is available. The probability that the user connects his vehicle to the charging station is called plug-in probability. There are several factors influencing plug-in probability. First, there is the incentive for a user to plug in his/her EV. Most importantly, the user is motivated to charge his EV for the next driving phase, where the desire could be to charge the EV directly or the possibility of smart or bidirectional charging. Since the incentives for EVs using bidirectional charging have hardly been investigated yet, there are no data on the plug-in probability of those EVs. Therefore, Figure 8a shows the influence of a changed plug-in probability on revenue potentials.

In all EV pool scenarios, there is a positive, approximately linear relationship between the plug-in probability and the revenues. If the EV is connected to a bidirectional charging station more frequently, a discharge process that maximizes revenues can be carried out more often. The gradient of the curves differs in the various scenarios. The increase in revenues in this investigation varies between 2 € for EV1 and 5 € to 6 € for EV3 with a 1% increase in the plug-in probability. Hence, for bidirectionally chargeable EVs participating in the spot markets, a higher plug-in probability means equally higher revenues. For investigations in this paper, a plug-in probability of 100% is assumed under the assumption that using bidirectional charging for arbitrage trading is profitable and users are incentivized to plug-in their EVs.

Charging Point Location

A bidirectional charging management system can only be operated if a bidirectional charging station is available at the EV's location. In accordance with the driving profiles from Section 2.4, possible locations for the EV are the place of residence, the place of work and the public space. An extensive expansion of bidirectional charging stations in public spaces is unlikely since the main reason for using public charging stations is the fast charging of the EV. Further analysis, therefore, concentrates on charging points at the place of residence and the place of work.

Figure 8b shows the revenue potentials of bidirectionally chargeable EVs depending on the charging point location. Comparing mean revenues at the place of residence and the place of work, there is a much higher incentive even for commuters to use bidirectional charging at the place of residence for the use case of arbitrage trading. This is due to the shorter period of time spent at the place of work while restrictions for minimum safety and departure SoC still have to be regarded. EVs can be discharged profitably less frequently than at the place of residence. In the non-commuter pool, 55% of the driving profiles are never located at a place of work, which is why an evaluation is not appropriate for these vehicle pools. If charging points are located both at the place of residence and at the place of work, revenues are slightly higher than if a charging point is only available at the place of residence. Compared to total revenues, the increase is quite low.

Consequently, the revenue potential of bidirectional charging at the place of work as opposed to the place of residence is low. Bidirectional charging should, therefore, be prioritized for EV users who are ready to install a bidirectional charging station at the place of residence. In the investigations within the framework of this paper, a charging station located at or near the place of residence is assumed.

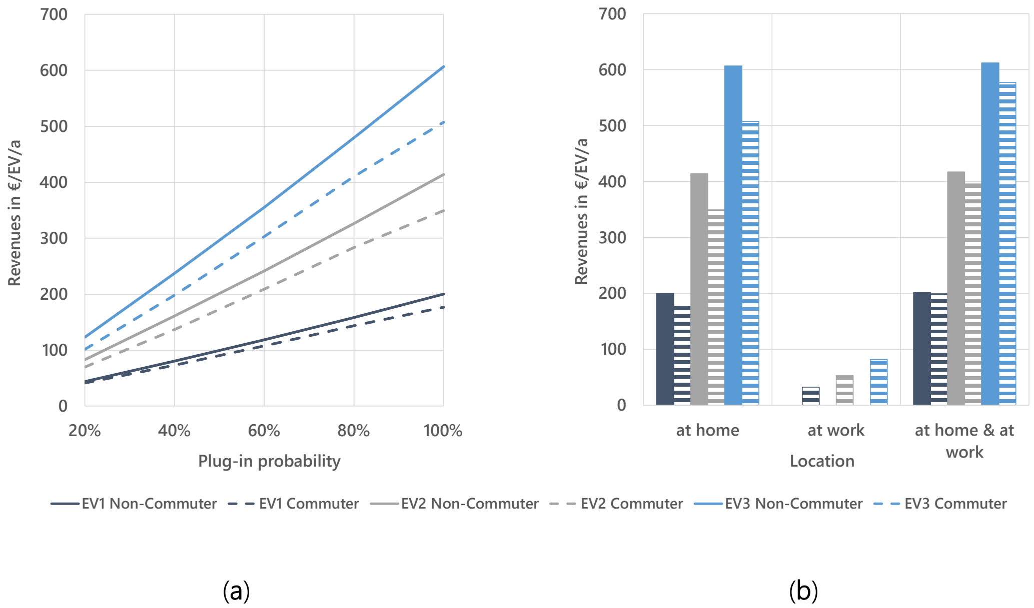


Figure 8. (a) Influence of plug-in probability on revenue potentials of bidirectionally chargeable EVs using arbitrage trading; (b) influence of charging point location on revenue potentials of bidirectionally chargeable EVs using arbitrage trading.

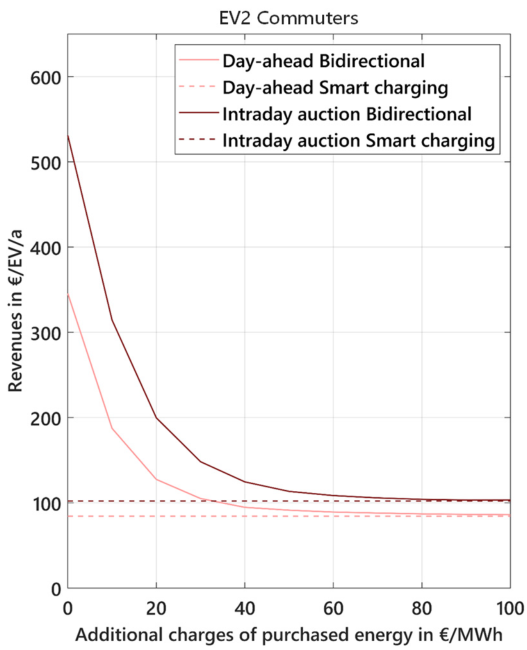
3.3.2. Impact of Regulatory Framework on Revenue Potentials

Bidirectionally chargeable EVs are a new technology whose regulatory framework conditions have not yet been developed at the European Union (EU) level [34]. An essential question is whether bidirectionally chargeable EVs are classified as storage devices and, consequently, what additional charges they have to pay for charged electricity that is discharged later.

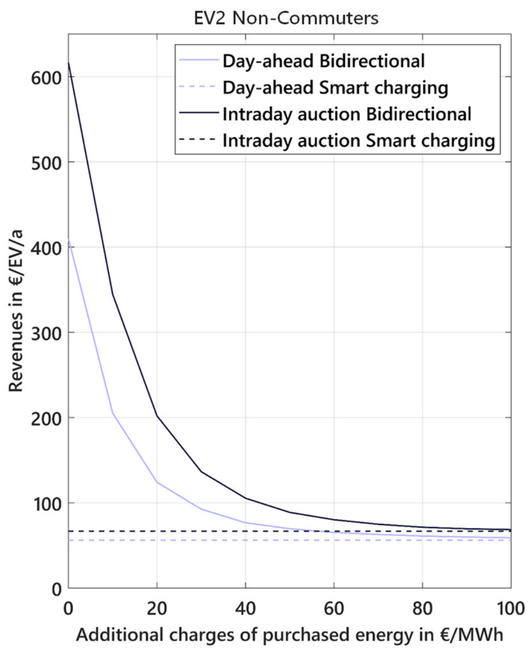
In Germany, the wholesale market price of electricity accounts for just around 15% (around 40 to 50 €/MWh) of the price of electricity for households. The other 85% (around 260 €/MWh) of the price is accounted for by additional charges such as the EEG surcharge (surcharge of electricity for remuneration of renewables) and grid fees as well as distribution [25]. Pumped storage facilities on the other hand are exempted from most of the EEG surcharge, grid fees and other levies, so that only additional charges of around 18 €/MWh have to be paid on electricity purchases [35],which can lead to a profitable arbitrage trading for storage facilities. As most of the exemptions refer to electricity purchases, storage losses are included [36].

For the use case of arbitrage trading, Figure 9 shows the influence of additional charges for purchased energy in the day-ahead or intraday market on revenue potentials of bidirectionally chargeable EVs for commuters and non-commuters. The solid lines represent revenues of bidirectionally chargeable EVs compared to unmanaged charging EVs and the dashed lines show revenues of smart charging EVs compared to the unmanaged charging ones. The diagram makes clear that possible revenues are strongly dependent on the regulatory framework. Starting from mean revenues with no additional charges at around 550 to 600 €/MWh for intraday auction trading, the revenues decrease by over 40% for additional charges of only 10 €/MWh. Non-commuters have an even sharper decrease since the starting revenues are a bit higher and the minimum revenues representing smart charging are lower. Revenue potential of smart charging is higher because of the increased annual driving the associated increase in the annual charging demand. If a bidirectionally chargeable EV is regulatory-equal to a pumped storage facility with additional charges of 18 €/MWh on purchased electricity, mean revenue of non-commuters will decrease by over 60%, and commuters will have less than 50% revenue. For additional charges of more than 50 €/MWh, the added revenue of bidirectionally chargeable EVs compared to smart charging EVs is less than 20 €/EV/a.

Consequently, the future regulatory framework will decide if there is a chance for profitable arbitrage trading for bidirectional EVs. In investigations in this paper, additional costs are set to zero €/MWh to show the potential revenues for bidirectionally chargeable EVs.



(a)



(b)

Figure 9. Influence of additional charges for purchased energy on revenue potentials of bidirectionally chargeable EVs compared to revenues of smart charging in the day-ahead market and intraday auction for commuters (a) and non-commuters (b).

4. Discussion

Bidirectionally chargeable EVs can use arbitrage trading to generate revenues for a potential improvement of their economic efficiency. Section 3.1 pointed out that revenues differ widely depending not only on the EV pool scenarios but also on the considered markets and the years under review. For an evaluation based on empirical prices of 2019 in Germany, revenues by bidirectional arbitrage trading range from 200 to 1300 €/EV/a depending on EV pool and market participation. Profits on other European day-ahead markets compared to the German day-ahead market vary between +70% and –90% and are, therefore, highly dependent on the structure of the considered energy system. For future electricity prices, there is high revenue potential for bidirectionally chargeable EVs, which is pointed out by revenues for arbitrage trading in 2050 up to six times as high as the revenue potentials determined for 2020.

Most V2G related studies in literature refer to profits in reserve markets [37–39]. However, some studies deal with V2G profits of arbitrage trading. Peterson et al. point out revenues of 140 to 250 US$/EV/a (120 to 210 €/EV/a) for 16 kWh EV batteries in local markets in three US cities [13]. Pelzer et al. determine 60 to 300 US$/EV/a (50 to 250 €/EV/a) depending on spatial and temporal variation in US and Singapore markets under consideration of battery degradation costs [14]. These revenues have a similar level as our calculated EV1 revenues for day-ahead trading in Germany in 2019. We do not consider battery degradation costs but show the maximization of revenues by consecutive trading in day-ahead and intraday markets and the crucial influence of user parameters and regulatory framework on revenue potentials.

Concerning analyzed user parameters, our results confirm those of Szinai et al., who found that smart charging value at residential locations is much higher than at work or public locations [40]. In addition, we found this to also be true for bidirectionally chargeable EVs. Geske et al. indicate that the minimum range and range anxiety are the most important determinants for users participating in V2G use cases [41]. In this regard, we show the quantitative effect of the parameters 'minimum SOC at departure' and 'safety minimum SOC' on the revenue potentials of bidirectionally chargeable EVs, thereby addressing the minimum range and range anxiety. Increasing these parameters leads to an exponential decrease of revenues depending on the EV type. Hence, a tradeoff exists between the users' range anxiety and potential revenues.

With regard to the indicated high future revenues for arbitrage trading, one has to consider the retroactive effects that bidirectional EVs participating in the considered markets will have on market prices. As for arbitrage trading, where EVs charge when spot prices are low and discharge when spot prices are high, a flattening impact on spot prices is foreseeable. From a spot market perspective, offers of electric energy increase during times of high spot prices, and the demand for electricity increases during times of low prices, leading to higher prices when prices are low and lower prices when prices are high. These retroactive effects will lower revenue potentials if significant quantities of bidirectionally chargeable EVs participate in the markets. For quantitative evaluation of these retroactive effects, an energy system model is needed that models the supply and demand curves and thus can model price changes attributable to bidirectionally chargeable EVs. This additional research will be addressed by the BCM project in a following publication.

For an assessment of the impact of bidirectionally chargeable EVs in the markets, Table 6 shows the market volumes of considered and relevant markets and fitting EV quantities with 10 kW bidirectional charging station that would cover the market completely. Regarding the table and considering Germany's aim of 10 million EVs by 2030, the probable retroactive effect in the markets can be derived. If a significant quantity of those EVs will have a bidirectional charging station and use V2G, there will be a high impact on prices in the intraday auction, and the quarter-hourly and the hourly continuous intraday trading market. A lower retroactive effect will occur for day-ahead prices in the German spot market.

Table 6. Average market volumes and fitting EV quantities for complete covering of considered and relevant German markets.

Market	Average Market Volume in Germany 2019	EVs with 10 kW Charging Station to Completely Cover the Market
Day-ahead market	26,000 MW (EPEX Spot) [1] 58,000 MW (German demand) [2]	2.6 mil (EPEX Spot) 5.8 mil (German demand)
Quarter hourly intraday auction	800 MW [1]	80,000
Hourly continuous intraday trading	4500 MW[1]	450,000
Quarter hourly continuous intraday trading	800 MW[1]	80,000

[1] Average power trading based on data of EPEX Spot [23].

[2] Average demand calculated by net consumption in 2019 of 512 TWh [42] divided by 8760 hours.

Besides restrictions of market volumes, Section 3.2 points out the effect of V2G use cases on full cycles and operating hours of the EV’s battery storage. For the use case of arbitrage trading, there is a high increase in battery usage resulting in an accelerated ageing of the battery. Although warranties for the full cycle lifetime of battery systems increase, the additional charge on the battery will reduce the use case’s economic efficiency. However, in Section 3.2.2, we point out that both full cycles and operating hours can be decreased significantly, while revenues are still high by implementing a minimum price spread for arbitrage trading. In the BCM project, a detailed battery-ageing model is used for evaluating the impact of V2G on the battery and power electronics of the EV.

Another important restriction is the regulatory framework. Section 3.3.2 has shown the immense effect of additional charges on the profitability of the use case of arbitrage trading. It will be decisive if bidirectionally chargeable EVs are regulatory classified as a storage and if so, which additional charges will arise.

Regarding model limitations, constant values are set for the efficiencies of charging and discharging in order to achieve much faster optimization times. For arbitrage trading, charging and discharging processes usually use the highest possible power as price signals express either purchasing, selling or doing nothing. In a following publication in the BCM project, revenues of vehicle-to-home (V2H) use cases are compared by using constant and non-constant efficiencies, in which it is pointed out that modeling a non-constant efficiency for V2H use cases is necessary.

For the use case of arbitrage trading, we model revenues without perfect foresight for a rolling horizon of two to three days. The implemented market prices are real and not forecasted prices, which are used for real trading. On the other hand, it can be assumed that price forecasts over- and underestimated actual market prices to the same extent and on an average alignment with real market prices resulting in a realistic modeling of revenues for bidirectionally chargeable EVs.

Finally, for the evaluation of the economy of V2G use cases, additional costs have to be considered. The main additional hardware costs result from a bidirectional charging station. Currently, the cost for the only bidirectional charging station soon available in the German market is around 6000 € [43]. Medium-term cost projections in the project BCM for a bidirectional charging station is around 2000 €. In regard to the current stage of the BCM project, cost projections for additional hardware and operating costs are not defined, and the economic efficiency of the use cases can, therefore, not yet be evaluated.

5. Conclusions

Based on the developed aggregated storage optimization model, revenues of bidirectionally chargeable EVs have been calculated for the V2G use case arbitrage trading. As a detailed description of optimization constraints and input data are provided, readers are able to reconstruct the indicated revenues of bidirectionally chargeable EVs. The major findings of this research are:

- We developed a rolling optimization model that regards real trading times of European spot markets and allows countertrading in consecutive traded markets while considering user behavior parameters leading to a realistic representation of revenue potentials of bidirectionally chargeable EVs using arbitrage trading.
- Revenues of bidirectionally chargeable EVs are dependent on user parameters. An increase of the safety minimum SoC at the place of residence or the minimum SoC at departure leads to an exponential decrease of revenues for bidirectionally chargeable EVs.
- For a participation of bidirectionally chargeable EVs in the German spot markets in 2019, potential revenues range from 200 to 1300 €/EV/a depending on the modeled EV pool scenario under the assumption of no additional charges for purchased electricity.
- Revenues of currently available EV models participating in the day-ahead market are comparable to findings of other literature, while our research shows a significant increase in revenues for consecutive trading in all spot markets.
- The regulatory framework concerning additional charges of purchased energy is the most decisive parameter for the potential revenues of bidirectionally chargeable EVs.
- Considering additional charges amounting for example to the payments of a pumped storage facility for bidirectionally chargeable EVs results in a decrease of revenues by 50% to 60%. Thus, if V2G arbitrage trading is supposed to give flexibility

to the future energy system, the market regulator will have to exempt bidirectionally chargeable EVs from the major part of additional charges.

- Unrestricted arbitrage trading of bidirectionally chargeable EVs results in a sharp increase of full cycles and operating hours by 200 to 600 full cycles/a, respectively, by 2000 to 6000 h/a resulting in much faster battery degradation. Restricted arbitrage trading with a minimum price spread can lower this additional load for EV and EVSE. For a minimum price spread of 10 €/MWh, operating hours and full cycles decrease by 50% while revenues only decrease by 20%.
- Revenues of bidirectionally chargeable EVs differ widely depending on the electricity production structure of the energy system. European day-ahead market revenues for EV2 in 2019 range from 50 €/EV/a in Norway to 700 €/EV/a in Ireland. Modeled potential future revenues are 2 times higher in 2030 and 5 to 6 times higher in 2050 than modeled revenues in 2020.

In general, potentially high revenue opportunities are identified for bidirectionally chargeable EVs in the electricity markets. Thus, participating in V2G use cases could promote electric mobility and, thereby, provide the flexibility needed for the energy system of the future. For future profitable usage of V2G use cases, the design of the regulatory framework and battery lifetime are decisive. For further investigations, especially retroactive effects of bidirectionally chargeable EVs on market prices and resulting decrease of revenue opportunities is of interest.

6. Data Availability

The driving profile data are available in supplementary material ´input and results data\driving profiles´. The modelled future electricity prices are available in ´https://openenergy-platform.org/dataedit/view/scenario/ffe_dynamis_emission_factors_marginal_cost´.

In Section 3.1 which analyzed revenue potentials of individual EVs for German spot market prices, European day-ahead market prices and future day-ahead market prices are available in supplementary material ´input and results data\revenues_Section_3_1´.

Supplementary Materials: The following are available online at http://www.mdpi.com/1996-1073/13/21/5812/s1,
Driving Profiles data: 50 commuter and 75 non-commuter driving profiles including quarter-hourly resolved time series for location and consumption of individual EVs: http://opendata.ffe.de/dynamis-emission-factors, Revenues Section 3.1: Individual user revenues depending on driving profiles as additional data for shown aggregated revenues in Section 3.1.

Author Contributions: Conceptualization, T.K.; Data curation, T.K.; Formal analysis, T.K. and P.D.; Investigation, T.K.; Methodology, T.K. and P.D.; Software, T.K.; Validation, T.K.; Visualization, T.K.; Writing—original draft, T.K. and P.D.; Writing—review & editing, T.K., P.D. and S.v.R. All authors have read and agreed to the published version of the manuscript.

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Appendix A

Table A1. List of time-dependent variables of the storage equation and their respective limit values.

Time-dependent Variables		Minimum Value	Maximum Value
State of charge	SoC	SoC_{min}	SoC_{max}
Charging power	P_{charge}	$P_{charge,min}$	$P_{discharge,max}$
Discharging power	$P_{discharge}$	$P_{discharge,min}$	$P_{discharge,max}$
Discharging boolean	b_{charge}	0	1
Charging boolean	$b_{discharge}$	0	1
Counter purchase power	$P_{counter-purchase}$	0	$\mathrm{P}_{schedule,sale}$
Counter sale power	$P_{counter-sale}$	0	$\mathrm{P}_{schedule,purchase}$
Counter purchase boolean	$b_{counter-purchase}$	0	1
Counter sale boolean	$b_{counter-sale}$	0	1
Supplementary power	$P_{supplement}$	0	∞
Fast charging power	$P_{fastcharge}$	0	∞

Appendix B

Influence of Forecast Period

For modeling realistic revenues of bidirectionally chargeable EVs, a rolling, limited time horizon is implemented. The selected limited time horizon is important for two reasons. Firstly, market prices are perfectly forecasted, which leads to a perfect EV charging strategy for the considered time horizon. As an example, if there are very low prices 10 days ahead of the starting point, the EV may shift its charging in the future. In reality, the low prices may depend on renewable energies that cannot be forecast 10 days in advance accurately. Secondly, EV driving behavior is perfectly forecast. In reality, regular driving (e.g., commuting to work) can be predicted most of the time, whereas more spontaneous driving (e.g., for free time activities) is much more uncertain. In this regard, it is hard to declare a realistic horizon for forecasting in the model.

The upper diagram in Figure A1 illustrates the effect of an adapted forecasting period on revenue potentials of bidirectionally chargeable EVs with no additional charges on purchased energy. Starting from a forecast horizon of ten days going down to four days, there is no change in revenues. A shorter forecast period results in slightly decreased revenues, but the impact of the forecast period on revenues is very low. This is mainly due to daily characteristics of the electricity price. Price spreads are used to charge with low prices and discharge with high prices with just a slight dependence on future departures or future electricity prices. Depending on the regulatory framework, additional charges can arise for purchased energy. The bottom diagram shows the effect of a varied forecast horizon on the revenues with additional charges of 100 €/MWh on purchased energy. There is huge decrease of revenues even resulting in negative revenues for short forecast periods, since EVs often do not know a future departure and consequently discharge although the future charging price is much higher. Only for forecast periods of 7 days and longer are revenues relatively stable compared to a horizon of 10 days.

The forecast horizon is mainly applied to prevent unrealistic future trading after the optimized period that is remunerated. For simulations with no additional charges, the rolling optimization is still necessary as it allows consideration of real sequential market trading. Consequently, for investigations in this paper a short forecast period of one day is defined. For an evaluation of the regulatory framework in Section 3.3.2, a longer forecast period of seven days is applied to prevent unrealistic discharging although charging prices are higher.

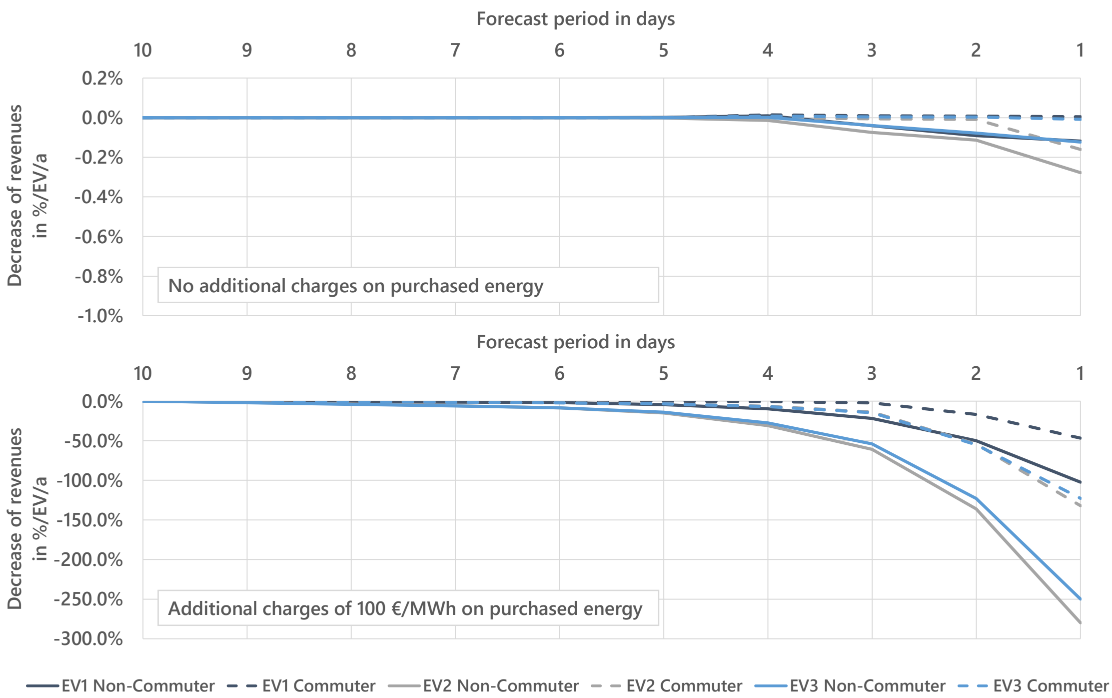
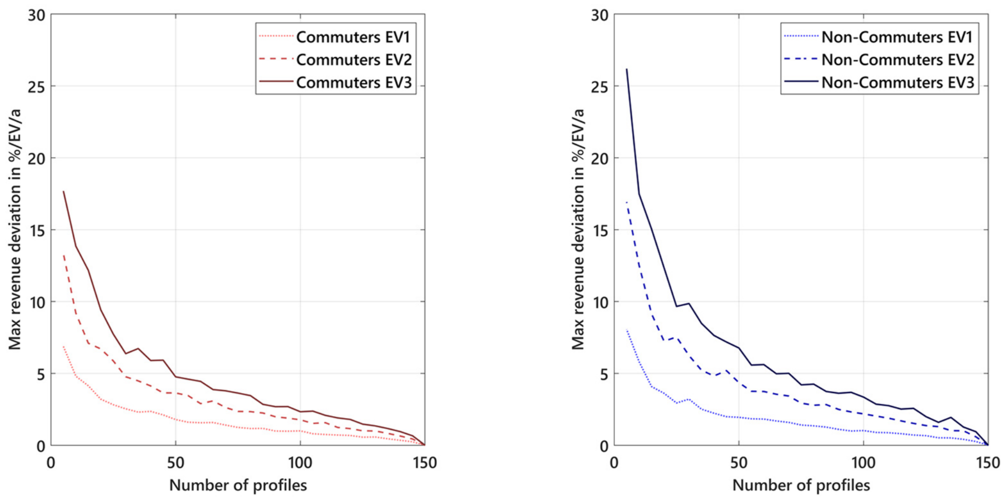


Figure A1. Influence of forecasting horizon on revenue potentials of bidirectionally chargeable EVs for the use cases of arbitrage trading with no additional charges (top) and additional charges of 100 €/MWh (bottom) on purchased energy.

Appendix C

Determination of a Realistic Pool Size

The modeling of a realistic vehicle pool is characterized by the EV pool size. The revenue potential of bidirectional charging of a single vehicle depends strongly on the individual driving profile of the user. In order to show a meaningful average revenue potential for different EV pool groups, a relevant number of vehicles must be determined for the model calculations. As computational time is linearly dependent on the number of profiles considered, a trade-off has to be faced. The aim of the investigations is to identify a pool size at which the addition of further vehicles has a low influence on revenues compared to the higher computational time. For all evaluated EV pool scenarios, the revenue potential on the German day-ahead market in 2019 was investigated for different pool sizes. For 5 to 150 profiles, a random drawing of 50,000 profile groups leads to a statistically significant analysis. Figure A2 shows the maximum revenue deviation for different numbers of profiles compared to the best case of 150 profiles. The maximum number of individual profiles is 150 in order to limit computational time. If all 150 profiles are drawn, there will be no revenue deviation to the best case of 150 profiles.



(a) (b)

Figure A2. Maximum revenue deviation for a varying number of profiles compared to the best case of 150 profiles for a drawing of 50,000 EV profile groups for commuters (a) and non-commuters (b).

The more vehicles that are modeled, the less is the maximum revenue deviation. A relevant pool size for the EV pool scenarios can be determined by the revenue difference falling below a defined threshold value. A maximum deviation of less than 5% per vehicle per year is assumed to be sufficiently accurate while limiting computational time. This results in a relevant pool size of 50 vehicles for a commuter EV pool. A representative non-commuter EV pool needs a number of 75 vehicles. Revenues of non-commuters are more heterogenic than revenues of commuters because commuters have a more regular driving profile during weekdays.

Appendix D

Table A2. Revenues, full cycles and operating hours for all EV scenarios (difference of bidirectional charging to smart charging) with restricted minimum price spread.

EV1—Commuter						
Minimum Price spread in €/MWh	Revenues in €/EV/a	Full Cycles per Year	Operating Hours per Year	Average Price Spread in €/MWh	Revenue/ Full Cycle in €/Full Cycle	Revenue/ Operating Hour in €/Operating Hour
0	125.1	231.0	1898	14.2	0.54	0.07
5	117.7	166.7	1363	18.6	0.71	0.09
10	97.8	102.9	841	25.0	0.95	0.12
15	75.5	60.4	494	32.9	1.25	0.15
20	59.7	38.7	319	40.6	1.54	0.19
25	46.2	25.6	210	47.4	1.80	0.22
30	37.1	18.6	153	52.6	2.00	0.24
35	27.7	13.1	109	55.7	2.12	0.25
40	17.2	8.0	67	56.8	2.16	0.26
45	6.6	2.8	24	62.9	2.39	0.27
50	2.7	0.9	7	77.2	2.93	0.35

EV1—Non-Commuter						
Minimum Price Spread in €/MWh	Revenues in €/EV/a	Full Cycles per Year	Operating Hours per Year	Average Price Spread in €/MWh	Revenue/ Full Cycle in €/Full Cycle	Revenue/ Operating Hour in €/Operating Hour
0	173.3	324.2	2737	14.1	0.53	0.06
5	162.5	226.7	1911	18.9	0.72	0.08
10	135.6	139.5	1173	25.6	0.97	0.12
15	107.1	85.0	712	33.2	1.26	0.15
20	86.1	56.1	472	40.4	1.54	0.18
25	68.7	38.8	327	46.6	1.77	0.21
30	56.5	29.0	245	51.3	1.95	0.23
35	44.2	22.1	189	52.7	2.00	0.23
40	33.7	16.5	140	53.9	2.05	0.24
45	19.9	10.1	87	51.9	1.97	0.23
50	10.8	5.5	48	51.4	1.95	0.23

EV2—Commuter

Minimum Price Spread in €/MWh	Revenues in €/EV/a	Full Cycles per Year	Operating Hours per Year	Average Price Spread in €/MWh	Revenue/ Full Cycle in €/Full Cycle	Revenue/ Operating Hour in €/Operating Hour
0	296.1	211.4	3963	14.0	1.40	0.07
5	278.2	150.5	2819	18.5	1.85	0.10
10	236.1	96.8	1815	24.4	2.44	0.13
15	187.3	59.9	1123	31.3	3.13	0.17
20	152.5	41.3	766	37.0	3.70	0.20
25	125.0	30.3	561	41.3	4.13	0.22
30	102.1	23.5	434	43.4	4.34	0.24
35	77.2	17.5	322	44.0	4.40	0.24
40	50.3	11.9	216	42.3	4.23	0.23
45	22.9	5.2	93	44.3	4.43	0.25
50	8.6	1.6	30	52.9	5.29	0.29

EV2—Non-Commuter

Minimum Price Spread in €/MWh	Revenues in €/EV/a	Full Cycles per Year	Operating Hours per Year	Average Price Spread in €/MWh	Revenue/ Full Cycle in €/Full Cycle	Revenue/ Operating Hour in €/Operating Hour
0	383.4	270.7	5113	14.2	1.42	0.07
5	361.0	192.5	3645	18.8	1.88	0.10
10	307.0	125.4	2383	24.5	2.45	0.13
15	245.0	78.7	1498	31.1	3.11	0.16
20	200.7	55.2	1045	36.4	3.64	0.19
25	167.5	41.9	795	40.0	4.00	0.21
30	142.8	34.5	654	41.5	4.15	0.22
35	117.1	28.5	541	41.0	4.10	0.22
40	88.6	22.8	429	38.9	3.89	0.21
45	58.5	15.9	299	36.8	3.68	0.20
50	34.7	9.3	174	37.3	3.73	0.20

EV3—Commuter

Minimum Price Spread in €/MWh	Revenues in €/EV/a	Full Cycles per Year	Operating Hours per Year	Average Price Spread in €/MWh	Revenue/ Full Cycle in €/Full Cycle	Revenue/ Operating Hour in €/Operating Hour
0	451.2	301.4	2994	15.0	1.50	0.15
5	430.6	227.5	2243	18.9	1.89	0.19
10	369.2	151.5	1487	24.4	2.44	0.25
15	290.4	92.4	898	31.4	3.14	0.32
20	231.8	60.6	582	38.3	3.83	0.40
25	187.6	42.6	402	44.0	4.40	0.47
30	152.0	31.9	297	47.7	4.77	0.51
35	123.6	24.5	227	50.4	5.04	0.54
40	85.1	17.1	156	49.8	4.98	0.55
45	41.7	8.5	75	49.2	4.92	0.55
50	16.7	2.8	25	59.1	5.91	0.66

EV3—Non-Commuter

Minimum Price Spread in €/MWh	Revenues in €/EV/a	Full Cycles per Year	Operating Hours per Year	Average Price Spread in €/MWh	Revenue/ Full Cycle in €/Full Cycle	Revenue/ Operating Hour in €/Operating Hour
0	574.6	397.5	3979	14.5	1.45	0.14
5	545.8	291.1	2913	18.8	1.88	0.19
10	466.9	191.4	1916	24.4	2.44	0.24
15	370.3	118.3	1188	31.3	3.13	0.31
20	298.4	79.2	795	37.7	3.77	0.38
25	243.9	56.8	568	42.9	4.29	0.43
30	202.6	44.2	444	45.9	4.59	0.46
35	171.8	36.2	365	47.5	4.75	0.47
40	132.8	28.4	287	46.7	4.67	0.46
45	92.3	20.7	211	44.6	4.46	0.44
50	56.0	12.7	128	44.1	4.41	0.44

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Publication 2 (Pub2): Revenue opportunities by integrating combined vehicle-to-home and vehicle-to-grid applications in smart homes

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Abstract: A smart integration of electric vehicles (EVs) in the future energy system will be crucial in decarbonizing the energy sector. Bidirectional EVs can provide flexibility for the system and generate revenues for the user through multiple use cases. We model both exclusive photovoltaic (PV) self-consumption optimization and the combined usage of PV self-consumption optimization and arbitrage trading for a household with an unmanaged, smart, and bidirectional charging EV in a linear (LP) and mixed-integer linear programming (MILP). Since power flows in a typical household are low, varying non-linear charging and discharging efficiencies of the bidirectional EV in the MILP result in more realistic revenues that are 30% lower than in the LP with fixed efficiencies. For a typical German household using a bidirectional EV for optimizing PV self-consumption, these revenues are about 310 €/a, mostly generated during the summer. Arbitrage trading well complements this vehicle-to-home use case in the winter months, resulting in revenues up to 530 €/a. These significant revenue potentials can lead to more profitable and interactive EVs incentivizing users to change from internal combustion vehicles to electric mobility.

Keywords: PV self-consumption optimization; arbitrage trading; bidirectional electric vehicles; V2G; V2H

Nomenclature

Abbreviations		$p_{el,\mathrm{sell},v2g}$	electricity selling prices for V2G
BCM	bidirectional charge management	$P_{EV,l,const,c/d}$	constant charging/discharging losses
BCM	Bidirectional Charging Management (project)	$P_{EV,l,const,st}$	constant standby losses of EV and EVSE
COM	commuter	$P_{HH,el}$	electrical household demand
EFC	equivalent full cycle	$P_{HH,th}$	thermal household demand
EV	electric vehicle	P_{PV}	PV generation
EVSE	electric vehicle supply equipment	SoC_{dep}	minimum SOC at departure
GCP	grid connection point	SoC_{safe}	minimum SOC when connected
HP	heat pump	t	timestep
LP	linear programming	T	total timesteps
MILP	mixed-integer linear programming	x	start timestep of V2G interval
OH	operating hour	y	end timestep of V2G interval

SBS	stationary battery storage		
SoC	state of charge	*Variables*	
V2B	vehicle-to-business	$\boldsymbol{b_{EV,c}}$	boolean variable if EV is charging
PV	photovoltaic		
V2G	vehicle-to-grid	$\boldsymbol{b_{EV,d}}$	boolean variable if EV is discharging
V2H	vehicle-to-home	$\boldsymbol{E_{EV}}$	charge level of EV battery
		$\boldsymbol{E_{EV,pub,c}}$	public charging energy
Parameters		$\boldsymbol{P_{EV,c}}$	charging power of EV
$\boldsymbol{b_{EV,dep}}$	timeseries if EV is departing	$\boldsymbol{P_{EV,d}}$	discharging power of EV
$\boldsymbol{C_{connected}}$	timeseries if EV is connected to the EVSE	$\boldsymbol{P_{EV,l,c}}$	charging losses of EV
$\boldsymbol{E_{EV,drive}}$	EV consumption while driving	$\boldsymbol{P_{EV,l,d}}$	discharging losses of EV
$\boldsymbol{m_c}$	gradient of charging losses	$\boldsymbol{P_{EV,l,s}}$	standby losses of EV and EVSE
$\boldsymbol{m_d}$	gradient of discharging losses	$\boldsymbol{P_{GCP,in}}$	power from grid
$\boldsymbol{n_c}$	minimum charging losses	$\boldsymbol{P_{GCP,in,v2g}}$	power from grid as V2G process
$\boldsymbol{n_d}$	minimum discharging losses	$\boldsymbol{P_{GCP,out}}$	power to grid
$\boldsymbol{\eta_{EV,roundtrip,max}}$	maximum roundtrip efficiency of EV	$\boldsymbol{P_{GCP,out,v2g}}$	power to grid as V2G process
$\boldsymbol{\eta_{SBS,roundtrip}}$	roundtrip efficiency of SBS	$\boldsymbol{P_{HP,el}}$	power consumption of heat pump
$\boldsymbol{p_{el,buy}}$	electricity purchase prices for household	$\boldsymbol{P_{PV,curt}}$	curtailment of PV generation
$\boldsymbol{p_{el,buy,v2g}}$	electricity purchase prices for V2G	$\boldsymbol{P_{SBS,c}}$	charging power of SBS
$\boldsymbol{p_{el,sell}}$	feed-in tariff	$\boldsymbol{P_{SBS,d}}$	discharging power of SBS

1. Introduction

The electrification of mobility is often considered an essential component in combatting climate change. While CO_2 emissions in the German energy sector have decreased sharply, because of the strong expansion of renewable energies, emissions in the transport sector have remained roughly the same as they were in 1990 [1]. Coupling of the energy and mobility sectors is seen as a major opportunity for reducing emissions in the transport sector, with electric mobility playing a key role [2]. The German government has introduced some subsidies, e.g. for private individuals purchasing electric cars, to increase the share of electric vehicles (EVs) on German roads [3]. Nevertheless, the target of one million registered electric vehicles in Germany by 2020 was missed. A survey by the German Association of Energy and Water Industries found that the high investment costs for an EV are the main argument against switching to electromobility [4]. If the economic viability of EVs could be increased, it would provide an additional incentive for citizens to purchase an electric vehicle.

Here, one possibility is use of bidirectional charging technology. In contrast to unidirectional charging systems, bidirectional charging systems not only allow energy to be drawn from the grid or a generation plant to charge the electric vehicle, but they also allow the energy from the vehicle to be fed back in a smart form. Therefore, during periods of inactivity, the vehicles can also be used in a manner analogous to a stationary battery storage (SBS) [5]. In vehicle-to-grid (V2G) applications, bidirectionally chargeable EVs can contribute to grid stability in a system-serving manner [6] while offering economic benefits for EV owners [7].

Similarly, vehicle-to-home (V2H) use cases offer the benefit of optimized use of locally generated renewable energy while also providing revenue opportunities; here some studies have already addressed the profitability of bidirectional charging. Salpakari et al. show that smart and bidirectional charging can save 8-33% of annual electricity costs compared to an unmanaged charging strategy in a household fitted with a photovoltaic (PV) system in

Sweden. The additional cost savings from vehicle-to-microgrid are small if battery degradation costs are taken in consideration [8]. Chen et al. study energy use optimization strategies without and with V2H for a household with a PV system in Shanghai, taking into consideration time-varying electricity tariffs with high and low tariff time windows. They show that economic benefits can be achieved for the household in all use cases. PV tariff, weather, and EV driving behavior are the key influencing factors here [9]. Erdinc et al. compare bidirectional charging and unmanaged charging for both V2H and V2G use cases for a household with a small PV system in Portugal, again using time-varying tariffs. In their calculations, they obtain a cost reduction potential of up to 48% by limiting power at peak times and up to 63% for time-variable tariffs by bidirectional charging compared to unmanaged charging [10]. Kataoka et al. evaluate the effect of V2H applications on the economic and environmental performance of a typical household in Japan. They find that V2H can be economically and environmentally more beneficial than SBSs, but results differ between commuters and non-commuters. For future work, they suggest further sensitivity analysis, e.g. regarding the size of EV battery or EV charge and discharge power [11]. The cost-effectiveness of a V2H system in Germany is investigated by Cacilo et al.. Yet, no economic evaluation of the vehicle's bidirectional capability, only smart charging, is performed [12]. Keiner et al. analyze smart homes for an average German single-family household including heat pumps (HPs), thermal energy storage systems, SBSs and EVs and find that V2H can assume the role of an SBS [13]. However, they largely focus on different thermal energy storages scenarios and not different EV charging strategies. The above-mentioned studies model fixed charging and discharging efficiencies and thus neglect energy losses resulting from low-powered, ineffective charging and discharging processes in V2H use cases [14]. Further, there is a lack of in-depth research in the literature investigating the influence of different household component set-ups on cost reduction potentials through the use of smart or bidirectional charging EVs.

Regarding V2G use cases, there are numerous papers that deal with the revenue potentials of EVs participating in the spot market [15]. Smart charging optimized by electricity prices can reduce charging costs [16], [17] and bidirectional charging can further reduce these costs or even generate revenues [18]. None of the studies mentioned deal with V2H use cases complementing arbitrage trading in spot markets. Since arbitrage trading often results in lots of operating hours (OHs) and equivalent full cycles (EFCs) of the battery [19], the temporary replacement by V2H use cases could reduce the battery ageing effect.

In this paper, we address the aforementioned research gaps by modeling V2H use cases exclusively with and without varying charging and discharging efficiencies. This novel evaluation of more realistic modeling of V2H as mixed-integer linear programming (MILP) with varying efficiencies versus modeling of V2H as linear programming (LP) with fixed efficiencies is necessary to assess whether MILP with varying efficiencies is beneficial or even necessary for V2H analyses. For this purpose, an optimization model is developed that optimizes the electric power flows of a household with the objective of minimizing electricity costs while taking technical restrictions into account. Three different charging strategies are compared regarding household energy flows: an unmanaged charging strategy, a smart charging strategy and a bidirectional charging strategy. The V2H revenue potentials are shown based on the influencing factors of PV size and PV feed-in tariff, household size, household components, EV size, maximum charging power and maximum operating hours. Finally, we model a combined application of V2H and V2G arbitrage trading to show differences and benefits on the electricity costs of a household. This combined, novel modeling of V2H and V2G can realistically combine the seasonally different revenue opportunities of the use cases and shows that a separate modeling of a V2H or V2G use case can underestimate the revenue opportunities. The investigations are embedded in the project 'Bidirectional charging management' (BCM) that analyzes the technical, economic, and regulatory issues of bidirectional charging [5].

2. Methodology

The methodological approach for investigating V2H use cases of bidirectional EVs is divided into two parts: first, we present the optimization model for considering V2H cases exclusively. Then, the combined modeling of V2H and V2G is outlined.

We developed an optimization model in order to assess revenue potential efficiently and accurately in the area of V2H applications. The model determines the best possible charging strategy for one or multiple EVs connected via a grid connection point (GCP) with multiple optional other components. This approach allows a wide range of different analyses, including V2H, V2G and V2B use cases. Figure 1 shows a schematic of the model structure. As displayed, the model structure *eFlame* (electric Flexibility assessment modeling environment) itself consists of two sub-models. Firstly, the household profile generator, where the electrical and thermal consumption of a specific household are modeled based on parameterization of the household and user behavior, modeling as well appropriate EV driving profiles [20]. Secondly, the optimization model *ResOpt* (Residential Optimizer) formulates the objective function and constraints of variable defined components.

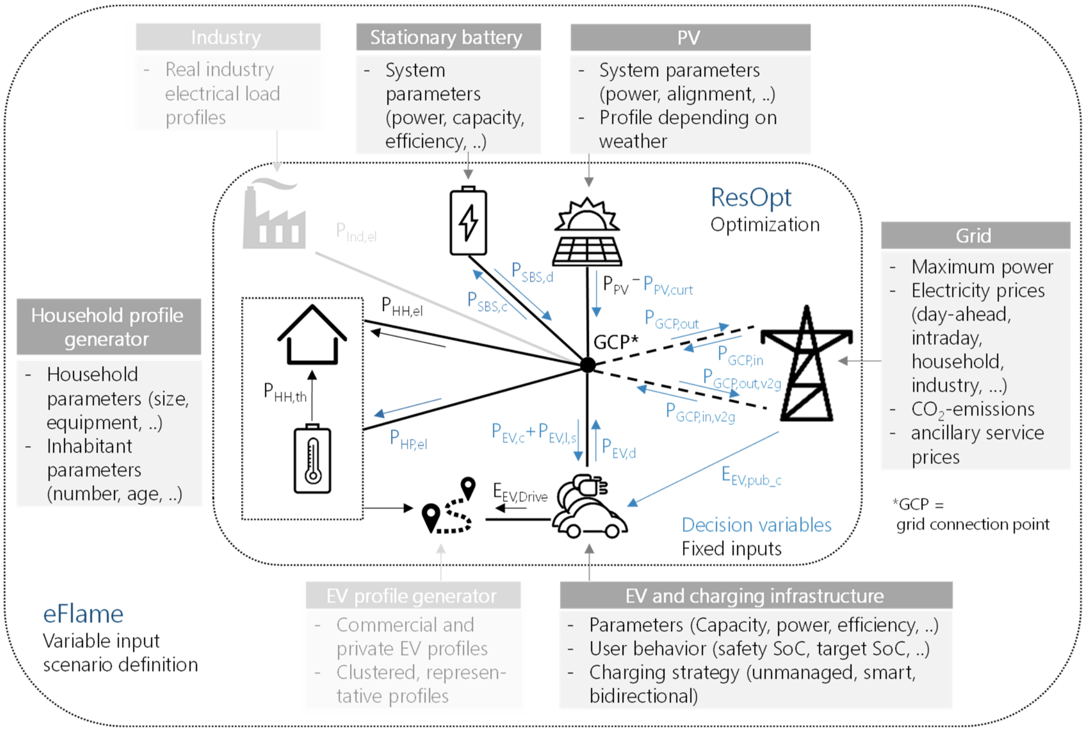

Figure 1: Schematic representation of the developed optimization model for use cases of bidirectional charging

The model ResOpt comprises several decision variables, the values of which are set for each time step in the course of the optimization: SBS charging $P_{SBS,c}$ and discharging $P_{SBS,d}$, PV curtailment $P_{PV,curt}$, HP demand $P_{HP,el}$, EV charging $P_{EV,c}$, discharging $P_{EV,d}$ and standby losses $P_{EV,l,s}$ as well as power from grid $P_{GCP,in}$ and power to grid $P_{GCP,out}$. For the combined modeling of V2H and V2G use cases (Section 2.2), we integrate the decision variables $P_{GCP,in,v2g}$ and $P_{GCP,out,v2g}$ that represent power from and to the grid that is additionally constrained. A fixed thermal $P_{HH,th}$ and electrical $P_{HH,el}$ household demand is provided as well as the fixed PV generation P_{PV}.

2.1. Modelling of V2H applications with fixed and varying efficiencies

The objective of V2H optimization is to minimize the household's electricity costs, which is expressed in the objective function in Equation 1. The German household's electricity costs to be minimized consist of the purchase costs $p_{el,buy}$ multiplied by the purchased power $P_{GCP,in}$ minus the feed-in tariff $p_{el,\text{sell}}$ multiplied by the power $P_{GCP,out}$, which is fed into the grid if an electricity generator is present, over all time steps t.

$$min\left(\sum_{t=1}^{T}\left[p_{el,buy}(t)\cdot P_{GCP,in}(t)-p_{el,\text{sell}}(t)\cdot P_{GCP,out}(t)\right]\right) \tag{1}$$

Relevant constrains are implemented for the household's grid connection point, the EV and other optional components. We refrain from a detailed description of the constraints for optional components such as SBS or HP at this point. Most importantly, the power fed into the grid or supplied from the grid must equal the sum of power generated and consumed within the boundaries of the system at any time:

$$P_{GCP,in}(t) - P_{GCP,out}(t) = P_{HH,el}(t) + P_{HP,el}(t) - P_{PV}(t) + P_{PV,curt}(t) \\ +P_{SBS,c}(t) - P_{SBS,d}(t) + P_{EV,c}(t) - P_{EV,d}(t) + P_{EV,l,st}(t) \quad (2)$$

Standby losses $P_{EV,l,st}(t)$ represent constant losses of the inverter and EV $P_{EV,l,const,st}$, which occur when the EV is connected $C_{connected}(t)$ at the household's charging point (electric vehicle supply equipment, EVSE) and is neither charging $b_{EV,c}(t)$ nor discharging $b_{EV,d}(t)$.

$$P_{EV,l,st}(t) = P_{EV,l,const,st} \cdot [C_{connected}(t) - b_{EV,c}(t) - b_{EV,d}(t)] \quad (3)$$

To account for such losses, the connection status $C_{connected}$(t) (a time series which is 1 if the EV is connected and 0 if it is not connected) and the discrete boolean variables $b_{EV,c}$ (1 if charging, otherwise 0) and $b_{EV,d}$ (equals 1 if discharging, else 0) are used. Thus, standby losses can only be included for MILP.

Another relevant constraint concerns the electric energy stored in an EV at time t, which is determined by Equation 4.

$$E_{EV}(t) = E_{EV}(t-1) + [P_{EV,c}(t) - P_{EV,l,c}(t)] \cdot \Delta t + E_{EV,pub,c}(t) \\ -E_{EV,drive}(t) - [P_{EV,d}(t) + P_{EV,l,d}(t)] \cdot \Delta t - P_{EV,l,const,c/d} \cdot [b_{EV,c}(t) + b_{EV,d}(t)] \cdot \Delta t \quad (4)$$

Here, energy losses affecting the EV's state of charge (SoC) occur during charging and discharging. Again, to maintain linear programming (LP) optimization, constant losses $P_{EV,l,const,c/d}$ would have to be neglected and charging $P_{EV,l,c}$ and discharging $P_{EV,l,d}$ losses modeled in proportion to charging and discharging power. As the EVSE in the case of bidirectional charging contains an additional inverter converting alternating current (AC) into direct current (DC) if charging and DC to AC if discharging, EVSE losses for bidirectional charging are modeled as variable over time in our work.

For this purpose, we draw on mathematical descriptions of the inverter efficiency deduced in [21], where inverter power losses are expressed as a quadratic function of the corresponding output power. By rearranging the respective equations as described in Appendix A, the inverter losses can be stated as functions of the AC-side power for both charging and discharging processes. As implementation of these non-linear loss functions directly resulted in unacceptably long computation times, we adopted a linear approximation approach. We linearized the power losses equations for charging and discharging by linear regression (method of least squares) as suggested by [22] in a similar context, which results in a linear system of equations:

$$P_{EV,l,c}(t) = m_c \cdot P_{EV,c}(t) + n_c \cdot b_{EV,c}(t) \quad (5)$$

$$P_{EV,l,d}(t) = m_d \cdot P_{EV,d}(t) + n_d \cdot b_{EV,d}(t) \quad (6)$$

Here, $m_{c/d}$ is the gradient of the function and $n_{c/d}$ represents the minimum losses at zero power.

By dividing the possible range of charging and discharging power into a number of equally large intervals and applying the method of least squares to each interval individually, the residual sum of squares can be reduced to improve accuracy. Hence, we conducted preliminary simulations to determine a suitable number of intervals for sufficiently high accuracy with acceptable computation time. The resulting deviations obtained when linearizing power losses for zero, one, or two intervals are presented in Table 1 (sum of constant EV losses and varying inverter losses), where zero losses correspond to constant losses. Since respective variations of efficiency are small in any case apart from the simulations with zero intervals, we implemented linearized functions of inverter power losses for both charging and discharging for a single interval $\left[0; P_{EV,c/d,max}\right]$ based on real inverter data to limit the complexity of the optimization problem.

Table 1: Deviation between real and linearized losses and efficiencies for a 11 kW EVSE

	Charging process			Discharging process		
Number of intervals	0 (LP)	1	2	0 (LP)	1	2
Maximum deviation of power losses	250 W	42 W	10 W	250 W	55 W	14 W

Additional constraints are related to the EV's SOC. If an EV is connected at the household's EVSE, the minimum amount of energy, represented by SoC_{safe}, must be reached at all times, which is ensured by Equation 7. Here, $E_{EV,max}$ is the maximum amount of energy to be stored in the EV (i.e. the battery's capacity). Equation 8 guarantees that at the time of departure, which must be set when arriving at the household, a fixed minimum amount of energy, represented by SoC_{dep}, is stored in the EV's battery. To do so, $b_{EV,dep}$ is introduced, which is 1 if t is the time of departure. Otherwise, $b_{EV,dep}$ equals 0.

$$E_{EV}(t) \geq SoC_{safe} \cdot E_{EV,max} \cdot C_{connected}(\mathrm{t}) \tag{7}$$

$$E_{EV}(t) \geq SoC_{dep} \cdot E_{EV,max} \cdot b_{EV,dep}(t) \tag{8}$$

Optional features of the model are the limitation of the EV battery's number of EFCs or the EV's OHs per day, which can be used to reduce battery aging or respectively the wear of the EV's power electronics. Equation 9 limits the maximum EFCs (EFC_{max}) and Equation 10 the average maximum OHs per day ($\mathrm{OH}_{max,day}$). Since OHs are related to the boolean variables $b_{EV,c}$ and $b_{EV,d}$, Equation 10 can only be used for MILP.

$$EFC_{max} \geq \frac{\sum_{t=1}^{T}([P_{EV,c}(t) - P_{EV,l,c}(t)] \cdot \Delta t + E_{EV,pub,c}(t))}{E_{EV,max}} \tag{9}$$

$$\mathrm{OH}_{max,day} \geq \frac{\sum_{t=1}^{T}[b_{EV,c}(t) + b_{EV,d}(t)]}{T} \cdot 24 \tag{10}$$

2.2. Modelling of combined V2H and V2G applications

Adding V2G arbitrage trading to the model leads to several adaptions in the objective functions and constraints of the optimization problem. The regulatory framework for arbitrage trading is not yet defined for bidirectionally chargeable EVs at the European Union level [23]. Since power purchased and sold through arbitrage trading by SBS is exempted from multiple duties and taxes [24], we assumed this exemption for V2G such that modeled V2G prices differ from the normal household prices for purchased and feed-in energy. Therefore, the objective function is expanded in Equation 10 by the costs and revenues of the V2G component, considering V2G prices $p_{el,buy,V2G}(t)$ and $p_{el,\mathrm{sell},V2G}(t)$, and V2G power $P_{GCP,in,v2g}(t)$ and $P_{GCP,out,v2g}(t)$.

$$min\left(\sum_{t=1}^{T}\begin{bmatrix} p_{el,buy}(t)\cdot P_{GCP,in}(t)-p_{el,\mathrm{sell}}(t)\cdot P_{GCP,out}(t)+ \\ p_{el,buy,v2g}(t)\cdot P_{GCP,in,v2g}(t)-p_{el,\mathrm{sell},v2g}(t)\cdot P_{GCP,out,v2g}(t)\end{bmatrix}\right) \tag{10}$$

The energy purchased $P_{V2G,in}(t)$ and feed-in $P_{V2G,out}(t)$ is added to the power balance of the household grid connection point in Equation 11.

$$\begin{aligned} &P_{GCP,in}(t)- P_{GCP,out}(t) + P_{GCP,in,v2g}(t)- P_{GCP,out,v2g}(t) = P_{HH,el}(t)+P_{HP,el}(t)-P_{PV}(t) \\ &+P_{PV,curt}(t)+P_{SVS,c}(t)-P_{SBS,d}(t)+P_{EV,c}(t) - P_{EV,d}(t)+P_{EV,l,st}(t)\end{aligned} \tag{11}$$

In contrast to a SBS, bidirectionally chargeable EVs consume electricity by driving and thus charging and discharging energy do not balance. Since V2G electricity prices will only be exempted from multiple duties and taxes if the same amount of purchased energy is fed back into the grid at a different time, we add constraints to the V2G powers in Equation 12. The purchased energy $sum\left(\sum_{t=1}^{T}\left[P_{GCP,in,v2g}(t)\right]\right)$ equals the fed-in energy $sum\left(\sum_{t=1}^{T}\left[P_{GCP,out,v2g}(t)\right]\right)$ divided by the maximum V2G roundtrip efficiency $\eta_{EV,roundtrip,max}$, because losses of a V2G roundtrip are included in the exemption from additional electricity charges [24]. The roundtrip efficiency refers to the charging and discharging efficiency of the bidirectionally chargeable electric vehicle (from AC to AC). The timeframe of the power equation *t*=*x* to *y* can be set variable depending on the regulatory framework of the considered household.

$$\left(\sum_{t=\mathrm{x}}^{y}\left[P_{GCP,in,v2g}(t)\right]\right) = \left(\sum_{t=\mathrm{x}}^{y}\left[P_{GCP,out,v2g}(t)\right]\right)/\eta_{EV,roundtrip,max} \tag{12}$$

To ensure that the purchased and fed-in energy is associated with the EV and not a different component of the household, we add Equations 13 and 14. Purchased energy $P_{GCP,in,v2g}(t)$ has to be lower than charged electricity $P_{EV,c}(t)$. In addition, fed-in energy $P_{GCP,out,v2g}(t)$ must be lower than discharging of the EV $P_{EV,d}(t)$.

$$P_{GCP,in,v2g}(t) <= P_{EV,c}(t) \tag{13}$$

$$P_{GCP,out,v2g}(t) <= P_{EV,d}(t) \tag{14}$$

Finally, considering a household with PV generation leads to possibilities of misuse when V2G energy is exempted from duties and taxes. In such a case, PV energy could first be charged into the EV and later be discharged into the grid as a V2G process (duties and taxes exemptions). As the EV is allowed to purchase the corresponding amount of energy described in Equation 12 as a V2G process, such an EV could purchase energy at a different time which would replace purchases of energy at household electricity prices. In this way, as much PV energy as desired can be fed through the EV into the grid in order to purchase the corresponding amount of energy at much lower prices at a different time. To prevent this effect, only V2H or V2G may be performed within a set period. Equations 15 and 16 constrain the optimization problem for a V2G time frame. If boolean variable b_{V2G} is set to 0 for a time interval t = *x* to *y*, V2G is not allowed. If b_{V2G} is set to 1, discharged energy of the EV must be fed to the grid and is not allowed to be fed to the household. Thus, V2H self-consumption optimization is not allowed for the respective time interval.

$$P_{GCP,out,v2g}(t) <= b_{EV,v2g}\cdot P_{EV,d,max} \tag{15}$$

$$P_{EV,d}(t) \leq P_{GCP,out,v2g}(t) + (1 - b_{EV,v2g}) \cdot P_{EV,d,max} \tag{16}$$

with $b_{EV,v2g} = [0,1]$ for time interval t = x to y

3. Results

Every scenario study includes three EV operation strategies: unmanaged charging, smart charging, and bidirectional charging. Revenues of a bidirectional or smart charging strategy are always compared to the reference of unmanaged charging.

3.1. Input data and set-up of average household scenario

To evaluate the economic viability of the use case 'self-consumption optimization' by bidirectional electric vehicles, a medium-sized single-family house (150 m² living space) is defined, which is subsequently referred to as the base scenario. Table 1 shows the main characteristics of the household and potential additional components. These optional components include a PV system, an EV, a SBS and a HP. Table 2 shows the parameterization of these components, additional input for their modeling, and the associated references. Prices and profiles are based on data from the year 2018.

Concerning the household profiles, Appendix B shows that 20 discrete profiles are sufficient to represent average revenues of a household class. Therefore, 20 profiles are used below, having on average the characteristics shown in Table 2. We focus on EVs that are used by non-commuters, since approximately 75% of EVs in Germany are non-commuting EVs [25], but show the revenues for a commuting EV as a sensitivity in chapter 3.2.

Table 2: Relevant parameterization of elements connected to the household

Element	Parameter	Value	Additional Input
Household	$\sum P_{HH,el}$ $\sum P_{HH,th}$	3800 kWh (yearly)* 9000 kWh (yearly)*	Load profile* Load profile*
Grid	$p_{el,buy}$	29.9 ct/kWh [26]	
PV system	$P_{PV,max}$ $\sum P_{PV}$ $p_{el,\mathrm{sell}}$	5.5 kWp*** 6200 kWh (yearly) 11.6 ct/kWh [27]	Generation profile**** based on [28]
EV	$P_{EV,c,max}$ $P_{EV,d,max}$ $E_{EV,max}$ $\eta_{EV,roundtrip,max}$ Annual mileage EV consumption (including charge losses)	11 kW** 11 kW** 60 kWh***** 85%** 10,000 km* 22 kWh/100 km**	Driving profile*
EV user	User type SoC_{safe} SoC_{dep}	Non-Commuter 20%** 70%**	
SBS	$P_{SBS,c,max}$ $P_{SBS,d,max}$ $E_{SBS,max}$ $\eta_{SBS,roundtrip}$	2.8 kW 2.8 kW 5.5 kWh****** 88%	

*Average load value, annual driving, load profile and driving profile are output from household profile generator [20] and provided in supplementary material
**Based on specifications of BCM project [5]
***Calculated by usable roof space multiplied by specific energy 0.15 kWp/m^2 [31]
****Provided in supplementary material
*****E.g. Volkswagen ID.3 Pro [32] / Opel Ampera-e [33]
****** Capacity and power of SBS based on PV power [34]

3.2. Revenues for V2H operation

Various sensitivity calculations are evaluated to assess the benefits of bidirectionally chargeable EVs for household owners. Figure 2 compares the revenues and PV self-consumption of smart and bidirectional charging strategies for the base scenario to the linear base scenario (LP optimization with constant efficiencies), the commuter EV scenario 'COM' and scenarios with the additional components HP and SBS.

Additional revenues for the base scenario are around 210 €/a for a smart charging EV and around 310 €/a for a bidirectionally chargeable EV. These revenues represent cost reductions of 25% to 36% compared to a household with an unmanaged charging EV. Self-consumption of electricity from the PV system increases on average from 23% for unmanaged charging to 45% for smart charging and 65% for a bidirectionally chargeable

EV. This improved use of cheaper PV energy rather than energy from the grid leads to higher revenues and a higher degree of autarky.

The 'Base linear' scenario shows a similar PV self-consumption increase, but significantly higher revenues for both smart and bidirectional charging compared to the base scenario. Since the household power demand and the PV power are both below 1 kW in 90% respectively 73% of all timesteps, where a varying inverter efficiency would drop significantly, the fixed efficiency of the EV's charging and discharging leads to a higher utilization with much lower losses. A more detailed description of the resulting differences in charging and discharging behaviour between fixed and varying efficiency is provided in Appendix C. PV self-consumption in the linear base scenario is slightly lower than in the non-linear base scenario due to lower charging and discharging losses. The diverging revenues of around 100 €/a for a bidirectionally chargeable EV compared to the base scenario (divergence of 32%) show that for our considered use case, it is not valid to model a LP with fixed efficiencies. Therefore, all of the following results are based on a MILP optimization with a varying efficiency for charging and discharging of the EV.

In the commuter EV scenario 'COM', we model a commuter EV instead of a non-commuter EV in the household. The average annual mileage increases from 10,000 km/a to 20,000 km/a and the average availability of the EVs at the charging point decreases from 91% to 67%. For smart charging EVs, the average commuter EV generates only slightly lower revenues compared to the revenues of the smart charging EV in the base scenario. The lower availability of the commuter EV is compensated by the higher EV consumption that leads to more possibilities of smart charging. In contrast, the bidirectionally chargeable, commuting EV generates revenues that are about 100 €/a lower than the non-commuting EV's revenues. The lower availability of the commuting EV during the day leads to fewer opportunities of charging PV electricity. Therefore, the PV electricity is used for consumption of the EV, but not for discharging to the household.

Adding additional smart components to the household leads to lower revenues for managed EV operation strategies, since these components also use the cheaper PV energy to optimize the household's electricity costs. In these scenarios, the reference case of unmanaged EV charging is already much more efficient than in the base scenario leading to a lower revenue potential of bidirectionally chargeable EVs. In scenario HP, the heat pump can be operated flexibly such that part of the low-cost PV electricity is used for heat generation. In particular, the battery storage in the SBS scenario acts similarly to the bidirectional electric vehicle, such that the revenue potential there is even more limited. The combination of these additional smart components in the household then provides the lowest revenue potentials. The impact on revenue potential is in turn linked to the level of self-consumption of the solar energy for the different EV operating strategies. With additional smart components in the household, a higher self-consumption is already apparent with unmanaged charging of the EV, such that the possible increase is limited.

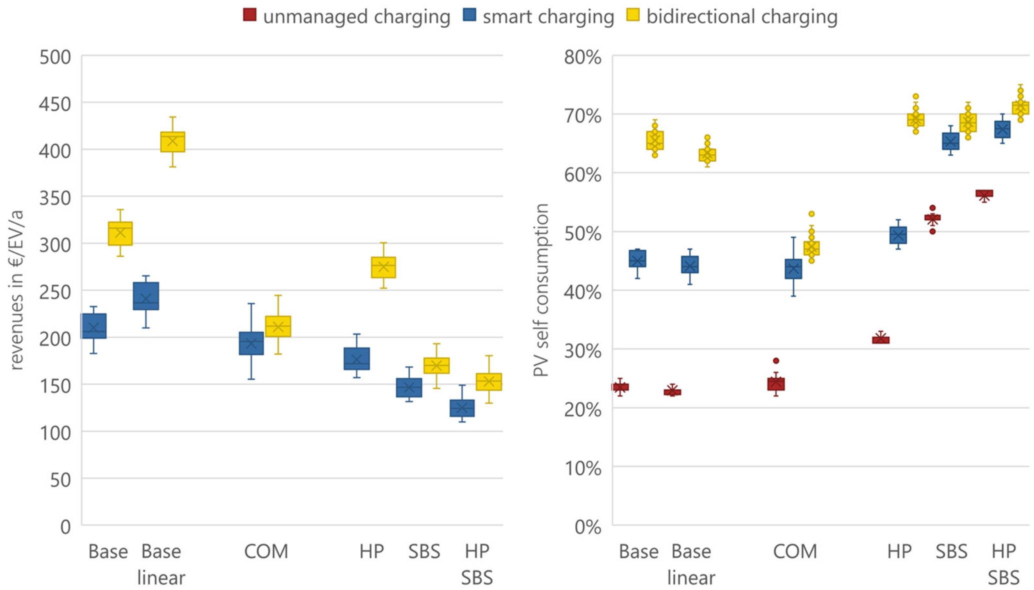

Figure 2: Revenues and PV self-consumption for base MILP scenario in comparison to base linear scenario, commuter scenario COM and added components scenarios HP, SBS, and HP SBS

Other relevant factors potentially influencing revenue potential include:

- EV battery capacity
- Maximum power of EVSE
- PV peak power
- PV feed-in tariff
- Household size
- Maximum OHs of EV and EVSE

Figure 3 shows the effect of parameter variation on the revenue potential for smartly and bidirectionally chargeable EVs. The use case of self-consumption optimization is highly sensitive. In particular, the design of the PV system has a strong impact on the revenues. A large PV system with a low feed-in tariff generates significantly higher revenues through both smart and bidirectional charging of an electric vehicle. The parameterization of the EV and the EVSE has much less effect. In this case, larger designs cause no or only small increases in revenue. As for the EV, the selected capacity in the base scenario is sufficient to exploit the major part of revenue potentials for the fixed household and PV configuration. The small effects of the EVSE are related to the configuration of the household in the base configuration (maximum PV feed-in 4.5 kW, maximum demand household 7.7 kW). An EVSE of 22 kW instead of 11 kW has no effect on revenues. In contrast, the household size has a large impact on the revenue potential for bidirectionally chargeable EVs, since a larger household with higher demand power enables more efficient discharging of the EV.

Additionally, we evaluate a limitation of the resulting OHs of the bidirectionally chargeable EV reducing the impact on battery ageing and the additional load on power electronics. OHs of the bidirectionally chargeable EV in the base scenario without limitation are around 6.9 h/d compared to 0.7 h/d for the unmanaged charging EV. EFCs are less affected and increase only by 18 EFC/a from 34 to 52 EFC/a for the bidirectionally chargeable EV. Since OHs are much more affected than EFC, we present constrained OHs per day to show the effect of limited usage on revenues. A reduction of OHs by 64% to 2.5 h/d results in a moderate revenue reduction of 19%. EFCs of the battery then reduce from 52 EFC/a to 41 EFC/a.

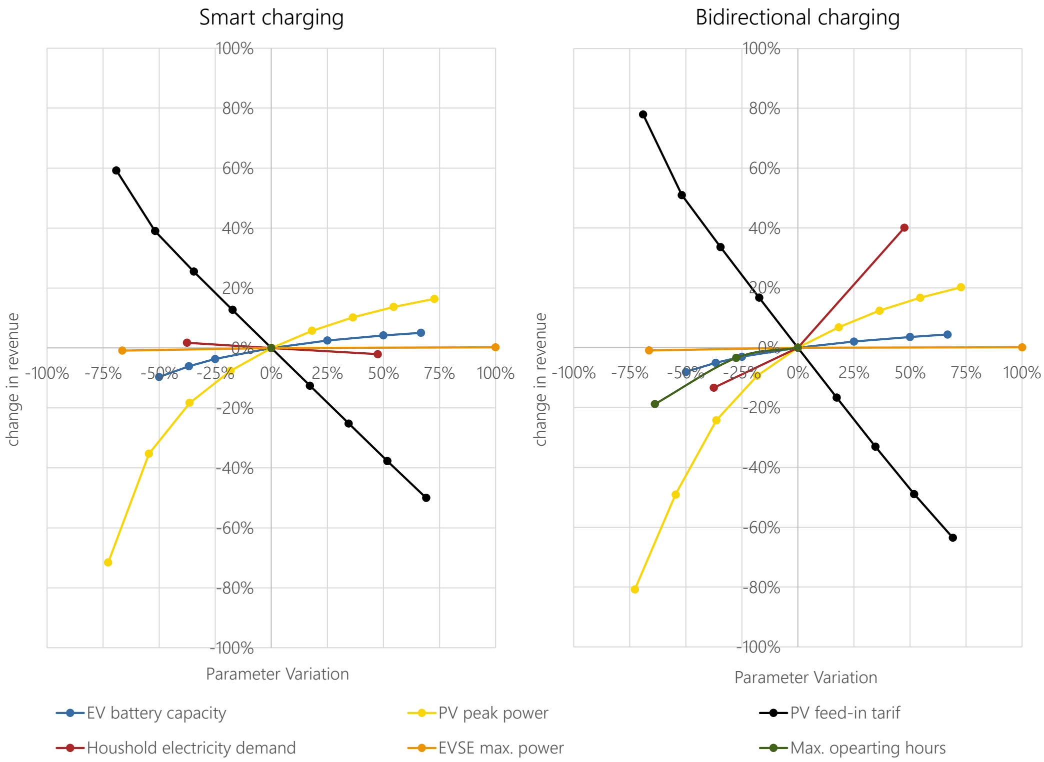

Figure 3: Parameters influencing revenues of V2H use cases for smart and bidirectional charging EVs

Lastly, for a maximum revenue estimate, we examine a household that has the best suited configuration of each of the analyzed parameters. An average annual household demand of 5900 kWh is combined with a 9.5 kWp PV system, which receives a feed-in tariff of 3.6 ct/kWh, and an EV with a battery capacity of 100 kWh. This household set-up receives revenues of 835 €/a for a bidirectionally chargeable EV and revenues of 390 €/a for a smart charging EV, showing the maximum potential revenues for the use case self-consumption optimization.

3.3. Revenues for combined V2H and V2G operation

Since self-consumption optimization achieves more profits when more PV energy is generated, V2H is more useful in summer times than in winter times. To benefit from the bidirectionally chargeable EV in the best possible way, we model a combined use of V2H and V2G arbitrage trading. For explained regulatory reasons, the EV is not allowed to optimize self-consumption and arbitrage trading at the same time. Instead, the optimizer can switch the use case of the bidirectionally chargeable EV daily.

For arbitrage trading, we use German day-ahead market prices from 2018 [35] matching the parameterization of the other components. Duties and taxes for purchased energy are not added to the electricity prices, because the regulatory framework for bidirectionally chargeable EVs is not yet fully defined. The revenues shown are thus an upper estimation.

Table 3 compares potential revenue of a combined optimization of V2H and V2G with and without restricted OHs to the revenues of the base V2H scenario. Revenue potentials of unrestricted, combined V2H and V2G increase by 220 €/a (plus 71%) compared to the base scenario, while EFCs increase by 270 EFCs/a and OHs by 5.5 OHs/d, meaning a significant additional load for the EV's battery. Limiting the maximum OHs to 10 h/d barely reduces revenues. In this case, EFCs are reduced by 70 EFCs/a relative to the unconstrained scenario, which is still an increase of 200 EFCs/a compared to the base V2H scenario. Limiting the maximum OHs to 5 h/d leads to revenues, which are 100 €/a higher than for the base scenario, yet 120 € lower than for the unrestricted combined scenario. Here, the EV usage is reduced significantly (only 70 EFCs/a more than the base scenario).

Table 3: Revenues, operation hours and EFCs for bidirectional operating strategy of the EV

Scenario		V2H base	V2H base + V2G	V2H base + V2G max. 10 OHs/day	V2H base + V2G max. 5 OHs/day
Average revenues in €/a	Total V2H V2G	310 310 -	530 300 230	510 300 210	410 270 140
EFCs/a		50	320	250	130
OHs/d		6.9	12.5	10	5

The generally increased revenues show that V2G arbitrage trading represents a very good complement to V2H use cases. To further analyze the combination of these use cases, Figure 4 shows the share of daily usage of V2H and V2G for the evaluated 20 households in the restricted optimization by 5 OHs/day as well as the weekly standard deviation of electricity prices and the weekly PV generation. The usage of V2H correlates to the PV generation that is the highest from April to September. In contrast, the daily standard deviation of day-ahead prices does not vary on a seasonal basis, meaning that daily arbitrage trading is on average equally profitable in summer and winter times. Therefore, V2G complements V2H in winter times. Since Figure 4 shows the OHs restricted optimization, there are days on which no V2G and V2H is used, which are days of low revenue potential.

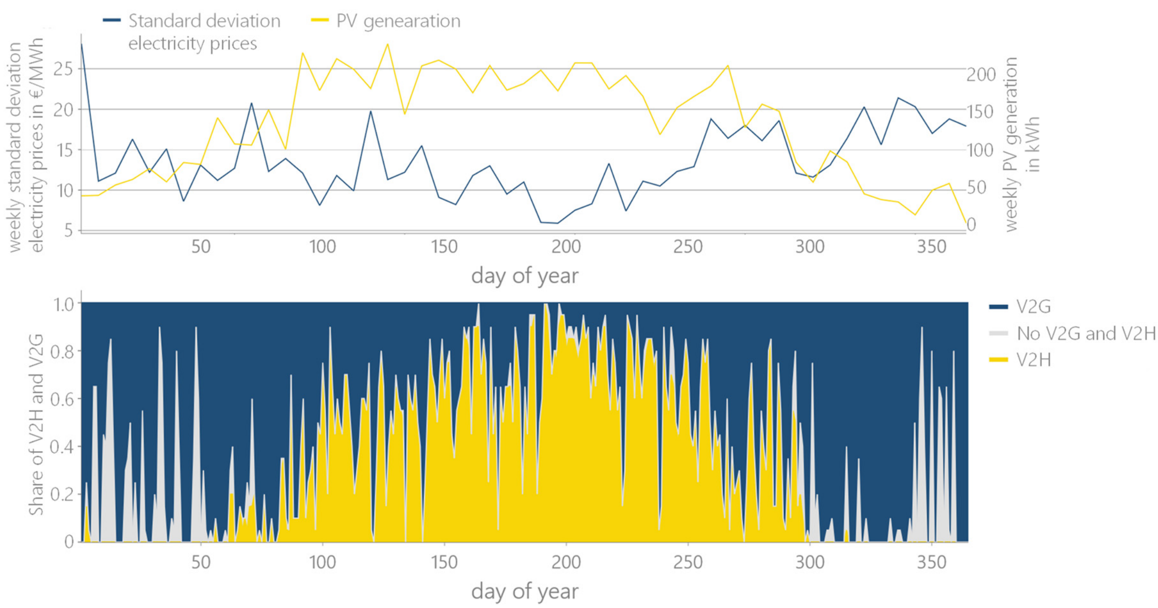

Figure 4: Daily share of households using V2H and V2G correlated to weekly standard deviation of electricity prices and weekly PV generation

4. Discussion on results and limitations

Our results show that smartly and bidirectionally chargeable EVs can reduce a household's electricity costs significantly by optimizing the self-consumption of PV energy. Profits of the V2H use case are highly sensitive to components of the household and their parameter variations. While the design of the EV and EVSE has a small impact on the revenues of the use case, the higher the maximum PV power and the lower the PV feed-in tariff, the more profitable V2H is. Our simulations show revenues of about 300 €/a for a typical German household with varying efficiencies (MILP). Potential cost reductions for households with bidirectionally chargeable EVs in a scenario best fitted for maximum revenues go up to 830 €/a, while households with smart charging EVs reach a maximum cost reduction of 390 €/a. Furthermore, we show that commuting EVs are not well suited for bidirectional self-consumption optimization but should rather only use smart charging. The average revenues indicated in this paper are slightly higher than revenues in the literature relating to V2H [8], [11], [13]. However, we show that revenues related to smart and bidirectional charging EVs are strongly sensitive to parameterization of household components.

By comparing results modeled as MILP with varying efficiencies to modeling with fixed efficiencies (LP), we found that it is highly important to model V2H use cases for bidirectional charging as MILP with varying charging and discharging efficiencies. Since for V2H applications only low charging and discharging powers are needed due to low household power demand and low PV system generation power, in reality low charging and discharging efficiencies occur at many times. Thus, modeling with a fixed efficiency (LP) led to revenues that are over 30% higher than the more realistic results of MILP, which is why we recommend to model V2H use cases exclusively with varying efficiencies.

All revenues presented are based on the German regulatory framework. However, through the sensitivity analyses, detailed conclusions can be drawn about V2H revenue potentials in other countries. The sensitivity analyses show that the difference between household electricity price and feed-in tariff is the most important influencing factor. According to Figure 3, a higher feed-in tariff of almost 20 ct/kWh results in 60% lower revenues, i.e. approx. 120 €/a for an average household. In a country with a price spread between household electricity price and feed-in tariff of 10 ct/kWh, these strongly reduced revenues can be expected. Similar conclusions can be drawn with regard to the country-specific revenues for V2G applications, which we discuss in detail in [19]. In this way, the detailed findings of the sensitivity analyses can be transferred very well to the conditions in other countries.

With the novel combined modeling of the use cases self-consumption optimization (V2H) and arbitrage trading (V2G), we show that the two use cases are highly complementary in terms of potential revenues. Since the V2H use case is strongly dependent on the PV generation, cost reduction options are high during the summer months. V2G arbitrage trading, where revenues do not alter significantly over the course of a year, can thus make greater use of the bidirectionally chargeable EV in the wintertime, resulting in an increased utilization of the vehicle. Dependent on the permitted usage of the EV, revenues of the base scenario increase from a maximum of 220 €/a to 530 €/a. As this increase shows, our more complex yet more realistic modeling highlights the great economic potential of combined V2H and V2G. As implementing multiple use cases at a time is likely to become common for EV users in the near future, our results show the future perspective of such multi-use-implementation for greater flexibility and higher revenues.

OHs and EFCs of the EV's battery increase for V2H use cases, but far less than for arbitrage trading [19]. We show that limited use of the EV of 2.5 h/d still generates high V2H revenues, which are only 19% below the unconstrained revenues. Comparing these limited OHs of around 900 h/a and EFCs of 41 EFC/a to currently warrantied lifetime values for battery and power electronics in automotive applications, which are around 10,000 OHs [36] and up to 5,000 EFCs [37], [38], additional OHs are more critical than additional EFCs, but V2H is still suitable as a use case for EVs. In this context, we want to emphasize the trade-off that although V2G arbitrage trading can generate significant additional revenues, it also leads to significant additional OHs and EFCs.

For the arbitrage trading, modeled electricity prices for selling and purchasing energy are equal. Depending on the regulatory framework there might be some additional duties and taxes for purchased energy, making the use case less profitable. Therefore, the presented revenues for arbitrage trading in the day-ahead market are to be interpreted as an upper bound of revenues. For a more detailed revenue estimation of arbitrage trading in European electricity markets, we refer to Kern et al. [19].

Finally, an economic evaluation of V2H and V2G use cases must include the additional investment costs of a bidirectional EVSE. To bring the presented revenue potentials into perspective for both present and future circumstances, we roughly estimate the economic viability of V2H by including additional annual costs via the annuity method [39]. Currently, there are only few offers for bidirectional EVSEs suitable for on low-volume production, resulting in high investment costs of around €6,000 [40]. The medium-term cost projections of experts in the BCM project for such an EVSE are around €2,000 [5]. Assuming an EVSE lifetime of 15 years [41], an interest rate of 3.5% [42] and unmanaged charging EVSE costs of €599 [43] leads to additional annual costs of the bidirectional EVSE of currently 469 €/a and medium term 122 €/a. A comparison with the V2H revenues of the typical German household of 310 €/a shows that V2H will most probably not be economical for this household at current costs but is likely to become profitable in the medium term. However, this is only a rough estimate and other additional costs should also be quantified for a more solid prediction, such as the installation costs of the bidirectional EVSE and potential additional costs for the bidirectional vehicle.

5. Conclusions

Vehicle-to-home (V2H) use cases and a combination of V2H and vehicle-to-grid (V2G) use cases can be highly beneficial for electric vehicle (EV) users. We provide a detailed description of the modeling and input data, that allows readers to reconstruct the revenues for these use cases. The major findings of our study are:

- Indicated revenues for an average German household are around 310 €/a for bidirectional charging and 210 €/a for smart charging compared to an unmanaged charging EV, increased to 830 €/a and 390 €/a respectively for a maximum revenue estimation.
- Revenues of V2H use cases should consider varying charging and discharging efficiencies in a mixed-integer linear programming, since modeled fixed efficiencies in a linear programming led to 30 % higher revenues and an unrealistic charging/discharging behavior.
- Revenues of bidirectionally chargeable EVs are highly case-sensitive depending on the composition of a household. The dimensioning of the photovoltaic system and the household size are more decisive than the size of the EV.
- Smart additional components in a household, such as heat pumps and stationary battery storages, significantly limit the revenues of a smartly chargeable or bidirectionally chargeable EV.
- V2G arbitrage trading works well with V2H self-consumption optimization because arbitrage trading revenues do not depend on the time of the year, while V2H primarily generates revenues during the summer.
- Combined use of V2H and V2G leads to maximum additional revenues of 220 €/a, but increases operating hours of the EV by more than 5 h/d and equivalent full cycles (EFCs) by as much as 270 EFCs/a.

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Appendix A

A key element of the presented model development is the varying efficiency of the charging and discharging process depending on the respective power. In the case of bidirectional charging, losses are neither constant nor directly proportional to the charging or discharging power due to the additional inverter at the charging point. Thus, we describe the derivation of the relevant equations for the MILP in detail. According to [21], power losses of an inverter P_l consist of a constant self-consumption v_{const}, voltage losses at diodes and transistors v_l that are proportional to the output power, and quadratic power-dependent losses caused by ohmic loss resistances v_q. As the efficiency of the inverter η is the ratio of output power P_{out} to input power P_{in}, we formulate the following equation:

$$\eta = \frac{P_{out}}{P_{in}} = \frac{P_{out}}{P_{out} + P_l} = \frac{P_{out}}{P_{out} + v_{const} + v_l \cdot P_{out} + v_q \cdot P_{out}^2} \quad (A.1)$$

We express the efficiency for charging η_c and discharging η_d as a function of the AC-side power. For charging, AC-power before the inverter is converted into DC-power. Thus, P_{in} equals $P_{AC,c}$ and P_{out} equals $P_{DC,c}$. We express $P_{DC,c}$ as a function of $P_{AC,c}$ (Equation A.2) to derive Equation A.4. For discharging, directions are reversed, such that P_{in} equals $P_{DC,d}$ and P_{out} equals $P_{AC,d}$ resulting in Equation A.3 and A.5.

$$\begin{aligned} P_{DC,c} &= \mathrm{P}_{AC,c} - \mathrm{P}_{l,c} = P_{AC,c} - \left(v_{const,c} + v_{l,c} \cdot P_{DC,c} + v_{q,c} \cdot P_{DC,c}^2 \right) \\ &= \frac{-\left(\mathrm{v}_{l,c} + 1\right) + \sqrt{\left(v_{l,c} + 1\right)^2 - 4 \cdot v_{q,c} \cdot \left(v_{const,c} - P_{AC,c}\right)}}{2 \cdot v_{q,c}} \end{aligned} \quad (A.2)$$

$$\begin{aligned} P_{DC,d} &= \mathrm{P}_{AC,d} + \mathrm{P}_{l,d} = P_{AC,d} + \left(v_{const,d} + v_{l,d} \cdot P_{DC,d} + v_{q,d} \cdot P_{DC,d}^2 \right) \\ &= \frac{-\left(\mathrm{v}_{l,d} - 1\right) + \sqrt{\left(v_{l,d} - 1\right)^2 - 4 \cdot v_{q,d} \cdot \left(v_{const,d} + P_{AC,d}\right)}}{2 \cdot v_{q,d}} \end{aligned} \quad (A.3)$$

$$\eta_c = \frac{P_{DC,c}}{P_{AC,c}} = \frac{-(\mathrm{v}_{\mathrm{l,c}} + 1) + \sqrt{(v_{l,c} + 1)^2 - 4 \cdot v_{q,c} \cdot (v_{const,c} - P_{AC,c})}}{2 \cdot v_{q,c} \cdot \mathrm{P}_{AC,c}} \tag{A.4}$$

$$\eta_d = \frac{P_{AC,d}}{P_{DC,d}} = \frac{2 \cdot v_{q,d} \cdot \mathrm{P}_{AC,d}}{-(\mathrm{v}_{\mathrm{l,d}} - 1) + \sqrt{(v_{l,d} - 1)^2 - 4 \cdot v_{q,d} \cdot (v_{const,d} + P_{AC,d})}} \tag{A.5}$$

Based on these equations, we express the inverter power losses of charging and discharging as a function of the respective AC-power (Equation A.6 and A.7). These equations constitute the basis for the linearization described for implementation in this work.

$$P_{l,c} = \mathrm{P}_{AC,c} - \mathrm{P}_{DC,c} = P_{AC,c} - \frac{-(\mathrm{v}_{\mathrm{l,c}} + 1) + \sqrt{(v_{l,c} + 1)^2 - 4 \cdot v_{q,c} \cdot (v_{const,c} - P_{AC,c})}}{2 \cdot v_{q,c}} \tag{A.6}$$

$$P_{l,d} = \mathrm{P}_{DC,d} - \mathrm{P}_{AC,d} = \frac{-(\mathrm{v}_{\mathrm{l,d}} - 1) + \sqrt{(v_{l,d} - 1)^2 - 4 \cdot v_{q,d} \cdot (v_{const,d} + P_{AC,d})}}{2 \cdot v_{q,d}} - \mathrm{P}_{AC,d} \tag{A.7}$$

Appendix B

To determine the number of profiles for a representative mapping of a household group, a number of profiles is randomly drawn from a maximum of 150 profiles. This is done 10,000 times per number of profiles. The calculated mean values of these 10,000 draws are compared to the mean value of the 150 profiles and the maximum deviation of these mean values is displayed in Figure B1. The deviations of the mean revenues are a maximum of 5% for 20 profiles, which is tolerated as a maximum deviation. Therefore, in the following, all studies are based on 20 randomly drawn, discrete household profiles.

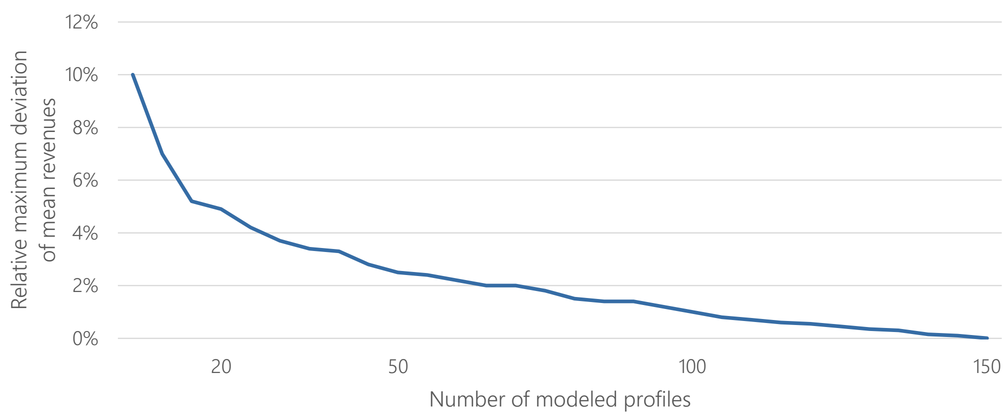

Figure B1: Relative maximum deviation of mean revenues in dependance on number of modeled profiles

Appendix C

Figure C1 shows the power flows at the GCP for a typical summer day. Power in the direction of the GCP is shown as positive. This includes EV discharging, PV generation and grid supply. Power flowing away from the GCP is shown as negative. This includes EV charging, household demand and grid feed-in (electricity supplied to the grid). For LP with fixed efficiency, household demand is balanced by EV discharging at night. For MILP with varying efficiencies, household demand is mainly balanced by grid supply, because the discharging efficiency of the EV is too low for these small power demands.

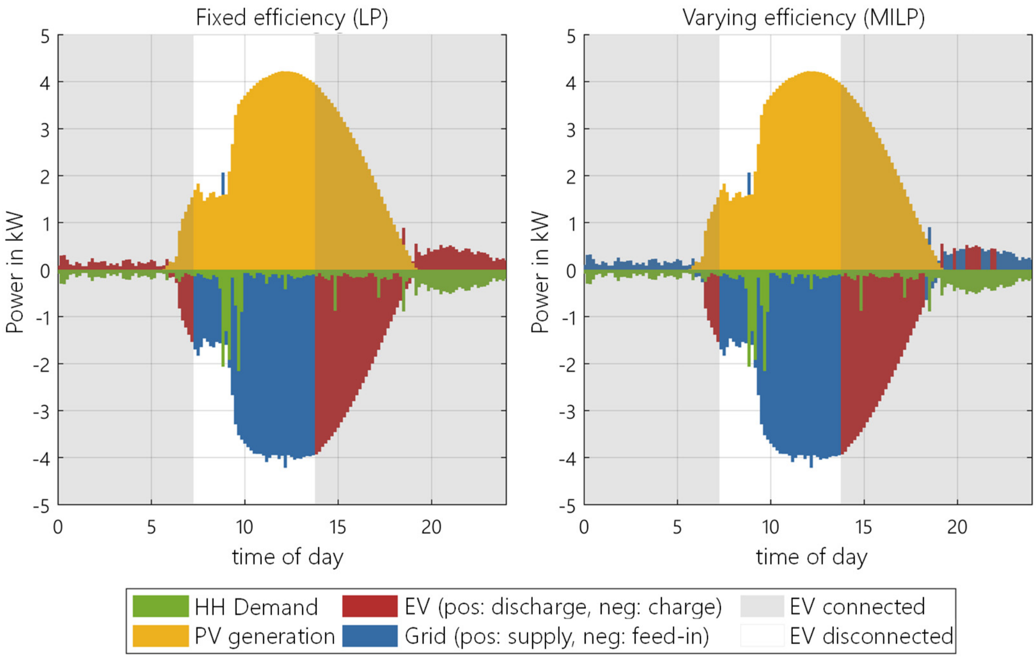

Figure C1: Power flows at the GCP for a typical summer day

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Publication 3 (Pub3): Modeling and Evaluating Bidirectionally Chargeable Electric Vehicles in the Future European Energy System

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Abstract: In addition to a massive expansion of renewable energies, a successful change towards a decarbonized energy system requires the flexibilization of consumers and the integration of storage and sector coupling technologies. Bidirectionally chargeable electric vehicles (EVs) represent such a consumer flexibility. They are able to charge when there is an electricity generation surplus and to discharge when there is a shortage in electricity generation. Therefore, they can act as a storage from the perspective of the energy system. This paper analyzes different modeling approaches of bidirectionally chargeable EVs in large-scale energy systems and evaluates the impact of bidirectionally chargeable EVs on the future European energy system design. We compare the modeling of discrete EV profiles, clustered EV profiles as well as an aggregated EV profile with simplified constraints. Aggregation of EV profiles per country leads to significantly lower computation times, while still achieving results close to the reference case. The number of bidirectionally chargeable EVs in a cost optimal future European energy system increases from 6 million EVs in 2025 to over 60 million EVs in 2050. We show that bidirectionally chargeable EVs lead to a better integration of PV generation, to lower installed capacities of gas- and hydrogen-fired power plants as well as stationary battery storages. They also lead to decreasing electricity prices and total European energy system costs.

Peer-review under responsibility of the scientific committee of the 7th International Conference on Advances on Clean Energy Research.

Keywords: bidirectionally chargeable EVs; vehicle-to-grid, V2G; energy system modeling; EV charging strategies; European energy system; flexibility options; demand-side flexibility

1. Introduction

In order to achieve the European climate protection targets, the future European energy system will be strongly characterized by volatile renewable energies [1]. Numerous studies analyze a future decarbonized energy system at the national level [2]. Due to the increase in renewable energies, additional flexibility is necessary to balance electricity generation and consumption in the energy system. Electric vehicles (EVs) represent a possible large demand-side flexibility. Smart charging allows EVs to charge when there is a surplus of electricity generation. Bidirectional charging allows to charge smartly, and even feed electricity back into the system when there is a shortage of electricity generation [3]. There are multiple use cases for bidirectionally chargeable EVs [4]. In vehicle-to-home (V2H) applications, energy from the EV is fed back into the household (on the *energy* user's side of the *meter*). Vehicle-to-grid (V2G) applications feed-back energy into the grid. The added value of bidirectionally chargeable EVs for the future energy system has not yet been sufficiently investigated. Therefore, in this paper we investigate modeling approaches of bidirectionally chargeable EVs in energy system models and resulting system-optimal penetration rates of smart and bidirectionally chargeable EVs in the future European energy system.

Numerous papers discuss the modeling of bidirectionally chargeable EVs from the user's perspective [5]. In V2H applications they must be modeled with varying charging and discharging efficiencies, since low power flows in a household lead to low efficiencies that cannot be modeled by one fixed efficiency [6]. Kern et al. show that revenue potentials vary strongly depending on user behavior, electricity prices and feed-in tariffs as well as other household components and usually range from 200 to 500 €/EV/a. Salpakari et al. model V2H applications in a household with a photovoltaic (PV) system in Sweden, quantify the annual electricity cost savings to 8% to 33% and show the impact on battery degradation [7]. Charging and discharging powers in V2G applications, like arbitrage trading, are usually at maximum charging and discharging power. Therefore, modeling a fixed charging and discharging efficiency is sufficient here [8]. Bidirectionally chargeable EVs can significantly reduce charging costs and even generate revenues to the owner of the EV [9]. Revenue potentials vary strongly depending on the EV and electric vehicle supply equipment (EVSE) characteristics, the regulatory framework, user behavior, and electricity market prices and usually range from 100 to 1,000 €/EV/a [8]. Since all aforementioned studies focus on the modeling of individual bidirectionally chargeable EVs, the impacts of bidirectionally chargeable EVs on the energy system are not evaluated. For example, neglected repercussions of EVs participating in the spot markets on electricity market prices potentially lead to overestimated revenues. Therefore, we model smart and bidirectionally chargeable EVs with a cost-optimal penetration rate in the energy system and estimate their revenues in future electricity markets.

There are some studies that discuss the impact of bidirectionally chargeable EVs on the electricity markets. Hanemann et al. discuss the flattening effect of EVs on electricity demand and electricity prices depending on the smart or bidirectional charging strategy of the EVs [10]. However, they model bidirectionally chargeable EVs highly simplified regarding the EV profiles and EV constraints and limit the observation area to Germany. Rodríguez et al. also show the smoothing effect of bidirectionally chargeable EVs on the electricity demand of Bogotá D.C. in Colombia, South America, resulting in a higher load factor [11]. However, once again the observation area is small and the modeling of the EVs is highly simplified. Huang et al. model the large-scale penetration of electric vehicles by a simplified charging behavior that is only according to statistic customers' travel needs [12]. They show that bidirectionally chargeable EVs can ensure the safe operation of distribution systems, but do not discuss repercussions on the energy system. Wei et al. optimize energy system planning with V2G applications and show the positive economic and environmental effect of V2G on the energy system [13]. However, the modeled EV fleet is simplified by stochastic features and the observation area is limited to cities, which leads to different requirements for the modeling approach compared to large energy systems. Child et al. show the decreasing impact of bidirectionally chargeable EVs on the need for storage and generation capacity for the Åland Islands near Finland [14]. In this paper, we also evaluate the impact of bidirectionally chargeable EVs on energy system components, such as electric storages and generation capacities. However, we will focus on the modeling approaches of bidirectionally chargeable EVs in more detail. Additionally, we evaluate their impact on total energy system costs and electricity prices in the European energy system.

None of the aforementioned studies model cost-optimal penetration rates of bidirectionally chargeable EVs in a highly coupled, large-scale multi-energy carrier system, since the optimization problem quickly becomes very complex. In this paper, we address this research gap. We formulate and analyze different modeling approaches of bidirectionally chargeable EVs and publish resulting EV profiles. In our results section, we use the best fitting modeling approach to evaluate cost-optimal penetration rates of bidirectionally and smart chargeable EVs in the future European energy system from 2025 to 2050. Therefore, this paper provides policy recommendations for action, i.e., where and when to promote the new technology of bidirectionally chargeable EVs in Europe. Furthermore, stakeholders in the field of energy can align business models with the cost-optimal expansion of this new technology. Ultimately however, scientists can also use the modeling approaches and the EV profiles for their own energy system analyses.

2. Methodology

2.1 Modeling approaches of V2G applications in energy system models

Bidirectionally chargeable EVs are modeled like stationary storage systems with additional constraints on availability and driving consumption. Therefore, the absolute battery state of charge (SoC) $SoC(t)$ in a timestep t is determined by the absolute battery SoC of the previous timestep $SoC(t\text{-}1)$ added to the charged energy $P_c(t) \cdot \eta_c \cdot \Delta t$ and subtracted by the discharged energy $\frac{P_d(t)}{\eta_d} \cdot \Delta t$ and the driving consumption $P_{con}(t) \cdot \Delta t$, where Δt is the time step length. P_c and P_d refer to charging and discharging powers, while η_c and η_d describe charging and discharging efficiencies.

$$SoC(t) = SoC(t\text{-}1) + P_c(t) \cdot \eta_c \cdot \Delta t - \frac{P_d(t)}{\eta_d} \cdot \Delta t - P_{con}(t) \cdot \Delta t \tag{1}$$

To model realistic user behavior, we introduce Equations 2 and 3 that further constrain the SoC. The minimum percentage safety SoC min_{safe} in Equation 2 represents the requirement to perform a safety-related drive, like a drive to the hospital, at any time when the EV is connected. The minimum percentage SoC at departure min_{dep} respects the user's desire of a minimum SoC of the EV battery when departing. The relative parameters min_{safe} and min_{dep} are multiplied by the maximum absolute SoC SoC_{max} to compare it to the absolute state of charge $SoC(t)$. If the EV is not connected to an EVSE, min_{safe} and min_{dep} are set to zero, since there is no minimum SoC desired by the user.

$$SoC(t) \geq SoC_{max} \cdot min_{safe} \quad \text{for all timesteps } t \text{ with connected EV} \tag{2}$$

$$SoC(t) \geq SoC_{max} \cdot min_{dep} \quad \text{for all timesteps } t \text{ with departing EV} \tag{3}$$

Furthermore, usual constraints restrict the charging and discharging power by maximum values $P_{c,max}$ and $P_{d,max}$ as well as the battery SoC by a parameterized maximum SoC_{max} in Equations (4-6) for all considered timesteps t. If the EV is not connected, $P_{c,max}$ and $P_{d,max}$ are set to zero, since charging and discharging is not possible.

$$P_c(t) \leq P_{c,max} \quad \text{for all timesteps } t \text{ with connected EV} \tag{4}$$

$$P_d(t) \leq P_{d,max} \quad \text{for all timesteps } t \text{ with connected EV} \tag{5}$$

$$SoC(t) \leq SoC_{max} \quad \text{for all timesteps } t \tag{6}$$

Since the modeling of the European energy system is a highly complex optimization problem, the integration of every single EV as a discrete element in the energy system model would lead to unacceptable computing times. For this reason, we further discuss three modeling approaches of bidirectionally chargeable EVs in energy system models. The described modeling of bidirectionally chargeable EVs can be equally applied for smart chargeable EVs with the restriction that the discharging power of the EVs is set to zero.

Modeling of bidirectionally chargeable EVs with discrete EV profiles

In the first approach, we model EVs by discrete driving and location profiles. The EV consumption profile sets the variable $P_{con}(t) \cdot \Delta t$ in Equation 1. The EV location profile is transferred to an EV connection profile. Depending on the modeled location of the EV supply equipment (at home, at work or in a public space), the EV status is connected or not connected. The connection status of the EV sets the variables in Equations 2-5.

Since the number of EVs in the future European energy system will increase to multiple millions, there is still a need to lower the number of discrete profiles. In an evaluation of synthetic EV profiles based on a mobility study in Germany in 2017 [15], Fattler shows that 10,000 discrete EV profiles are statistically viable to represent the average German mobility behavior [16]. Randomly drawing 1,000 EV profiles from this pool of 10,000 EV profiles leads to a deviation of indicators, such as equivalent full cycles or daily charging hours of below 3%. Therefore, in this approach, we integrate the bidirectionally chargeable EVs in the energy system model by 1,000 synthetic EV consumption and location profiles.

Since 1,000 modeled EV elements differ from the number of bidirectionally chargeable EVs integrated into the energy system in reality, a scaling factor is introduced to set the constraining variables in Equations 1-6. In Equation 7, we calculate the scaling factor $f_{num,EVs}$ by the number of bidirectionally chargeable EVs n_{EVs} divided by 1,000, which represents the 1,000 equally weighted EV elements.

$$f_{num,EVs} = \frac{n_{EVs}}{1{,}000} \tag{7}$$

The scaling factor is used to set the constraining variables according to Equations 8-11. The parameters of a single EV $E_{con,1EV}(t)$, $P_{c,max,1EV}$, $P_{d,max,1EV}$ and $SoC_{max,1EV}$ are multiplied by the scaling factor. As a result, one EV element represents $f_{num,EVs}$ EVs with the same features. One million integrated bidirectionally chargeable EVs, for example, would consequently result in one discrete EV element representing 1,000 EVs.

$$E_{con}(t) = E_{con,1EV}(t) \cdot f_{num,EVs} \tag{8}$$

$$P_{c,max} = P_{c,max,1EV} \cdot f_{num,EVs} \tag{9}$$

$$P_{d,max} = P_{d,max,1EV} \cdot f_{num,EVs} \tag{10}$$

$$SoC_{max} = SoC_{max,1EV} \cdot f_{num,EVs} \tag{11}$$

Modeling of bidirectionally chargeable EVs with clustered, discrete EV profiles

Since 1,000 discrete bidirectionally chargeable EV elements integrated in an energy system model might still lead to high computing times, we further reduce the number of EV elements by using clustering algorithms. We use a k-means algorithm for the clustering of EV profiles based on an approach shown by Schmidt-Achert et al. [17] to best represent the mobility behavior of EVs.

We define representative driving and location profiles for each cluster by a three-step approach. First, features for the clustering algorithm are defined. Since the location, and thus the availability, of the EVs is most important for the value of smart or bidirectional charging [8], the availability at home and at work for 6-hour time frames per weekday results in 56 features for the clustering, e.g., Monday from 0am to 6am is one feature. Second, a k-means clustering algorithm is applied to find a predefined number of clusters to represent the population best. Third, the best representative of a cluster is chosen. Like Schmidt-Achert et al., we also define representatives by minimizing the sum of maximum and mean error compared to the reference, instead of using the traditional selection of the closest representative to the centroid. This approach leads to an economically viable choice of representatives, e.g., avoiding unrealistic low availabilities.

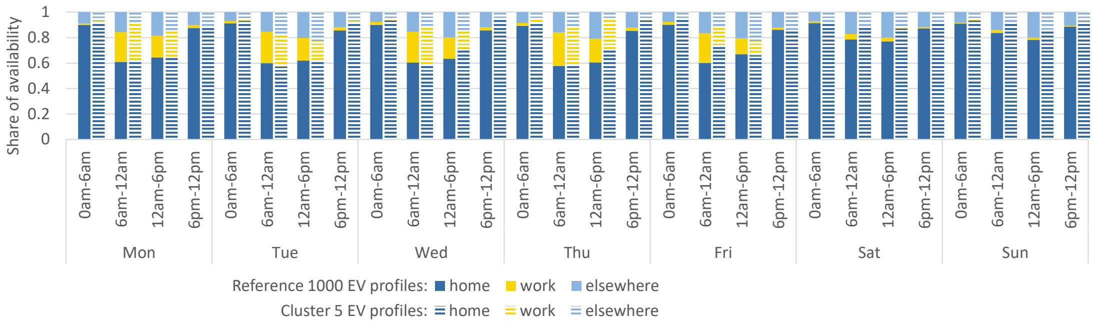

Fig. 1. Location of EVs in each feature for reference of 1,000 EV profiles compared to 5 discrete clustered EV profiles.

In this paper, we develop clustered EV profiles by using the described approach for 5, 10, 20 and 50 clusters. Figure 1 shows a comparison of defined features for the reference case of 1000 EV profiles (a) and a representation of EV profiles by 5 clusters (b). The fundamental characteristic of the reference can be represented well by the 5-cluster approach. The lowest availability of EVs at home is just below 60%, the availability of EVs at work from Monday to Friday from 6am to 6pm is around 20% and the availability of EVs elsewhere (meaning at public spaces or driving) mostly varies from 10% to 20%. However, one can recognize concise differences. The availability of EVs at home during the weekend is much higher for the clustered profiles, leading to lower availabilities at work and elsewhere in this time frame. The same EV profile differences can be recognized during the weeknights.

In Table 1, we further analyze the different statistical behavior of clustered EV profiles (*CluX* for X discrete EV profiles) in comparison to the reference case of 1,000 EV profiles (*Ref*). The overall mean availability of EVs at home, at work and elsewhere is represented quite well by the clustered profiles. However, one can observe that the deviation of all characteristics from the reference increases with a decreasing number of clusters. The availability of EVs at home is increasingly overestimated with a decreasing number of clusters and the availability of EVs at work and elsewhere is increasingly underestimated with a decreasing number of clusters. Taking a closer look at the maximum and mean absolute deviation of the availability of EVs in each defined feature, the deviation of the characteristics from the reference increases for all clustered EV profiles. The extent of the influence of these deviating characteristics on other elements in the energy system is analyzed in Chapter 3.1 to further evaluate the clustered EV profiles.

Table 1. Availability at home, at work or elsewhere for clusters *Clu50*, *Clu20*, *Clu10* and *Clu5* in comparison to reference scenario *Ref*.

	Mean availability					Max deviation from Ref				Mean deviation from Ref			
	Ref	Clu50	Clu20	Clu10	Clu5	Clu50	Clu20	Clu10	Clu5	Clu50	Clu20	Clu10	Clu5
Home	77.6%	79.5%	80.9%	81.0%	81.4%	6.5%	9.6%	10.7%	12.6%	2.1%	3.4%	3.6%	4.4%
Work	8.6%	8.5%	7.6%	8.1%	8.3%	3.4%	7.0%	7.0%	7.5%	0.9%	1.3%	1.8%	2.2%
Elsewhere	13.8%	12.0%	11.5%	10.9%	10.2%	6.3%	6.1%	7.7%	14.6%	1.9%	2.4%	3.3%	4.4%

The clustered EV profiles include discrete EV location and consumption profiles and a share for each EV representative of the total EV number. Consequently, the number of EVs for each discrete EV profile is calculated by multiplying the total number of EVs n_{EVs} with the share of each EV profile:

$$f_{num,EVs} = n_{EVs} \cdot share_{EV} \tag{12}$$

Taking into account the scaling factor $f_{num,EVs}$, the constraining variables and parameters are set by Equations 8-11. The clustered, discrete EV profiles are published in [18].

Modeling of bidirectionally chargeable EVs with aggregated EV profile

To further reduce the complexity of the optimization problem, we aggregate all initial 1,000 EV profiles into one EV location and consumption profile that represents the total EV fleet. The aggregated profile contains shares of EV locations and average consumptions of EVs. This leads to a simplified modeling of bidirectional chargeable EVs, since discrete correlations cannot be mapped.

Figure 2 illustrates the different modeling of aggregated and discrete EV profiles by showing the minimum and maximum availability of a single EV at home compared to the aggregated EV profiles for an exemplary week. The maximum availability of the discrete EV profile is either one or zero, while the maximum availability of the aggregated EV profile varies between 50% and 95%. The minimum availability is determined by the minimum state of charge at departure (example set to 70%) and the minimum safety state of charge (example set to 30%). For the discrete EV profile, it is either 0%, 30% or 70%, while the aggregated minimum availability varies between 15% and 35%. Modeling discrete EV profiles leads to time-dependent correlations that are neglected by the modeling of aggregated EV profiles. A discrete EV that departs with an SoC over 70% comes back with an SoC depending on the SoC at departure. Using the aggregated EV profiles neglects this correlation, but still considers the overall SoC restrictions for the EV pool by the aggregated minimum availability.

Since the aggregated profile is normed to one EV, the scaling factor $f_{num,EVs}$ is equal to the number of EVs n_{EVs} as shown in Equation 13. Again, the constraining variables and parameters are set by Equations 8-11. The aggregated EV profiles are published in [18].

$$f_{num,EVs} = n_{EVs} \tag{13}$$

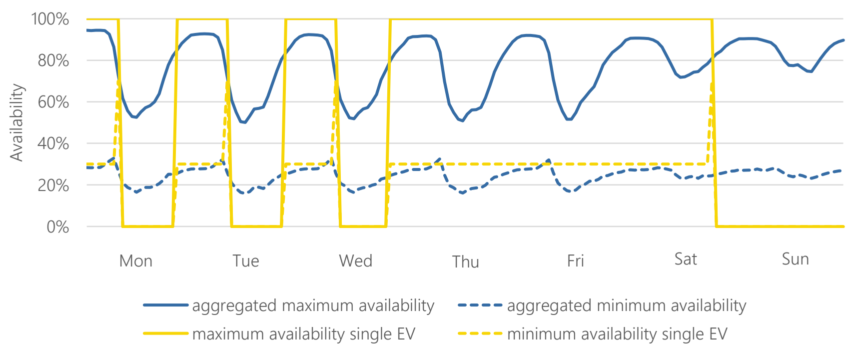

Fig. 2. Different availability of aggregated and discrete EV profiles for an exemplary week.

2.2 Integration of V2G applications in the energy system model ISAaR

We use the linear optimization model ISAaR (Integrated simulation model for unit dispatch and expansion with regionalization) that provides a cost-optimal expansion and dispatch of units to model the future European energy system. Figure 3 illustrates the elements and energy carriers that are modeled in ISAaR. There are multiple elements that couple different energy carriers. Examples are gas-fired power plants or power-to-x technologies that produce other energy carriers from electricity. In addition, storage elements for electricity, heat, hydrogen, and methane provide additional flexibility to the energy system. Energy carriers from outside the geographical scope of ISAaR can be integrated from the model via import. Final energy consumption models provide the energy demand as input data for the optimization. A detailed description of the final energy consumption models Smind EU for the industry sector, TerM EU for the tertiary sector, TRAM EU for the transport sector and PriHM EU for the building sector can be found in [19].

ISAaR minimized the total energy system costs, while balancing consumption and generation per energy carrier for every timestep and every region. Equation 14 shows these system constraints. The demand of the final energy consumption sectors for every energy carrier *c,* every timestep t and every region *r* P_{demand} is equal to the generation P_{gen} of all elements added to the imports of the energy carrier P_{import} subtracted by the consumption of all elements P_{cons} and the exports of the energy carrier P_{export}. A storage element, such as a bidirectionally chargeable EV, that discharges results in a generation P_{gen} from the energy system's perspective. A storage element that charges represents a consumption from the energy system's perspective. A more detailed description of the ISAaR energy system model can be found in [20].

$$\begin{gathered} P_{demand}(t,r,c) = \sum_{elements} P_{gen}(t,r,c) - \sum_{elements} P_{cons}(t,r,c) \\ +P_{import}(t,r,c) - P_{export}(t,r,c) \\ for\ every\ timestep\ t, region\ r\ and\ energy\ carrier\ c \end{gathered} \tag{14}$$

The final energy demand of the transport sector modeled in TRAM includes the electricity demand of passenger cars for every European country. Since the demand is transmitted to ISAaR statically, TRAM models all passenger cars as unmanaged charging electric vehicles. The integration of bidirectionally chargeable EVs (`BCM-EVs`) leads to a decrease in unmanaged charging EVs. Since TRAM provides a static input of electricity demand, the decreasing number of unmanaged charging EVs is modeled by a negative demand `-Unman EVs` reflecting the electrical load of the integrated bidirectionally chargeable EVs. This approach allows a dynamic, model endogenous increase of bidirectionally chargeable EVs in ISAaR. If ISAaR decides to integrate a bidirectionally chargeable EV, this will result in a decrease of the static demand of the transport sector representing a removal of an unmanaged charging EV.

There are two options to integrate bidirectionally chargeable EVs into the energy system model. First, the number of bidirectionally chargeable EVs n_{EVs} can be fixed for future years, meaning a stock element from the model's perspective. Second, bidirectionally chargeable EVs can be modeled as an expansion element with expansion costs. In this case, their number n_{EVs} is endogenously determined by ISAaR. The expansion costs reflect the differential costs of a bidirectionally chargeable EV including EVSE versus an unmanaged charging EV including EVSE.

The described approach for the integration of bidirectionally chargeable EVs in the energy system model can be applied equally for smart chargeable EVs.

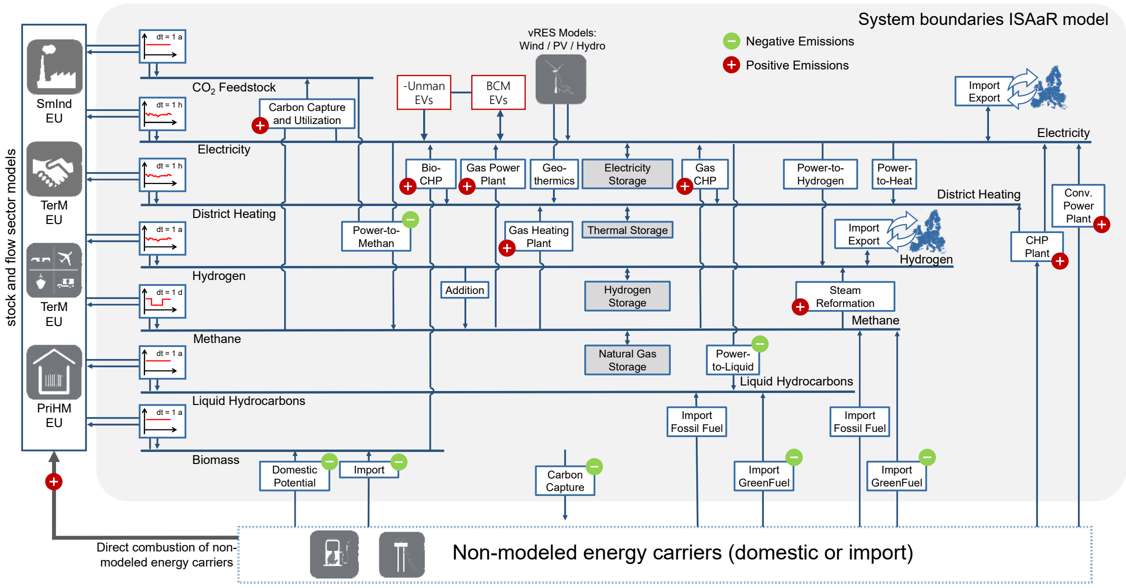

Fig. 3. Illustration of technologies in the multi-energy system model ISAaR and added elements for modeling bidirectionally chargeable EVs.

3. Results

In the results section we discuss the advantages and disadvantages of the presented modeling approaches of bidirectionally chargeable EVs for an exemplary integration of the EVs in Germany. This is followed by a scenario evaluation of the European energy system with smart and bidirectionally chargeable EVs for the timeframe 2025 to 2050.

3.1 Evaluation of modeling approaches of bidirectionally chargeable EVs

For the evaluation of the different presented modeling approaches, we model the European energy system for the year 2030 with the ISAaR energy system model and integrate bidirectionally chargeable EVs into the German energy system. The parameterization of all modeled elements in the energy system, e.g., generation, consumption, or storage units, is based on the solidEU scenario of the eXtremOS research project. A detailed scenario description of solidEU is published in a summary report [1]. Table 2 shows the parametrization of the bidirectionally chargeable EVs. The EVs are parameterized by a medium passenger car battery capacity of 50 kWh [21].

Table 2. Parametrization of bidirectionally chargeable EVs.

Battery capacity $SoC_{max,1EV}$	Charging/ discharging power $P_{c,max,1EV}$ and $P_{d,max,1EV}$	Charging/ discharging efficiency η_c and η_d	Minimum safety SoC min_{safe}	Minimum SoC at departure min_{dep}	Location of bidirectional EVSE	Number of bidirectionally chargeable EVs n_{EVs}
50 kWh	11 kW	94%	30%	70%	At home	13 million EVs

The maximum charging and discharging power are set to 11 kW, based on the technical design of the EVSE in the BCM project [4]. The charging and discharging efficiencies of 94% (losses in EV and EVSE included) are the future efficiencies expected by experts from the BCM project [4]. The safety minimum SoC and the minimum SoC at departure are set to 30% and 70%, respectively, and the location of the bidirectional EVSE is at home. The fixed EV number of 13 million EVs is oriented to the underlying solidEU scenario [1].

We evaluate the three different modeling approaches presented in Chapter 2 in regard to differences in simulation results and computing time. The first presented modeling approach of a discrete EV modeling is the most detailed and thus serves as a reference for the other modeling approaches. Table 3 summarizes the impact of the different EV modeling approaches with respect to computation time, EV behavior and repercussions on the energy system.

The discrete EV modeling leads to a computation time of 410 million ticks for the one-year energy system optimization, which corresponds to a computation time of 3 days on the computing servers[1] used. The discrete clustered EV modeling results in much lower computation times of 155 million ticks for 5 EV profiles to 175 million ticks for 50 EV profiles. The aggregated EV profile modeling also has a computation time in this range with 172 million ticks. Although in this approach the EVs are modeled with only one profile, the computation time is slightly higher than for the approaches with 5, 10 and 20 discrete clustered EV profiles. This may be due to the more complex aggregated EV profile, but also to the feedback effects of the EV profile on the energy system.

As a second evaluation of the EV modeling approaches, Table 3 shows the EV behavior of the 13 million EVs modeled in the German energy system. The minimum, maximum and mean availability refers to the availability of the EVs at home over all simulated 8760 hours of the year. For the EV fleet in Germany, represented by the 1,000 discrete EV profiles, the minimum availability is 48%, the maximum availability is 95% and the mean availability is 78%. These characteristics are matched perfectly by the aggregated EV profile. The discrete clustered EV profiles lead to a large error for the minimum availability, especially for 5 to 20 EV profiles. This can lead to unrealistic scarcity situations, where hardly any EVs can interact with the energy system. The charged and discharged energy varies between the modeling approaches, but only by a maximum of 5%. The aggregated EV profile matches the reference very well. The revenues per EV are calculated by the EV energy sold minus the EV energy purchased, times the electricity prices and also vary by a maximum

[1]Hardware: 2xAMD EPYC 7F52 – 16 Core, 1008 GB RAM
Software: Matlab [22], Gurobi Optimization [23]

of 5%. Again, the aggregated EV modeling approach matches the reference and thus reflects the EV behavior very well.

Table 3. Impact of different EV modeling approaches on computation time, EV behavior and repercussions in the energy system.

Modeling approach	Specifi-cation	Compu-tation time (ticks)	EV behavior						Repercussions on the energy system				European modeling as expansion element
			min avail-ability	max avail-ability	mean avail-ability	charge in TWh	dis-charge in TWh	revenues per EV	Overall costs in bn€/a	Wind onshore in TWh in DE	Wind offshore in TWh in DE	PV in TWh in DE	
Discrete EV profiles	1000 EV profiles	410 million	0.49	0.95	0.78	124.4	91.9	158.25	410.40	261.6	185.8	219.3	no
Discrete clustered EV profiles	50 EV profiles	175 million	0.38	1.00	0.80	124.2	95.4	165.51	410.25	261.9	188.5	219.5	no
	20 EV profiles	162 million	0.19	1.00	0.81	124.4	96.2	161.42	410.39	261.8	180.2	227.6	no
	10 EV profiles	157 million	0.11	1.00	0.81	123.1	96.6	163.53	410.37	262.0	178.9	229.0	no
	5 EV profiles	155 million	0	1.00	0.82	120.2	96.0	164.08	410.42	261.8	195.4	227.2	no
Aggregated EV profile	1 EV profile	172 million	0.49	0.95	0.78	125.9	91.7	158.33	410.38	262.2	191.3	231.8	yes

Finally, Table 3 shows the repercussions of the modeling approaches on the energy system. The overall costs represent all costs in the European energy system, with a large part of the costs being in the electricity sector. The overall costs in the different modeling approaches vary only slightly, with the aggregated EV profile matching the reference case very well. Furthermore, we evaluate the expansion of volatile renewable energies in Germany (DE). The electricity generated by wind turbines or PV plants varies by maximum 6%. In general, the expansion and generation of wind onshore, wind offshore and PV is well represented by the discrete clustered and aggregated modeling approach.

For a final evaluation of the modeling approaches, one must consider that the modeling will be applied to all European countries in the ISAaR energy system model. Furthermore, we will also evaluate an optimized expansion of bidirectionally chargeable EVs, which brings even more complexity. The modeling approach with 1,000 discrete EV profiles already has strong computational time disadvantages when modeling German bidirectionally chargeable EVs and is therefore excluded. The aggregated profile shows slight performance advantages compared to the discrete clustered EV profiles, especially for the EV behavior. A European modeling includes 30 European countries and results in 30 times more EV profiles than in our test simulations. In an optimized integration of bidirectionally chargeable EVs for all modeled European countries, the modeling of an aggregated EV profile resulted in a computation time similar to the test scenario, while the modeling of 5 discrete clustered EV profiles per country already led to 4 times higher computation times. For these reasons, we recommend modeling bidirectionally chargeable EVs with an aggregated EV profile per country to significantly reduce computation time, while still providing a good realistic representation of bidirectionally chargeable EVs.

3.2 Future European Energy System with and without V2G applications

To evaluate the integration of smart and bidirectionally chargeable EVs in Europe, we set up a European reference scenario for the years 2025 to 2050 based on the solidEU scenario of the research project eXtremOS. A detailed scenario description of solidEU is published in a summary report [1]. This reference scenario *'Ref'* is characterized by a harmonized decarbonization of the European energy system until 2050. It does not integrate smart and bidirectionally chargeable EVs. For evaluating the value of smart and bidirectionally chargeable EVs, we set up a second scenario *'BCM'* that enables the integration of these EVs. The number of smart and bidirectionally chargeable EVs can be expanded endogenously in every European country using the energy system model. Since there are no European country-specific data for EV profiles publicly available, we use the aggregated German EV profile for every European country. This approach neglects country-specific driving behavior, but considers the weekly and seasonal driving characteristics, which in other European countries do not differ fundamentally from the German characteristics, since working days and working hours are similar in all European countries.

The smart and bidirectionally chargeable EVs are parameterized by the characteristics of a mid-size passenger car described in Table 2. The number of the EVs is endogenously optimized and not fixed by parameters. For this optimized integration, Table 4 shows the additional investment costs of smart and bidirectionally chargeable EVs compared to unmanaged charging EVs. These additional investment costs include additional investments and installation costs for the EVSE and for additional required measuring equipment. The costs do not include additional investment costs for the EV itself. The assumptions for the additional investment costs were made within the BCM research project in consultation with various experts [24]. Currently, only a few offers for bidirectional EVs and EVSEs are available that are consequently high-priced. The only available offer for a bidirectional EVSE in Germany is around 6,000 € [25] compared to around 500 € for an unmanaged EVSE [26] resulting in difference costs of 5,500 € only for the purchase of the EVSE. Table 4 shows that experts in the BCM research project expect a high cost degression for bidirectional EVSEs in the timeframe up to 2040, when unit numbers in production go up. The lifetime of the smart and bidirectionally chargeable EVs, including their EVSE, is set to 15 years [27] and the interest rate from the energy system's perspective is 3.5% [28]. Both values are needed for the calculation of annual investment costs in the energy system model.

Table 4. Additional investment costs of smart and bidirectionally chargeable EVs compared to unmanaged charging EVs.

	Year	2025	2030	2035	2040	2045	2050
Additional investment costs for EV in €/EV	Smart chargeable EVs	960	760	760	760	760	760
	Bidirectionally chargeable EVs	2840	2190	1890	1590	1590	1590

Figure 4 analyzes the EV numbers from 2025 to 2050 in a cost-optimized future European energy system in the *BCM* scenario. Supplementary Appendix A presents the exact numbers of EVs per charging strategy per country from 2025 to 2050. In Figure 4 (a), one can see the number of smart and bidirectionally chargeable EVs compared to unmanaged charging EVs. The first thing that stands out is that almost no smart chargeable EVs are added endogenously by the energy system model. This means that the added value of bidirectionally chargeable EVs to the energy system significantly exceeds the additional costs of these EVs, when costs are considered as shown in Table 4. The number of integrated bidirectionally chargeable EVs goes up from 7 million EVs in 2025 to 62 million EVs in 2050 and has the highest share in 2045 of 37%. This significant increase indicates that the future European energy system becomes more efficient with the provided flexibility through bidirectionally chargeable EVs.

Figure 4 (b) shows the integration of bidirectionally chargeable EVs in the six countries Germany (DE), Spain (ES), France (FR), Italy (IT), Poland (PL) and United Kingdom (UK) representing the European countries with the highest number of integrated EVs. The increase in bidirectionally chargeable EVs is not occurring equally in different countries, but rather has characteristic differences. In Spain and Italy, the energy system model already integrates around 2 million bidirectionally chargeable EVs in 2025, significantly more than in the other countries displayed. As of the year 2035, the countries Germany, France and Italy have the most bidirectionally chargeable EVs. In 2050 in Germany there is a sharp decrease in bidirectionally chargeable EVs, meaning that some of the previous bidirectionally chargeable EVs that reached their lifetime are replaced by unmanaged charging EVs. In 2050 in Germany, expanded hydrogen-fired power plants provide flexibility leading to a lower flexibility needed on the demand-side.

If unmanaged charging EVs are replaced by bidirectionally chargeable EVs, the EV loads due to additional equivalent full cycles (EFCs) of the battery will be increased. The EFCs of bidirectionally chargeable EVs are highest in 2025 at 280 EFCs/a, going down to 200 EFCs/a in 2035 and 185 EFCs/a in 2050 compared to approximately 60 EFCs/a for an unmanaged charging EV with 50 kWh battery capacity.

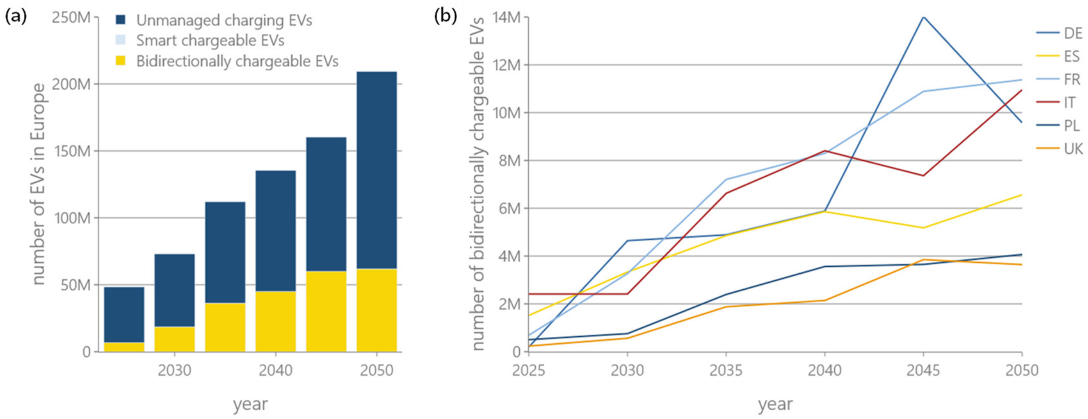

Fig. 4. Analysis of future EV numbers from 2025 to 2050 in a cost-optimized European energy system: (a) total EV number per charging strategy; (b) integrated bidirectionally chargeable EVs per country.

For a more detailed European evaluation of the integration of bidirectionally chargeable EVs, Figure 5 analyzes the shares and numbers of EVs per charging strategy per country in 2030 and 2050. As additional information, the coloring of the countries is related to the full load hours of PV generation. In 2050, there are both higher numbers of EVs and higher shares of bidirectionally chargeable EVs in most countries compared to 2030. The integrated shares of bidirectionally chargeable EVs are much higher in most southern European countries compared to the northern European countries. It is noticeable that the share of bidirectionally chargeable EVs is higher in the countries that have higher full load hours of PV generation. This dependance can be explained by the fact that bidirectionally chargeable EVs often act as daytime storages. The parameterized EVs have an energy/power ratio of 50kWh/11kW. This means they can charge or discharge for a maximum of four and a half consecutive hours. The PV generation represents a regular daily generation profile with only seasonal differences. Therefore, bidirectionally chargeable EVs can provide the necessary flexibility to more evenly feed-in the PV generation into the energy system. Higher full load hours of PV generation indicate a more cost-effective expansion of PV generation and thus indicate a more attractive location for bidirectionally chargeable EVs.

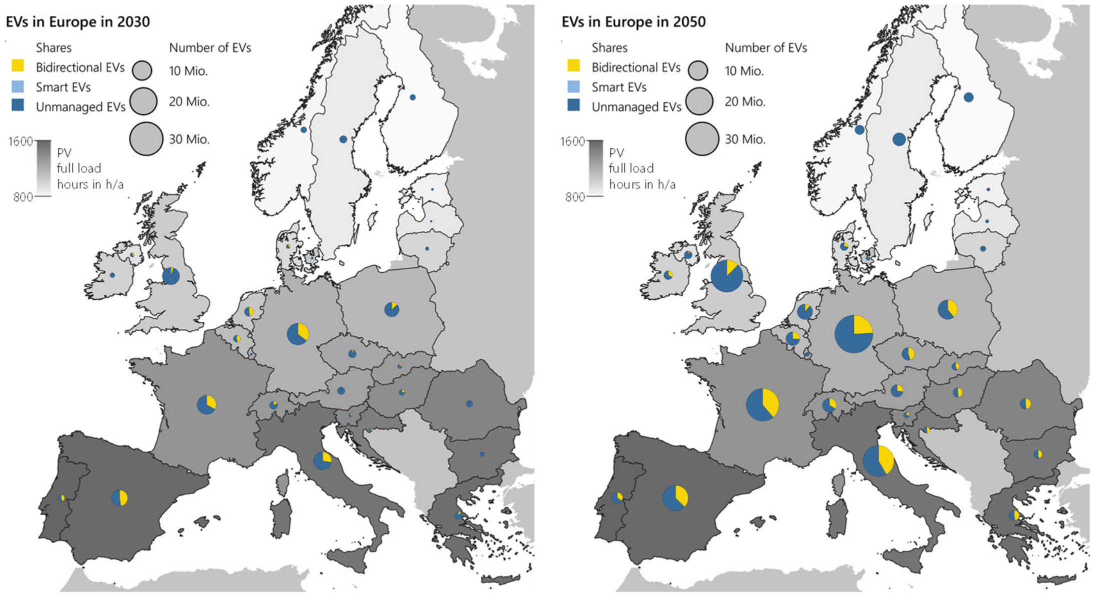

Fig. 5. Dependance of shares and numbers of EVs per charging strategy per country in 2030 and 2050 on the full load hours of PV generation.

As a detailed scenario comparison, Figure 6 shows the capacities of conventional power plants, volatile renewable energies, and storage technologies for the scenarios *Ref* and *BCM* for the years 2030, 2040 and 2050 in Europe. The analysis points out structural differences, but also similarities, in the future European energy system. There is a high increase in all volatile renewable technologies in future years due to the ongoing decarbonization of the energy system. However, there are some differences between the installed capacities of renewable energies in the scenarios *Ref* and *BCM*. In general, the *BCM* scenario prefers an expansion of PV generation compared to an expansion of wind onshore and wind offshore generation. Bidirectionally chargeable EVs act as a daytime storage increasing the consumption at the time of peak PV generation and thus raise the market value of PV generation. Therefore, bidirectionally chargeable EVs are an incentive to the integration of PV generation that is the volatile renewable energy source with the lowest levelized cost of electricity in ISAaR.

The installed capacities of conventional power plants increase from 2030 to 2050, although the full load hours and thus the electricity output decreases by over 50%. PV plants and wind turbines are characterized by a fluctuating electricity generation that leads to a higher demand of conventional power plants as back-up capacities. The gas-fired power plants in 2050 generate electricity with synthetic methane produced by renewable energies. When comparing the two scenarios *Ref* and *BCM*, it is noticeable that less gas-fired and hydrogen-fired power plant capacity is expanded in the BCM scenario. Bidirectionally chargeable EVs discharge and thus feed-in electricity into the energy system when there is a high need for electricity generation due to a high consumption or a low generation or both. Consequently, gas- or hydrogen-fired power plants can lower their electricity generation in these situations. Therefore, from the energy system's perspective, bidirectionally chargeable EVs lead to a decreased need for flexible gas- and hydrogen-fired power plants.

The installed capacity of storage technologies increases significantly from 2030 to 2050 in both considered scenarios. In the reference scenario *Ref*, the only storage expansion option for the energy system model is the increase of stationary battery storages. The BCM scenario has the expansion options of stationary battery storages and bidirectionally chargeable EVs. Pumped storage hydropower is set fixed for future years and cannot be endogenously expanded. The *BCM* scenario clearly favors the integration of bidirectionally chargeable EVs over the expansion of stationary battery storages. The lower investment costs of bidirectionally chargeable EVs compared to stationary battery storages outweighs the disadvantage of limited availability of EVs. In terms of one MWh of storage capacity, bidirectionally chargeable EVs have investment costs of 31,800 € in 2050 compared to stationary battery storages that cost around 123,000 € in 2050 based on eXtremOS project [29]. These cost advantages outweigh the limited availability of the EV's storage capacity due to the connection status of the EV to the EVSE and minimum SoC constraints because of the user behavior. These results show that bidirectionally chargeable EVs significantly lower the need for other storage technologies in a cost-optimal future European energy system.

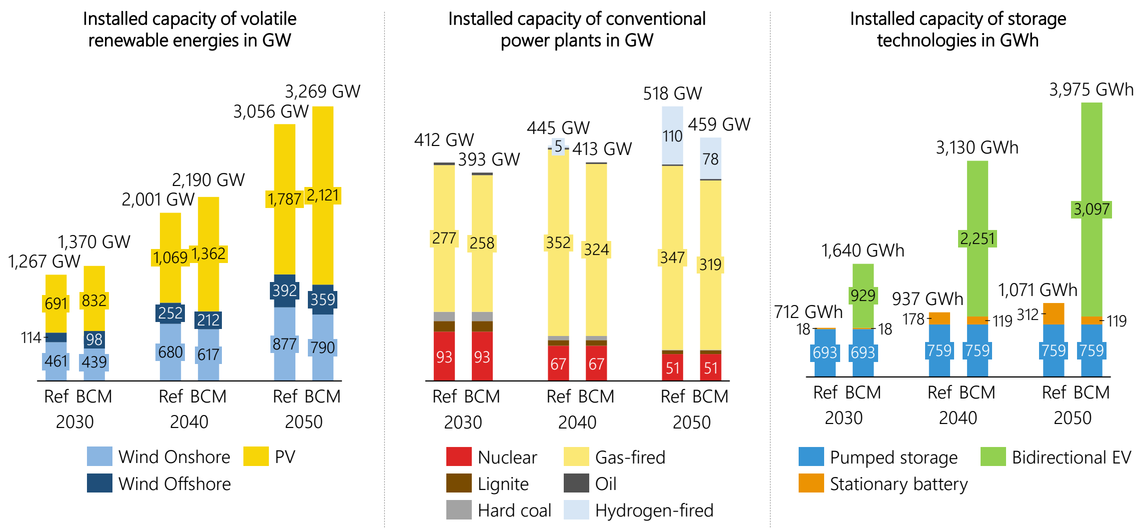

Fig. 6. Installed capacities of conventional power plants, volatile renewable energies, and storage technologies for the scenarios *Ref* and *BCM* for the years 2030, 2040 and 2050 in Europe.

For the analysis of electricity prices, Figure 7 shows the annual hourly duration curve of electricity prices in Italy (IT) and the United Kingdom (UK) as exemplary countries with a high and a low share of bidirectionally chargeable EVs for the years 2030 and 2050 for both scenarios *Ref* and *BCM*. In general, the *Ref* scenario results in a slightly higher annual electricity price duration curve. Bidirectionally chargeable EVs in the *BCM* scenario charge when electricity prices are low, resulting in a partly electricity price increase of the low prices. On the other hand, they discharge when electricity prices are high, leading to a partly decrease of the highest electricity prices. These effects result in an overall smoothing of the electricity prices. Italy has a much higher share and number of bidirectionally chargeable EVs than the United Kingdom. Consequently, the impact of the bidirectionally chargeable EVs on the electricity price is also higher in Italy compared to the UK. But while the share of bidirectionally chargeable EVs in the UK, at 6% in 2030 and 12% in 2050, is comparably low, the impact on electricity prices is nevertheless strongly recognizable.

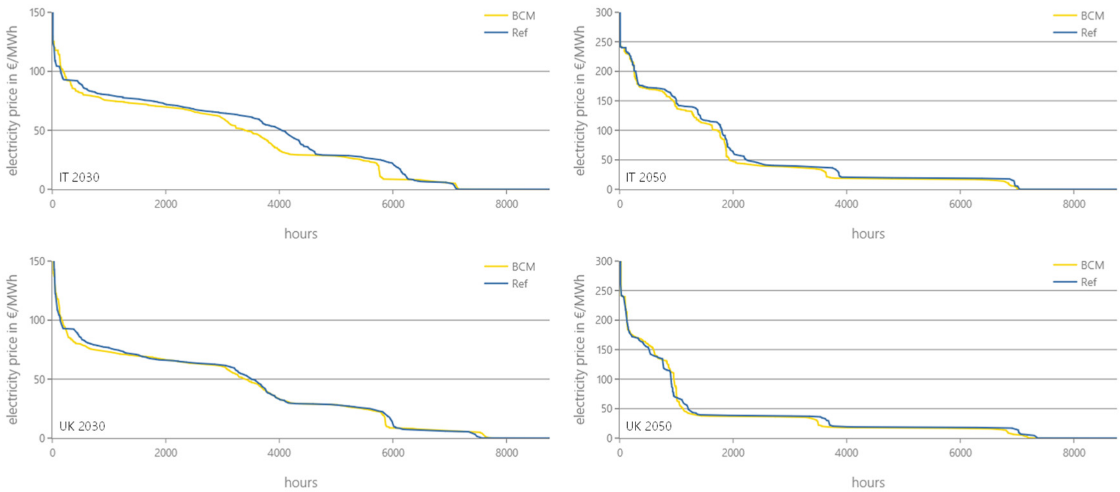

Fig. 7. Annual hourly duration curve of electricity prices in Italy (IT) and the United Kingdom (UK) for the years 2030 and 2050 for both scenarios Ref and BCM.

The difference in the design of the energy system between the scenarios *Ref* and *BCM* leads to a difference in overall energy system costs and mean electricity prices. Table 5 summarizes these key indicators for both scenarios for the years 2025 to 2050. The mean European electricity price is calculated by the demand-weighted electricity price over all modeled European countries and timesteps. Bidirectionally chargeable EVs cause a decrease in electricity prices by up to 12% in 2040. Renewable energies are better and more cost-effectively integrated into the energy system, thus the use of expensive thermal power plants is reduced. The overall energy system costs are also reduced. While total energy system costs are only slightly lower in *BCM* than in *Ref* in 2025, costs decrease by over 9 billion €/a in 2045. Reduced costs on the power supply side clearly outweigh the additional investment costs of bidirectionally chargeable EVs.

Table 5. Overall energy system costs and mean European electricity price for the years 2025 to 2050 for scenarios *Ref* and *BCM*.

Year	Overall energy system costs in billion €/a		Mean European electricity price €/MWh	
	Ref	*BCM*	*Ref*	*BCM*
2025	432.4	431.7	44.6	42.6
2030	414.6	412.4	42.5	39.4
2035	354.9	350.1	43.1	39.1
2040	332.2	325.7	44.6	39.4
2045	323.5	314.4	44.4	41.1
2050	353.1	345.0	41.6	38.8

4. Discussion

Bidirectionally chargeable EVs represent an essential component of the future energy system. In this study, we analyze different modeling approaches of bidirectionally chargeable EVs in a complex multi-energy system model and evaluate their integration as well as their impact on the European energy system in future years. For complex energy system models, we recommend the modeling of one aggregated EV profile to limit computation time, while modeling a realistic representation of the EV composition of a country. We show numerous positive effects of bidirectionally chargeable EVs:

- Bidirectionally chargeable EVs support the integration of PV generation. This is of great importance for the future energy system, since wind generation, especially onshore wind generation, deals with various acceptance issues across Europe [30].
- Bidirectionally chargeable EVs lower the required installed capacities of conventional power plants, such as gas- or hydrogen-fired power plants. Replacing the need for power plant capacities that operate with very few full load hours through bidirectionally chargeable EVs means contributing to the security of supply of the energy system.
- Bidirectionally chargeable EVs lower the required installed capacities of other storage technologies, such as stationary battery storages, and thus cause a lower demand of battery capacities.
- Overall energy system costs and electricity prices decrease with an integration of bidirectionally chargeable EVs, which makes the European energy system more cost-efficient and results in lower costs for the end user of electricity.

Therefore, our results support studies from Hanemann et al. [10], Rodríguez et al. [11], Wie et al. [13], Child et al. [14] that already showed positive impacts of smart or bidirectionally chargeable EVs on local energy systems. We further show interrelated effects in the coupled European energy system, discuss different detailed modeling approaches of bidirectionally chargeable EVs in a large-scale energy system model and finally output cost-optimal penetration rates of bidirectionally chargeable EVs in the future European energy system.

However, there are some limitations of the modeling and the results that show the need for further research. The aggregated EV profile is based on German mobility data of passenger cars. More detailed mobility data of other European countries could have an influence on repercussions in the energy system. However, the basic findings should not be affected. The effect of the parametrization of the EVs, including investment costs for smart and bidirectionally chargeable EVs, should be investigated further. Possible larger EV battery capacities in the future could even increase the added values of bidirectionally chargeable EVs.

The additional load on EVs through bidirectional charging is high. 200 EFCs per year in 2035 with a lifetime of 15 years result in a total of 3,000 EFCs for the EV battery capacity. However, comparing these EV loads to current EFC lifetime values for station battery storage systems that are around 5,000 EFCs ([31], [32]) suggests that these EV loads will be sustainable in the future.

The ISAaR energy system model optimizes the European energy system in an hourly annual simulation. Each European country represents one node. The European transmission grid is only modeled by cross border transfer capacities between countries, while the distribution grid is not modeled. Therefore, the impact of bidirectionally chargeable EVs on grid utilization is not addressed by this study and should be further investigated. Due to the high simultaneity of EV charging or discharging operations with market-driven use of EVs, there is a risk of grid overloading. Müller et al. [33] already deal with the impact of smart and bidirectionally chargeable EVs on the distribution grid utilization and show decreasing and increasing grid overloads dependent on the use case and the charging strategy.

Finally, the results of the future cost-optimized energy system shown in Chapter 3.2 are from the perspective of the energy system and not from the perspective of the users. Consequently, there are no fees and taxes on electricity prices modeled that could change the dispatch of storage units, like bidirectionally chargeable EVs.

5. Conclusion

To evaluate the impact of electric vehicles (EVs) on the future European energy system, we analyze modeling approaches of smart and bidirectionally chargeable EVs in a large-scale multi-energy system model and model the future European energy system with and without the option of integrating these EVs. We show that aggregated EV profiles per country are sufficient to realistically model the EV behavior and the repercussions on the energy system. We find future cost-optimized penetration rates of bidirectionally chargeable EVs per country from the energy system's perspective, and thus support stakeholders in the industry in planning their future business models. Furthermore, we encourage policy makers to enable bidirectional charging of EVs through regulatory measures in order to realize the presented positive impacts on the energy system. Finally, the paper is intended to support scientists by providing detailed descriptions of modeling approaches of bidirectionally chargeable EVs and data of EV profiles.

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Appendix A.

Table A1. Number of EVs per country in million EVs (Unma = Unmanaged charging EVs; Bidi = Bidirectionally chargeable EVs).

Country	2025		2030		2035		2040		2045		2050	
	Unma	Bidi	Unma	Bidi	Unma	Bidi	Unma	Bidi	Unma	Bidi	Unma	Bidi
AT	0.74	0	1.5	0	2.08	0.12	1.63	0.96	2.13	1.12	2.97	1.12
BE	0.46	0.12	0.71	0.63	1.47	1.34	1.71	1.55	2.35	1.9	3.9	1.39
BG	0.31	0	0.52	0	0.99	0.02	1.04	0.06	0.72	0.65	0.98	0.89
CH	0.95	0.02	1.42	0.3	1.44	1.31	1.77	1.6	2.3	2.06	3.57	1.78
CZ	1.38	0	1.57	0.11	1.2	1.09	1.8	1.09	1.86	1.69	2.45	2
DE	7.59	0.2	8.45	4.64	15.15	4.89	19.46	5.88	18.16	14.02	30.14	9.57
DK	0.34	0.01	0.47	0.18	0.96	0.3	1.13	0.3	1.06	0.75	1.76	0.58
ES	3.91	1.52	3.67	3.33	5.35	4.86	6.45	5.86	8.89	5.18	11.04	6.56
FI	0.7	0	0.92	0	1.4	0	1.68	0	1.99	0	2.53	0
FR	4.58	0.69	6.72	3.27	7.93	7.21	9.13	8.29	13.44	10.89	17.94	11.37
GR	0.91	0.19	1.29	0.19	1.2	0.75	1.19	0.94	1.41	0.92	1.51	1.37
HU	0.52	0.22	0.71	0.22	0.72	0.65	0.84	0.77	1.19	0.66	1.28	1.16
IE	0.35	0.02	0.63	0.02	1.17	0.03	1.18	0.3	1.1	0.71	1.43	0.71
IT	3.52	2.41	6.39	2.41	7.29	6.62	9.91	8.4	13.17	7.36	15.38	10.96
LT	0.37	0	0.35	0.01	0.51	0.03	0.63	0.03	0.62	0.04	0.82	0.03
NL	0.97	0.32	1.22	1.08	2.36	1.08	2.96	1.08	4	1.12	5.78	0.71
NO	0.66	0	1.01	0	1.4	0	1.67	0	2	0	2.49	0
PL	5.1	0.5	5.09	0.75	4.96	2.39	4.45	3.56	5.08	3.65	6.39	4.07
PT	0.93	0.09	0.6	0.55	0.94	0.85	1.16	1.06	1.51	1.2	2.18	1.11
RO	1.13	0	1.18	0	1.69	0.03	2.03	0.12	1.27	1.16	1.65	1.5
SE	0.89	0	1.56	0	2.5	0	2.98	0	3.8	0	4.73	0
SI	0.11	0.1	0.21	0.1	0.24	0.22	0.28	0.25	0.48	0.25	0.66	0.25
SK	0.3	0	0.38	0.08	0.42	0.38	0.51	0.46	0.64	0.58	0.87	0.65
UK	4.75	0.24	8.14	0.56	13.14	1.88	15.88	2.14	20.45	3.85	26.46	3.64

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Publication 4 (Pub4): Added Value of Providing Transmission Grid Congestion Management via Bidirectionally Chargeable Electric Vehicles

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Abstract: Congestion management in the European transmission grid is currently mostly provided by conventional power plants. As electricity generation in the future will be increasingly characterized by volatile renewable energies, new technologies need to be integrated into congestion management. This paper develops a methodology for modeling storages in congestion management and investigates the potential for bidirectional electric vehicles (EVs) in 2030. A direct current load flow via Power Transfer Distribution Factors (PTDF) is used to model the load flow in the transmission grid. Since the modeling involves great complexity due to time-coupling constraints of storages, different modeling approaches are investigated. The results show that bidirectional EVs can take over a significant part of the congestion management due to their decentralized distribution. A total of 26 TWh of positive redispatch of conventional power plants in 2030 can be replaced by the optimized use of bidirectional EVs.

Index Terms: congestion management; bidirectionally chargeable electric vehicles; European energy system; redispatch; vehicle-to-grid.

I. Introduction

To achieve the European climate protection targets, the future European energy system will be strongly characterized by volatile renewable energies [1]. Since wind turbines and solar plants are placed on revenue-maximizing locations and not near the highest electricity demand like power plants usually are, the stress on the transmission grid increases. Consequently, the volumes of congestion management will most likely increase in the future. In Germany, congestion management initially included the curtailment of renewable energies and separately the provision of redispatch via conventional power plants. Redispatch refers to a short-term adjustment of a scheduled generation or consumption of an asset to lower congestions in the transmission grid. In 2019, NABEG 2.0 integrated combined heat and power plants and the curtailment of renewable energies into a uniform regulatory regime, so that the most effective and cost-efficient plants can be called upon for redispatch [2]. The 'Redispatch 2.0' introduced in 2021 standardizes this even more and also integrates smaller, remotely controllable assets and electricity storages of a power 100 kW or more [3] into congestion management. Bidirectionally chargeable electric vehicles (bidirectional EVs) represent an alternative option to provide redispatch by adjusting their scheduled charging and discharging power and could thus be integrated into the redispatch process as well. In Germany, the goal has been set to integrate 15 million electric vehicles by 2030 [4]. Increasingly, these electric vehicles will be equipped with bidirectional charging management technology [5]. Consequently, bidirectional electric vehicles can potentially have a large impact on the provision of ancillary services. Therefore, this paper analyzes the impact of bidirectional EVs integrated in the European redispatch process on the dispatch and thus emissions of conventional power plants.

Storages, and thus bidirectional EVs, reduce inter-temporal price volatility leading to smoothed electricity prices, while inter-regional price volatility may increase [6]. Regarding the provision of redispatch services, there are numerous papers that deal with stationary and mobile storages. Meyer-Huebner et al. show that preventive generator redispatch can be reduced by reserving positive or negative storage capacity by modeling a 5-bus test system with 192 timesteps [7]. However, they do not include bidirectional EVs and limit their investigations on a small-scale test system. Xiong et al. develop a two-stage model incorporating the day-head spot market and subsequent redispatch and find out that Power-to-Gas (PtG) assets providing redispatch services reduce the curtailment of renewable energies by 12% [8]. They model PtG assets like storages with time-depending constraints, but do not include mobile storages. Eickmann et al. also develop a two-stage model with a day-ahead market simulation followed by a redispatch evaluation [9]. They point out that pumped hydroelectric energy storages participating in the redispatch process reduce congestion management energy and costs. Müller et al. model time variant redispatch provided by virtual power plants that include biogas-combined heat and power plants, controllable loads and storage systems [10]. However, they do not include mobile storages and limit their optimization on Germany for 8h in 15 min time steps. Gutermuth et al. analyze the benefit of grid operator owned stationary storages by an hourly simulation of the German transmission grid in 2030 showing a simplified iterative modeling approach to reduce complexity [11]. All aforementioned studies focus on stationary storages and limit the optimization to small-scale test systems, to only few timesteps or to simplified modeling. Since we want to evaluate the benefits of bidirectional EVs providing redispatch services in the large-scale European energy system, we set up a modeling of mobile storages, and analyze the complexity of the optimization with different parameterizations. There are also few studies that investigate bidirectional EVs integrated in the redispatch process. Staudt et al. model bidirectional EVs providing redispatch services in Germany but simplify the EV behavior and redispatch provision by a heuristic approach [12]. Thormann et al. model bidirectional EVs that provide redispatch focusing on the medium-voltage grid but simplify modeling by only comparing charging and discharging patterns with redispatch system needs [13]. We model the optimal operation of bidirectional EVs by realistic profiles and user behavior to show the influence of bidirectional EVs on the energy system.

II. Modeling

A. Two-stage market and transmission grid optimization in energy system model ISAaR

Congestion management in the energy system model ISAaR (Integrated Simulation Model for Unit Dispatch and Expansion with Regionalization) is modeled in a two-step approach. First, a multi-energy market optimization run is conducted. One market area is represented by one node. Energy transfers between market areas are allowed up to maximum net transfer capacities (NTCs). In the following step, the resulting dispatch of generation, load and storage instances is taken as a base for the transmission grid optimization run, in which the costs of congestion management (curtailment of renewable energies and provision of redispatch services) are minimized. Here, a node represents a transmission grid node. For a more detailed description of the multi-energy market optimization, we refer to Kigle et al. [14]. The transmission grid optimization run is previously described in [15] and [16]. In this publication, we extend the transmission grid optimization by integrating mobile and stationary storages with a focus on bidirectional EVs.

B. Time-dependent modeling of bidirectional EVs in multi-energy system model ISAaR

Bidirectional EVs in the multi-energy system model ISAaR are modeled according to [17]. The most important constraint of a bidirectional EV is its time-coupled energy conservation as shown in (1). The state of the battery energy E at a time t is equal to the energy of the previous time step added by the charged energy $P_i(t) \cdot \eta_i \cdot \Delta \mathrm{t}$ and subtracted by the discharged energy $\frac{P_o(t) \cdot \Delta \mathrm{t}}{\eta_o}$ as well as the driving consumption E_{con}, where η_i and η_o refer to the fixed charging and discharging efficiency.

$$E(t) = E(t\text{-}1) + P_i(t) \cdot \eta_i \cdot \Delta t - \frac{P_o(t) \cdot \Delta t}{\eta_o} - E_{con}(t) \quad (1)$$

The charge and discharge power of the EV supply equipment (EVSE) P_i and P_o are constrained by a maximum power $P_{i,max}$ and $P_{o,max}$. The battery energy is further constrained by a minimum state of charge (SoC) at a connection of the EV to the EVSE and a minimum SoC at the departure of the EV. These constraints are included in the profile of the minimum energy E_{min}, which is applied in addition to the constraining maximum energy E_{max} in (2).

$$E_{min} \leq E(t) \leq E_{max} \quad (2)$$

C. Modeling of the transmission grid optimization run

The transmission grid is modeled at a regional resolution, with the highest level of detail for Germany and higher aggregation of transmission grid nodes for more distant countries. Figure 1 shows the mapping of the transmission network. For example, in Spain and Portugal, all nodes are aggregated into one, Great Britain has 10 nodes and Germany is mapped with 460 nodes. In total, this results in 1,580 nodes, which leads to a high complexity of the optimization problem. The transmission grid data is provided by the static grid models described in [16] and extended by the German [18] and European [19] grid development plants. Highly aggregated parallel transmission lines are modeled as direct current (DC) lines, since the reactance of the lines would otherwise become very small [20], resulting in an unrealistic load flow.

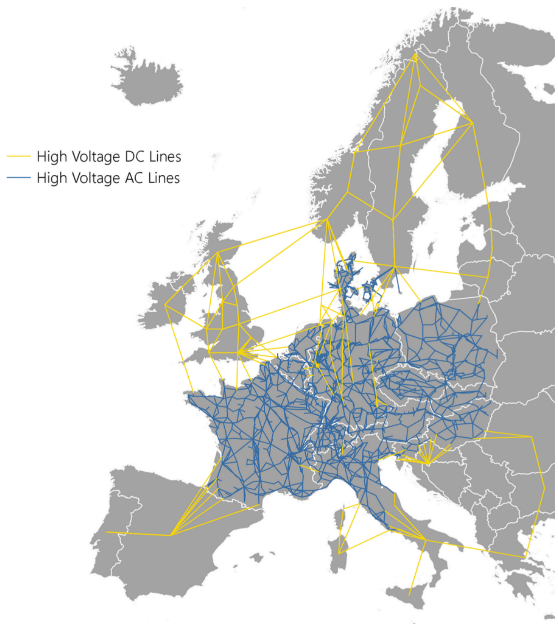

Figure 1: European transmission grid modeled in energy system model ISAaR

Böing [15] describes the applied, linearized approximation of the non-linear alternating current (AC) load flow by applying a DC load flow based on PTDF (Power Transfer Distribution Factors). Assuming that there are no voltage drops (voltage amplitude is equal for all nodes), reactive power is neglected, line losses are neglected, and the voltage angle differences are small, the simplification of a DC load flow is justified [21]. Since the reactive power consumption of the AC lines increases quadratically, modeling the AC load flow via a DC load flow is no longer permissible for high loads [22]. In addition, since line outages must be considered, the AC lines are limited to a maximum load of 70%, which represents the single outage contingency operational criterion (n-1) well [23]. The load flow of AC lines $P_{line,AC}$ is determined by the injections and withdrawals of grid nodes P_{node} multiplied by the PTDF matrix according to (3). The PTDF matrix is formed by the incidence matrix *A* describing the grid topology and the diagonal matrix with line susceptances *B* according to (4). A detailed derivation of the equations can be found for example in [24], and [21].

$$P_{line,AC} = PTDF \cdot P_{node} \tag{3}$$

$$PTDF = (B \cdot A) \cdot (A^T \cdot B \cdot A)^{-1} \tag{4}$$

The converters at the end and at the beginning of a DC line can fully control its power flow [24]. Therefore, line flow from a node *x* to a node *y* can be modeled via a transport model according to (5):

$$P_{line,DC} = P_{x \to y} \tag{5}$$

D. Modeling of congestion management via power plants and renewable energies

To model congestion management, a few constraints are introduced. Equation (6) shows the power balance based on electrical output of the market run, the optimized output, and the redispatch provisions of conventional power plants. The result of the marked optimization run $P_{M,pp}$ for each power plant *pp* is set as a fixed bound. The electrical output ($P_{o,pp}$) is optimized under consideration of positive ($P_{p,pp}$) and negative ($P_{n,pp}$) redispatch services. The lower and upper bounds of the redispatch services are shown in (7) and (8).

$$P_{o,pp}(t) - P_{p,pp}(t) + P_{n,pp}(t) = P_{M,pp}(t) \tag{6}$$

$$0 \leq P_{n,pp}(t) \leq P_{M,pp}(t) \tag{7}$$

$$0 \leq P_{p,pp}(t) \leq P_{o,max,pp}(t) - P_{M,pp}(t) \tag{8}$$

Variable renewable energy sources (vRES) are modeled without variable operational cost. Therefore, all vRES operate at maximum output in the market optimization run and no positive redispatch is possible through vRES. Thus, Equation (6) is shortened to (9), where $P_{c,vRES}$ represents the curtailment of vRES, $P_{M,vRES}$ the output of the market run and $P_{o,vRES}$ the electrical output of the transmission grid run. Equation (10) restricts the curtailment of vRES.

$$P_{o,vRES}(t) + P_{c,vRES}(t) = P_{M,vRES}(t) \tag{9}$$

$$0 \leq P_{c,vRES}(t) \leq P_{M,vRES}(t) \tag{10}$$

E. Modeling of congestion management via stationary and mobile storages

The modeling of congestion management with electricity storage systems is challenging due to their time-coupling constraints [15]. Modeled storage systems in ISAaR include pumped hydroelectric energy storages, stationary battery storages and bidirectional EVs.

The transmission grid optimization run is conducted parallel with several subproblems to save time and to keep the problem solvable. The whole optimization period of 8760 h for an annual simulation is therefore divided into equal time slices. At the first timestep of a time slice, the preceding storage level is unknown because there is no link between the parallel optimized time slices. Therefore, the storage level at the end of a time slice is fixed to the result of the market optimization run and the same value is handed over to the next time slice to maintain a coupling (of the time slices) as shown in Figure 2.

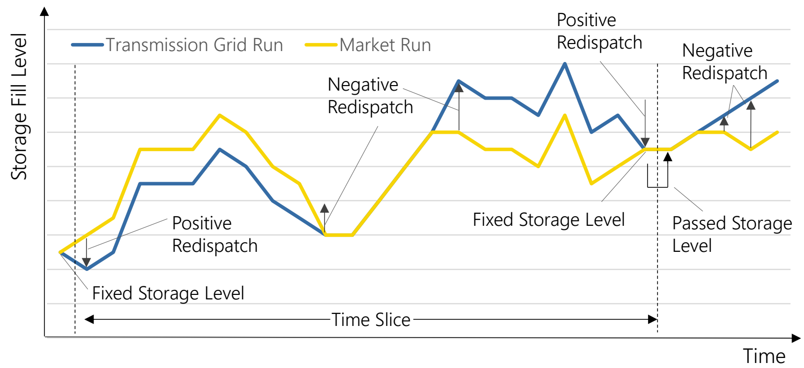

Figure 2: Schematic modeling of the restricted storage fill level at the start and the end of a time slice

By changing the length of the time slice, the flexibility of the storage operation while providing congestion management is affected. Due to the fixed storage level at the end of each time slice, every change of operation from the market schedule is limited. Therefore, shorter time slices lead to a bigger limitation of flexibility of the storages. Thus, long time slices are recommended to avoid unrealistic restrictions on modeling.

To calculate the redispatch services of storage systems *st*, (6) is extended by the input power $P_{i,st}$, resulting in (11). The power balance of storage systems providing redispatch services differs from normal power plants, because of the bidirectional power flow. A reduction in charging power as well as an increase in discharging power causes positive redispatch. On the other hand, a reduction in discharging power as well as an increase in charging power causes negative redispatch. The upper bounds of the redispatch variables are shown in (12) and (13): Appendix A visualizes the flexibility limits of congestion management provision by storages.

$$-P_{i,st}(t) + P_{o,st}(t) - P_{p,st}(t) + P_{n,st}(t) = P_{M,st}(t) \tag{11}$$

$$0 \leq P_{n,st}(t) \leq P_{i,max,st} + P_{M,st}(t) \tag{12}$$

$$0 \leq P_{p,st}(t) \leq P_{o,max,st} - P_{M,st}(t) \tag{13}$$

F. Cost optimization of congestion management

The transmission grid run minimizes the total system costs C under consideration of congestion management. These costs C shown in (14) result from the specific costs $f_{t,n,i}$ and the utilization of the optimization variables $x_{t,n,i}$ for all time steps t, nodes n and instances i. Variable $x_{t,n,i}$ include generation, consumption and import of all modeled energy carriers. Investment decisions in instances of any elements of the energy system model are fixed for the transmission grid run and thus not included in the system costs.

$$C = min \sum_{t \epsilon T} \sum_{n \epsilon N} \sum_{i \epsilon I_n} (f_{t,n,i} \cdot x_{t,n,i}) \tag{14}$$

Costs of congestion management are also included in (14). Appendix B visualizes the applied order of instances providing congestion management. Costs for positive redispatch and revenues for negative redispatch services of power plants are set dependent on the specific operational costs of every individual plant. The operational costs get a surcharge to avoid unnecessary redispatch provisions. The revenues of curtailing vRES are set to zero. Due to this, it is ensured, that the power plant with the highest operational costs reduces its output first, while vRES is curtailed last. Costs of storages for positive redispatch are assumed to be low at 5 €/MWh; revenues of storages for negative redispatch are slightly lower.

III. Results

A. Market run results

Our evaluation scenario for the year 2030 is based on the 'SolidEU' scenario of the eXtremOS research project [1]. The scenario is characterized by a joint European decarbonization strategy reaching a reduction in greenhouse gas (GHG) emissions of 55% by 2030 with respect to 1990 levels. For an updated modeling of the German climate targets, the German targeted high installed capacities of vRES in 2030 according to the coalition agreement are taken into account [25]. The scenario does not exogenously quantify the share of smart and bidirectional EVs. These shares are optimized endogenously as described in [17]. The optimization of the energy markets in 2030 leads to the generation and storage capacities for the EU in 2030 shown in Table 1 compared to the capacities in 2020. The installed generation capacities show a sharp increase in vRES capacities, while many coal-fired and nuclear power plants are shut down. Further, Table 1 shows the integrated mobile and stationary storage capacities. Mobile storages refer to bidirectional EVs and stationary storages include large-scale battery system and pumped hydroelectric energy storages participating in the electricity day-ahead market. Storage capacities increase significantly by 2030 to balance volatile generation from vRES. Installed power plant, renewable energies, and storage capacities per country and per transmission grid node are shown in Appendix C.

Table 1: Generation and storage capacities resulting from the market run for the EU in 2030 compared to 2020

	Wind	PV	Nuclear	Coal	Gas	Mobile storage	Stat. storage
EU 2020	200 GW	140 GW	120 GW	130 GW	250 GW	0 GWh	530 GWh
Scenario EU 2030	520 GW	910 GW	90 GW	50 GW	260 GW	790 GWh	710 GWh

B. Computation time analysis of transmission grid run

The computation time of the grid optimization run in the model ISAaR depends on many different parameters. The optimization problem of the computation time analysis is limited to a horizon of 672 hours and is based on the scenario described in 0. The varied parameters include the length of the time slices and the number of threads for each parallel run. In an additional evaluation case, 'no ST', the influence of storage systems is investigated by excluding storage systems from the congestion management. Table 2 shows the work units, optimization time and RAM usage for the considered evaluation scenarios. The hardware of the system and an explanation of the evaluation values is described in Appendix D.

The results in Table 2 indicate the following: As the size of the time slice increases, there is generally an increase in complexity accompanied by an increase in optimization time and in RAM usage per run. Excluding storages from the congestion management run slightly lowers complexity. An increased number of threads per run with fewer parallel runs decreases the work units for the time slice of 168 hours. Time slices of 336 and 672 hours are not computable on the specified hardware (Appendix D).

Table 2: Computation time analysis of different parameter sets and their impact on the optimization time

No. of analysis	Parameter variation:			work units	optimization time (h)	RAM usage per run (GB)
	time slice	parallel runs	threads per run			
1	6	4	6	31,430	2	14
2	48	4	6	154,010	6.75	40
3	168	4	6	191,190	7.75	110
4	168*	4	6	178,050	6.75	110
5	168	2	12	114,600	7.75	110
6	336	2	12	-**	-	265
7	62	1	24	-***	-	-

* No storages

** No results, since the optimization cannot be performed parallel due to a lack of random-access memory (RAM)

*** No results, since the model is too big to solve

Appendix D also discusses the differences in the results of the first 3 investigation scenarios. Since the flexibility of bidirectional EVs is very much limited for smaller time slices and the computation time for the 168h time slice is not significantly higher, we use a time slice length of 168 hours with two parallel runs for the simulations in the following.

C. Added value of bidirectionally chargeable EVs providing redispatch services

In the following, the effects of bidirectional EVs on the congestion management process are shown based on two different transmission grid runs. In scenario *Ref*, we perform an optimization of the provision of congestion management services without bidirectional EVs. In the *BCM* scenario, bidirectional EVs (but no other storage units) are included in the congestion management process. Figure 3 shows the volumes of congestion management measures per country and for different technologies for the *BCM* run, Figure E1 (Appendix E) shows in comparison the congestion management of the run *Ref*. Displayed are those nine countries with the highest volumes of congestion management. In scenario *Ref*, there is a total volume of positive congestion management of 600 TWh compared to a total electricity production of just under 5,000 TWh. This indicates an overall congested grid situation due to the strong electrification and expansion of vRES. The results show that bidirectional EVs provide congestion management in many countries. Overall, 26 TWh or 4% less positive redispatch is provided by conventional power plants in the *BCM* scenario. Positive redispatch of backup capacities ('Slack') is even reduced by 13.5 TWh (16%). The curtailment of vRES decreases by 23 TWh or 5% and the provision of negative redispatch from conventional power plants decreases by 9 TWh in the *BCM* scenario, mainly by nuclear power plants. Thus, a total of 17 TWh less electricity is generated from conventional power plants leading to a reduction of emissions of 12 mio. t CO_2.

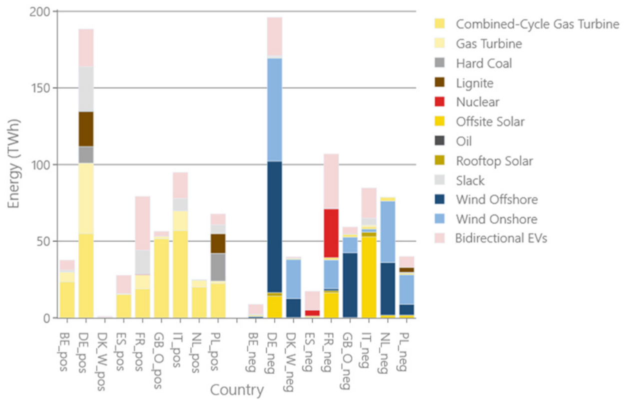

Figure 3: Congestion management per country split up in different technologies for the BCM optimization run

The maps in Figures F1 and F2 (Appendix) show the location of the negative and positive congestion management, respectively. Additionally, the medium line usage of the modeled AC and DC lines is shown. The share of negative redispatch compared to the amount of curtailment is quite small. It is noticeable that curtailed vRES are mainly located in coastal areas in the north of Europe beside the aggregated grid nodes in the south of Italy. Positive redispatch must be provided on the other side of the congestions, especially in areas with high demand.

The maps in Figure 4 and Appendix G show the positive and negative congestion management per grid node split up into different technologies for the *Ref* and the *BCM* scenario. The negative congestion management in the coastal areas of Europe is mainly caused by wind turbines. Bidirectional EVs provide more than the half of the negative redispatch, 120 TWh of 230 TWh in total. The positive redispatch of bidirectional EVs is slightly lower due to losses of additional charging and discharging. As bidirectional electric vehicles are decentralized distributed, they can contribute greatly to both negative and positive congestion management.

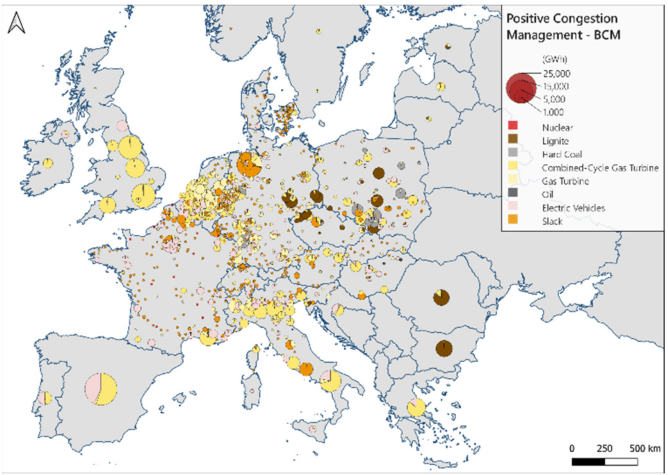

Figure 4: Positive congestion management per grid node split up in different technologies, run BCM

IV. Discussion

Our results indicate that bidirectional EVs can play a large part in congestion management in the future energy system, leading to added value on many levels: Due to the decentralized distribution of bidirectional EVs, they can provide congestion management at numerous nodes in the transmission grid. This reduces the positive redispatch of conventional power plants by 4%. The use of backup power plants is even reduced by 16% leading to saved costs and CO_2 emissions.

Our modeling of congestion management by bidirectional EVs has several limitations that must be considered. The length of the integrated optimized time slice was set to one week, in whose last time step the storage level is fixed. This limits the flexibility of bidirectional EVs. However, since perfect foresight does not exist in reality either, this is an acceptable limitation. Regarding the load flow calculation and the mapping of the electricity grid, several simplifications have been made. Voltage levels below the extra-high voltage level are not modeled and loads and generations are aggregated to the transmission grid nodes. The calculated load flow is a linearization of the AC load flow, resulting in deviations from the real load flow. However, since the grid optimization run already leads to a very high complexity due to the time coupling of the bidirectional EVs, these simplifications are necessary to ensure computability. Furthermore, the correct regionalization of elements is associated with uncertainties. For example, the negative redispatch of a few nuclear power plants in France revealed their incorrect regionalization. Due to a too-low grid connection, their full power could not be fed into the system. The future grid connection points of wind offshore plants have also not yet been determined in some cases, so that problems arose here in feeding their energy into the system.

Overall, due to high congestion management, the modeled transmission grid does not appear to be designed for the installed capacities of wind and PV energy resulting from the market run, although planned grid expansion projects have been considered. Resulting congestion management volumes in Germany around 330 TWh are more than 10 times as much as real volumes in 2020 of around 23 TWh [26]. One possible explanation is the lack of modeled overhead line monitoring and high-temperature transmission lines, which underestimates the thermal capacities of the transmission grid [27]. Nonetheless, the 2030 grid simulations reveal major challenges in integrating renewables into the system. Here, bidirectional EVs can demonstrably support the provision of congestion management to reduce the curtailment of renewable energies and thus ultimately also bring about a reduction in CO_2 emissions.

V. Conclusion

Due to the increasingly reduced capacities of conventional power plants, a future alternative provision of congestion management is of great importance. In this paper, we developed an approach that allows modeling of European congestion management with storage despite the high complexity of time-coupled conditions. Our results show that bidirectional electric vehicles (EVs) can take over a significant share of congestion management in the future energy system and thus save costs and CO_2 emissions. This gives stakeholders in the energy industry and politics the task of creating regulatory framework conditions to enable an integration of bidirectional (EVs) into the process of congestion management.

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Appendix

A. Flexibility limits of congestion management provision by storages

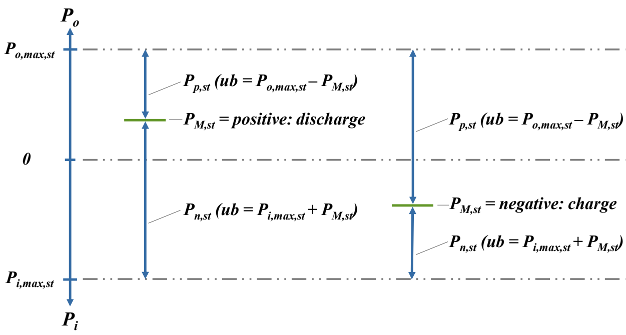

Figure A1: Flexibility limits of congestion management provision by storages

B. Applied order of congestion management provision

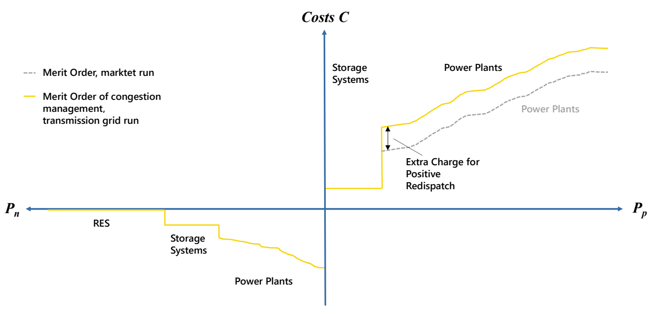

Figure B1: Applied order of congestion management provision

C. Installed capacities

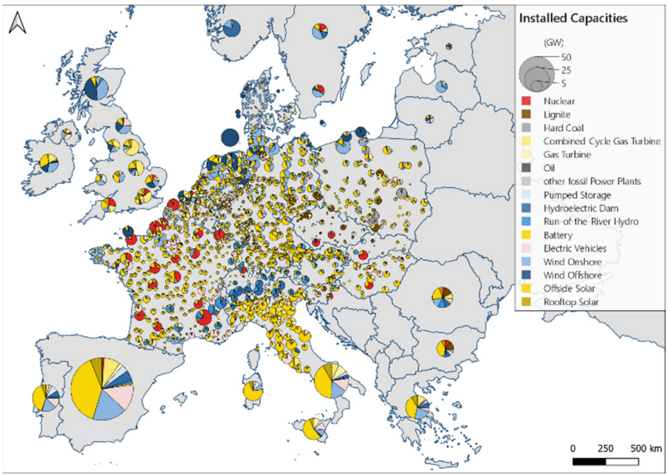

Figure C1: Installed capacities of different technologies per grid node

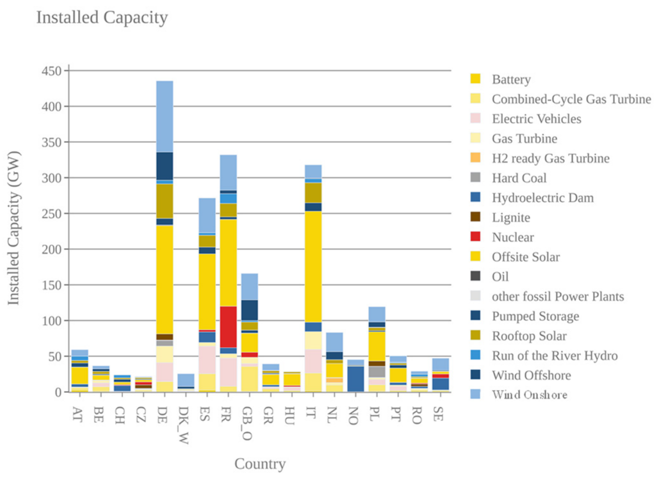

Figure C2: Installed capacities for different technologies, countries with higher capacities than 25 GW

D. Computation time analysis

The used computation server has the following specifications:

- operating system: Linux
- Solver: Gurobi Optimization [28]
- 2x AMD EPYC 7F52 – 16 Core
- 1008 GB RAM

The ‘work unit’ value in Table 2 is a unit that measures the work spent on an optimization problem. It is a deterministic unit thus the same amount of work is needed when optimizing the same problem with the same set of parameters and the same hardware. The optimization time is not deterministic, meaning it will take probably a different time to solve the same problem with the same set of parameters and the same hardware. But the optimization time is the point of interest for the modelers, since this time indicates how long it takes to obtain results. We do this analysis without any parallel running process on the server, so all capacities can be used for solving the problem trying to reduce other influences on the optimization time. The shown optimization time displays the time from the start of an optimization till its end and is not the totaled time of every (partly) parallel conducted run.

The following Figure D1 shows the storage fill level of runs 1 to 3 in Table 2 in comparison with the market run, for one exemplary week at an exemplary grid node. It can be seen that the light blue line always has to reach the market result after every sixth hour and thus is not as flexible as the dark blue and red line, respectively. It is noticeable that the second and third transmission grid runs (time slices: 48 h, 168 h) are quite similar during the mid-hours of a 48 h time slice but differ in the hours around the end of one slice and the start of another (marked by dashed lines). This shows that long time slices enable more flexibility to the system to reach a cost optimal solution.

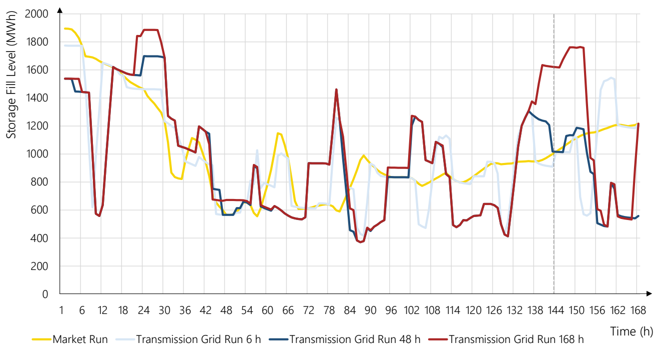

Figure D1: Comparison of storage fill levels from different parametrized optimization runs for an exemplary week at an exemplary grid node

E. Congestion management per country split up in different technologies for the Ref run

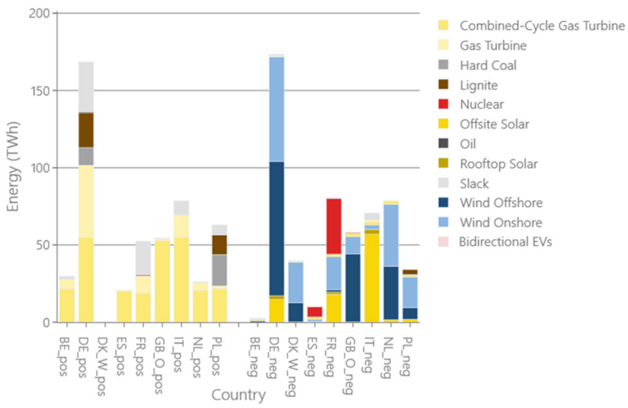

Figure E1: Congestion management per country split up in different technologies for the Ref run

F. Congestion management and mean line usage for the BCM optimization run

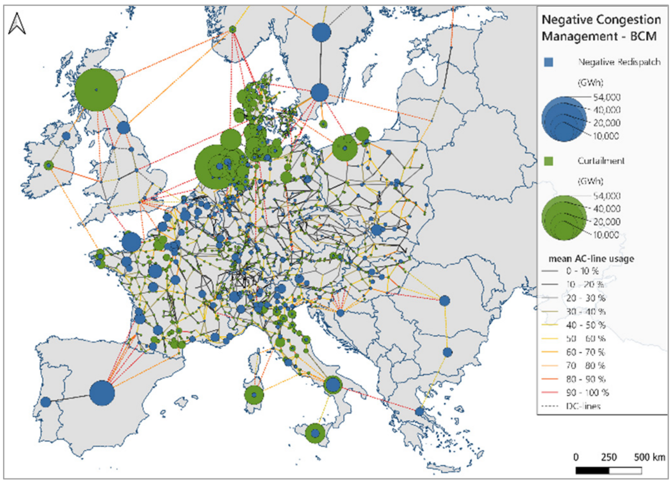

Figure F1: Negative congestion management and mean line usage for the BCM optimization run

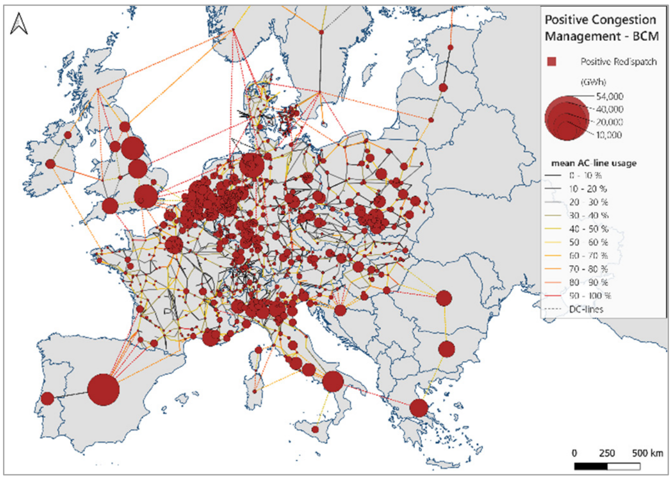

Figure F2: Positive congestion management and mean line usage for the BCM optimization run

G. Congestion management per type for the BCM and Ref optimization run

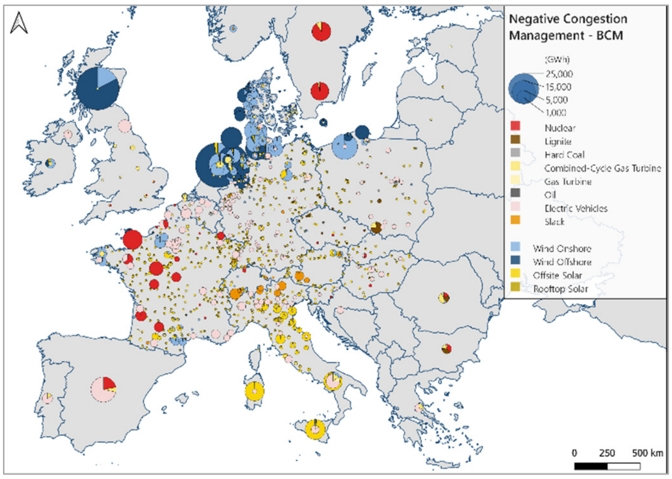

Figure G1: Negative congestion management per grid node split up in different technologies, run BCM

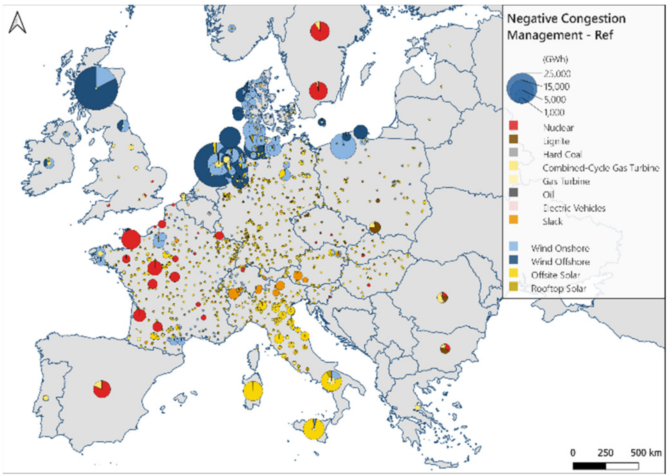

Figure G2: Negative congestion management per grid node split up in different technologies, run Ref

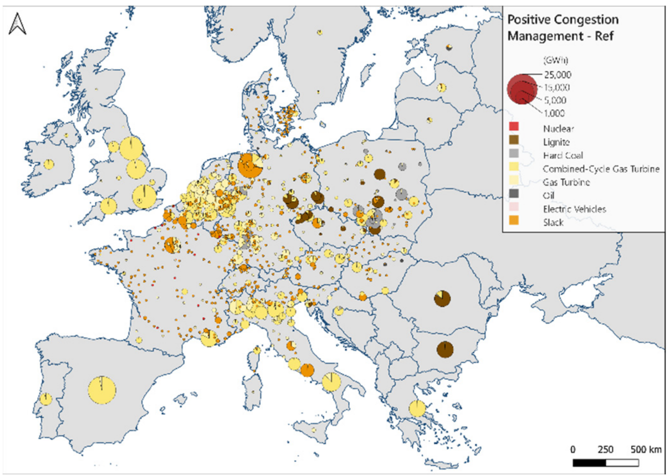

Figure G3: Positive congestion management per grid node split up in different technologies, run Ref

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