OPTIMIZATION OF ELECTRIC VEHICLE CHARGING STATION PLACEMENT AND CHARGE SCHEDULING IN CURRENT AND FUTURE ENERGY SYSTEMS

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VORWORT

Die vorliegende Dissertation entstand im Rahmen meiner Tätigkeit als Wissenschaftlicher Mitarbeiter an der Georg-August-Universität Göttingen und an der Universität Duisburg-Essen. Beide Lehrstühle wurden von Prof. Dr. Jutta Geldermann geleitet, deren Unterstützung und Anregungen von größter Bedeutung für die erfolgreiche Fertigstellung dieser Arbeit waren.

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In tiefer Dankbarkeit,
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ABSTRACT

Considering the current global scenario, battery electric vehicles will play a pivotal role in personal mobility in the future; thus, necessitating an increase in charging infrastructure. According to several studies, greater diffusion of these vehicles can be expected to have an impact on electricity demand. Furthermore, as electricity generation is becoming increasingly volatile, increasing the flexibility of electricity demand is imperative.

The current electric vehicle charging models aim to coordinate vehicle charging in a predefined charging network to optimize an objective, such as meeting the demands of all vehicles or cost minimization (electric vehicle charge scheduling problem). Another stream of literature aims to optimize the placement of charging stations and the design of the charging infrastructure. In models supporting these decisions, the charging demand is predefined, and differences in demand over time are not explicitly considered. In this thesis, a decision support model is developed to determine the relationships between different charging network layouts, and to optimize vehicle charging in current and future energy system configurations. To achieve this, a mixed integer linear programming model, which simultaneously optimizes the layout of the charging network and vehicle charging while considering factors related to mobility and the electricity system, was developed. Exact and heuristic solution approaches are presented to solve the model that combines the charging station placement problem and electric vehicle charge scheduling. Furthermore, the geographically and temporally resolved mobility data required for the real-world application of the model is synthetically generated using an activity database and an open-source geographic information system, while factors related to the electricity system are derived from existing energy scenarios.

To evaluate how the developed model can support real-world decision-making, it was applied to a case study of charging station placement and coordination of charging activities in Essen. The results were analyzed based on factors such as the geographical and temporal distribution of the charging activities or the economic and ecological effects of the optimized charging network and coordinated vehicle charging. In the case study, the results of a combined optimization of charging station placement and vehicle charging indicate that the joint consideration of both decision problems can influence the charging pattern, yielding different and in some parts more exact results than the previously considered approaches.

The model can be used to analyze the impact of changes in the electricity system configurations, changes in mobility behavior, and vehicle charging technology on the energy system, and it can be used to support decisions of charging infrastructure planners, network operators, or policymakers.

ZUSAMMENFASSUNG

Aktuellen Prognosen zufolge werden batterieelektrische Fahrzeuge in Zukunft eine entscheidende Rolle im Individualverkehr spielen, was einen Ausbau der Ladeinfrastruktur erfordert. Die stärkere Verbreitung elektrisch betriebener Fahrzeuge wird außerdem zu einer höheren Stromnachfrage führen, während auch die Stromerzeugung - aufgrund der Verschiebung hin zu einer Erzeugung aus erneuerbaren Quellen - volatiler wird. Die Sektorenkoppelung ist ein entscheidender Baustein, damit die Integration von batterieelektrischen Fahrzeugen in ein erneuerbares Energiesystem gelingt. Aktuelle Studien beschäftigten sich unter anderem mit der Ladeinfrastrukturplanung oder Ladeplanung, wobei beide Bereiche in der Regel in getrennten Forschungsgebieten und Entscheidungsproblemen behandelt werden. Die Koordination des Ladens von Elektrofahrzeugen erfolgt in einem vordefinierten Ladenetz, um ein Ziel, z. B. die Minimierung der Ladekosten oder Maximierung des verwendeten Ladestroms aus erneuerbaren Quellen, zu optimieren. Ladeinfrastrukturplanungsmodelle hingegen gehen von einem vordefinierten Ladebedarf aus und unterscheiden in der Regel nicht, wie die Nachfrage über die Zeit variieren kann, berücksichtigen allerdings die geografische Verteilung des Ladebedarfs.

In dieser Arbeit wird ein Optimierungsmodell entwickelt, um beide Entscheidungen simultan zu berücksichtigen. Dieses gemischt-ganzzahlige lineare Optimierungsmodell erlaubt gleichzeitig die Auslegung des Ladenetzes und die Optimierung des Ladens von Fahrzeugen unter Berücksichtigung, der variierenden Standorte von Elektrofahrzeugen und volatilen Stromerzeugung. Zur Lösung dieser miteinander verknüpften Planungsaufgaben des entwickelten Modells werden exakte und heuristische Lösungsansätze entwickelt und vorgestellt. Geographisch und zeitlich aufgelöste Mobilitätsdaten, die für die reale Anwendung des Modells erforderlich sind, werden synthetisch aus einer Aktivitätsdatenbank und einem Open-Source-Geoinformationssystem generiert, während die Kenngrößen, die mit dem Stromsystem zusammenhängen, aus bestehenden Energieszenarien abgeleitet werden.

Zur Evaluation wird das entwickelte Modell in einer Fallstudie für die Platzierung von Ladestationen und die Koordination von Ladeaktivitäten in der Stadt Essen angewendet. Die Modellergebnisse werden nach Faktoren wie der räumlichen und zeitlichen Verteilung der Ladeaktivitäten oder den ökonomischen und ökologischen Effekten des optimierten Ladenetzes und der koordinierten Ladung der Fahrzeuge analysiert. Ergebnisse einer kombinierten Optimierung der Platzierung von Ladestationen und der Fahrzeugladung zeigen, dass die gemeinsame Betrachtung beider Entscheidungsprobleme zu Ergebnissen führen kann, die sich von denen bisheriger Ansätze unterscheidet.

Das entwickelte Modell und die entwickelten Lösungsansätze ermöglichen es, die Auswirkungen von Änderungen der Energiesystemkonfiguration, des Mobilitätsverhaltens und der Ladetechnologie auf das Energiesystem zu analysieren. Das Modell kann eingesetzt werden, um die Entscheidungen von Ladeinfrastrukturplanern, Netzbetreibern oder politischen Entscheidungsträgern zu unterstützen.

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ABBREVIATIONS

AC alternating current

BEV battery electric vehicle

CAPEX capital expenditures

CO_2 carbon dioxide

CO_2e carbon dioxide equivalents

CPO charging point operator

CPU central processing unit

CSPP charging station placement problem

CSP-EVCSP charging station placement and electric vehicle charge scheduling problem

DC direct current

DSM demand side management

DSO distribution system operator

EAC equivalent annual cost

EEG Renewable Energy Sources Act (*ger. Erneuerbare-Energien-Gesetz*)

EEX European Energy Exchange

EMP e-mobility provider

EnWG law on electricity and gas supply *(ger. Gesetz über die Elektrizitäts- und Gasversorgung)*

EV electric vehicle

EVCSP electric vehicle charge scheduling problem

FCEV fuel cell electric vehicle

GIS geographic information system

ICE internal combustion engine

IEC International Electrotechnical Commission

LCA life-cycle assessment

LCOE levelized cost of energy

LCOS levelized cost of storage

MCDA multi-criteria decision analysis

MODM multi-objective decision making

MiD Mobility in Germany *(ger. Mobilität in Deutschland)*

MILP mixed-integer linear programming

MWp megawatt peak
NPV net present value
OPEX operational expenditure
OSM OpenStreetMap
PV photovoltaic
PWMP projected wholesale market prices
RLM power metered *(ger. Registrierenden Leistungsmessung)*
SCP set covering problem
SCO successive community optimization
SLP standard load profile *(ger. Standardlastprofile)*
SoC state of charge
SVOM single vehicle optimization model
TCO total cost of ownership
TSO transmission system operator
ISO International Organization for Standardization
V2G vehicle-to-grid
V2B vehicle-to-building
V2X vehicle-to-everything
WACC weighted average cost of capital
WLTP Worldwide Harmonized Light Vehicles Test Procedure
WMP wholesale market price
WTW well-to-wheel

1 INTRODUCTION

The long-term target established by the Paris Climate Agreement (COP 21), which is ratified by Germany and 192 other countries, is to limit the global temperature increase to 2°C or less compared to preindustrial levels and take further action to try and limit the increase to 1.5°C (IEA, 2020a). To achieve this, the total anthropogenic carbon dioxide (CO_2) emissions to the atmosphere need to be limited (Meinshausen et al., 2009). Using the current and targeted atmospheric CO_2 concentration, it is possible to calculate a CO_2 budget (Romanovskaya and Federici, 2019). For Germany, a total budget of 2.0–6.1 Gt CO_2 is estimated to limit the warming to 1.5°C–1.75°C with a 67% probability (SRU, 2022). In 2019, the total CO_2 emissions in Germany amounted to 702 million tons. Assuming that the emissions remain at this level, the budget would be depleted by 2030. An annual reduction of around 39 million tons of CO_2 would be necessary to achieve CO_2 neutrality by 2040 while staying within the budget.

Figure 1.1 shows the emissions for the transport, the power, and other sectors. Emissions have decreased on average by 28% across sectors since 1990. In 2019, the power and transport sectors had the highest emissions and made up 55% of all CO_2 emissions in Germany. The total CO_2 emissions that can be attributed to the power industry decreased by 36.1% (Crippa et al., 2021). While the overall electricity consumption has increased by 14.2% compared to 1990 to 547 TWh in 2019, the CO_2 specific emissions of the German electricity mix have decreased to 408 g CO_2/kWh or by 47.5% compared to 1990 (UBA, 2021). The decrease in specific emissions can be primarily attributed to the growth in power generation from renewable energy sources, which offset the electricity production from fossil fuel power plants.

The transport sector was responsible for 22% of the total CO_2 emissions and showed the smallest reduction of less than 1% compared to the base year (1990). Of the 157 million tons of CO_2 emitted by the transport sector in 2019, more than 50% were caused by motorized personal transport, equal to more than 11% of the total emissions (IEA, 2019; Crippa et al., 2019; Allekotte et al., 2020a; Hütter, 2013).

The number of passenger cars and CO_2 emissions in the motorized personal transport sector have increased since 1995, and in 2019 3.62 million personal vehicles were newly registered. The total number of personal vehicles in Germany as of March 2022 is 47.7 million and represents a ratio of approximately 1.15 vehicles per household (KBA; 2022). Dependent on the fuel (diesel/petrol), CO_2 emissions per vehicle have on average decreased by 9%–18% from 210.8 g CO_2/km - 211.3 g CO_2/km in 1995 to 178.3 g CO_2/km – 192.6 g CO_2/km in 2019 (Allekotte et al., 2020b). However, the reduction in emissions was offset by a larger fleet of vehicles and a general increase in passenger traffic (VDA, 2020a).

To reduce CO_2 emissions of the power and transport sectors in Germany and other countries, incumbent and new technologies need to be leveraged. The German Federal Government aims to achieve this by installing additional renewable energy generators, predominantly based on wind and solar energy. In the transportation sector, electric vehicles are seen as a means of reducing

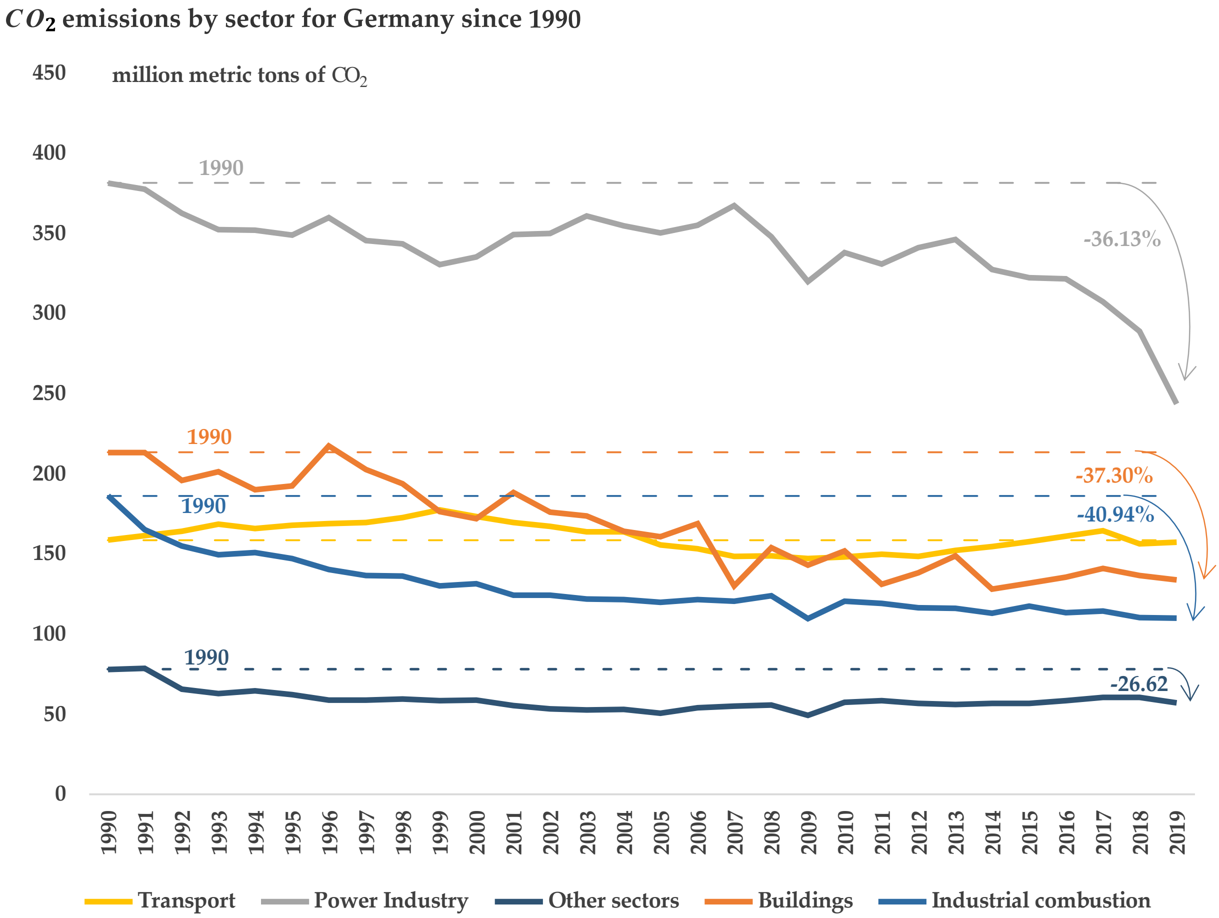


Figure 1.1: Development of CO_2 emissions in Germany by sector (1990–2019). Percentages show the CO_2 reduction from 1990 to 2019. Based on data by Crippa et al. (2021).

emissions. The goal of the German government is to have 10 million registered electric vehicles and 1 million charging stations installed by 2030 (Bundesregierung, 2019). For individual electric mobility, several challenges arise regarding the charging infrastructure. This work focuses on the charging infrastructure required for daily personal mobility and its possible interaction with the energy system. In this problem, the location of the parked vehicle is a decisive factor in the efficient placement of the charging infrastructure.

To achieve decarbonization of personal transport, generation of electricity from renewable sources is an important prerequisite. Synergy opportunities arise from the linkage of these sectors, which have been largely separated until now (Helgeson and Peter, 2020). To improve the planning for the energy system and by considering the energy demand, generation, and characteristics of different sectors, the concept of integrated energy system planning postulates a holistic view of all sectors and enables a cheaper, socially acceptable, and ecologically sustainable energy system. Shunning traditional single-sector approaches, through integrated planning and models that consider intersections between sectors, a superior configuration of the energy system is possible (Helgeson and Peter, 2020; Mathiesen et al., 2015).

This thesis thus develops a model that analyzes the relationship between different configurations of charging networks and the scheduling of charging activities of electric vehicles in potential future configurations of the energy system. Several specific research questions guide this examination and will be answered with the help of the presented findings.

1. What are the projected changes in electricity generation and how will these changes affect future planning of the layout of the charging infrastructure and charge patterns of electric vehicles?

To answer this question, an overview of the status quo in the electricity sector and personal transport is presented in Chapter 2. This involves a description of the guiding principles and relevant actors in the energy markets to highlight their implications on the electricity transition. The current state of the integration of electric vehicles with the electricity sector will be presented. The effect of increased electrification of vehicles is projected to be affected by two main factors, the design of the charging infrastructure, i.e. the locations of charging stations, as well as the timing of charging activities. Based on the derived information, the following chapter explores how these factors can be integrated into a decision model and is guided by the question:

2. How can geographically resolved travel and charge profiles for electric vehicles, as well as factors associated with the electricity system, be combined into a model that simultaneously considers the planning of the charging infrastructure of electric vehicles and the timing of charging?

The decision problem includes two subdomains: the design of the charging network and the charge planning of electric vehicles. In Chapter 3, the current state of the art in these research areas is presented. Based on the findings of this literature review, a mixed integer optimization model is developed, which includes the most important decision variables in the objective function and maps possible constraints. Possible exact and heuristic solution approaches for the developed model are presented. To apply the decision model developed here, several parameters related to the mobility activities of individuals, their geographic location throughout the day, and factors related to the electrical system are required. Therefore, Chapter 4 explores the question:

3. How can the geographically and time-resolved mobility patterns of electric vehicles, as well as the costs and emissions of prospective energy systems, be derived and applied in the model?

Geographically and time-resolved mobility patterns are derived using data from an activity database and open-source geographic information. Potential emissions and costs related to energy generation are determined using a linear optimization model. The decision on the design of the charging infrastructure and scheduling of charging activities also has economic and ecological effects. To show how these effects can be quantified, the developed model is used to optimize the placement of the charging infrastructure and the charging of vehicles in the city of Essen. The case study presented in Chapter 5 aims to answer the following questions:

4. What are the possible benefits and effects of optimizing the placement of electric vehicle charging stations on electricity demand and renewable electricity consumption on a local and country-wide scale? How can these factors be quantified?

Finally, Chapter 6 presents concise answers to the research questions and discusses the findings of this thesis.

2 CURRENT STATE AND FUTURE TRENDS IN THE ELECTRICITY AND MOBILITY SECTOR IN GERMANY

The intertwining of the mobility and electricity sectors is inevitable with the increasing market penetration of electric vehicles (EVs). In Germany, far-reaching changes are expected in both sectors and are guided by the legislature and governmental targets. Therefore, this chapter summarizes the current state and future trends in the electricity and mobility sectors. The aim is to show how the two sectors are interconnected and to highlight the actors involved and their objectives and decisions in this context.

This chapter highlights important factors for the integration of EVs into the current and future electricity system. First, the current setup of the electricity system, its actors, and development within the constraints of the energy policy triangle and the goals of the German government are presented (Subsection 2.1). Secondly, the current state of electric vehicles, electric vehicle charging technology, and expansion of charging stations is summarized (Subsection 2.2). Finally, the current status of the integration of both sectors is presented in the third subsection (2.3).

2.1 STATE AND PROSPECTS OF THE GERMAN ELECTRICITY SYSTEM

To characterize the current state of the German electricity system, as well as possible future developments, an overview of the current economic and technical characteristics, markets, and actors in the electricity system is presented. Thereafter, the energy policy goals are described and possible ways to operationalize the technical, ecological, and economic criteria are presented. Finally, possible future developments of the German electricity system are presented along with characteristics, obstacles, and requirements of an electricity system largely based on renewable electricity generation.

2.1.1 An overview of the current electricity system in Germany

Figure 2.1 illustrates the layout and actors involved in the German electricity sector. Electricity must be **generated**, **transmitted and distributed** and sold on **energy markets** to meet the electricity **demand** of commercial, residential, or industrial entities.

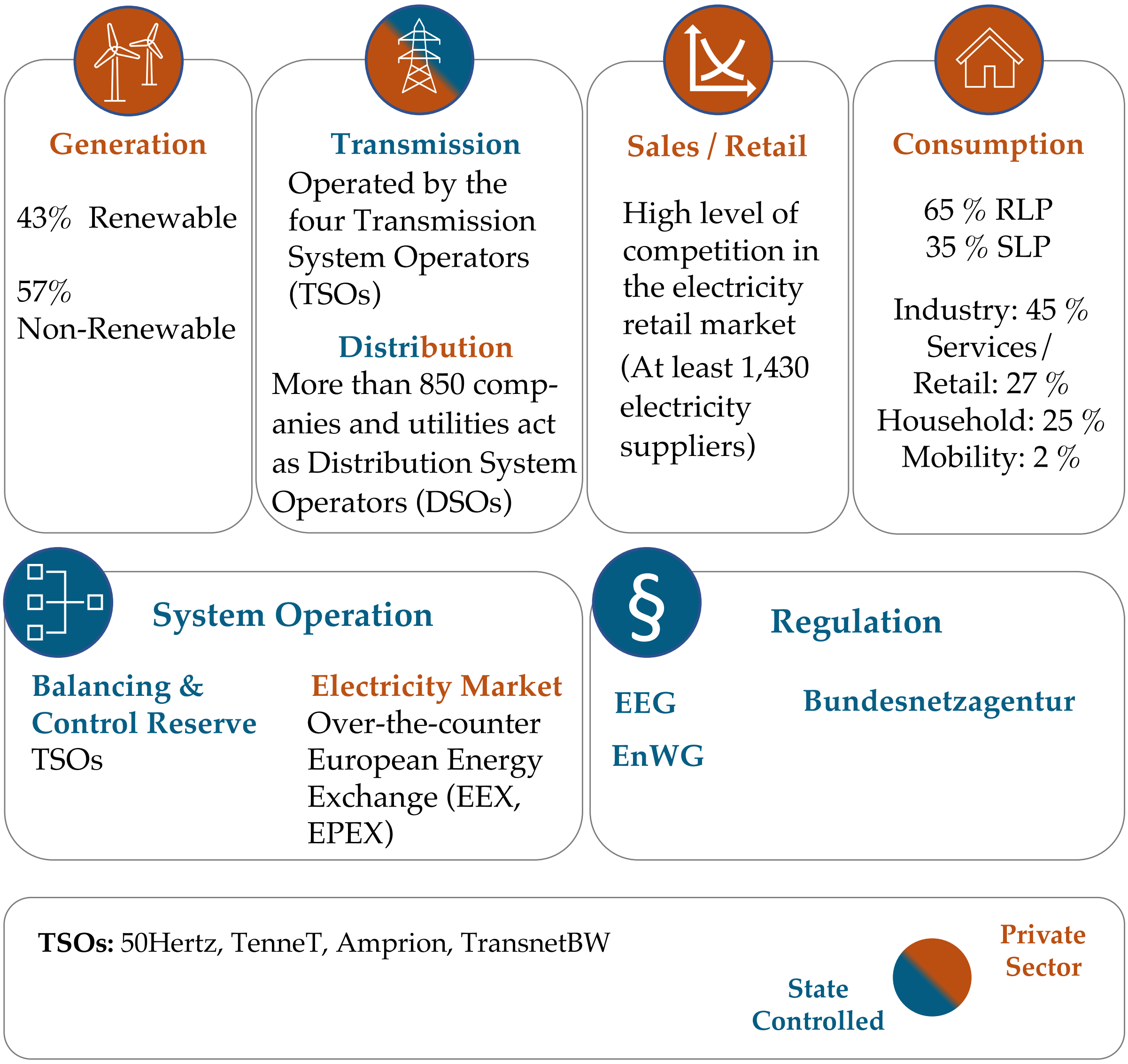


Figure 2.1: Overview of the German electricity market (Bundesnetzagentur, 2020).

This process of conversion of primary energy to useful energy and the entities and markets involved must comply with national and international **regulation**. The analysis in the following sections is based on the annual electricity generation and consumption values of 2019, as they are not affected by the global Covid-19 pandemic (2020 - 2022) and the war in Ukraine (2022), which affected energy prices in Germany and Europe (Halbrügge et al., 2022; Tollefson, 2022).

2.1.1.1 *Electricity generation*

As a form of secondary energy, electricity is not freely available in nature and therefore must be converted from renewable forms, e.g., solar or wind energy or non-renewable primary energy, for example, fossil fuels (Konstantin, 2017). In 2019, coal was the primary energy source for electricity generation worldwide and 36.4% of the electricity generated worldwide based on coal, while 26.1% of the total electricity generated worldwide (including hydroelectric) was generated from renewable resources (BP, 2020). In Germany, renewable generation has doubled from 1990 (18.93 TWh) to 2000 (36.23 TWh) and increased more than six times until 2019 to 244.29 TWh. Renewable power generators made up more than 53% of the installed power generation capacity in Germany, while coal power stations only represented 20.9% of the installed capacity in 2019. More than half of the electricity from renewable sources is generated by onshore (41.4%) and offshore wind turbines (10.1%). The generation of electricity from solar energy (19.5%) and biomass (17.5%) represents most of the remaining generation. Renewable power generators make up more than half (55%) of the total installed power generation capacity in Germany. While lignite(coal)-fired power stations generated 64% of their full load capacity, offshore wind power generation only generated 21% and photovoltaic 11% of their potential capacity, mainly due to the variable nature of the primary energy source (BDEW, 2020a). In 2019, the annual full load hours of nuclear (7,460 h/a) and lignite (5,570 h/a) were higher than those of photovoltaic generators (960 h/a) or offshore (3,510 h/a) and onshore wind generators (1,880 h/a).

Table 2.1 shows the minimum and maximum electricity generation and consumption[1] in Germany in 2019. The variability in the generation of wind and solar energy has an impact on these values. For example, during the peak generation time, wind energy made up 45.29% of total power generation, while during the minimum generation period of electricity, only 25% of the total generating capacity were supplied by solar and wind. In 2019, onshore wind generation capacity fluctuated from 0.24 GW (02.08.2019 - 09:15 a.m.) to 40.3 GW (13.01.2019 - 07:30 p.m.).

Table 2.1: Overview of the minimum and maximum hourly electricity generation and consumption in Germany, for all electricity generators in the year 2019 (SMARD, 2022).

	Date	Time	MWh
Max Generation	15. Jan 2019	1:00 p.m. - 2:00 p.m.	84,959
Max Consumption	09. Jan 2019	5:00 p.m. - 6:00 p.m.	76,903
Min Generation	10. Jul 2019	3:00 a.m. - 4:00 a.m.	31,894
Min Consumption	22. April 2019	3:00 a.m. - 4:00 a.m.	29,104
Highest Generation Deficit[2]	23 May 2019	8:00 p.m. - 9:00 p.m.	(-)14,269
Highest Generation Surplus	5. Jan 2019	6:00 a.m. - 7:00 a.m.	19,992

1 To increase readability of the text the term electricity/energy consumption is used throughout this thesis. According to the first law of thermodynamics (the Law of Energy Conservation), energy cannot be created, consumed, or destroyed, but only changed from one form of energy to another (Schmitz, 2017).

2 After deduction of electricity consumption, excluding exports and imports.

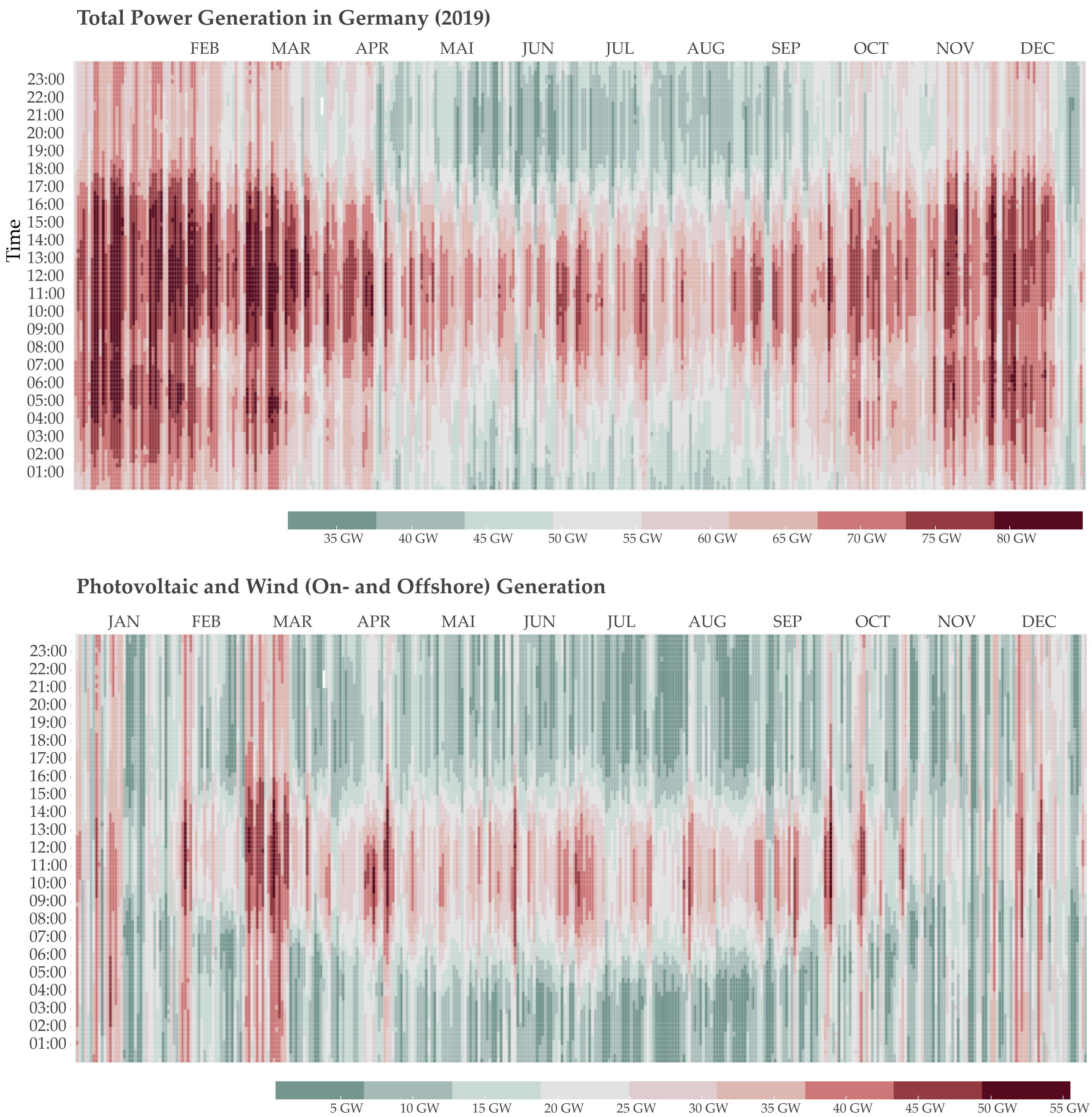


Figure 2.2: Electricity generation in 2019 for all energy carriers in Germany (top) and photovoltaic and wind generation in Germany (bottom). Based on data from SMARD (2022)

Figure 2.2 illustrates the overall generation of electricity (top) and the generation of electricity based on volatile energy sources (bottom). In 2019, total electricity generation was highest in the early morning to early afternoon, and more electricity was generated in winter than in summer. Volatile renewable generation also shows a similar pattern during certain times of the year, such as late February or December, while only a small amount of electricity was generated from renewable sources in early November, as can be seen in the representation of the shares of renewable generation in 2019 presented in Figure 2.2 (bottom).

The CO_2 emissions from electricity generation in Germany have decreased by 40% from 1990 to 2019. This is in line with an 41% increase of renewable energy generation over the same period. The German electricity mix had a CO_2 emissions factor of 401 g CO_2/kWh in 2019. This reduction in comparison to 1990 (-363 g CO_2/kWh) also compensates for the changes in electricity consumption that has increased by 14% compared to 1990 (UBA, 2021).

2.1.1.2 Electricity demand

Electricity demand is currently not actively controlled by third party entities such as utilities and varies depending on the time of day or season (Strbac, 2008). The largest electricity consumer in Germany in 2019 was the industrial sector, which represents half of electricity consumption, equivalent to 234 TWh. The services and commerce sector, as well as households, consumed approximately a quarter of all electricity in Germany, while the transport sector only represented 2.3% of electricity consumption (BDEW, 2020b). 62.11% of electricity was delivered to power metered *(ger. Registrierenden Leistungsmessung)* customers, while 37.89% of electricity was delivered to non-metered customers under the application of one of the 12 different standard load profile *(ger. Standardlastprofile)* (SLP) or through an individual customer load profile (synthetic method)[3]. Currently, there is no SLP that considers the additional consumption of electricity from EVs, for example, in households, where it can double the consumption of electricity and has been shown to alter the load pattern of households (Hashemifarzad et al., 2019).

The upper part of Figure 2.3 illustrates how energy consumption differs throughout the year and by time of day. Different patterns of energy consumption can be observed during the summer and winter months. Electricity consumption generally increases in the winter months and earlier in the day (around 4:00 a.m.). During weekends and holidays, less electricity is consumed. The bottom part of Figure 2.3 shows the difference between energy consumption and generation.[4] The greatest electricity surplus in 2019 occurred in the evening hours in winter. In the summer months, the highest surpluses occur during the noon hours and on Sundays. The pattern of electricity generation through photovoltaic and wind power illustrated in Figure 2.2 is also visible in the electricity surplus, which is highest during the midday hours. The values in Table 2.1 also show the impact of periods when the limited generation of renewable electricity and the high demand for electricity coincide and vice versa. During the period of the greatest electricity generation deficit, solar and wind generation electricity was only able to supply 4.9% of total electricity demand, while wind onshore and offshore supplied 68% of consumption during the period with the highest generation surplus.

3 Utilities differentiate among two types of customers, power metered *(ger. Registrierenden Leistungsmessung)* (RLM), billed according to the annual demand charge (€/MWh) and the annual maximum demand (€/ MW) for the respective billing horizon and non-metered customers with a demand smaller than 100 MWh per year. For non-metered customers, the law on electricity and gas supply *(ger. Gesetz über die Elektrizitäts- und Gasversorgung)* (EnWG) prescribes the use of standard load profiles SLP, e.g., for household, services, or agricultural customers (Bundesnetzagentur, 2021). While the non-power-metered customer reports their electricity consumption annually, the power-metered customer is metered at a time resolution of 15 min.

4 Without considering electricity import or export.

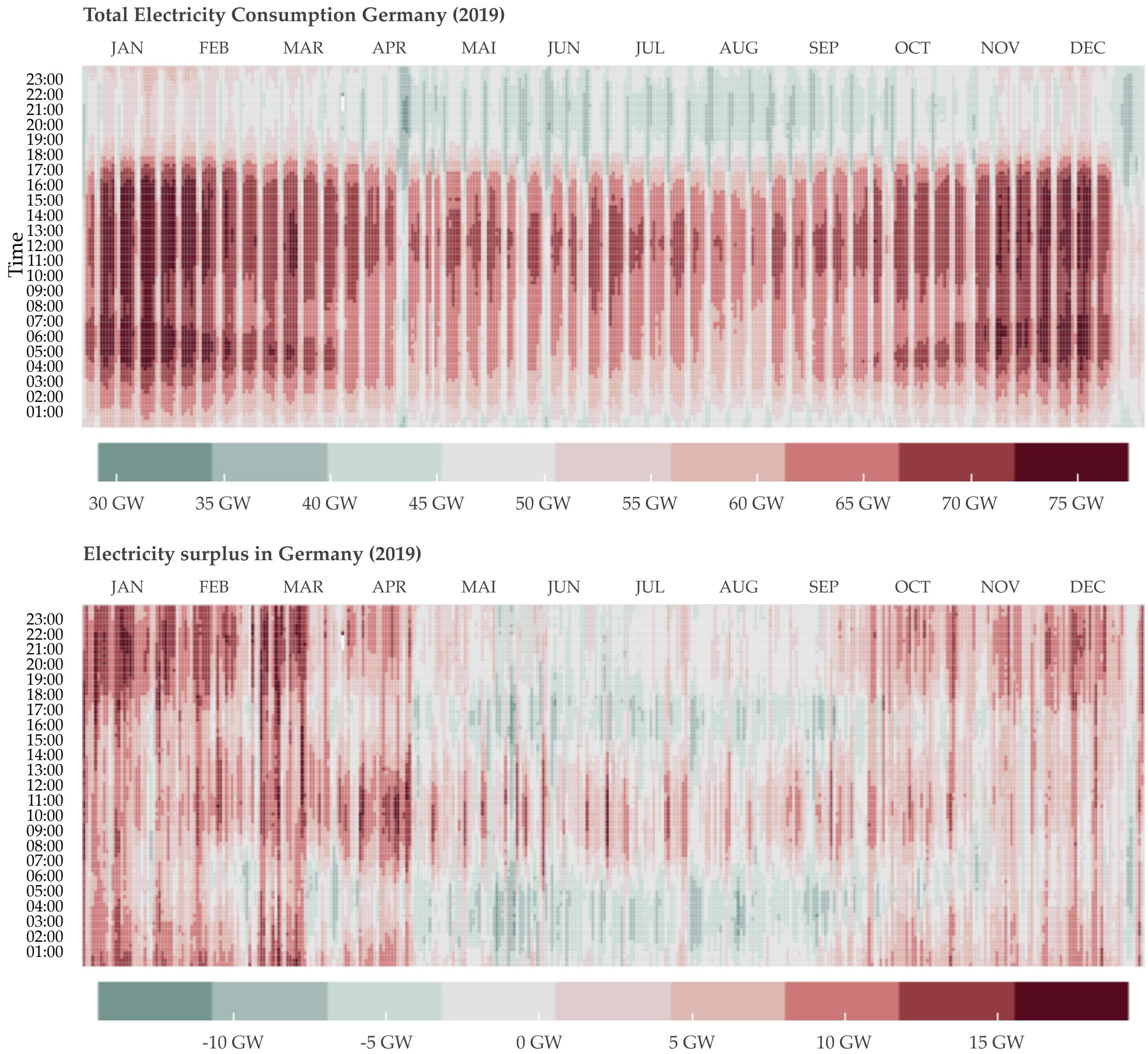


Figure 2.3: Electricity consumption patterns (top) and electricity generation surplus and deficit (bottom) in 2019 for Germany (without consideration of imports and exports). Based on data from SMARD (2022)

Although the negative and positive discrepancies have a high fluctuation, they have been reduced by transmission system operators (TSOs) by reducing (curtailing) the input of renewable energy. The curtailment of (renewable) electricity has increased from 73.1 GWh in 2009 to 6,272.5 GWh in 2019 (Bundesnetzagentur, 2020). While the curtailed electricity has increased 85-fold since 2009, installed wind generation capacity doubled from 25.77 GW to 52.93 GW in the same time frame in Germany (Fraunhofer ISI, 2021). The curtailment measures led to costs [5] of

5 Costs for curtailed electricity are equal to the compensation for lost revenue paid to renewable power generators if their electricity generation is curtailed.

€709.5 million in 2019 which is a significant increase in comparison to €6 million in 2009 (Bundesnetzagentur, 2017, 2019b). To alleviate this problem, several measures are possible (Bauknecht et al., 2016; Konstantin, 2017; Langrock et al., 2016; Sterner et al., 2014):

- Redirecting power to other parts of the grid and grid reinforcement,
- redispatch of conventional power generation,
- energy storage,
- utilizing demand flexibility.

In 2019, almost 100% of the flexibility of controllable consumer devices in Germany was provided by electric heating, for example, by heat pumps or night storage heaters. A total of 1.5 million controllable consumer devices were registered in 2019 (Bundesnetzagentur, 2020). Furthermore, the future potential to use demand flexibility is estimated to be greatest in the household sector (Langrock et al., 2016). However, almost all electricity tariffs in Germany are charged per kWh, without explicit consideration of current electricity availability or prices, and only a few companies offer flexible hourly or daily rates (Hack et al., 2021). A prerequisite for flexible tariffs are smart meters that 0.74% of private consumers had installed in 2019 (Bundesnetzagentur, 2020).

Given the current largely inflexible demand and the increase in uncontrollable wind and solar power generation, mismatches in electricity supply and demand and the need for power curtailment could increase in the future. EVs will further increase electricity demand and can potentially shift electricity consumption (for example, to the evening / night (Hashemifarzad et al., 2019), leading to a greater mismatch between electricity generation and demand. Charging EVs during times when surplus electricity generation is available can mitigate the electricity generation and consumption mismatch.

2.1.1.3 *Electric power transmission and distribution*

To meet the needs of industry and the public for useful energy, electricity must be provided to the customer through the transmission and distribution network. TSOs are responsible for transregional transmission of electricity, including stable and secure operation and maintenance of the required transmission network (Konstantin, 2017). The German extra high-voltage grid (150, 220 or 380 kV) is divided into four control areas operated by TSOs with the task of ensuring stable frequency and voltage and the operational management of the grid including the task of restoring the electricity supply in faulty parts of the grid (Dena, 2014).

In contrast to the high concentration of actors in the transmission system, there were more than 880 distribution system operators (DSOs) in 2019, responsible for the remaining part of the grid and the distribution of electricity to the end customer (Bundesnetzagentur, 2020). The German distribution grid consists of the high-voltage (60 - 100 kV), medium-voltage (3 - 30 kV) and low-voltage (230 or 400 V) networks. Similarly to TSOs the DSOs are responsible for stabilizing the distribution grid, mainly through voltage regulation and congestion management measures (Löschel et al., 2020; Schmid et al., 2019). Power generators with high generation capacity or large offshore wind farms are connected to the transmission grid. Generators with a smaller power capacity, such as renewable power generators, feed their electricity into the distribution network.

The shift to renewable energy-based electricity generation causes increased generation capacities to be connect to the distribution network. The same is true for electricity demand. EV fast charging stations are connected to the medium-voltage to high-voltage distribution network and to the low-voltage network for private and public charging stations with a capacity below 22 kW (Maier et al., 2019; Söder, 2003).

As noted above, an important role for DSOs and TSOs is to ensure high supply security. An indicator to assess this supply security are the minutes of supply interruption. With an average supply interruption of approximately 12.2 minutes per year (2019), supply security in Germany is at a high level according to international standards (Bundesnetzagentur, 2020).

The energy transition is concentrated almost exclusively in the distribution network, that is, in the expansion of renewable energy-based generators and new types of consumer, such as EVs or heat pumps. This shifts the responsibility for the stability of the grid to DSOs (Maier et al., 2019; Moser et al., 2016; Tretschick et al., 2021). For DSOs, it is therefore becoming more difficult to operate their network. The task is further complicated by the fact that currently grid status information is often insufficient to operate the grid. To this end, an increasing investment in digital infrastructure, such as monitoring and measurement systems, is required (Consentec, 2016). These changes and investment requirements are reinforced by regulatory changes that extend the legal responsibility of Redispatch[6] measures to DSOs, known as Redispatch 2.0. Instead of considering conventional power plants with a generation capacity greater than 10 MW, all plants of 100 kW or more[7] must be integrated in redispatch measures starting from October 2021. To evaluate the technical potential of dispatch measures, forecasts must be made for each generator, leading to increased data requirements and the need for data processing for both DSOs and TSOs (BDEW, 2021a).

Although the direct relationship between an increase in electric vehicle penetration and redispatch measures has not yet been extensively studied, charging stations are generally connected to the low or medium voltage level (Staudt et al., 2018b; VDE, 2019). Electric vehicle fast charging stations have a capacity of 50 kW and can exceed 200 kW and therefore could contribute to alleviate Redispatch 2.0 needs, by increasing or decreasing their charging rate.

2.1.1.4 Electricity system dependencies and markets

In 2019, there were at least 1,430 electricity suppliers operating in Germany (Bundesnetzagentur, 2020). They consist of four large interconnected utilities (E.ON[8], EnBW, RWE and Vattenfall), municipal energy suppliers (municipal utilities), independent energy suppliers, and networks of municipal and private energy suppliers. To be connected to the grid and to be allowed to supply end customers with electricity, electricity suppliers must belong to a balance group. The balance group operator is required to provide the responsible TSO with a schedule of electrical requirements or offers on a daily basis. The responsible balancing group must pay the associated

6 Redispatch refers to the short-term shifting of planned electricity generation of power generators of 10 MW and greater by the TSOs to avoid grid congestion (Konstantin, 2017).
7 This includes renewable power plants and battery storage.
8 In 2016, the German energy company E.ON split its business into two independent companies - E.ON and Uniper SE. E.ON focused on renewable energy, networks, and customer service, while Uniper SE focused on conventional power generation and energy trading. As of December 2022, Uniper the German State has a stake of 99.12% in the company (Uniper SE, 2023).

balancing energy costs (BMWi, 2015a; Bundesnetzagentur, 2021). As of November 2022 there were 3.304 balance groups within the TenneT transmission system, while there were 703 balance responsible parties (Tennet, 2022).

The liberalization of the electricity market has created new opportunities for electricity trade. Most of the electricity consumed in Germany is sold through bilateral direct contracts between generators and consumers. This so-called "over-the-counter" trading accounts for a large part of the traded electricity volume. The volume traded in these direct contracts can only be estimated, as these bilateral contracts are not settled on a firmly defined and monitored marketplace. A survey by the German Federal Network Agency of brokers active in this area indicates a volume of 5,770 TWh for 2019, representing an increase of approximately 16% compared to the previous year (4,956 TWh) (Bundesnetzagentur, 2020). Since 2000, it has also been possible to trade energy on the European Energy Exchange, enabling smaller market participants to participate in energy trading on the spot and forward market. In the forward market, also known as the day-ahead market, participants can enter into contractual agreements that provide them with the ability to establish fixed prices for the delivery of energy at predetermined dates in the future. The electricity of the current day (intraday) is traded on the spot market. If the prices for the next day are fixed, continuous bilateral quantities can be traded on the intraday market up to 30 minutes before physical power delivery. The volume of electricity traded on the European Energy Exchange (EEX) increased by 29% compared to the previous year to 1.345 TWh for the Phelix-DE-Future. The prices of the Phelix-Day Base and the Phelix-Day Peak ranged from −65.94 to 102.74 €/MWh, with 80% of the prices concentrating within the interval between 27.79 and 53.47 €/MWh. In 2019, there were 211 hours with negative electricity prices, the most since 2012 (Hein et al., 2020). Negative electricity prices can be caused by technical restrictions and opportunity costs of plant operators. For example, conventional plants cannot arbitrarily change their generation due to low flexibility or the necessity of having a minimum power level to enable stable operation. Contractual obligations or the regulatory framework can also cause negative electricity prices. For a detailed analysis of the causes of negative electricity prices in the German market, see Höfling et al. (2015).

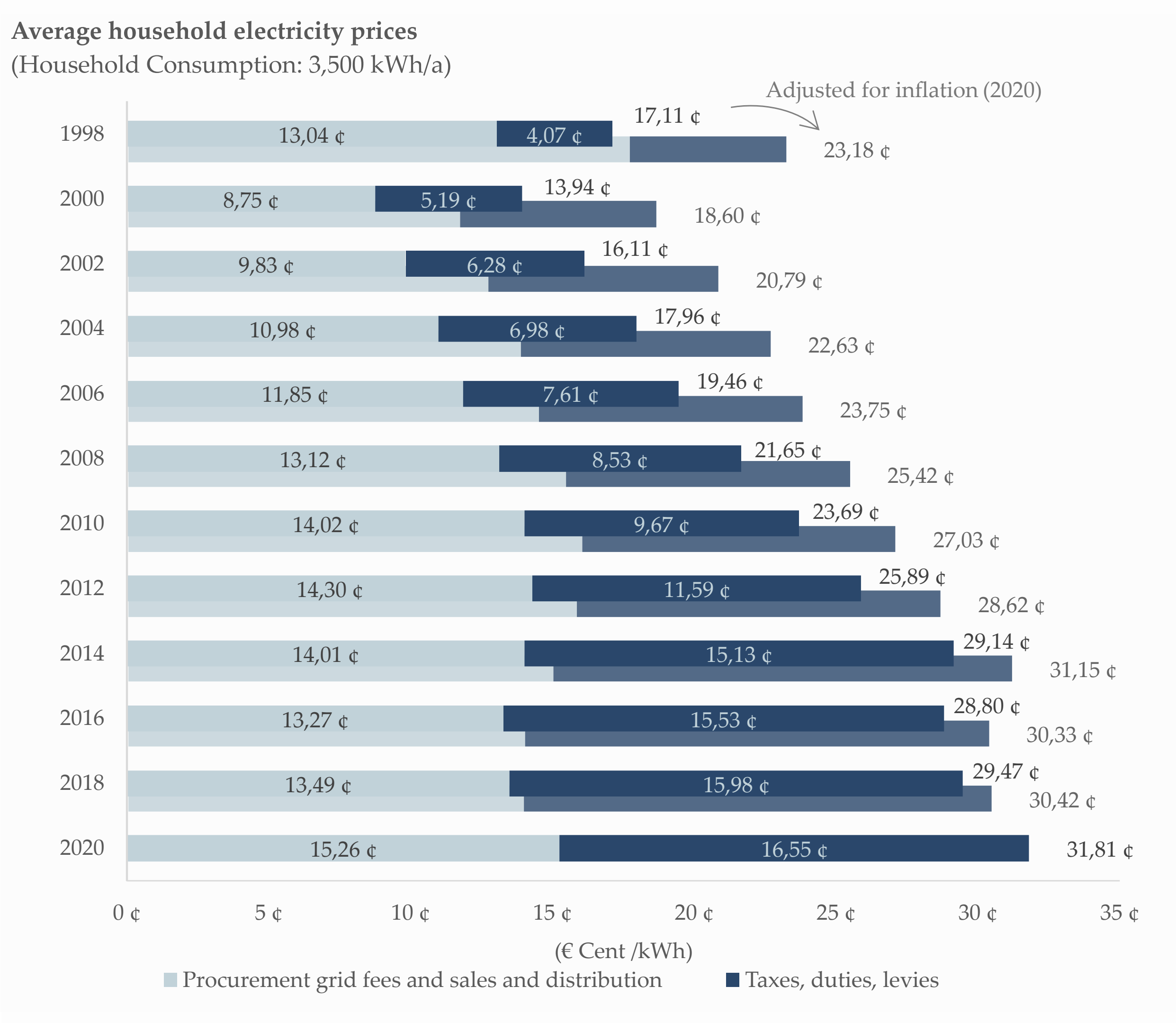


Figure 2.4: German residential electricity prices since 1998 (nominal and adjusted for inflation) (BDEW, 2021b; Statistisches Bundesamt, 2021).

Figure 2.4 shows the development of residential electricity prices since 1990, nominal and adjusted for inflation. The electricity prices in Germany for households[9] increased by 7.91% between 1990 and 2000. From 2000 to 2019, electricity prices nearly doubled for household customers, from 15.34 cents / kWh to 29.81 cents / kWh. This increase can be primarily attributed to additional and higher taxes and levies. Electricity generation and transport costs only increased from 11.96 cents/kWh to 13.96 cents/kWh. Taxes and levies make up 52.5% of the total electricity costs. Due to the increasing renewable power capacity, times of high renewable feed-in have increased in the last years. During these times, electricity from renewable sources displaces electricity from the most expensive conventional power generators and lowers the exchange price (merit order effect). Several methods have been developed to predict the volatile electricity

9 Households - direct current (DC) (annual consumption: 3,500 kWh of which night 1,300 kWh)

generation of renewable power plants on a daily basis (Hanifi et al., 2020; Nespoli et al., 2019). Although these methods can achieve high accuracy, the generated electricity demand or generation can deviate from the estimated schedule due to several factors. In the event of an imbalance within the balance group, the balance group operator is charged with balancing electricity prices set by the control reserve market.

The control reserve is divided into three types, according to their activation and deployment times. Positive control energy is fed into the grid to counteract a frequency drop, whereas negative control energy reduces the energy fed into the grid to increase the frequency of the grid. Primary and secondary control are system services, and capacity costs are distributed uniformly and paid through network charges. The energy costs of secondary and tertiary control are settled through the balancing energy price. Costs are borne by the balance groups that cannot show a balanced power account on the billing date. The remuneration for balancing energy is divided into the capacity price paid for the willingness to keep the capacity on standby and an energy price for the secondary and minute reserve power, paid per megawatt of control energy delivered.

For short-term stability of the electricity system, previous studies have projected an increase in storage requirements along with an increase in renewable electricity generation (Brouwer et al., 2014; Holttinen et al., 2011). It remains an open question if and how EVs could be used to mitigate this problem. In Germany, the frequency containment reserve, which compensates for frequency deviations lasting more than 30 seconds, decreased by 50% between 2011 and 2017. At the same time, the generation of electricity based on wind and solar energy has increased by 120% (Hirth and Ziegenhagen, 2015). This phenomenon is described as the "German Balancing Paradox" and is believed to have been caused by more efficient and flexible trading options and markets (Hirth and Ziegenhagen, 2015; Koch and Hirth, 2019; Ocker and Ehrhart, 2017).

In 2018 there was a total capacity of approximately 7,400 MW installed in Germany (Bundesnetzagentur, 2019a; Figgener et al., 2020; Schiffer, 2019). Pumped hydro constitutes the majority of the storage capacity (6,357 MW), small-scale home battery storage and large-scale battery storage are estimated to have the second-highest storage capacity (800 MW), while one compressed air storage system is installed with a capacity of 290 MW. The storage capacity of the pumped hydroelectric energy is concentrated in 25 systems, with an estimated energy equivalent to 37.4 GWh (Heimerl and Kohler, 2017). Small-scale home battery storage systems are distributed over 180,000 home battery storage systems with an average storage capacity of 2.2 kW.

The total (alternating current (AC)) charging capacity of all EVs registered in Germany as of September 2022 is estimated to be between 5.38 GW and 14.8 GW. The total amount of energy that can be stored in their batteries is estimated to be between 48.4 GWh and 55.9 GWh. EVs can be a viable storage alternative for the electrical grid, and their storage capacity and flexibility could be offered in the energy exchange or as reserve capacities (Hecht et al., 2022). Among other incentives and guarantees (see Section 2.3.2), monetary incentives are required. When considering the price of consumer electricity, incentives through cost savings are limited by the high share of taxes, duties and levies (< 50%).

2.1.1.5 *Electricity regulation*

The law on electricity and gas supply *(ger. Gesetz über die Elektrizitäts- und Gasversorgung)* (EnWG) is the basis for the energy regulations in Germany and is complemented by sector-specific policies, strategies, guidelines, laws, and regulations (BMWi, 2021; Scholz and Wessling, 2021). Several initiatives and regulations have fostered the transition of the electricity system in Germany. The Electricity Feed-in Act (*ger. Stromeinspeisegesetz*), was one of the first acts to promote electricity generation from renewable sources such as wind and solar (Lüdeke-Freund and Opel, 2014). The Renewable Energy Sources Act (*ger. Erneuerbare-Energien-Gesetz*) (EEG), which followed, stipulates the preferential feed-in of electricity from renewable sources and guarantees fixed input tariffs for its generation, regardless of current power demand in the grid (Cheung et al., 2019). As a result of the regulations, renewable energy generators have neither a purchase risk nor a price risk, as grid operators must prioritize purchasing electricity from renewable energy. The further liberalization of the electricity market has led to electricity trading. Through the unbundling of the network from generation, trade, and distribution, the importance of electricity trade has increased significantly. General access to electricity transport networks, combined with non-discriminatory transport fees, have created conditions for electricity trading between different market players (Borchert et al., 2006). In an attempt to further amplify the use of electricity generated from low-carbon sources, power plants have to pay for their CO_2 emissions through the European emissions trading system. However, the analysis shows that this regulatory mechanism is inferior and has not fully produced the desired results (Schäfer, 2019) since its introduction in 2005 (UBA, 2019).

As of 2022, EEG and EnWG do not explicitly consider EVs. However, according to §14a of the EnWG operators of electricity distribution networks can reduce network charges to suppliers and final consumers in the low-voltage network, if they operate their devices in a grid-friendly way and have a separate metering point. More legislation or modifications to legislation are required for a practical integration (Håvard Nymoen et al., 2022).

2.1.2 Guiding the transformation of the electricity system

After describing the current situation in the electricity system in the previous section, this section presents the factors guiding the transformation to a renewable energy system, namely the energy policy triad and the energy policy of the European Union (IEA, 2020a). The section also highlights how the goals and objectives described in the policies are operationalized.

Two main factors have shaped the development of the electricity system in recent years. First, the decarbonization of electricity generation by replacing fossil fuel-based power generators with wind and solar-based generators and second, the goals of the energy policy triad which are explicitly stated in the (EnWG, § 1), namely: environmental protection, cost-effectiveness, and security of supply.

Similar goals are also pursued by the European Union's energy policy, which aims are environmental sustainability, supply security, economic effectiveness, and promotion of the interconnection of energy networks (Braun, 2011). As the goals of environmental sustainability, energy security, and energy affordability are divergent, some publications and organizations also call this circumstance the energy policy trilemma (Šprajc et al., 2019; World Energy Council, 2019). McKenna et al. (2017) and Arciniegas and Hittinger (2018) show that certain operational strategies and system configurations of energy storage can be economically beneficial but can also increase CO_2 emissions.

Some studies have introduced financial indicators to include the costs of storage required by the renewable power generator to provide the same uninterrupted power as conventional electricity generators (Ueckerdt et al., 2013). While the two examples address an isolated conflict (economic / environmental, economic / security of supply), other studies often use multi-criteria assessment methods to present the trade-offs between the generation of electricity from renewable and non-renewable resources (Antunes and Henriques, 2016; Witt et al., 2020). In the following section, several indicators are summarized that enable the quantification of the abstract policy goals defined in the policy triad.

2.1.2.1 Environmental protection

According to the definition of Daly (1990) environmental protection or environmental sustainability can refer to three factors: sustainable yield, reduction of pollution, and reduction of the depletion of non-renewable resources. Various impact indicators have been developed, for example, to quantify the depletion of non-renewable resources through human activity (Belyakov, 2019; Matuštík and Kočí, 2020). Pollution can also be measured using various indicators, however as carbon dioxide emissions are the key global climate change driver only CO_2e emissions are addressed in this section.

The CO_2e [10] emissions for commercially available electricity generation and storage technologies are presented in Figure 2.5. These emissions can be calculated using life-cycle assessment (LCA), which is a systematic method to analyze the possible environmental impacts of products throughout their life cycle (Klöpffer and Grahl, 2009). A structured process for carrying out such an assessment is laid out in International Organization for Standardization (ISO) Norm 14040 (Environmental management - Life cycle assessment - Principles and framework). Depending on the scope of the LCA different life-cycle phases can be distinguished. A Cradle-to-grave assessment is a complete life cycle assessment and considers all life cycle phases from the extraction of raw material (cradle) to the disposal phase (grave) (International Organization for Standardization, 2006). The quantified description of the performance requirements desired as the output of a product system is defined as a functional unit. In Figure 2.5, the functional unit for power generation technologies is a kilowatt hour of electrical energy generated. For electricity storage technologies, for example battery storage, the functional unit is one kWh of electricity stored in the battery and delivered back to the grid, i.e. considering the round-trip efficiency.

As the measurements and parameters of LCA depend on site- and case-specific factors, the error bars are added in Figure 2.5 to visualize the uncertainty related to the evaluation. The estimation of CO_2e emissions is uncertain for both the electricity generators but also for the energy storage. Various factors, such as the energy mix used to build power plants or storage utilization, have an impact on the assessment of a technology (Baek et al., 2018; McKenna et al., 2017; Turconi et al., 2013; Wevers et al., 2020).

10 CO_2 equivalent (global warming potential) is a measure for the relative contribution of a chemical compound to the greenhouse effect. It indicates how much a given mass of a greenhouse gas contributes to global warming compared to the same mass of CO_2 (Klöpffer and Grahl, 2009).

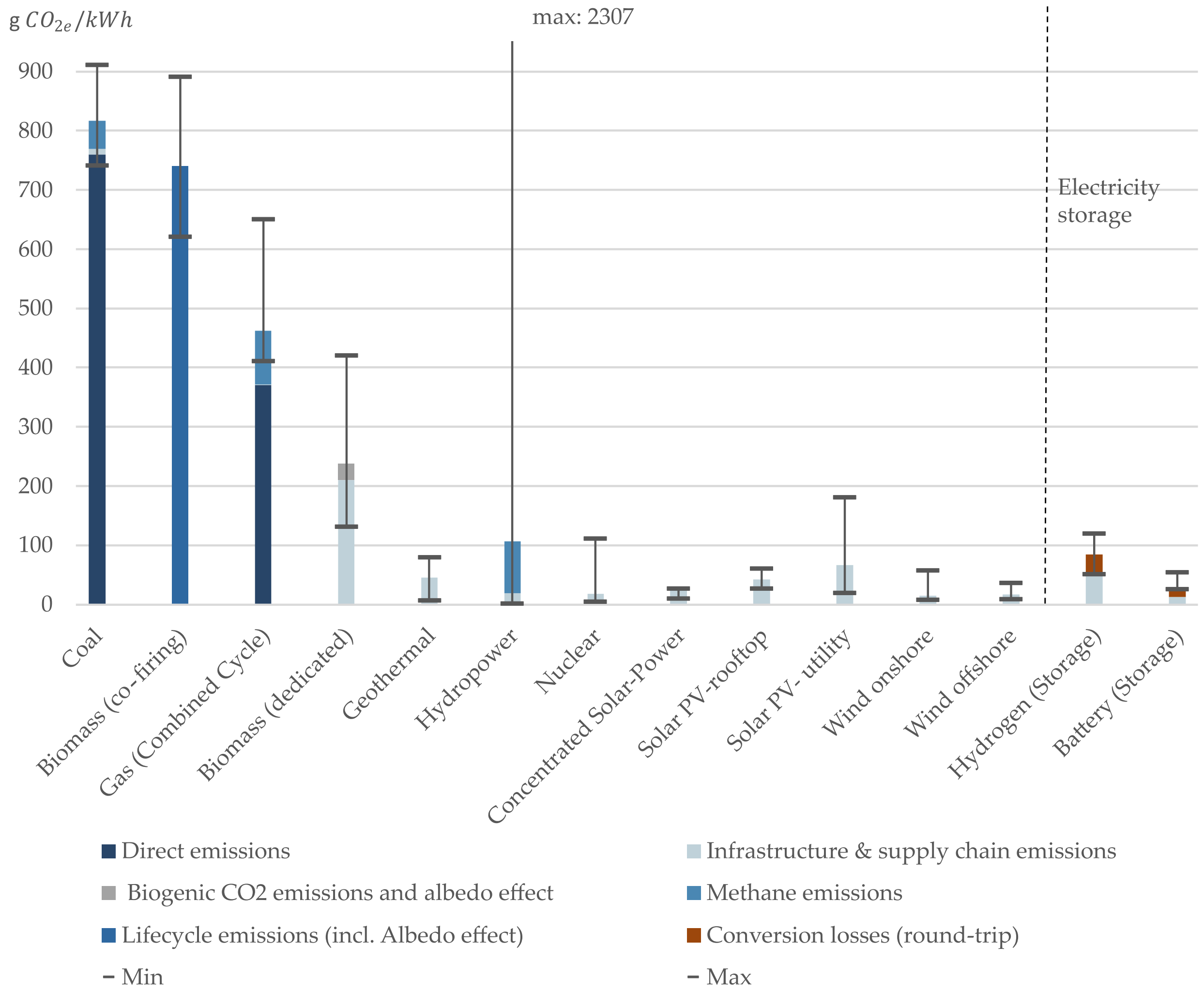


Figure 2.5: CO_2e emissions for commercially available power generation and storage technologies. Calculation and depiction based on IPCC, (2015), Schmidt et al. (2019b), Thomas et al. (2020), Turconi et al. (2013), Wang et al. (2019), and Xie et al. (2020).

The results in Figure 2.5 show that electricity generator emissions differ not only in the total emissions emitted during the life of the technology but also in the life cycle phase in which they are emitted. For power generation from conventional sources, such as gas, oil, or coal, most of the emissions occur in the use-phase of the technology. Over all life-cycle phases, these technologies have much higher emissions. Compared to coal and gas generators, wind- or solar-energy-based electricity generation can reduce emissions by 90%-99%. As illustrated by the error bars and highlighted in studies, the emissions of hydroelectric power generators can deviate significantly. High CO_2e emissions can occur in tropical regions and in areas with high sediment content, where a lot of trapped emissions are released when organic material flowing from rivers into dams decomposes (Bertassoli et al., 2021; Deemer et al., 2016).

In most cases, the storage of a kWh of electricity has a greater environmental impact than the generation based on renewable primary energy sources. For battery storage, the operational strategy and battery chemistries are shown to have a decisive impact on CO_2e emissions (Schmidt et al., 2019b; Thomas et al., 2020). For residential battery storage, Thomas et al. (2020) calculate emissions of 40 - 80 g CO_2e/ kWh when cycled once per day. The round trip efficiency is significantly higher (82%–89%) than that of hydrogen storage when considering the conversion of water to hydrogen by electrolysis and back to electricity using a fuel cell (approximately 30%-40%) (IEA, 2019b; Pellow et al., 2015)[11]. For these losses, emissions of 14.5 g CO_2e/ kWh were assumed, the average emissions for electricity generation technologies based on volatile primary energy sources. While the exact emissions vary, the general notion that renewable power plants have lower emissions is true; however, site-specific factors must be considered.

2.1.2.2 *Energy generation and storage costs*

For the economic assessment of electricity generation and storage technologies, levelized cost of energy (LCOE) (2.1) and levelized cost of storage (LCOS) (2.2) allow comparisons of power generators and electricity storage with different generation, storage, and cost structures (Zapf, 2017). They denote the costs necessary to convert energy from a form of primary energy to electricity or for the LCOS costs of storing electric energy. The resulting LCOE and LCOS are constant revenues (per kWh) required over the life of a power generation or storage technology to break even while covering all costs and paying investors a minimum acceptable rate of return (Kuckshinrichs and Koj, 2018). The calculation is based on the net present value method. The numerator sums up all investment and operational expenses in the respective years (t), which can include fuel, operations and management, carbon offset or decommissioning of the power plant or storage system. The denominator sums up the average annual electricity generation of that plant, discounting the generated energy with the same discount factor as the total operational expenditure (OPEX) and capital expenditures (CAPEX) the time value of future revenues is considered (Konstantin, 2017; Mostafa et al., 2020; Ueckerdt et al., 2013).

$O\&M$	Cost for operations and management for each time period t
$Elec_{discharged}$	Electricity discharged over the life-time
r	interest rate
t	time period
n	Number of periods
Carbon	Cost of emissions (e.g, CO_2 certificates)
Fuel	Cost of fuel
Electricity	Generated electricity
Decommissioning	Cost of dismantling and removal at the end of its operational life
Investment	Initial investment of building or installing the energy infrastructure

11 See Figure 2.11 for energy conversion efficiencies

$$\mathrm{LCOE} = \frac{\sum_{t=1}^{n} \frac{\text{Investment}_t + \text{O\&M}_t + \text{Fuel}_{\ t} + \text{Carbon}_{\ t} + \text{Decommissioning}_{\ t}}{(1+r)^t}}{\sum_{t=1}^{n} \frac{\text{Electricity}_{\ t}}{(1+r)^t}} \tag{2.1}$$

$$\mathrm{LCOS} = \frac{\text{Investment} + \sum_{t=1}^{n} \frac{\text{O\&M cost}}{(1+r)^t} + \sum_{t=1}^{n} \frac{\text{Charging cost}}{(1+r)^t} + \frac{\text{End-of-life cost}}{(1+r)^{n+1}}}{\sum_{t=1}^{n} \frac{\text{Elec}_{\text{discharged},t}}{(1+r)^t}} \tag{2.2}$$

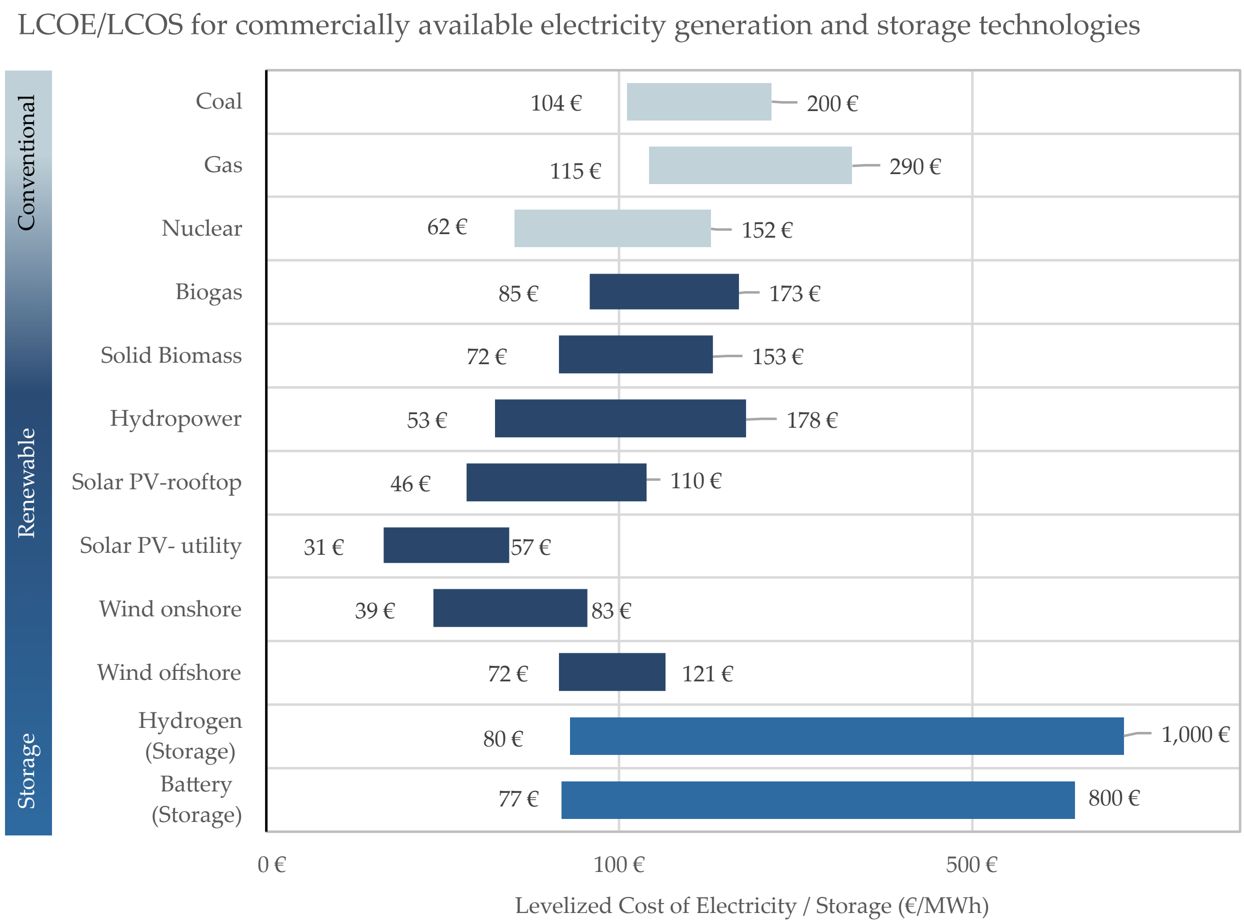


Figure 2.6: LCOE and LCOS for commercially available electricity generation and storage technologies (BMWi, 2015b; FCHO, 2022; Fraunhofer ISE, 2021; Hiesl et al., 2020; Jülch, 2016; Lazard, 2021; Ram et al., 2017; Steckel et al., 2021).

Figure 2.6 presents an overview of the current LCOE of different technologies operating in Germany. Currently, the two cheapest options for electricity generation in Germany are ground-mounted photovoltaic (PV) systems with a capacity greater than megawatt peak (MWp) in southern Germany (31 €/MWh) and wind onshore, for strong wind sites with a mean wind speed greater than 7.8 m / s (39 €/MWh). The LCOE of conventional power generators such as coal and gas have significantly increased due to higher CO_2 certificate prices in the last years and in the in some cases exceed the most expensive solar or wind generators (Fraunhofer ISE, 2018, 2021).

The LCOS for the storage of electricity have declined due to factors such as technological improvements and economies of scale. However, costs are mainly dependent on discharges per year and storage duration (Schmidt et al., 2019a). Cost predictions are still highly uncertain and are dependent on numerous other factors, making a comparison difficult. Assuming an average cost of hydrogen generation of 5.35 €/ kg and low storage losses, as well as a high fuel cell efficiency of 60% domestic hydrogen generation for grid-scale storage in Germany could reach LCOS of 267 €/MWh. In the best case, for other European countries, hydrogen LCOS could reach 90 €/MWh (FCHO, 2022).

In the electricity system, the generation and consumption of electricity must be balanced at all times. As a mismatch between electricity generation and consumption can lead to a deviation from the nominal frequency (50 Hz or 60 Hz) of the electrical grid, and in addition to a variety of negative consequences leading to the emergency shutdown of the power system (Dixon, 2019; Hirth and Ziegenhagen, 2015; Konstantin, 2017). Mismatches that need to be corrected arise for several reasons. On a longer time scale (monthly scale), the electricity generation by solar power in the Northern Hemisphere is greater in summer while the electricity consumption is lower, leading to a mismatch in a renewable power system largely dependent on solar electricity generation. On the midterm timescale (days to weeks) "dark doldrums", i.e. random periods sunless and windless periods, can lead to a power shortage (Matsuo et al., 2020). In the short term (seconds to an hour), there are various other causes of a mismatch between electricity generation and consumption, and an intricate control mechanism has been developed to compensate for short-term electricity shortages (Hirth and Ziegenhagen, 2015).

Depending on the proportion of variable renewable power plants in the total energy mix, dispatchable renewable generators may not be able to fully compensate for an electricity shortage. In this case, energy storage may be necessary. The function of energy storage is to decouple energy generation from energy demand. In the case of electrical energy, this decoupling can only be achieved to a limited extent by storing electricity (Sterner and Stadler, 2017).

The graphs in Figure 2.7 show different energy storage technologies and their projected relative LCOS according to discharges per year and hours per discharge. Depending on the discharge time, energy capacity, or storage duration, different storage forms of energy storage (electrical, mechanical, or chemical) are preferable. Their suitability depends on the requirements of the energy system, including technological and economic factors. The CAPEX associated with a certain storage technology are mainly determined by its operating hours, efficiency, and costs per unit of energy and power. While the energy costs of battery storage can increase by a ratio of one to one for increasing storage capacities, the specific investments to increase the energy storage capacity while keeping power unchanged are lower for hydrogen (Wolf, 2015). This means that for longer storage duration, with the requirements of a higher energy and lower power capacity, hydrogen storage is preferable, whereas battery storage is preferred vice versa. Other factors that make hydrogen more suitable for long-term storage are its low self-discharge and long useful life (Sterner et al., 2015). For a sustainable energy system, therefore, a combination of storage technologies is preferable (Davis et al., 2018; Schmidt et al., 2019b; Sterner and Thema, 2017; Sutter et al., 2019). As EVs store the electricity required for propulsion in a lithium-ion battery, the question arises what type of storage EVs can provide for the electricity system.

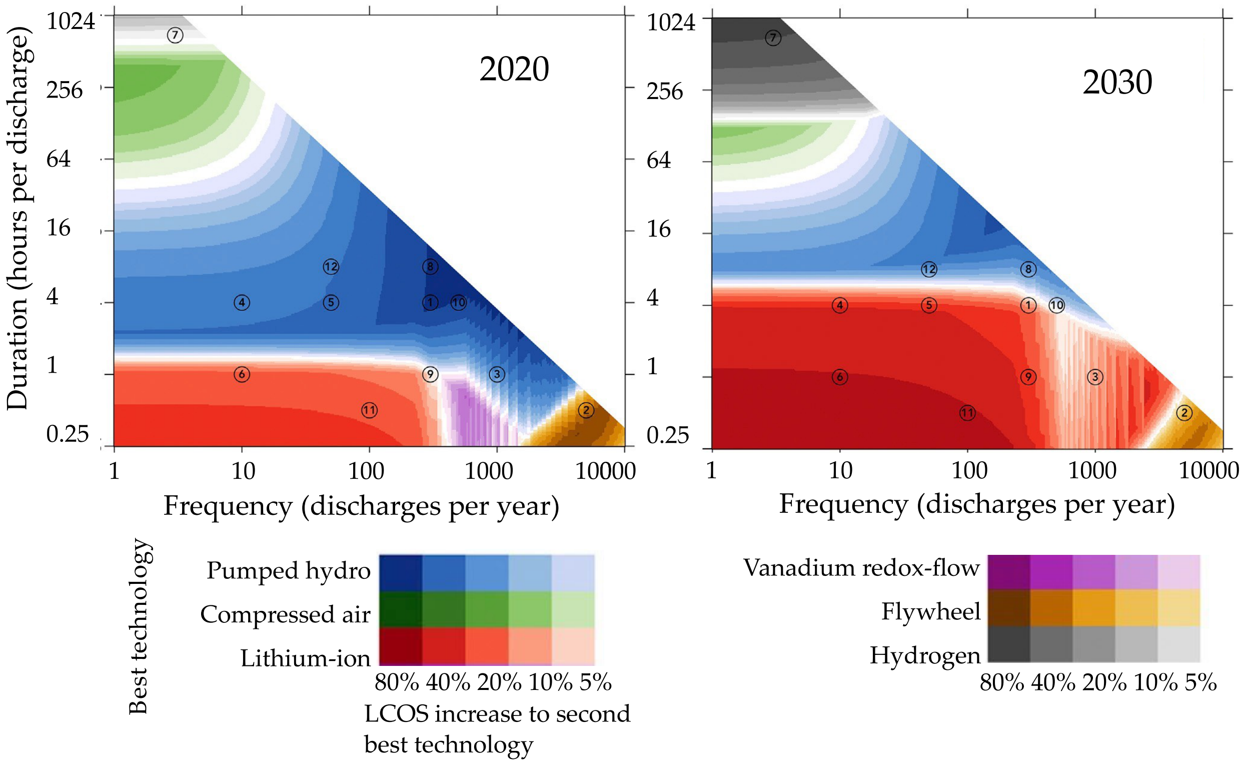


Figure 2.7: Projected LCOS for different electricity storage technologies adapted from Schmidt et al. (2019a).

2.1.3 Transformation towards a renewable electricity system

As highlighted in Section 2.1.1, the generation of electricity from volatile primary energy sources, such as wind and solar energy, induces a particular pattern of electricity generation. For example, photovoltaic system generation is bell-shaped, with a peak around 12:00 p.m., while wind electricity generation is stronger in the winter months and at night. Depending on the configuration of the future electricity system, different requirements and problems will arise. These can affect electricity prices and the need to increase or to decrease power consumption during certain times of the day, which can also have an impact on the charging behavior of EVs. The German legislature e.g., the EEG, describes general goals for the expansion of power generation based on renewable resources. As these goals do not clearly specify the configuration of a fully renewable electricity system or the possible paths to such a system, several energy scenarios have been developed and a summary is presented, as these have an impact on how EVs can be integrated into the electricity system.

An amended version of the EEG entered into force on 17 December 2020 (EEG 2021). After the nuclear accident in Fukushima in 2011, Germany decided to phase out nuclear power generation. Furthermore, the German government has committed to end coal-fired power generation by 2035 and the latest by 2038 (Bundesregierung, 2020). Due to the long time horizons and uncertainty of aspects such as technological development, regulations, or societal views, energy scenarios and scenario planning can be used to develop a shared understanding of these uncertainties (Stewart and Durbach, 2016). An energy scenario describes a possible future development of the examined energy system (Dieckhoff et al., 2014; Grunwald et al., 2016; Witt et al., 2020).

Numerous energy system scenarios have been developed for Germany. The guiding factor for many energy scenarios in Germany are the proposed targets of the federal government with respect to the stepwise reduction of total greenhouse gas emissions in all sectors. To achieve these goals, energy scenarios consider measures such as increasing energy efficiency, carbon capture and storage, and increasing power generation through renewables. Scenarios apply different methods to model and simulate the developments of the energy system under different underlying assumptions (Hillebrandt et al., 2015; Kobiela et al., 2020). Figure 2.8 presents the projected share of renewables of net electricity generation and installed capacity for the years 2030, 2040 and 2050 in 18 scenarios described by studies published since 2016. Moreover, the goals stipulated in the EEG 2021 and the preliminary goals for the year 2023 are shown.

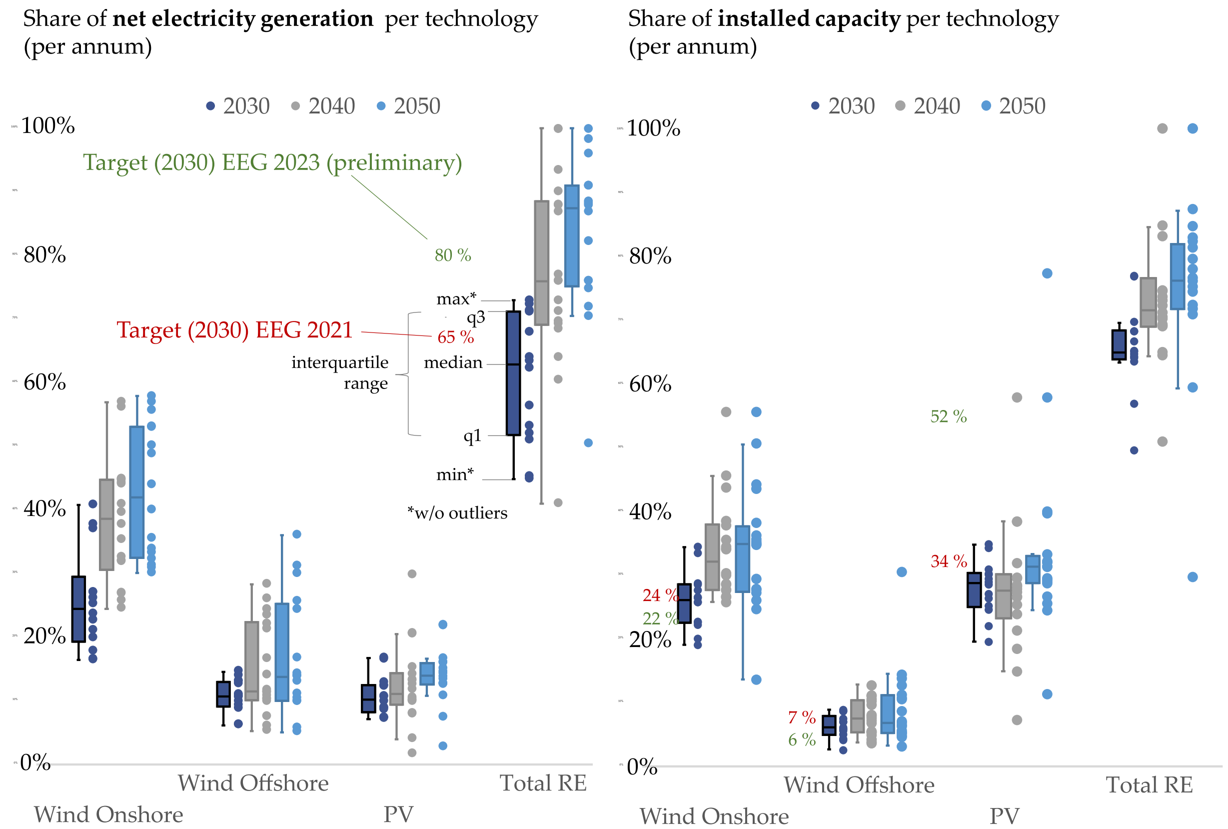


Figure 2.8: Renewable energy generation in different studies and scenarios in contrast to the targets stipulated in the EEG 2021 and preliminary values for the EEG 2023 for Germany and the years 2030, 2040, 2050 (Dena, 2018; Gerbert et al., 2018; Nitsch, 2017; Pfluger et al., 2017; Prognos AG et al., 2021; Quaschning, 2016).

In their review of different scenarios for future energy systems in Germany, Hillebrandt et al. (2015) present an overview of the different assumptions made in studies and scenarios and show that the results can vary significantly and are dependent on the underlying assumptions and modeling techniques. For instance, while the *"Government Target Scenarios"* project only a moderate substitution of fossil fuels through electricity and does not foresee any carbon capture and storage, *"90% Greenhouse Gas Reduction Scenario"* projects carbon capture and storage technology to reduce industrial emissions. As the electricity sector is seen as a key factor in the reduction of CO_2 emissions, studies often put an emphasis on it. Most energy scenarios have an overall guiding objective. For example, in the five scenarios described and modeled by Pfluger et al. (2017), the potential effects of a limited expansion of the transmission and distribution grid, a larger geographical distribution of electrical generators, or the discontinuation of renewable power generators are considered. All of these assumptions have an impact on the total capacity and type of renewable energy generator installed and lead to various energy system configurations.

In a study by Quaschning (2016) two scenarios show different efficiency perspectives for electricity consumption. The *"without efficiency measures"* scenario has an energy demand of $3,120\ TWh_{el}$ while in the scenario *"with efficiency considerations"* $1,320\ TWh$ electrical energy are required. In comparison to the electricity demand in 2019, this is equal to a 2.6-fold increase in the scenario considering efficiency measures and 6.1 times in comparison to the scenario without efficiency measures. In the efficiency scenario, more energy efficient technologies, such as electric vehicles, are considered in contrast to hydrogen, reducing the required electricity demand by $665\ TWh_{el}$. Other studies based on hydrogen mobility also show a similar increase in energy demand (Hansen et al., 2019; Pfluger et al., 2017; Weißermel, 2021). Efficiency measures have a significant impact on the required electricity demand. The goals of increasing efficiency are specified in *National Energy Efficiency Action Plan* and *"Germany's Energy Efficiency Strategy 2050"*. They are defined for the years 2030 and 2050 by the federal government for all sectors (heating, transport industry, and electricity) (BMWi, 2019, 2020). Compared to 2008, total primary energy consumption in all sectors should decrease by 30% in 2030 and 50% in 2050. A study commissioned by the German *Federal ministry for economic affairs and energy*, estimates that gross electricity consumption will increase to 655 TWh by 2030 (+/-10 TWh), largely due to the increase in electrification of the transport and heating sector (Kemmler et al., 2021).

2.1.4 Characteristics of a renewable electricity system

The EEG 2021 stipulates the goal that all electricity (generated or consumed) in Germany by 2050 should be carbon neutral. Furthermore, the interim goal of a share of 65% renewable electricity generation by 2030, is defined. To achieve this, installed capacities for onshore wind energy (71 GW), offshore wind energy (20 GW), photovoltaic (100 GW), and biomass (0.84 GW) projected. Regarding total renewable energy generation, this capacity would generate 303 TWh[12] in the year 2030, which is equal to 60% of the electricity generated in the year 2019.

12 Assuming the annual full-load hours of 2019 (BDEW, 2019).

Figure 2.9: Calculated electricity surplus and deficit shown over one year for the electricity generation mix defined in the targets of the EEG (2021) for the year 2030. In 15 Minute aggregation on the top and weekly aggregation on the bottom (without imports and exports). Based on data of BDEW (2019) and SMARD (2022).

To illustrate how the electricity generation pattern could deviate from the values of 2019, the electricity generation is adapted according to the values specified by the EEG. For the calculation of the 2030 values, photovoltaic and wind generation of 2019 was proportionally scaled up and down for biomass and other sources to the capacity targets specified by the EEG and full-load hours of 2019. Figure 2.9 presents two different representations of the results, assuming that the electricity consumption patterns remain the same as in 2019. The first part of the figure presents a scenario for the electricity surplus. The generation by non-renewable sources was scaled down to account for 35% of the total generation. Nuclear energy was reduced to zero, since Germany has committed to end all nuclear power generation by 2022. In total, electricity generation is reduced by 1.32% (6.8 TWh) when considering 2019 total load hours for 2019 and the assumption that renewables should comprise 65% of electricity generation in 2030, as stipulated by the EEG 2021. As the total load hours fluctuate and to make the comparison between 2019 and the projected values for 2030 possible, the 6.8 TWh are evenly distributed among all generation technologies.

The weekly aggregation in the second part of Figure 2.9 demonstrates the effects of additional renewable power generators entering the power mix. The surplus electricity shows two distinct changes compared to the values of 2019 (see Figure 2.3). Throughout the year, electricity generation in the evening and night is lower than in the case of the 2019 electricity mix and greater in the morning to afternoon hours. In particular, the effects of increased photovoltaic-based generation are visible. On average, the electricity surplus from 8:00 a.m. - 4:30 p.m. is 2.6 times as high as in the case of 2019. While on average there is a greater surplus in the morning and afternoon hours compared to 2019 there are also more hours in the night that show an electricity deficit. The second part of Figure 2.9 shows the weekly energy balance for 2019 and the simulated values for 2030. As the data for 2030 were fitted to the 2019 values, the total electricity surplus is 24 TWh in both cases. While there is generally an electricity surplus in the summer in the end of January, February, and October, there are weeks with a high deficit, while the first two weeks of March show a high surplus. Figure 2.10 shows two exemplary weeks, considering an unchanged demand pattern, the highest electricity deficit and surplus presented for simulated energy generation in 2030. On Sunday the 30th July, the electricity surplus at 12:00 p.m. is the greatest. During this time, photovoltaic electricity generates 63.5 GW of electricity, equivalent to 129% of electricity consumption. In contrast, the greatest electricity deficit is present on Thursday the 24th of January. At 16:45 p.m., electricity from volatile primary energy generators only constitutes 3.87% of the total electricity generation, resulting in a deficit of 31.484 GW. Compared to the base values for 2019 (see Table 2.1), the maximum surplus is 284% and the deficit is 218% greater. Although total electricity generation was sufficient in 65% of the weekly intervals to meet electricity demand in 2019, this is possible in 51% of the weekly intervals in the projection of the year 2030.

This simplified calculation omits certain factors, such as changes in electricity demand, for example, increased installation of heat pumps may lead to demand surges, especially in the winter months or the geographic distribution of electricity generation and consumption (Abiven et al., 2020; Ruhnau et al., 2019). The potential geographic location of the energy generation capacity is affected by factors such as wind speed or radiation. The average wind speed is higher in the northern part of Germany, whereas the annual solar irradiation is higher in the southern part of Germany (Schmidt and Mühlenhoff, 2010). On the other hand, current energy demand is distributed with a higher electricity demand concentrated in some industrial cities (Elsland et al., 2016; Priesmann et al., 2021; Statistisches Bundesamt, 2020). Studies estimate that the electricity demand for urban regions will increase in the coming years, whereas many counties in the new federal states and areas located in the peripheral parts could decrease electricity consumption (Boßmann et al., 2013; Elsland et al., 2016). Staudt et al. (2018a) base their simulation of the transmission grid on the development goals stipulated in the federal network agency's grid development plan (Bundesnetzagentur, 2016b). The simulation results indicate that the need for redispatch measures occurs in the north and south of Germany, that is, in the TenneT and 50Hertz transmission networks. Furthermore, most re-dispatch is required in the time from 5 to 10 a.m. and 3 to 8 p.m.

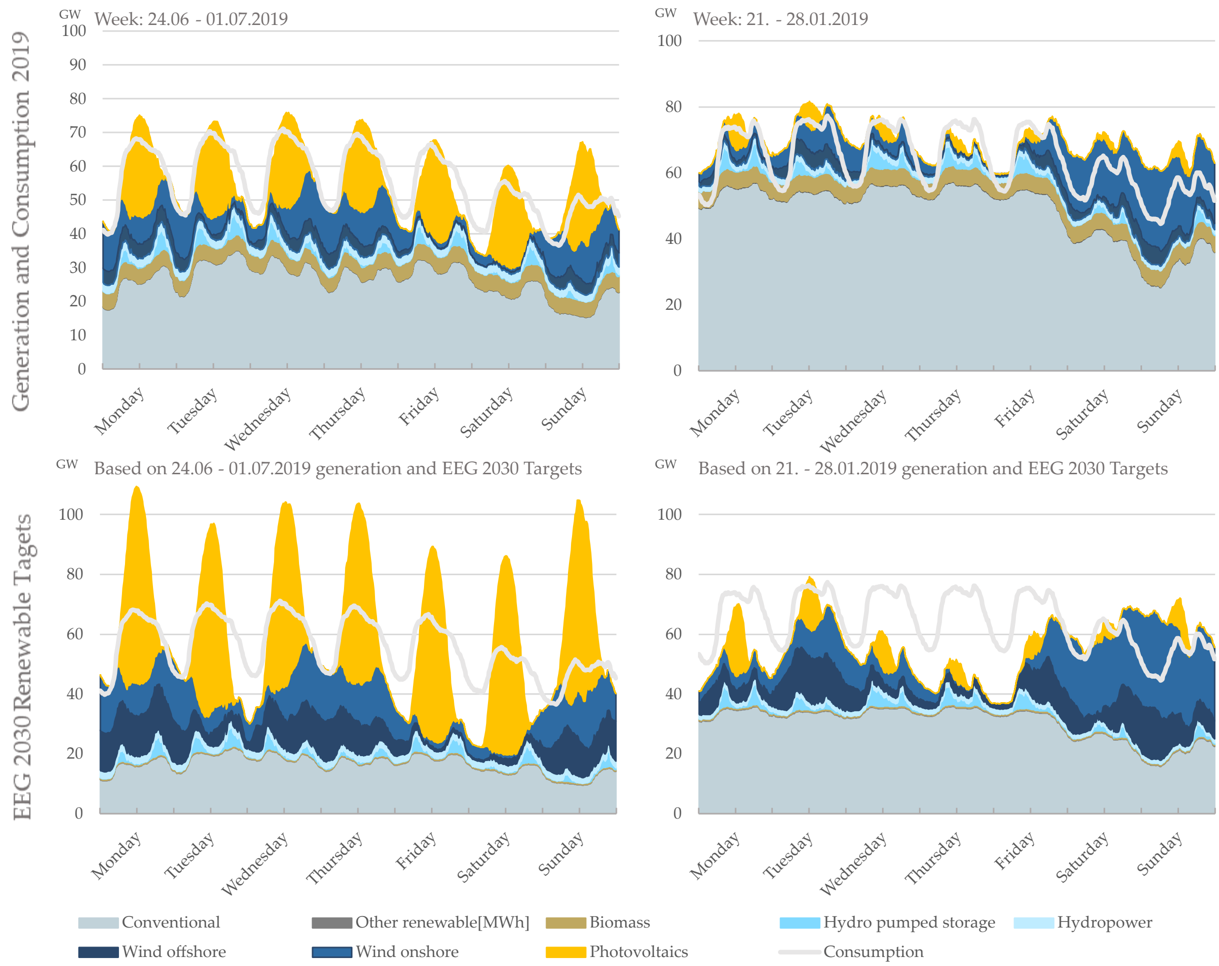


Figure 2.10: Electricity generation and consumption in two exemplary weeks in 2019 and under consideration of the Targets for Germany (2030) as specified in the EEG 2021 for 2030 and under consideration of the full load hours of 2019. Based on data of BDEW (2019) and SMARD (2022).

The results of the calculation of the electricity generation for the year 2030 indicate that in the summer months large shares of renewable photovoltaic electricity generation will be available at noon. If electricity consumption stays similar to the year 2019, this would result in a large surplus of electricity during these times. For the winter month, no clear result can be drawn. From a more long-term perspective, there are weeks with an overall generation surplus or deficit throughout the year. Both of these results may be of interest to the planning of the charging infrastructure of EVs and to the planning of the charge process.

2.2 ELECTRIC VEHICLES IN THE MOBILITY SECTOR

In 2021, more than 16 million personal EVs were registered worldwide, making up 1.4% of all registered vehicles. Most vehicles (11 million) were BEV and hybrid EVs (5.2 million), 56% of BEVs were registered in China followed by 12% in the United States and approximately 6% in Germany and 4% in Norway (IEA, 2021). As of 2021 China also has the highest number of publicly accessible electric vehicle charging stations. Compared to the proportion of BEVs to the total number of new passenger vehicles registered, Norway (≈54%), Iceland (≈45%) and the Netherlands (≈20.5%) had the highest penetration rates of EVs in 2020 (Netherlands Enterprise Agency, 2021; OFV, 2021; Samgöngustofa, 2021).

In Germany 90% of the total 48.5 million personal vehicles are registered to private individuals. More than 97% of all personal vehicles are powered by a diesel or petrol engine. In 2021 BEVs made up 1.3% of the registered personal vehicles, 3.4% are hybrid EV and 808 fuel cell electric vehicle (FCEV) have been registered in Germany (KBA, 2022a).

As EVs are seen as an effective technology to reduce CO_2 emissions in the personal transport sector, many countries have introduced policies to support their deployment. Including measures on an international scale, such as the new fuel economy standards of the European Union (Helgeson and Peter, 2020), national scale, such as the phaseout of internal combustion engine (ICE) vehicles through a sales ban from 2030 or subsidies and policies on a municipal or city scale, e.g., incentivizing the installation of charging stations. These measures also support the adoption of EVs in Germany to reach the target specified in the German climate protection program of 7 - 10 million EVs and 1 million charging points by 2030 (BMU, 2019).

2.2.1 Battery electric vehicles: economic and ecological factors

An electric vehicle (EV) uses an electric motor for some or all of its propulsion. The definition of the term EV varies. For example, the German Federal Motor Transport Authority understands EVs to be only those "propelled exclusively with an electric energy source" (KBA, 2021). Vehicles "with at least two different energy converters and two different energy storage systems" are defined as hybrids. The United States Department of Energy defines EVs as vehicles that "derive all or part of their power from electricity supplied by the electric grid." In addition, they distinguish between all-electric vehicles and plug-in hybrid EVs. The International Energy Agency differentiates between BEV and Plug-in Hybrid EVs (DOE, 2021). Overall, three distinctions can be made:

- Hybrid EVs use an additional powertrain technology and do not solely rely on the electric motor. Most often the electric motor is combined with an internal combustion engine that relies on some form of fossil fuel.
- Fuel cell EVs (fuel cell electric vehicle) only use the electric motor for propulsion, however, alongside a battery energy is also stored in the form of hydrogen and converted to electricity using a fuel cell.
- If the EV can be recharged from an external electricity source, it can be defined as a plug-in EV. A subcategory of these plug-in EVs are **battery electric vehicles**.

In this thesis, the term BEV refers to vehicles that purely store the energy required for propulsion in electrical form and directly use this energy to generate propulsion. Electricity is recharged to the battery from an external source. Although there are many types of EVs already used in the transportation sector today, the number of personal EVs has increased since the 1990s and its growth was especially accelerated with the introduction of the lithium-ion battery at the beginning of the 21st century (IEA, 2020b).

Different types of storage have been used and proposed for EVs. Currently, lithium-ion batteries are the dominant battery chemistry (Helmers and Marx, 2012; Lamp, 2013; Marques et al., 2019). A lithium-ion battery generates electromotive force through the displacement of lithium-ions. A variety of different anode and cathode materials have been proposed, resulting in a unique performance (Peters et al., 2017; Wentker et al., 2019). To determine whether and how suitable a battery is for the application in an electric vehicle, numerous characteristics are important, among the most frequently cited are costs, energy density/weight, performance, durability, and environmental impact (Marques et al., 2019). Such as in the environmental policy triad, these characteristics are usually conflicting. For instance, in previous generations of lithium-ion batteries cobalt was used in the cathode of the battery, making the battery more durable and allowing for higher performance, i.e. increasing the charging and discharging capacity of the battery. At the same time, the material is also scarce, making it costly.

Table 2.2 shows an overview of commercially available BEV models that were delivered in the first half of 2022 in Germany. Vehicles are available in different configurations that affect their price and range. Most vehicles were sold by the brands Tesla and Volkswagen. The battery capacity of most vehicles is within the range of 52 kWh to 77 kWh and all have an AC charging capacity of 11 kW.

Table 2.2: Overview of BEV and characteristics and registrations in Germany (status October 2022) (KBA, 2022b).

Model	Price	Battery	Range [13]	Charging Power		Vehicles
	€	kWh	km	kW (AC)	kW (DC)	registered
Tesla Model Y	53,990 - 64,490	57.5, 75	430 - 533	11	250	24,177
Fiat 500e	23,560 - 32,560	23.8, 42	245	11	85	19,219
Tesla Model 3	42,900 - 58,000	54, 75	491 - 602	11	250	17,464
VW ID.4/ID.5	36,950 - 56,455	52, 77,82	326 - 501	11	100-125	14,785
VW ID.3	43,995 - 49,040	58; 77	416 - 549	11	100-125	12,802
Hyundai Kona	33,971 - 40,795	39.2; 64	305 - 484	11	70	10,922

From a consumer perspective, there are several factors such as economic, technical or environmental that drive or inhibit the adoption of a new vehicle technology such as BEV or FCEV (Kumar and Alok, 2020). These factors can be further operationalized into measurable indicators such as CO_2 emissions (Cox et al., 2020; Letmathe and Suares, 2017).

13 Worldwide Harmonized Light Vehicles Test Procedure (WLTP).

In a complete LCA more than 19 environmental indicators can be assessed for BEVs (Tintelecan et al., 2019). The results of selected studies are shown in Table 2.3. Some studies only compare BEVs with ICE vehicles, but isolated studies e.g., Miotti et al. (2017) also consider FCEVs. The resulting CO_2 emissions depend on a multitude of factors e.g., quality and actuality of the data and the assumptions made regarding mileage and the characteristics of the vehicles considered, and therefore differ considerably. For example, in the technical report by Volkswagen AG (2019) compact vehicles are investigated, while Karaaslan et al. (2018) examine larger sport utility vehicles. On average, these studies result in about 0.158 kg CO_2e/km for BEVs, 0.229 kg CO_2e/km for FCEVs and 0.224 kg CO_2e/km for ICEs.

Table 2.3: Overview of kg CO_2e/km of different vehicle technologies.

Study	BEV kg CO_2e/km	ICE kg CO_2e/km	FCEV kg CO_2e/km
Volkswagen AG (2019)	0.059- 0.183	0.141- 0.173	-
Pero et al. (2018)	0.129	0.203	-
Evangelisti et al. (2017)	0.130	0.175	0.135
Held and Schücking (2019)	0.138	0.179	-
Bekel and Pauliuk (2019)	0.140	0.168	0.326
Singh et al. (2014)	0.180	-	0.13
Wulf and Kaltschmitt (2013)	0.189	0.439	0.219
Miotti et al. (2017)	0.215	0.280	0.240
Tesla (2022)	0.029 - 0.157	0.298	-
Karaaslan et al. (2018)	0.240	0.366	-

Emissions related to a vehicle occur in the production, use-phase or recycling of the vehicle. While the majority of emissions for an ICE vehicle occur in the use-phase, the production of the battery is responsible for most emissions of the EV and especially the BEV. While the emissions related to the production of a BEV can be 70% to 130% greater than those of a comparable ICE vehicle, the emissions related to the use-phase are smaller, leading to a reduction of CO_2 emissions of 15 to 30% over the whole life-cycle (Thielmann et al., 2020).

In the use-phase, energy conversion efficiency can have an important effect. Figure 2.11 shows the well-to-wheel (WTW) energy conversion efficiency of three vehicle technologies in a Sankey diagram. The left side of the diagram shows the primary energy (*well*) required for the useful energy (*wheel*) to drive 100 km. The efficiency of the ICE can achieve a ratio of 21.9% primary energy (192 MJ) to useful energy (42 MJ). Most of the energy is converted to heat in the combustion process, resulting in low tank-to-wheel efficiency. For FCEV renewable primary energy from wind or solar energy is converted to electricity. Through electrolysis, this electricity can be converted to hydrogen, which can be stored in the vehicle, hydrogen is converted back to electricity using a fuel cell and stored in a battery, which powers the electric motor (Klell et al., 2018). Most of the energy is lost in this conversion process, resulting in an energy efficiency of 29.8%. For BEVs energy is lost through electricity transmission and the charging process. BEVs have the highest energy conversion efficiency of 71.19% (Edwards et al., 2014).

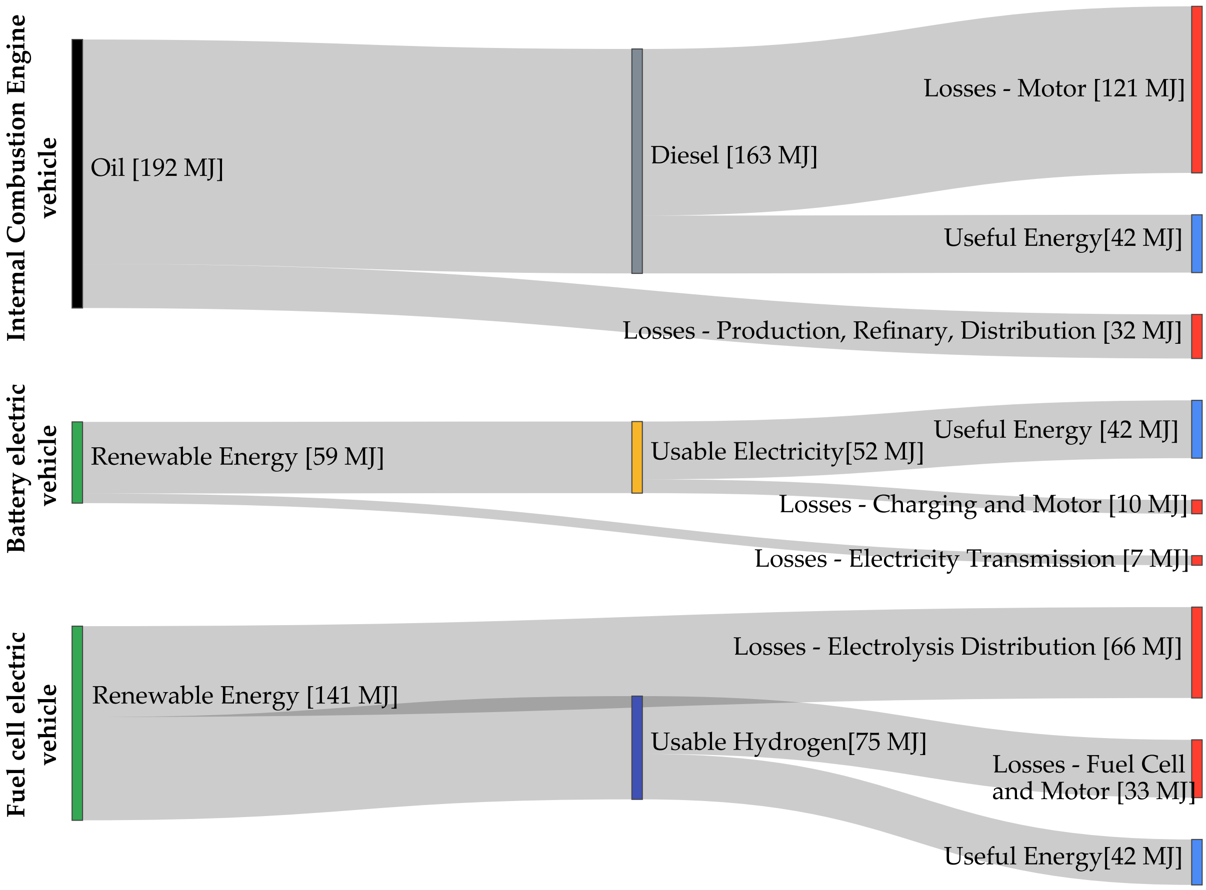


Figure 2.11: Sankey diagram of the energy efficiency of three propulsion systems. Representation based on data from Edwards et al. (2014).

Figure 2.11 shows the highest WTW efficiencies possible for all technologies discussed. For FCEV and BEV only renewable primary energy sources are considered. The use of other primary energy sources, such as coal, can significantly decrease the WTW efficiency of the BEV and FCEV. However, a higher energy conversion efficiency leads to lower tailpipe emissions when considering the same primary energy source.

The conversion efficiency also has an impact on the total electricity demand of the mobility sector (see for instance *"inefficient Scenario"* versus the *"efficient Scenario"* by Quaschning (2016)[14]) and the total cost of a vehicle over its lifetime. To assess the economic viability of a BEVs, most studies adopt the total cost of ownership financial model and use it to calculate the lifetime costs of a vehicle (Velzen et al., 2019). The total cost of ownership (TCO) assessment model takes into account all one-off and ongoing costs, as well as direct and indirect costs of an investment, which are compared on an accrual basis (Ellram, 2002; Scorrano et al., 2020). In some studies, the TCO are discounted to the time of acquisition. For example, Parker et al. (2021) and Santos and Rembalski

14 In the mobility sector, the study estimates an additional electricity consumption of the *"inefficient Scenario"* in contrast to the *"efficient Scenario"* of 445 TWh per year for the individual mobility sector. While the *"efficient Scenario"* assumes BEV as the main technology, the *"inefficient Scenario"* assumes Power-to-Liquid Fuels.

(2021) perform a TCO based analysis for different car models and find that currently BEV are close to reaching cost parity with ICE vehicles. The price premium of the BEV in contrast to a comparable ICE vehicle is largely due to the cost of the battery pack, which Liu et al. (2021) estimate makes up more than 70% of the total vehicle cost. BEV have lower electricity (fuel) (up to 55%) and repair and maintenance costs (up to 50%) compared to ICE vehicles (Harto, 2020) that can compensate for the higher purchase price. For example, in the United States smaller vehicles with a range of up to 320 kilometers may reach the cost parity after five years (Liu et al., 2021).

Mobility in Germany differs for urban or rural areas, means of transport, level of employment, and age. Various studies have been conducted to measure changes in mobility behavior (see Chapter 4). On average, a passenger car covers a distance of 14,700 km per year in Germany. The average daily distance is 25 km in metropolitan areas and 33.7 km in rural areas. In general, 64% of car trips are shorter than 10 km and 95% are shorter than 50 km (Infas, 2019b). Compared to comparable ICE vehicles, the range of BEVs is often smaller. This factor and insufficient charging infrastructure has led to a fear by the consumer described as *range anxiety*, i.e., the fear of running out of battery charge before reaching a final destination (Melliger et al., 2018; Schuller, 2013). However, studies estimate that for inhabitants of cities such as Hamburg or in other countries, up to 90% of trips can be achieved with a home charger and a vehicle range of 30 kWh and a range of 300 km combined with a fast charging infrastructure is sufficient to cover 99% of mobility needs and alleviate *range anxiety* for most drivers (Greaves et al., 2014; Melliger et al., 2018; Vial and Schmidt, 2019).

BEVs are becoming increasingly popular and can reduce emissions compared to conventional or FCEVs. When comparing the energy conversion efficiency of different propulsion technologies BEVs also have the potential to reduce the primary energy input by more than 70% when compared to vehicles propelled by a ICE. The high electricity conversion efficiency of BEVs may lead to a 60% smaller electricity demand compared to that of FCEVs. As only a small portion of the battery capacity is required for the daily mobility needs of individuals, the remaining battery capacity could be charged according to the needs of the electricity system.

2.2.2 Electric vehicle charging

To implement the charging process of a BEV in the model, the real world charging process and its characteristics and actors are described in this section.

Rechargeable batteries consist of an anode and a cathode, between which an electrolyte and a separator are inserted. The separator isolates the two electrodes from each other and is permeable for ions, e.g. lithium-ions. The two electrodes of the battery are connected by an external conductor. When the battery is discharged, the ions migrate from the negative electrode (cathode) through the ion-conducting electrolyte and separator to the positive electrode (anode), while the electrons flow from the negative electrode to the positive electrode via the current conductor, thus generating a discharge current (Leuthner, 2013).

Vehicles equipped with lithium-ion batteries can be recharged in several ways, which vary in terms of charging performance or convenience. Charging technologies can be distinguished by connection type (wired / wireless), charging speed (fast charging / regular charging), or the possibility of charging and discharge of the battery from the grid (unidirectional / bidirectional charging) (Falvo et al., 2014; Tan et al., 2016). The most common form of charging an EV is currently through a wired connection in a unidirectional way.

Table 2.4: Charging modes as defined by the standard International Electrotechnical Commission (IEC) 61851 (Hanauer, 2018).

Charging mode	Communication safety	Current (A), voltage (V), phases
Mode 1		16 A and 250 V AC, 1-phase
		16 A and 480 V AC, 3-phase
Mode 2	✓	32 A and 250 V AC, 1-phase
		32 A and 480 V AC, 3-phase
Mode 3	✓	16/32/70 A and 250 V AC, 1-phase
		63 A and 480 V AC, 3-phase
Mode 4	✓	200/250 A and 600 V DC
		200 A and 1000 V DC

The IEC describes four different charging modes in the standard IEC 61851. Table 2.4 shows the different modes as described by the standard. In modes 1 - 3, AC is delivered to the vehicle, which is converted through an onboard rectifier to DC, which is required to charge the battery. In mode 4, DC is provided by the charging point and is fed directly to the battery. The modes also differ in safety features and communication. In mode 1, the vehicle connection is made directly to a regular wall socket without additional safety features or communication between the vehicle and the charging point. This type of connection is forbidden in most European countries (Hanauer, 2018). In modes 2 - 3, additional safety measures are required, such as an integral ground fault interrupter and requirements related to the charging connector. For communication between the vehicle and the charging point, the control pilot function is used. It allows the vehicle to initiate and end the charging process. The main differences between modes 2 and 3 are that additional safety measures and communication functions are implemented in mode 3. This allows for a higher maximum current in comparison to mode 2 as well as more sophisticated control functions. For mode 4 charging, another layer of safety and communication features is required. This mode allows fast charging speeds. Different types of charging ports and charging connectors are used depending on the charging mode (AC or DC) and geography or manufacturer (Das et al., 2020).

The specified current, voltage, and phases are equal to a certain charging power (kW) available for charging. For mode 1 a maximum power of 13.3 kW is possible, for mode 2 26.6 kW, mode 3 66.5 kW and mode 4 300 kW. The maximum charging power is dependent on the AC/DC rectifier of EV (Das et al., 2020). The typical maximum charging power in most European countries, which is also reflected in the values presented in Table 2.2 are 3.7, 11, 22 kW, for AC charging and 50-200 kW for DC charging (BDEW et al., 2020). The German regulatory body considers charging points with a capacity below 22 kW to be normal charging points, whereas those with a capacity above 22 kW are considered fast charging points (Bundesnetzagentur, 2016a). The charging speed depends on several factors, such as state of charge (SoC) of the battery, losses related to the charging process, and ambient temperature (Tomaszewska et al., 2019).

Figure 2.12 shows the charging power compared to SoC of the vehicle for fast (DC) and normal charging (AC). As the fast charging process depends on several factors, such as battery size, battery cooling, or voltage, it is presented for three exemplary vehicles. As can be observed, the charging power is dependent on the SoC of the vehicle battery. In particular, the fast charging process shows a deviation from the available charging power. For the normal charging process, the available power mainly differs in three intervals:

- ≈ 0 to 85% SoC: 11 kW (11 kW) - 22 kW (22 kW)
- ≈ 85 to 95% SoC: 7.5 kW (11 kW) - 12 kW (22 kW)
- ≈ 95 to 100% SoC: 1.7 kW (11 kW) - 2.9 kW (22 kW)

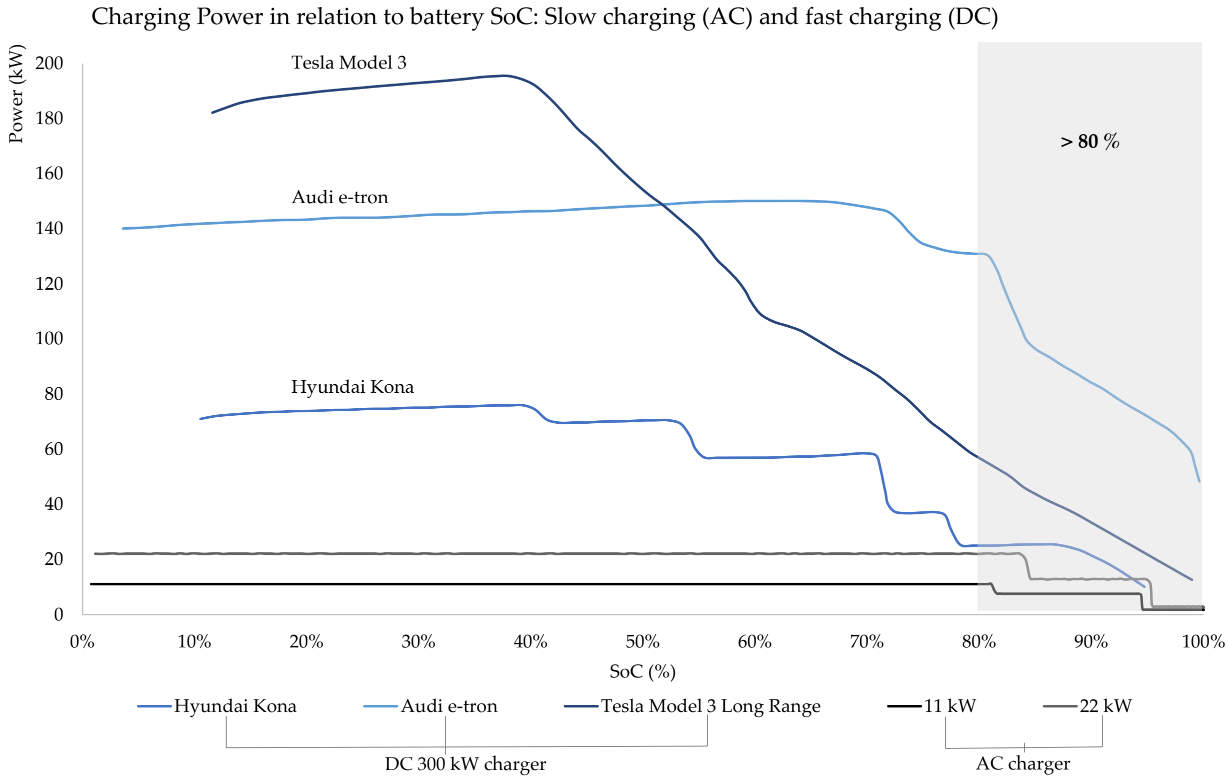


Figure 2.12: Charging power of DC charging for three vehicles (300 kW fast charger) and two AC on-board chargers in relation to the battery's SoC. Based on Montoya et al. (2017) and Schaden et al. (2021).

To charge an electric vehicle, it needs to be connected to a charging point at a charging location that can supply power in one of the aforementioned ways. A charging station combines one or more charging points (Bundesnetzagentur, 2016a; Christ et al., 2015; Linnemann and Nagel, 2020). Charging stations, charging points, charging speed, and communication between the vehicle and the back-end are standardized in several national and international norms; e.g., ISO 15118 is a standard that defines bidirectional communication between EVs and charging stations (Hanauer, 2018; NPE, 2017). Charging locations can be subdivided by the location they are built and the access to the stations. In general, a distinction is made between (Bamberg et al., 2020; NPE, 2015):

- public - with no access restriction
- semi-public – daily access times are restricted, e.g., only accessible during operating or opening hours
- private – only accessible with the permission of the owner, e.g., family homes or company properties.

For private charging stations, predominantly AC charging stations are installed. If the charging capacity exceeds 4.6 kW, German grid operators stipulate a three-phase connection, in case the capacity exceeds 12 kW, installation approval is required from the grid operator (Volkswagen AG, 2018).

Studies show that a public charging infrastructure should be widely available and is seen as another key factor to accelerate or inhibit the diffusion of BEVs (Biresselioglu et al., 2018; Melliger et al., 2018; Schulz and Rode, 2022). In July 2022, 44,200 charging stations were installed in Germany with a total capacity of 1,258 GW (Bundesnetzagentur, 2022). A study by the German Association of Automotive Industry (VDA) shows the distribution of publicly accessible charging points and EVs by region. In November 2020, the Regen district in Bavaria had the highest ratio of EV charging stations (161) per registered vehicle (298) of 1.9. The average number of vehicles per charging point in all 500 investigated districts is 13. The highest number of EVs are registered in Munich (15,954) with a vehicle-to-charging-point ratio of 12.7. The city also has the highest number of public charging points (1,252) (VDA, 2020b). According to the European directive on the development of alternative fuel infrastructure and according to NewMotion (2020), NPE (2018) estimate that currently 14 vehicles should be supplied by a public AC charging point. Furthermore, the study estimates that the number of vehicles per charging point will increase to 16.5 with increasing vehicle battery range. For fast charging, 140 or 165 [15] vehicles are projected per charging point.

According to a survey conducted by the company NewMotion (2020) next to publicly available charging points, most drivers also have a charging point installed at home (70%) or at work (41%). Taking these numbers as a reference, 0.88 - 1.11 charging points are available to owners of EVs at work or at home, while only 0.07 publicly accessible charging points per EV currently exist in Germany (NPE, 2018). The distribution of these private or semi-public charging points is highly dependent on the living situation of a vehicle owner. While vehicles are parked 95% of the time, their parking location varies (Infas, 2019b). For example, about half of the residents of metropolitan areas park on public streets. In rural areas, in contrast, this proportion drops to about 8%, while 89% of vehicles are parked in private parking spaces (Infas, 2019a). Bamberg et al. (2020) estimate that 80% of vehicle owners living in detached housing have access to private parking spaces, while only 55% of apartment-house inhabitants have access to private parking. Overall, the authors estimate a potential of 8.8 million parking spaces for households in buildings

15 With an increased vehicle battery range.

with three apartments or more and 13 million parking spaces on properties of buildings with one or two apartments in Germany.

Studies conducted for other countries with higher BEV penetration rates, such as the Netherlands, calculate a ratio of 5 vehicles per charging station for public AC charging stations, a ratio of 200 vehicles per charging station for public DC fast charging stations, and 2.5 for private charging stations (RVO, 2019). In Norway more than 55% of the vehicle fleet were EV, of which 346,822 are BEV. In November 2021, 14,218 AC charging stations and 5,892 DC fast charging stations were installed. A study conducted by the Norwegian EV Association compared the charging behavior of owners of EVs living in detached houses and apartment buildings[16]. The results show that 97% of the vehicle owners living in detached houses charge their vehicle daily or weekly at home, while this is only the case for 64% of those living in apartment buildings. On the contrary, these vehicle owners are more likely to charge their vehicle at public charging stations (28% versus 11%). With a percentage of 36% for detached housing and 38% for apartment building inhabitants, both groups charge their vehicle at their workplace (Lorentzen et al., 2017).

There are various market stakeholders involved in the construction and operation of public and private charging infrastructure in Germany, an overview is provided in Figure 2.18. The charging point operator (CPO) operates the charging stations and is legally responsible for them and is considered an end consumer of electrical energy and not an electricity supplier. Service providers or e-mobility providers (EMPs) allow customers to access charging points by providing auxiliary services such as payment processing and authentication (Bundesnetzagentur, 2016a; Christ et al., 2015; Linnemann and Nagel, 2020; Wolbertus et al., 2020). The boundaries between CPOs and EMPs are not clear, and some CPOs assume both roles (Strommenger et al., 2020). The utilities and the energy supplier enter into a contractual agreement with CPOs, regulating the required electricity and capacity. In addition, a grid usage contract and a supplier framework contract are made with DSO, as well as a balancing group contract with TSO. The grid operators (DSO and TSO) are responsible for the physical delivery of the electricity to the charging point. In addition to the contracts made with the energy supplier, the TSO enters into a grid connection contract with the CPO (Linnemann and Nagel, 2020).

16 At the time the study was conducted, 5.11% of the vehicle fleet was made up of EVs (Norwegian Electric Vehicle Association, 2021).

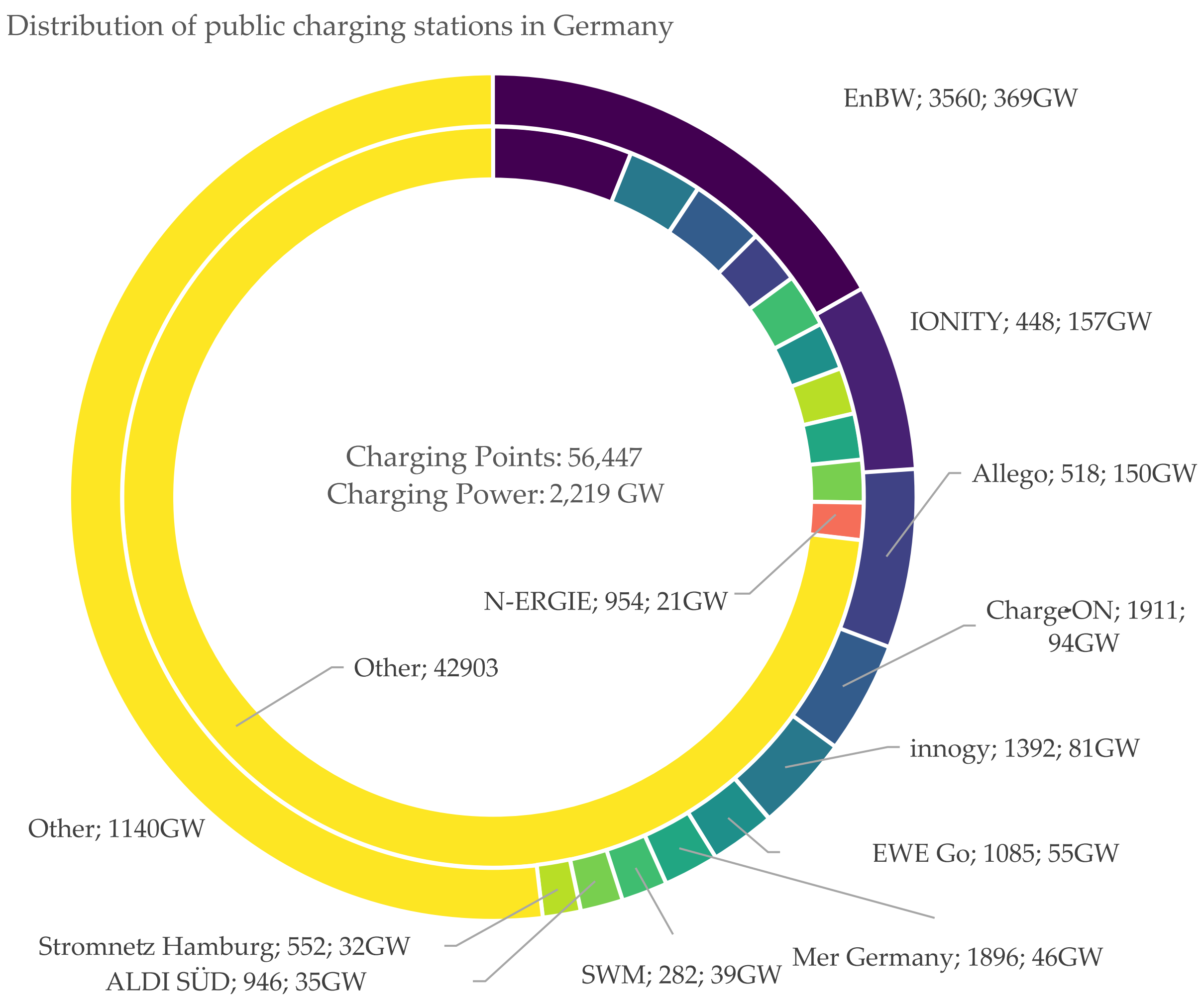


Figure 2.13: Charging point (inner circle) and charging power (outer circle) by CPO in Germany in July 2022 (Bundesnetzagentur, 2022).

It is possible for a single company or entity to take several roles in the public charging market. For example, a CPO can also be a utility company, a EMP, or a company that offers demand response services (IRENA, 2019a). Figure 2.13 shows the distribution of charging points in Germany and the charging power of publicly accessible charging points. The CPOs are classified according to the installed charging capacity and the number of charging points. It can be observed that the highest number of charging points and charging capacity is operated by companies owned by utilities (EnBW, Innogy, EWE Go, Charge-On, Stromnetz Hamburg, SWM), car manufacturers (Ionity, VW), asset management (Allego) and supermarket chains (Aldi) (Bundesnetzagentur, 2022). Some CPOs focus on fast charging points, such as Ionity, while others such as SWM or Innogy SE operate only regular speed charging stations. The charging points are operated by many actors, with the largest company (EnBW) operating 6.31% of all charging points.

An important factor that influences the distribution of the charging infrastructure are the required investment and operational expenses. The installation costs, including the connection

Table 2.5: CAPEX and OPEX for a private and public charging point. Based on NPE (2015), NPM (2019), and Volkswagen AG (2018).

Type	Capacity	Planning and Installation	Hardware	OPEX
Private	AC $\leqslant$ 22 kW	€200 - 3,000	€300 - 1,500	€0 - 1,000
Public	AC $\leqslant$ 22 kW	€1,500 - 5,000	€2,500 - 8,000	€0 - 1,500
	DC > 22 kW	€10,000 - 40,000	€15,000 - 75,000	€900 - 3,000

to the power grid, are presented in Table 2.5. They are highly dependent on specific conditions (e.g., distance to the next grid connection point) or installed power capacity (Bünger et al., 2019). While the NPM (2019) estimates costs of €2,500 for a private charging point (22 kW), the costs of a public charging point (22 kW) are estimated to be twice as high, while those for the fast charging infrastructure range from €80,000 to €127,000. The costs of the charging infrastructure are projected to decrease by up to 35% by 2030, with the highest decrease for public charging points with a charging infrastructure of 22kW (NPM, 2019).

The cost of the charging infrastructure can be subdivided into CAPEX and OPEX. CAPEX include the initial investment in hardware, installation, as well as the costs of planning and obtaining permits. The CAPEX are dependent on the type of charging station installed. DC charging stations require a rectifier, to convert AC power to DC, resulting in 6 – 10 times higher hardware cost. Depending on the technical limitations of the vehicle battery, DC chargers also allow a higher charging capacity. In most cases, the installation of AC chargers does not require grid reinforcements, while this may be necessary for DC charging stations if they are connected to the low-voltage grid (Schroeder and Traber, 2012).

OPEX are continuous cash flows, while CAPEX are one-off expenses. To compare both expenses, equivalent annual cost (EAC) are calculated, i.e., CAPEX are distributed over the lifetime of the infrastructure. The EAC represent the annualized cost of purchasing and operating an asset over its useful life. In contrast to other investment planning methods, such as the net present value method that calculates a total profit, EAC can break down costs or profits into a single period, for example, year, quarter, or month. Equation 2.3 shows the calculation of EAC (Sinnott and Towler, 2020).

AF	Annuity Factor	K_0	(Net) present value	r	interest rate / cost of capital
D	Debt	N	Number of periods/ life-time	r_d	Cost of debt
E	Equity	t	Corporate tax rate	r_e	Cost of equity

$$EAC = K_0 \cdot AF(N; r) \tag{2.3}$$

To calculate the annuity, the (net) present value (K_0) is multiplied by the annuity factor AF (see Equation 2.4). This financial factor converts a fixed present value into a series of equal payments over a limited period of time, considering interim interest rates. The annuity factor is also called the recovery factor or capital recovery factor and is the reciprocal factor of the present value factor.

$$AF(N; p; r) = \frac{1}{V(N; r)} = \frac{r}{1 - q^{-N}} \tag{2.4}$$

The cost of capital r depends on the type of financing. For example, the cost of equity (r_e), the cost of dept (r_d) or a combination of both e.g., weighted average cost of capital (WACC) can be considered. The WACC considers the cost of equity and debt financing of a firm and its weighted average ratio (Noosten, 2018). For the calculation of annualized expenses, a value of 6% is used, similar to the one published by EnBW (2019).

$$r_{WACC} = r_e \cdot \frac{E}{E + D} + r_d \cdot \frac{D}{E + D} \cdot (1 - t) \tag{2.5}$$

Figure 2.14 presents an overview of annualized expenses for different configurations of the charging infrastructure. In the literature, the expenses of private charging points are reported to be 6 - 7 times lower for residential charging stations that are not exposed to the elements and do not require a dedicated payment than charging infrastructure installed in the public space. The CAPEX also include the cost of installation and network connection cost and indirect costs such as planning and registration or the cost of permits.

The OPEX include the operating and maintenance expenses of charging stations, as well as the cost of data and network contracts. Studies estimate that the annual maintenance and repair cost of the public charging infrastructure accounts for 9 - 10% of the initial infrastructure investments (Schroeder and Traber, 2012).

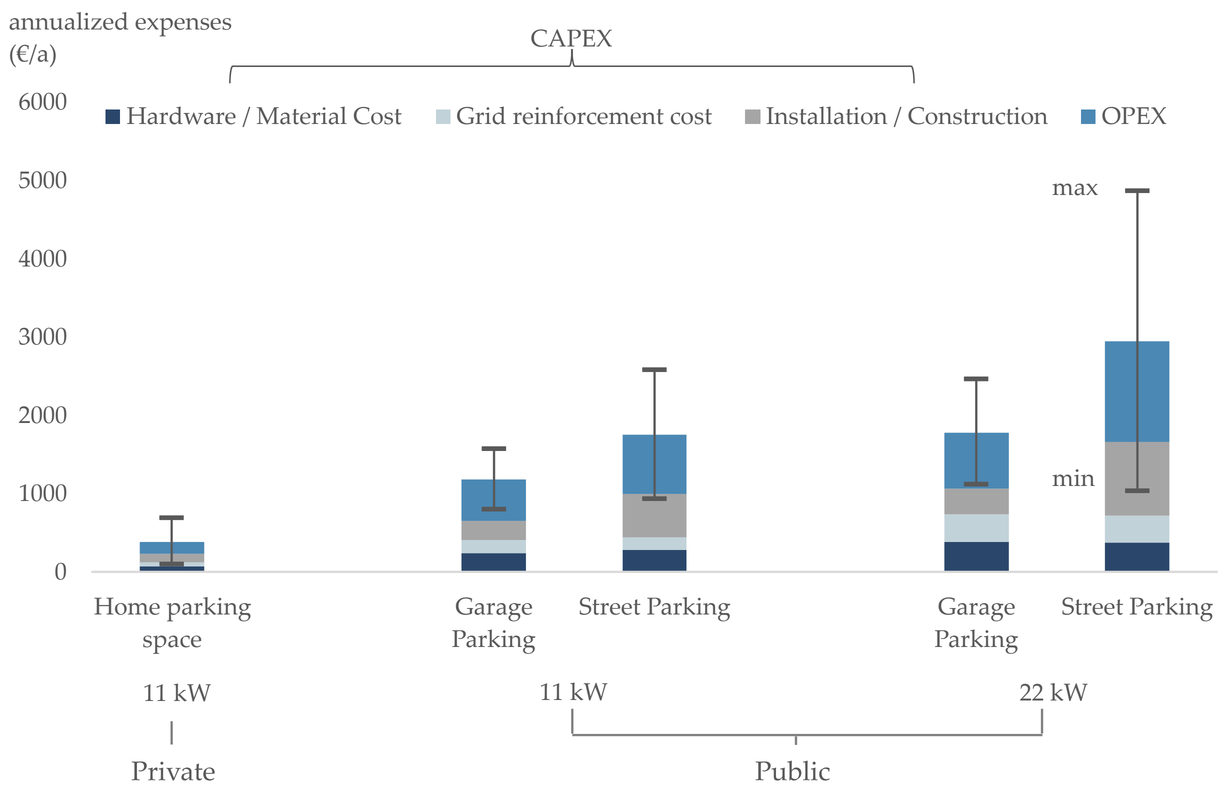


Figure 2.14: Overview of the annualized CAPEX and OPEX for charging infrastructure by location and capacity. Calculation based on Bruckmüller (2020), Bünger et al. (2019), Funke (2018), and NPE (2018).

In a study by Nelder and Rogers (2019), the authors investigated which measures and components have the greatest potential for cost reduction. They find that generally most cost savings are possible through consolidation of charging points, e.g., by building more charging points in one location, installation cost, and CAPEX can be distributed over a larger number of charging points. Furthermore, the authors also see managed charging as a potential to offset costs.

An important factor to consider when installing the charging infrastructure are emissions. As has been highlighted, the overall goal of the German legislature and the international community is to move to a carbon-neutral energy system. Although the charging infrastructure also has an environmental impact, only few studies have considered the environmental impact of different configurations of the charging infrastructure[17] (Kabus et al., 2020; Marmiroli et al., 2019; Nansai et al., 2001; Rangaraju et al., 2015; Zhang et al., 2018). Zhang et al. (2018) calculate the CO_2e emissions for Belgian conductive 3.7 kW – 50 kW charging stations using the ReCipe impact assessment methodology. The functional unit is *"one kilowatt-hour (1 kWh) of electricity delivered to the battery"*. In the manufacturing phase of the (3.7 kW – 22 kW) charging stations, less than 0.02 kg CO_2e is emitted for each kWh delivered over the lifetime of the infrastructure. The main emissions can be attributed to the charging pole and rectifier. For fast charging stations with a

17 e.g., battery supported stations or inductive charging infrastructure

power rate of 50 kW the authors calculate minimal emissions of 0.1 kg CO_2e for each kWh charged over the lifetime. Both of these values include the on-board charger which contributes about 50% of the emissions that can be attributed to the production phase. No study could be found that conducts a full LCA that also includes the installation and construction process.

To evaluate the financial performance of different charging station networks, annualized costs are an important indicator. Specifically, studies show that for charging stations with a charging capacity of 11 kW and 22 kW, profitability is difficult to achieve and new business models and use cases are necessary. In addition to the annualized OPEX and CAPEX mentioned above, the cost of electricity procurement also need to be considered in a complete analysis. The prices of the EEX, varied between -0.06 and 0.1 €/kWh in 2019. If fluctuations in electricity prices are exploited, they can provide an opportunity to increase the profitability of charging stations for CPOs. On the same note, when comparing the emissions attributed with the charging infrastructure (0.1 kg CO_2e /kWh) and the average CO_2e emissions of the German grid electricity, the emissions 405 kg/MWh as well as the large deviation between emissions of electricity generators (11 kg CO_2e/MWh - 900 kg CO_2e/MWh) it is apparent that emissions can be significantly reduced by taking advantage of hours with a high penetration of renewables even at the cost of necessitating a greater expansion of the charging network, than to satisfy charging demand or maximize profits.

2.2.3 Charging station planning and effects of electric vehicle charging

The goal of the German Federal Government is to install one million publicly available charging points by 2030. Through the Federal Ministry of Transport and Digital Infrastructure and several tools based on geographic information system (GIS), such as the *Standorttool* or the *Flächentool*, the German government supports the planning and development of the future charging infrastructure in Germany. The *Standorttool* calculates and visualizes how the charging demand could evolve at the local level until 2030, while *Flächentool* supports DSOs in finding sites to locate a new charging infrastructure. Figure 2.15 shows the calculation and visualization of a specific scenario in 2030 for the city of Essen. To identify suitable locations for demand estimation, the model considers socio-economic, demographic, traffic flows, and vehicle market information. (Nationale Leitstelle Ladeinfrastruktur, 2021).

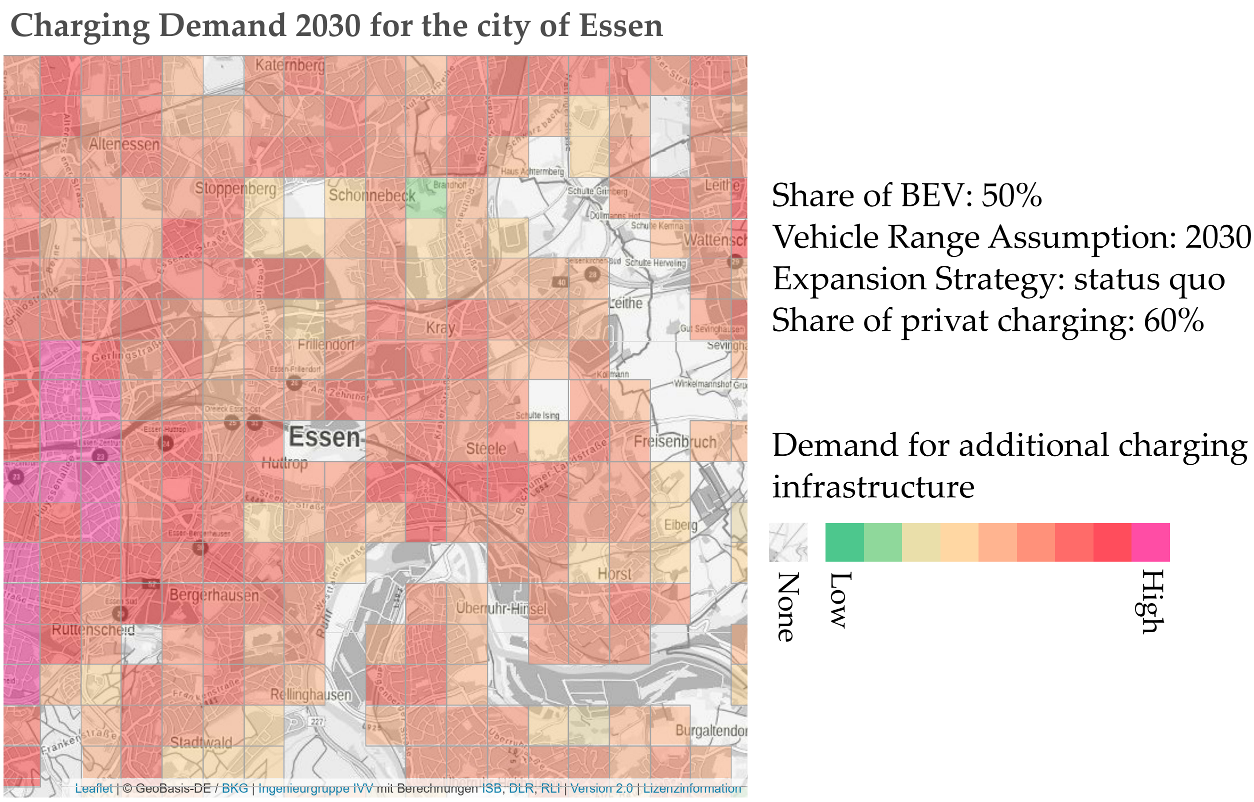


Figure 2.15: Charging demand for the city of Essen and year 2030 as estimated by the *Standorttool*. Based on (Ingenieurgruppe IVV, 2021).

Several factors have an impact on the type, location, and accessibility of charging stations. A study conducted by NPE (2015) predicts that 60% to 85% of the charging processes will take place at private charging stations and 15% to 40% at public stations, in the first few years of the market development of EVs. The VDA (2022) sees an increase in the importance of public charging points as the market penetration of EVs increases and estimates a ratio of private to public charging infrastructure of 60% to 70% (private) to 30% to 40% (public).

The impact of increased adoption of EVs and their charging pattern can impact the electricity system on multiple levels. For each additional BEV, it is projected that the annual electricity demand will increase by 2.4 to 3.09 MWh (Bermejo et al., 2021; Kühnbach et al., 2020). This leads to an increase in the electricity demand of 108 TWh - 139 TWh (assuming 42 million BEVs in Germany). As up to 90% of trips can be achieved with a home charger (Greaves et al., 2014; Vial and Schmidt, 2019), most studies estimate that charging peaks will occur in the evening hours. Without any incentive, vehicle owners are more likely to plug in their vehicle and immediately start charging after the last trip of the day, for most full-time employees, when arriving home after work (Cenex, 2021; Foley et al., 2013). For example, a study conducted for the United States estimates that the peak demand for electricity would increase by 19% with a penetration rate BEV of 25% (Chitkara et al., 2016). Bermejo et al. (2021) estimate that peak load (at approximately 7:00 p.m.) in the winter month would increase by 4.7% (80.4 GW to 84.21 GW) for 8 million vehicles in case vehicle charging is not managed. In their calculation, they expect more than 70% of charges during peak times to occur at home. In uncontrolled charging of 4 million vehicles Kühnbach et al. (2020) calculate a peak load increase of 1.3 GW.

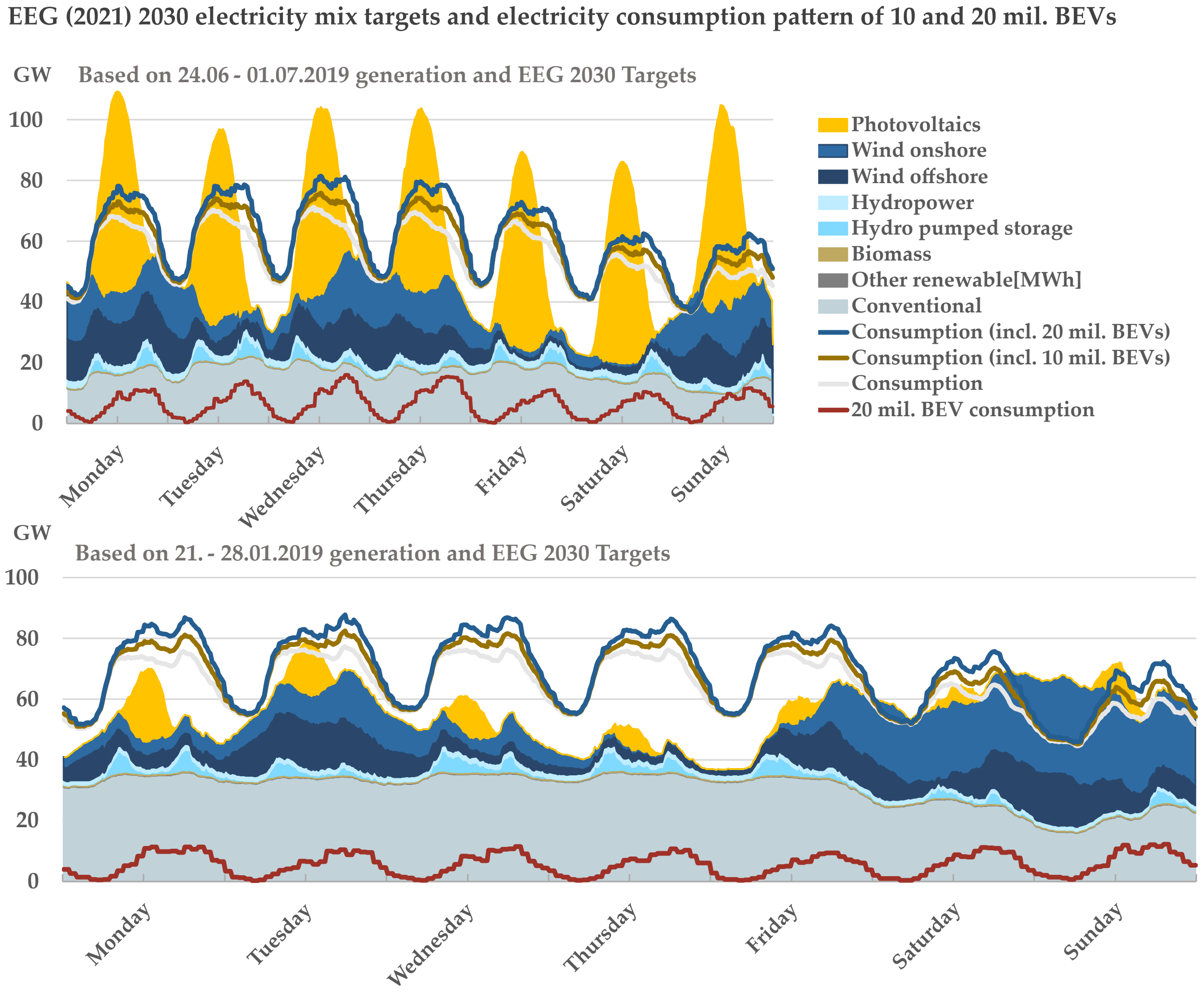


Figure 2.16: Estimation of additional electricity demand due to 10 million and 20 mil. BEVs charging (Muratori, 2018; Muratori et al., 2013).

Figure 2.16 shows the effect of charging 10 million and 20 million BEVs taking into account the mix of renewable energy targeted in EEG 2021 for the year 2030 (see 2.1.4). The charging data is based on 200 uncontrolled charging profiles (Muratori, 2018; Muratori et al., 2013) and an electricity requirement of 2.66 MWh per vehicle and year. Throughout the year, the electricity demand of the entire fleet of 10 and 20 million vehicles increases the total electricity demand by 26.6 and 53.2 TWh, an increase of 4.6% and 9.4% compared to the 2019 electricity demand. Demand is increased in the late evening hours creating additional demand during times when electricity generation is low. Controlled charging of BEVs could alleviate this discrepancy by charging vehicles during times of electricity surplus.

The effect of increased charging of BEV was investigated for different levels of the power grid. The study by Staudt et al. (2018a) investigates the effect of uncontrolled charging of 2 - 8 million EVs on transmission grid congestion in a German electricity system with 70% renewable generation capacity. Their model predicts that the German transmission grid will not be able to support six million EVs without grid enforcement measures that exceed those proposed by the German government. For the effect of EVs on the distribution network, the meta-analysis conducted by Vennegeerts et al. (2018) highlights that due to the network reinforcement measures required by the increased penetration of renewable power generators in the distribution network, most studies consider the limited expansion of charging stations for EVs unproblematic, and only in cases with high penetration rates of charging stations problems may occur (Vennegeerts et al., 2018). An important factor is the simultaneity of charging activities. In their study Kühnbach et al. (2020) assume a maximum simultaneity of charging activities of 75% for an EV diffusion of 5% and below 40% for an EV diffusion greater than 20%. Other studies have also found that the simultaneity of charging activities can decrease due to diversification effects, when vehicle diffusion rates are higher (Rehtanz et al., 2017). However, in the case of high simultaneity, charging EVs can increase the stress on the distribution grid, e.g., due to transformer or power line overloads or voltage band violations (Gómez and Morcos, 2003; Maier et al., 2019; Masoum et al., 2011; Paul et al., 2017; Pieltain Fernandez et al., 2011). These effects may require grid reinforcement measures, which can lead to additional costs. For example, Kühnbach et al. (2020) calculate the costs of grid reinforcement measures in the distribution grid induced by uncontrolled charging. In their study, these range from €1,800 per vehicle with high EV distribution rates (30%) to €10,900 per vehicle for low EV distribution rates (5%). Relative costs decrease with increasing vehicle penetration rates due to fewer simultaneous charging sessions.

2.3 SMART ENERGY SYSTEMS

To increase storage and flexibility, *smart energy systems* are proposed. The term smart energy (system) is used to describe a holistic and joint approach to planning and optimizing energy systems (Lund et al., 2017, 2014). The German government has been encouraging the transition to a smart energy system through legislation (Gesetz zur Digitalisierung der Energiewende (GDEW)) and through a specialized road map (BMWi, 2018) Among the goals are the reduction of the overall energy consumption, increasing energy efficiency in all sectors, and the development towards an integrated energy system. (BMWi, 2017). To achieve these goals, various integrations such as power-to-heat, power-to-gas, or power-to-transport have been proposed (Dena, 2018; Wietschel et al., 2018).

An important factor in the electricity sector is demand side management (DSM). DSM refers to the planning, implementation, and management of measures to influence energy consumption to reduce primary energy consumption or peak loads (Arteconi and Bruninx, 2018; Gellings, 1985; Strbac, 2008). In the electricity system, the hourly, daily, or seasonal electricity demand known as load can be altered using various strategies and to achieve different objectives (Gellings, 1985). Figure 2.17 illustrates four demand response strategies: peak clipping, valley filling, load shifting, and flexible load shaping.

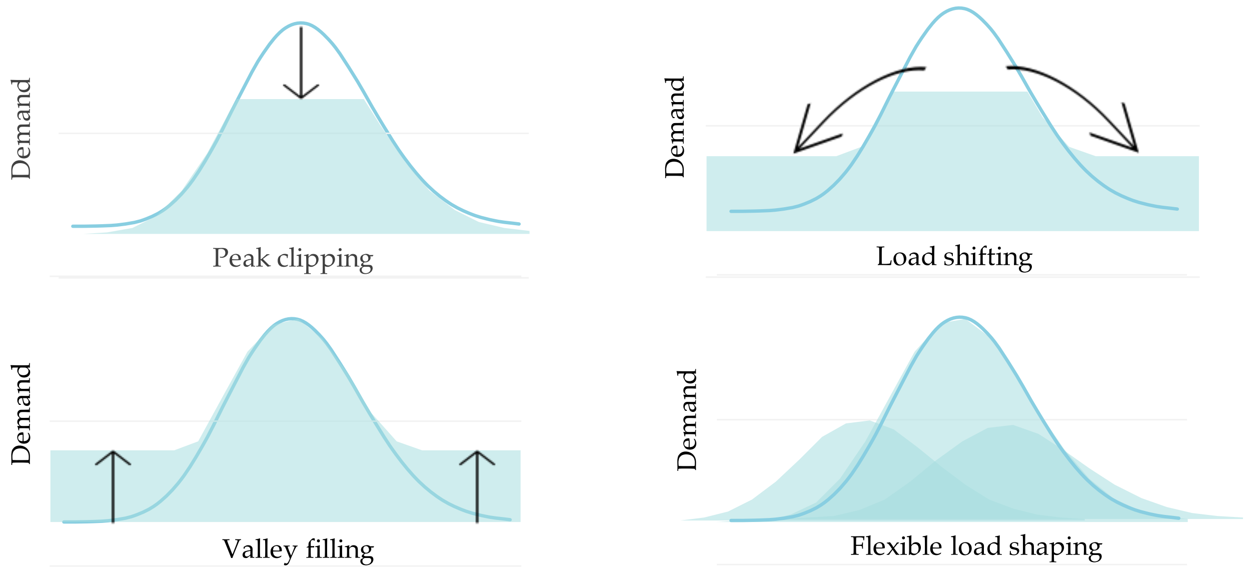


Figure 2.17: Load management and demand response strategies in demand side management (Gellings, 1985; Lampropoulos et al., 2013).

Peak clipping is employed to reduce peak loads. It is achieved by cutting off the power of certain non-essential equipment (Dharani et al., 2021). If additional consumption is added during low demand times, without the power being decreased at other times of the day, this strategy is referred to as *valley filling*. If energy-related activities are not bound to a specific schedule and can be performed at another time throughout the day, these loads can be shifted from periods of high demand to periods of low demand (*load shifting*). *Flexible load shaping* refers to loads that can be fully modified (are fully flexible), sometimes within certain constraints. In addition to these four load management strategies, which are often referred to as demand response and are applied on a second or hourly basis, there are two long-term or permanent strategies (Lampropoulos et al., 2013; Palensky and Dietrich, 2011). *Strategic growth* or electrification refers to an overall increased load, for example, through electrification, e.g., replacing an ICE vehicle with a BEV. *Energy efficiency* leads to a long-term reduction in electricity demand while retaining the same quality of service, for example, through the installation of efficient lighting (Arnold and Janssen, 2016; Gellings, 1985, 2017). Unlike peak clipping and valley filling, which only have a short-term effect, these measures are implemented to achieve long-term or permanent changes in demand. Burre et al. (2020) provide a delimitation between electricity storage and DSM. In contrast to electricity storage, DSM modifies the operation or functionality within processes or replaces them altogether to shift, increase, or decrease loads.

The power generation capacity must be able to meet the maximum demand (Strbac, 2008). In a system based on renewable power generators, energy storage and DSM play an integral role. Through DSM peak power demand can be decreased or shifted and requires only small to no investment. Overall studies highlight that DSM has the potential to decrease CO_2 emissions and overall system costs (O'Connell et al., 2014; Palensky and Dietrich, 2011; Sterner et al., 2015; Summerbell et al., 2017).

2.3.1 Smart charging actors and implementation

Demand response activities involving the charging and discharge process of an EV can be described by the term *smart charging*. Smart charging describes the direct or indirect adaptation of the charging behavior to the impulses of the power system, while respecting the needs and preferences of the vehicle user (Paschero et al., 2013). Controlled and bidirectional charging and discharge with load control, also called vehicle-to-everything (V2X), are distinguished. V2X can be further differentiated, for instance, in vehicle-to-grid (V2G) or vehicle-to-building (V2B). In V2B or vehicle-to-home, the EV battery is used to increase the self-consumption of locally generated power or to increase the autarky of a home or building (Borge-Diez et al., 2021). In this behind-the-meter optimization, there is no interaction with the grid as in V2G, where the EVs battery is used, e.g., by DSO or TSO to provide ancillary services (Gschwendtner et al., 2021; Kempton and Tomić, 2005; Nanaki, 2021).

Figure 2.18 shows an overview of the possible actors that could participate in smart charging. The possible benefits of the implementation of smart charging are highlighted at the bottom of the figure. Depending on the type of service, types of regulation, and horizontal integration, not all of the mentioned actors need to be involved, or they can take several roles in the market (e.g., see Figure 2.13).

When selling electricity in forward markets, the time lag between bid and actual contract fulfillment included delivery may be substantial. For energy generators that rely on volatile primary energy sources, an electricity generation forecast is used to estimate marketable electricity. Prediction models are only accurate to a certain extent, and accuracy decreases with the forecast horizon (Castillejo-Cuberos et al., 2021; Hanifi et al., 2020), making corrections necessary on the intraday market. In such cases, the flexibility offered by EVs to consume or deliver electricity back to the grid can be valuable in balancing their portfolio (Al-Awami and Sortomme, 2012). Grid operators (DSO and TSO) are mainly interested in stable grid operation. EVs can help with this task by providing ancillary services e.g., frequency control, balancing energy or sheddable load (Castillejo-Cuberos et al., 2021). Particularly, due to the new obligations of the DSO within Redispatch 2.0, there may be increased interest in controllable loads. At the level of the utility or the balancing group operator, EVs also present an important flexibility to avoid balancing energy. For the participation of the end customer, V2X measures can be incentivized through their ecological benefits and economic incentives (Delmonte et al., 2020). An overview of the value created by smart charging for the consumer, the system operator and the aggregator is provided by Heilmann and Friedl (2021) and Sovacool et al. (2018). In the simplest case, the charging process of an EV can be optimized to maximize the self-consumption of locally generated power, reducing electricity costs and increasing the share of renewable electricity utilized (Fachrizal and Munkhammar, 2020). Through the participation in V2G measures, the EV owner is remunerated, which can lead to a reduction in the TCO.

In addition to these actors that are directly involved in the provision or procurement of electricity or flexibility, the aggregator or EMP aggregates data, information, and commitments of different

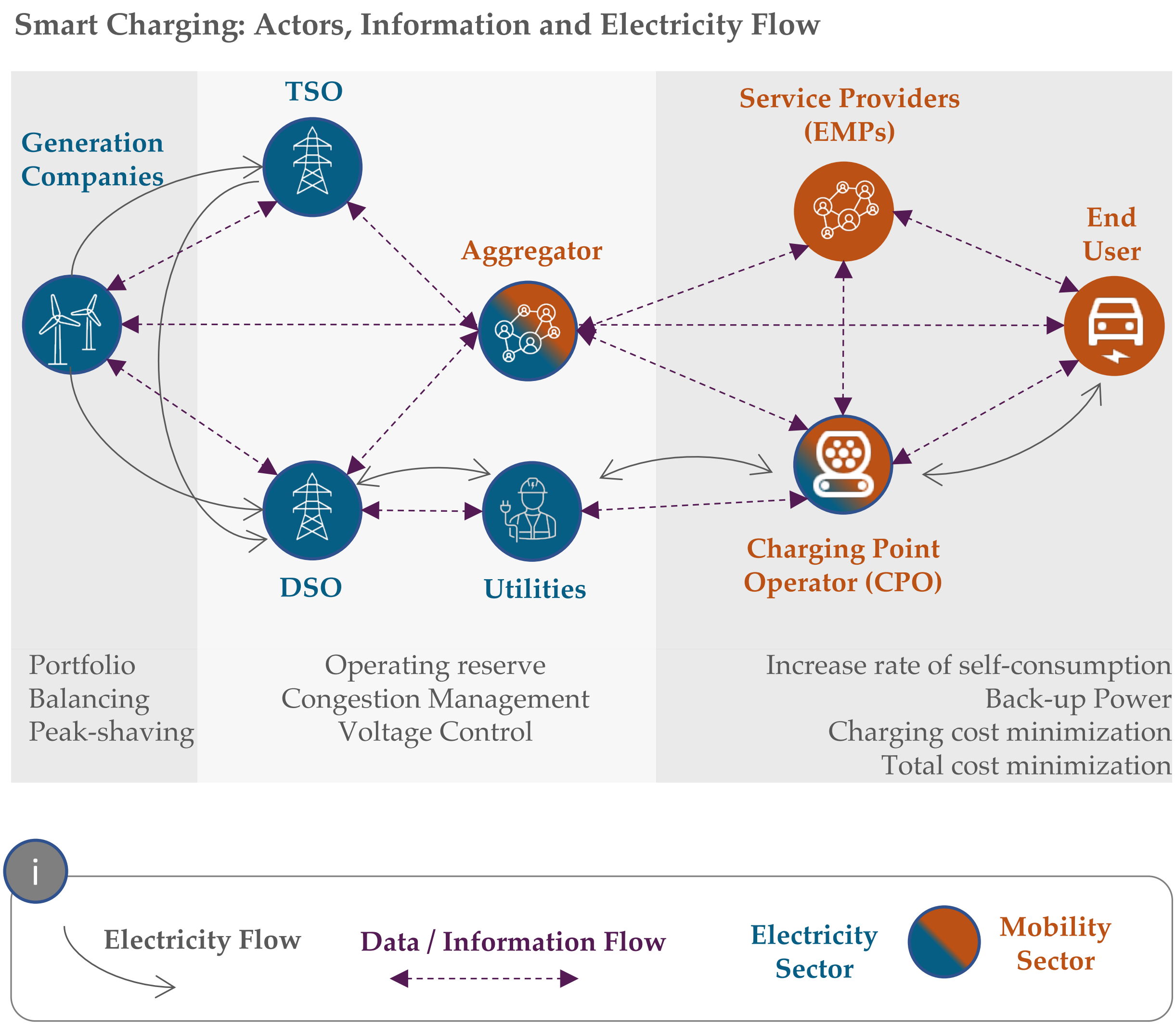


Figure 2.18: Overview of actors involved in smart charging.

entities to enable or facilitate participation in V2G services. While the EMP is responsible for handling the mobility needs of the end user, the aggregator can act as an intermediary between the electricity sector and the mobility sector. As an intermediary, the aggregator aggregates power capacities and markets them. Depending on local regulation and responsibilities, different entities can assume the role of an aggregator, such as an electric distribution company or an automobile manufacturer. For example, a capacity of 1 - 2 MW could be available to participate in the energy markets if 500 vehicles are aggregated (IRENA, 2019a; Kempton et al., 2001). In most cases, the CPO of a private charging point is also the end user, however, in the case of public charging infrastructure, the CPO needs to provide the appropriate technology and incentives to enable smart charging. Depending on the depth of integration, the incentive to do so may be driven by their roles in the energy market (e.g., see the overview of the market participants in Figure 2.18).

The adaptation of vehicle-to-grid measures and the flexibility offered by an EV depend on several factors, such as user behavior, time of day, technology, or regulation (IRENA, 2019e).

Demand response programs can be classified into market (non-dispatchable) and reliability (dispatchable) programs (Amin et al., 2020; Jabir et al., 2018; Palensky and Dietrich, 2011). In market-based programs, the user manages participation and indirect load control is achieved through price-based incentives, for example, dynamic prices (Badtke-Berkow et al., 2015; McKenna and Thomson, 2014; Schweppe et al., 1988). Examples of such tariffs are illustrated in Figure 2.19 and vary depending on demand.

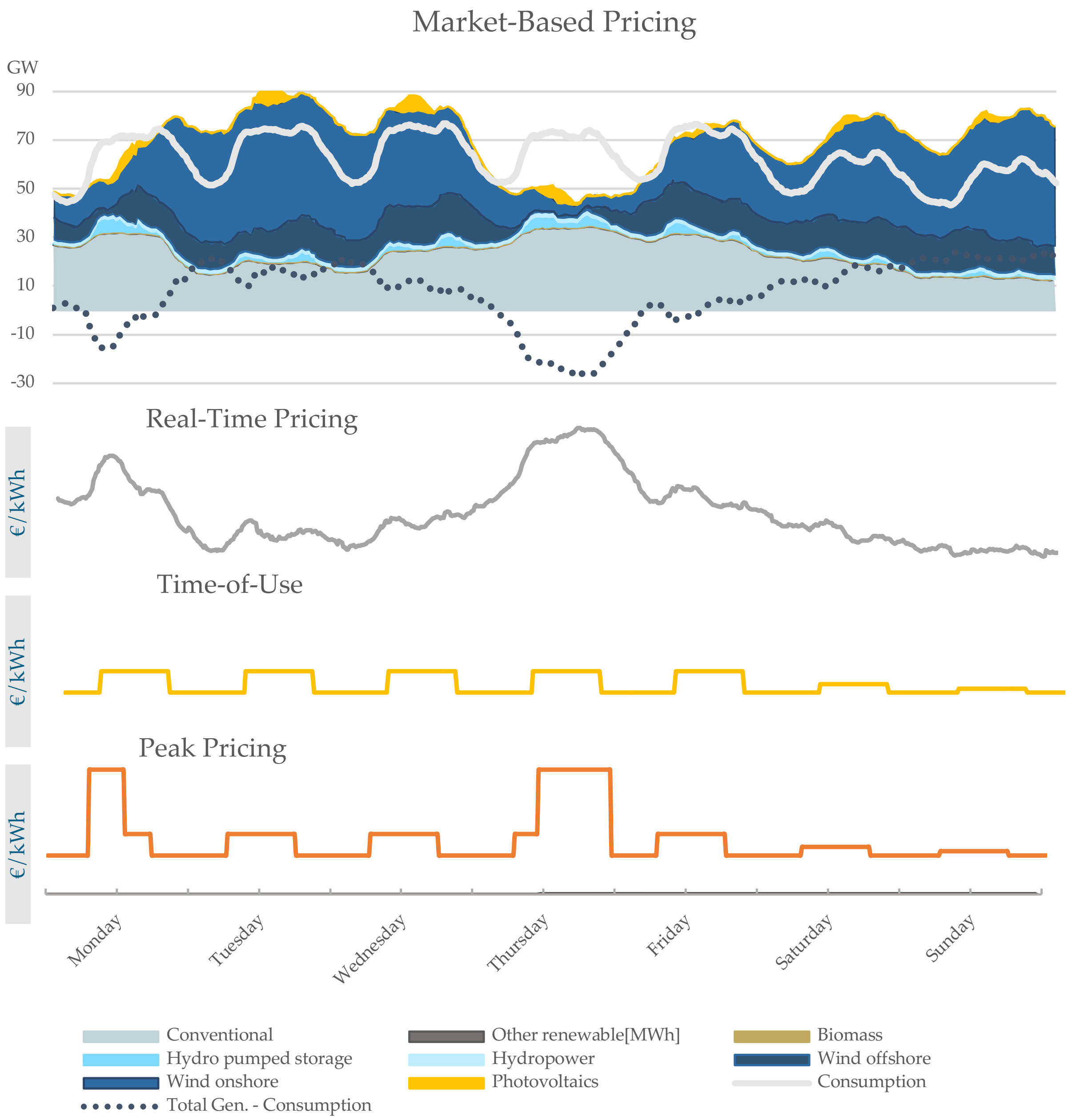


Figure 2.19: Schematic representation of load management and demand response strategies in DSM (Gellings, 1985; Lampropoulos et al., 2013).

Time-of-use prices vary throughout the day but remain fixed day-to-day. By providing the customer with a static time-based but daily price, e.g., reduced prices during the midday or at night, customers are encouraged to shift charging activities (Chunlin et al., 2018). This pricing strategy has the advantage of being easily implementable without the requirement of direct control of the vehicle battery. The disadvantage is that this implementation is still inflexible and cannot react to dynamic changes in electricity generation; moreover, if all customers face the same tariff structure, this can cause temporal or geographic "rebound charging peaks" through the synchronous engagement of incentivized charging (Muratori and Rizzoni, 2016). A similar mechanism is critical peak pricing, with the difference that this tariff structure also reacts to price changes due to critical demand or generation events (e.g., dark doldrums) by increasing electricity costs during these events or compensating customers for reducing their consumption (critical peak rebate). Real-time prices reflect the actual situation in the energy market and change at short intervals of 15 minutes or 1 hour.

As electricity consumption is often limited to certain processes or activities and market prices may not fully represent the current grid load situation, reliability-based programs exist. Reliability-based programs aim to alleviate system emergencies or contingencies through contractual or voluntary programs, e.g., through ancillary services (Callaway and Hiskens, 2011). In contrast to market-based programs, incentives do not correspond to the real-time market situation; instead, the customer is remunerated on a yearly basis for a certain staked controllable power. Different agreements determine the obligations of the participating customer. For example, in direct load control programs, the system operator is in full control of some parts of the customers' load, while in interruptable or curtailable load programs, the customer retains control over their equipment and responds to curtailment requests manually. The customer receives a remuneration based on the curtailable power provided or is penalized if they do not meet the requirements stipulated in the contract (Arteconi and Bruninx, 2018; Ribó-Pérez et al., 2021; York and Kushler, 2005).

The integral part of all smart charging measures is the vehicle operator or the end user. The load-shift mechanisms illustrated in Figure 2.17 can be encouraged using different incentives and mechanisms. Delmonte et al. (2020) present the results of a study conducted with BEV owners in Great Britain on charging preferences. The results indicate that significant savings (up to 30 to 50% of the total charging cost) are necessary for some vehicle owners to participate in smart charging activities. For supplier-controlled charging, trust is an important factor. Past surveys and studies have found that vehicle owners may be deterred by the fear that their vehicle may be charged insufficiently, for instance, to carry out unforeseen or emergency journeys. Other concerns are associated with battery degradation due to participation in smart charging programs (Bailey and Axsen, 2015; Cenex, 2021; Delmonte et al., 2020). Other studies on general demand-response measures indicate that the behavior of an individual often does not coincide with economic models and may be motivated by other intrinsic factors (Allcott, 2011; Thorsnes et al., 2012). As noted in Sovacool et al. (2018), previous studies have focused on the technical dimensions of V2G, while topics such as environmental performance, financing, and business models have been mostly neglected. Schuller and Hoeffer (2014) for instance show that the mobility profile and availability of charging points can have a significant impact on the renewable electricity charged. Their analysis shows that for some individuals, the share of wind energy charged can be more than doubled if smart charging.

Practical implementations and studies of smart charging show that there are several obstacles to implement smart charging. Optimization models can help overcome these obstacles in two ways. First, if concerns such as a minimum available range in each vehicle or capacity constraints of the local grid are considered in optimization models, e.g. using constraints, the likelihood of their occurrence can be reduced. For example, in optimization models that support the strategic objective of expanding the charging infrastructure, the state of charge of the vehicle battery can be explicitly considered. Second, by applying optimization models in case studies and analyzing the results obtained, it is possible to assess the probability that unwanted effects occur, which may reduce fears of participating in smart charging programs.

2.3.2 Benefits of smart charging

The benefits of smart charging can be assessed using a variety of indicators and modeled using different methods. A comprehensive review of recent studies is provided by Heilmann and Friedl (2021). In their review article, the authors analyzed smart charging strategies from several perspectives and aimed to measure the effect of aspects such as charging power, vehicle technology, or the type of service provided on revenue and net revenue. The summary of the studies does not show a clear indication of the attainable economic benefits. Studies report a wide range (€0 to €4,090 vehicle revenues) that can be obtained by BEVs participating in energy trading or secondary frequency control (€23 to €4,140). These large variations are dependent on various factors; however, using a multivariate ordinary least squares model, the authors find that the charging capacity (controlled charging or V2G) and the charging power have the greatest impact on net revenue.

Most studies have reduced their scope to a certain geographic region, as the corresponding markets and regulations vary and can also have an impact on possible technologies and attainable revenue and net revenue. A case study conducted by Taljegard et al. (2019) for the Scandinavian-German region, for different energy system configurations, investigates the impact of two charging strategies (controlled charging and V2G) of EVs on peak power. Compared to the case without integration of BEVs, optimized charging has the potential to decrease the required peak power capacity by 21%-59% and up to 100% for V2G. A simulation of the German market by Schuller et al. (2014) shows that for people working full time and, compared to a non-optimized charging strategy, electricity procurement costs can be reduced by 32% through controlled charging and 44.8% through V2G measures. As noted by O'Connell et al. (2014), demand response revenues depend on the structure of the electricity price, that is, the ratio between fixed price components such as taxes and levies unaffected by demand response and volatile price components that can be reduced through demand response measures. In Germany, more than 50% of electricity costs of residential customers can be attributed to taxes and duties that cannot be reduced by participating in smart charging programs (see Figure 2.4). Thus only lower relative savings can be achieved compared to other countries with different electric price structures. This must be contrasted with the additional costs that arise from a V2G charging point. In the Cenex (2021) project, costs of approximately €4,300 for hardware and installation of a V2G charge point were incurred. The authors estimate that these costs could decrease to €1,300 through mass production of the required hardware. In the study by Jargstorf and Wickert (2013), controlled charging was used to intelligently charge a fleet of up to 16,000 vehicles to provide a secondary downward reserve for frequency control. The study highlights the difficulty faced by an aggregator in achieving a constant and reliable load, in participating in the balancing markets, since the number of vehicles simulated had to be increased from 10,000 to 16,000 vehicles to meet the minimum requirement of 1 MW. The resulting income per car and month was between €0.84 and 3.3 with a maximum capacity price of 1000 €/MW and an off-peak of 4000 €/MW. The study by Rücker et al. (2020) investigates two forms of services; first, different forms of V2X "behind the meter[18]" services and their effect on the self-consumption rate of locally generated electricity and the resulting reduction in the cost of electricity, and secondly, participation of the vehicle in the automatic frequency restoration reserve. Customers achieved an electricity cost reduction of 4.9%–17.6% (controlled charging), 13.8% –26.1% (V2G), 26.4%-27.2% (V2B). In a study conducted by Kühnbach et al. (2020), their calculations indicate that up to €10,900 of the cost of grid reinforcement costs per vehicle could be saved by smart charging measures, leading to a decrease in residential electricity costs of up to 3.7%, compared to the case without BEVs.

Several practical projects have been started to test smart charging, in different configurations (Cenex, 2020; IRENA, 2019e). The projects *ChargeForward* and *ChargeForward* 2.0 were carried out by BMW with 400 households in the San Francisco Bay Area. The purpose of the program was the real-world implementation of smart charging and the evaluation of several use cases (Kaluza et al., 2017; Spencer et al., 2021). The use cases offered different incentives and times for EV users to participate in charging events. The results of the primary study showed that EV users are willing to participate in charging programs to increase the share of electricity charged that was generated from renewable sources. However, to participate in charging programs during the day (9 a.m.- 4 p.m.), most participants indicate the need for monetary incentives. Furthermore, the authors state that to optimize charging of vehicles parked away from home, the availability of the charging infrastructure is a key factor that should be assessed in future studies. In one project use case, incentives for participants to plug in their EVs were increased. This led to 46% more plugins in general and 38% increases in plugins at home, compared to the baseline case without increased incentives (Spencer et al., 2021). The project *Sciurus* was carried out in the United Kingdom with 320 V2G chargers installed and three types of services, namely, tariff optimization and two forms of grid services; Firm Frequency Response (primary control or secondary control) and dynamic containment (primary control) (Hollinger et al., 2018). The average required charge of electricity per vehicle was equivalent to 2,402 kWh / a and the vehicles were on average available 71% of the time to participate in the aforementioned services. On average, participants were able to generate £120 (€140.5)-£725 (€850.5) providing the various services. The lowest value was earned through controlled charging and the highest was achieved by providing dynamic containment through V2G.

Although smart charging of EVs is already possible with the technology available today, see, e.g., the implementation in the *ChargeForward* project, there are still significant obstacles to achieve market integration. For example, the configuration of the energy markets and the minimum energy requirements e.g., 1 MW(h) are an obstacle that requires a significant number of vehicles (500 - 1,000). New technological standards are needed to implement even the simplest form of smart

18 Behind the meter refers to the processes which occur behind the utility meter of individuals or organizations with the aim of reducing the electricity bill. For example, a customer might install a rooftop photovoltaic system to reduce the electricity purchased from the grid (Sioshansi, 2020).

charging. Grid services could be remunerated through a reduced network surcharge, as according to §14a EnWG network operators have the option to charge a reduced grid fee to controllable load suppliers and end consumers if a separate metering point is available. The law explicitly highlights that EVs are considered controllable load suppliers (Strommenger et al., 2020).

2.4 SUMMARY

This chapter presents an overview of the current state of the energy system and the mobility sector, as well as the interaction of both sectors. It shows that today, the integration of EVs with the power system can be sensible from several viewpoints. For example, by simultaneously planning and integrating both sectors, it is possible to use generated electricity and existing (grid) infrastructure more efficiently. Driven by the expansion targets of renewable energy generation, the volatility of electricity generation will increase. This circumstance requires additional storage capacities in the power system and flexible power consumers. EVs have a high power consumption and charging power and, therefore, represent an important flexible actor in the power system that can be harnessed by integrating planning in the power and mobility sectors.

However, several innovations and adaptations are needed to accelerate the integration of both sectors and use them on a large scale. The results of previous studies and practical tests show that intelligent and controlled charging of EVs is particularly promising. To implement these solutions, existing actors (TSOs and DSOs and energy suppliers) must cooperate with new players CPOs and EMPs. The vehicle driver/user also plays a critical role. Surveys show that uncertainty is a decisive factor for vehicle owners to refrain from participating in innovative charging programs. When this is taken into account in optimization models, this uncertainty can be minimized. Furthermore, the application of controlled charging of EVs in model studies and simulations can quantify the effects of controlled charging to broaden the information base for users and reduce uncertainties.

From today's viewpoint, especially operators of normal charging stations ($\leqslant$ 22 kW) have a hard time making profits. Price pressure requires the development of new business models to increase profitability. The location of the charging stations can be another important factor, as they directly influence the charged energy. At the same time, locations also influence the charging behavior of EVs and can thus promote or hinder the possibility of controlled charging. To estimate this trade-off, an optimization model is developed and presented in the following chapter. The model considers both variable charging costs and infrastructure costs. It can provide important information to utilities, charging site operators, and vehicle users to accelerate the application of controlled charging in practice.

3 SIMULTANEOUS OPTIMIZATION OF THE PLACEMENT OF CHARGING STATIONS AND THE CHARGING OF ELECTRIC VEHICLES

The ongoing changes in electricity generation towards renewable energy and in electricity demand caused by the increasing electrification in all sectors call for flexible electricity consumption and integrated energy system planning (Helgeson and Peter, 2020). Practical smart charging trials have shown that smart charging can have a significant effect on electricity demand and can provide several levels of grid services depending on the depth of integration of BEVs and the grid. In such practical trials of these measures, a critical number of vehicles are required to examine certain business models and to quantify their contribution to DSM. The low diffusion of EVs may impede the evaluations of business models. Likewise, high cost, low user adoption rates or technological readiness may also obstruct trials of technological innovations. Synthetic data generated using simulation models can help to model changes in the electricity and mobility sector. Operations research and the application of optimization models can support strategic and operational decision-making. Applying optimization to model business models on the basis of synthetically generated data, can be a powerful tool in the assessment of innovations. Simulation models can be used for generating synthetic mobility profiles, while optimization models allow a quick adaptation of parameters and can support strategic decision-making in light of the imminent changes to the decision problem, e.g., changing mobility behaviour of individuals.

In this section, an optimization model that simultaneously optimizes the placement of charging stations and the charging of EVs is presented. As shown in Figure 2.18, several stakeholders, with sometimes contradicting goals, are involved in the placement of charging stations, their operation and utilization. To represent the decision problem and impact of the individual stakeholders behavior in an integrated energy system model, taking into account the interconnection between sectors, the following model prerequisites should be met:

Consideration of fixed and variable cost components and revenues.

When selecting a charging location that maximizes profit from a set of possible locations, e.g., as a charging point operator, the consideration of costs and revenues is indispensable. While one-off costs can differ, depending on the location of the charging point or installed technology, revenues are obtained through selling electricity and depend on various factors such as the utilization of a charging point or the profit contingent on procured electricity. To assess the impact of the placement of charging infrastructure on the overall charging pattern and vice versa, both fixed and variable cost as well as revenue components should be represented in the model and establish a connection between the changes in the electricity sector and the decisions of the individual stakeholders in the mobility sector.

Geographic and temporal representation of the mobility behavior.

The mobility behavior of individuals influences the location of BEVs and the required charging energy throughout the day. It therefore influences both the decision of station placement and scheduling of charging activities. To determine the ability of charging station configurations to meet the charging requirements of a vehicle, a geographic and temporal representation of charging behavior is modeled. While for the placement of fast charging infrastructure the consideration of individual mobility profiles may not be necessary or possible, as the trips are not recurring it is relevant for placing normal charging stations for day-to-day charging, as the individual activities remain mostly similar over time.

Consideration of technical factors relating to vehicle and charging behavior.

For a model to incorporate real world data and for the results to be applicable to real-world planning situations, certain technical factors related to the representation of a charging infrastructure and charging process need to be considered. While technical factors such as the exact representation of the battery state-of-charge can be approximated without having a significant impact on the model results, other factors such as the assignment of one charging point to one vehicle are important to consider, as they can have a more significant impact on the results of the model.

The modeling of a representative planning horizon and number of vehicles.

As the energy generation and consumption is dependent on temporal factors, the costs of electricity procurement or its availability may differ throughout the year. For instance, in Germany, more electricity is generated from photovoltaic in the summer while more electricity is generated from wind in the winter. To consider this variability, the model should consider a time-horizon that incorporates these seasonal effects. Moreover, certain effects, such as the sharing of charging points by several vehicles may, only occur with a large enough vehicle base. Therefore, the number of vehicles represented by the model should be large enough to consider these effects. In previous studies, 500 to 1000 vehicles were considered sufficient to capture these effects (IRENA, 2019a; Kempton et al., 2001; Strommenger et al., 2020).

While some of these prerequisites have been addressed in different areas of scientific literature, a consideration in a single model does not exist to the knowledge of the author. Although tools to support the planning and development of charging infrastructure such as the *Standorttool* (Ingenieurgruppe IVV, 2021) can represent spatially distributed electricity consumption of EVs, they rarely incorporate future developments in the electricity system, changes in the mobility behavior or a combination of both of these factors. However, when planning the distribution of charging stations and the controlled charging of EVs, the expected mobility behavior and the changing electricity generation in the short and long term must be taken into account. Two distinct literature streams in the field of Operations Research have addressed the problem of charging EVs and the placement of charging stations. Thus, the coordination of the charging process of EVs and planning the layout of the charging infrastructure have been addressed using different methods and regarding different objectives. Currently, these objectives are addressed by two different problem formulations, the charging station placement problem and electric vehicle charge scheduling problem. In the following section a review of the current state of applied methods and implementations is presented. Following this overview, a model for the concurrent charging station placement and EV charging that satisfies the above defined prerequisites is presented.

3.1 THE CHARGING STATION PLACEMENT PROBLEM (CSPP)

Generally, location science deals with the question of where to place an object in a given space to minimize or maximize a criterion or a number of criteria. A general distinction between discrete, network or continuous location models is often made (Laporte et al., 2019). Location problems are especially prevalent within the area of production and supply chain management, for instance, to determine the location of production facilities, retail branches or warehouses (Chopra and Meindl, 2013).

The aim of the charging station placement problem is the siting and sizing of charging stations, while minimizing or maximizing an objective e.g., minimizing the total distance of all vehicles to the nearest charging station or maximizing the flow i.e., number of vehicles passing by a station (Deb et al., 2021; Hodgson, 1990; Lam et al., 2014). The literature can be categorized in a number of different ways, e.g., by means of the employed solution methods or objectives of the decision problem (Arora and Barak, 2009; Deb et al., 2021, 2018b; Islam et al., 2015; Karakitsiou et al., 2018; Pagany et al., 2019). Most studies differentiate among node and flow-based approaches. This classification can also be found in related infrastructure placement problems e.g., for (alternative) refueling stations or for optimizing the placement of other public infrastructure such as police stations (Honma and Kuby, 2019).

Figure 3.1 shows a comparison of the node and flow-based approach. In the flow-based approach, paths or flows are modeled between nodes. In Figure 3.1 the thickness of transport network lines represents flow weight and the arcs of the transport network. Nodes represent sources (O) and sinks (D) of flows, while a travel activity can cross several nodes. The goal of the flow-based approach is to maximize the flows captured by a node. Most models are based on the flow-capturing location model originally described by Hodgson (1990). In the application of this approach to the charging station placement problem (CSPP), charging stations are placed at the nodes that maximize the captured flows, while considering a given set of constraints (Deb et al., 2018b; Kim and Kuby, 2012). The approach assumes that the utilization of charging stations is determined by the vehicle flows passing a node. As is the case for traditional ICE-vehicles, the charging procedure is seen as a planned *refueling* stop. The approach has been applied to planning fast-charging infrastructure, for instance, along expressways usually utilized for long distance travel (Chung and Kwon, 2015; Jochem et al., 2019; Wang et al., 2021a). Other flow-based approaches deviate from the flow maximization objective and consider the flows implicitly through corresponding constraints, e.g., Wang and Lin (2009) minimize the total costs for building charging stations under the conditions that all vehicles can be refueled to meet their mobility requirements. Other variants of the problem cover the possibility of drivers to make detours (Li and Huang, 2014) or explicitly consider the long-term, dynamic and uncertain nature of the infrastructure planning problem and involved actors (Chung and Kwon, 2015; Li et al., 2016; Vries and Duijzer, 2017). In comparison to other refueling placement models, the range of the vehicle is more relevant for EVs. This aspect is therefore modeled and considered in constraints in order to generate feasible travel profiles (Alhazmi et al., 2017; Hess et al., 2012). A prerequisite for the application of flow-based models are detailed mobility, travel and transport patterns that are often obtained through vehicle tracking systems (Cai et al., 2014; Csiszár et al., 2019; Deb et al., 2018b).

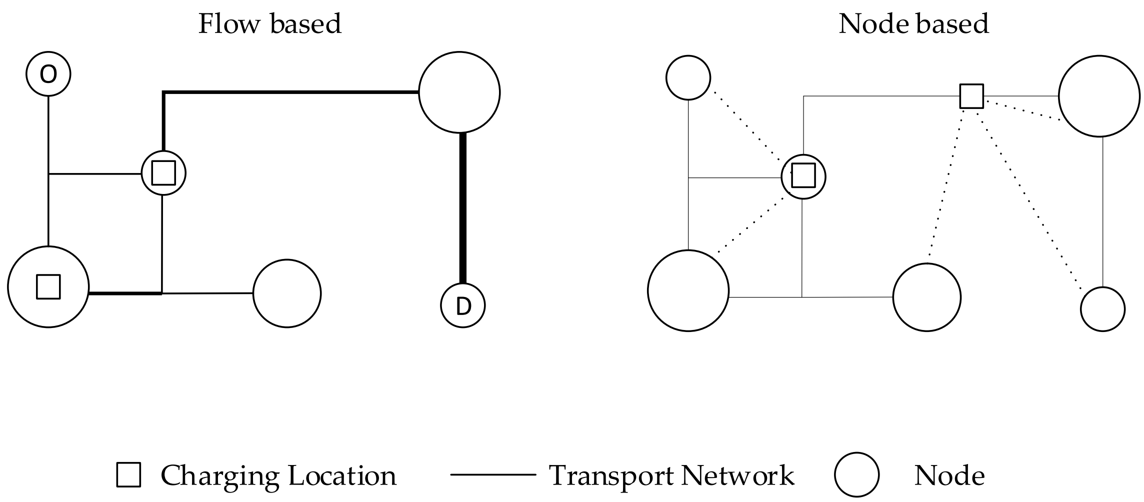


Figure 3.1: Illustration of the flow- and node-based approach of the CSPP.

In the node-based approaches, the CSPP is modeled as a facility location problem (Daskin, 2008) where charging demand is represented by nodes and charging stations are placed in order to satisfy charging demand (Galadima et al., 2019; Honma and Kuby, 2019). In this application the demand at the nodes is usually predetermined, for instance, using geospatial or user survey data (Frade et al., 2011; Ko et al., 2017; Niels et al., 2019). In Figure 3.1 the size of the nodes represents the demand at a node (Baouche et al., 2014). This representation of the problem is based on the p-median problem, and charging locations are placed to minimize or maximize a predefined objective e.g., minimizing the weighted euclidean distance of the demand (nodes) to the charging locations (Upchurch and Kuby, 2010). Other approaches are based on maximum covering or the p-center problem (Karakitsiou et al., 2018). These approaches allow the selection among different potential charging locations or can be applied to support the search for possible charging locations.

The objectives of node-based approaches are diverse and they are utilized to support the placement of normal and fast charging stations. For instance, Bouguerra and Bhar Layeb (2019) present a set covering problem that aims to place fast charging stations within an acceptable range, while also considering infrastructure investments and convenience in the form of travel costs of the EV owner. In the maximum covering model by Frade et al. (2011), only normal charging stations are considered and the model is applied to planning a charging infrastructure for the city of Lisbon. A temporal aspect is introduced in their node-based approach through the separate consideration of daytime and nighttime charging demand in the objective function. The model by Adenaw and Lienkamp (2020) uses a similar approach to differentiate between nighttime and daytime demand, while other studies take a more of a long-term planning approach and consider multiple expansion stages (Hu and Song, 2012). In node-based models, constraints are related to the power grid, budget or constrain the maximum number of charging stations to be located (Adenaw and Lienkamp, 2020; Deb et al., 2018b).

Upchurch and Kuby (2010) compare the results of applying a node and flow-based model for planning charging infrastructure on a city and state scale. The objective of the considered flow-based model is to maximize the traffic passing the charging locations while for the node-based model the objective is to minimize the weighted distance between a demand node and a charging location. Two performance criteria are calculated for both models i.e., the flow volume and distance between charging and demand nodes. Their results show that the flow-based model outperforms the node-based approach in both measures and especially when the distance between nodes increases, as in the state scale. They infer that the node-based approaches may be better suited for the allocation of EV charging stations in urban areas, while the flow-based approaches also perform well for the allocation of fast-charging stations. Similarly, Tian et al. (2019) argue that there are two types of demand arising for charging EVs. The demand within a city can be represented as a node, while the demand along a route, for traveling between cities e.g, on a highway, occurs along a route and the path or flow-based approaches are better suited to model this type of problem. Tian et al. (2019), introduce a location model that includes both a point and flow-based approach.

The objectives of the flow and node-based charging station placement problem are reviewed by Bilal and Rizwan (2020), Deb et al. (2018b), and Galadima et al. (2019). Next to maximizing vehicle flow and minimizing distance to the next charging station or costs such as construction, land or access costs, several other objectives have been considered in previous studies. Social factors are operationalized by maximizing installed stations coverage (Asamer et al., 2016) or minimizing the total trip time (including recharging) (He et al., 2015). Deb et al. (2018b) highlight that home or private charging constraints have not been considered in the CSPP. However, the authors emphasize the requirement to consider these factors in future studies.

Another stream of literature is predominantly concerned with objfectives concerning the electrical grid (Deb et al., 2018a). The placement and charging of EVs, utilizing normal and fast charging stations, can have an impact on multiple components and characteristics of the power grid (Avdakovic and Bosovic, 2014; Geske et al., 2010). Studies have therefore considered factors such as voltage stability, system reliability or power loss both in the objective function (Deb et al., 2018a; Martins and Trindade, 2016) and in the model constraints (Frade et al., 2011; Liu et al., 2013).

On a broader energy system related scope, recent studies have pointed to the necessity to include energy generation, especially electricity from renewable resources, in the planning of the infrastructure (Karakitsiou et al., 2018). So called *solar-to-vehicle* charging stations aim to supply EV charging requirements through solar energy (Birnie, 2009). In the study presented by Huang et al. (2019) the objective is to simultaneously place charging stations along with PV systems, with the goal of minimizing the charging stations construction costs and charging costs. While several studies have examined the relationship between EV charging and wind energy generation, the impacts of the location of stations has been neglected (Bellekom et al., 2012; Ekman, 2011). Other studies are predominantly concerned with the scheduling of the charging procedures to meet the generation by renewables. These studies will be discussed in Section 3.2.

Several methods have been applied to conduct the placement of EV charging stations in the node and flow-based literature (Islam et al., 2015). While there have been some studies that applied simulation methods, such as agent-based modeling or multiagent transport simulations (Marquez-Fernandez et al., 2019; Sweda and Klabjan, 2011), the majority of studies applied optimization methods. Multi-objective models consider economic criteria and social criteria such as the net benefit simultaneously through multi-criteria decision analysis (MCDA) methods such as the Analytic Hierarchy Process (Zhao and Li, 2016) or Preference ranking organization method for enrichment evaluation (PROMETHEE) (Erbaş et al., 2018; Wu et al., 2016) or by applying multi-objective decision making (MODM) methods (Pan and Zhang, 2016; Yao et al., 2014). As multi-criteria decision analysis methods require a discrete set of alternatives that is not always given in the charging station placement problem and multi-objective decision making models are harder to solve, the majority of studies however only consider a single objective. In an attempt to preserve model complexity some studies implicitly consider multiple objectives through soft constraints and penalty costs [1] or by transforming the objectives to a common measure (e.g, monetary units) in order to simultaneously maximize or minimize them (Deb et al., 2021).

A variety of approaches is used to solve the node- and flow-based optimization models (Deb et al., 2021, 2018b; Islam et al., 2015). Integer and mixed-integer programming models for the flow-based model are presented by Chung and Kwon (2015), Cruz-Zambrano et al. (2013), and Jia et al. (2012). The same techniques have also been used in node-based problems (Asamer et al., 2016; Baouche et al., 2014; Hosseini and MirHassani, 2015). Due to the complexity of the problems, several (meta)heuristic[2] algorithms have also been applied such as nature inspired algorithms, e.g., genetic algorithm or particle swarm optimization (Deb et al., 2021).

3.2 ELECTRIC VEHICLE CHARGE SCHEDULING PROBLEM (EVCSP)

Scheduling problems are prevalent in production planning literature and are often applied to optimize the allocation of resources e.g., time or human resources, to tasks (Herrmann, 1984). Scheduling theory is concerned with the development and application of scheduling models and algorithms e.g., to determine which job is executed when (in which order) and on which production machines (Baker and Trietsch, 2009). Over the years multiple model formulations have been developed to incorporate single or multiple machines, due dates or uncertainties (Chen et al., 1998; Ruiz and Maroto, 2005). The problem of coordinating charging activities of EVs, can also be formulated as a scheduling problem where the resource to be allocated is the charging power or the available charging points to meet the charging requirements of vehicles that represent jobs (Binetti et al., 2015). The electric vehicle charge scheduling problem has been the focus of several review articles regarding methodological (Rahman et al., 2016; Richardson, 2013; Yang et al., 2015) or practical questions (Finn et al., 2012; Jia and Long, 2020; Solanke et al., 2020). The goal of charge scheduling models is to allocate charging activities of a single or multiple vehicles within a

1 In contrast to *hard constraints* that cannot be violated in a feasible solution, this is possible for *soft constraints* at predetermined costs (Williams, 2013).
2 See Kunche and Reddy (2016) for details on the distinction between heuristic and metaheuristic.

predetermined timeframe and to minimize or maximize an objective function while considering several technical constraints. Depending on the research question addressed and the modeled system, studies are either focused on theoretical algorithm development, on developing practical algorithms to deploy in real-world settings or to assess the effect of certain charging algorithms on the overall power grid or other connected services (retrospective optimization) (Weitzel and Glock, 2018). Two types of time horizons can be distinguished in charge scheduling models, namely the optimization horizon and the forecasting horizon (Amjad et al., 2018; Weitzel and Glock, 2018). The optimization horizon is determined by the type of market participation to be optimized i.e., retrospectively the day-ahead market, the intraday market, or a combination of both. The forecasting horizon is conditional on the available forecast information or the time-horizon to be forecasted. While in retrospective optimization models no forecast information is considered, day-ahead or intraday, scheduling models consider a forecast horizon of up to two days.

Charging can either be organized in a centralized or decentralized manner with some studies also differentiating between decentralized and price varying scheduling as a special form of decentralized charging control. The distinction between centralized and decentralized control is determined by the entity that initializes the charging process. In the centralized approach, the aggregator directly coordinates charging among several vehicles simultaneously (Mohammad et al., 2020). In the decentralized approach, the charging or discharging process is controlled by the individual vehicle. While the decentralized approach shifts the computational burden of initializing the charging process to the individual vehicles, the centralized approach needs to incorporate and assess this decision for all vehicles, while also considering trade-offs or other interactions in-between the charging schedules of the individual vehicles. Due to the distribution of the computational load, decentralized charging control is viewed as more scalable and flexible (Binetti et al., 2015). However, as the decentralized approach does not explicitly consider the interaction between the charge schedules of individual vehicles, it may lead to suboptimal charge schedules in comparison to a centralized approach (Jin et al., 2013; Mukherjee and Gupta, 2015). Studies further differentiate between decentralized charging incorporating a two-way or one-way communication. In the two-way process, a negotiation takes place between a central control unit and the vehicle e.g., regarding price, charging or discharging electricity or time. In case of one-way communication, charging is incentivized through the price of charging (e.g., through time-of-use prices) (Amin et al., 2020; Mohammad et al., 2020). Another differentiation between past approaches can also be made regarding unidirectional and bidirectional power flow (Tan et al., 2016). As bidirectional charge control enables further integration with the power system, more system services are modeled, often leading to a higher degree of complexity and requiring more sophisticated modeling and solution techniques (Mohammad et al., 2020; Tan et al., 2016). Scheduling models consider economic, technical, social or ecological objectives.

Economic objectives consider the minimization of cost or maximization of revenue or profit associated with the charging or discharging of EVs. The goal of cost minimization is addressed by several studies, and an overview is provided in Ghofrani et al. (2016) and Liu et al. (2015). For EV-owners cost reductions can be achieved by minimizing charging costs e.g, when facing a flexible electricity cost function. For electricity generators, aggregators, TSOs, and DSOs, cost reductions can be achieved through integrating and charging EVs e.g., through an improved utilization of renewables and the minimization of operational cost. Studies explicitly model electricity generators and their properties for instance, as part of a unit commitment problem

(Aunedi and Strbac, 2013) or more commonly by implicitly considering them though mapping in a cost function (Chiao-Ting Li et al., 2012; Sortomme and El-Sharkawi, 2011; Verzijlbergh et al., 2014). Modeled costs include costs due to power imbalance, cost of emissions (e.g., cost of emission certificates to offset CO_2 emissions), maintenance costs of the system, electricity generation or procurement costs. Studies that model the charging problem from the perspective of the vehicle owner mostly take into consideration the charging cost to optimally coordinate the charging behavior while adhering to the mobility behavior (Van Der Klauw et al., 2015; You et al., 2012). Other studies also include revenues from the provision of services or electricity in the objective function and maximize profits or revenues, for instance, by maximizing energy sold on the wholesale market or to vehicles or participation of the vehicles in the day-ahead and reserve market (Sarker et al., 2016; Sortomme and El-Sharkawi, 2011; Vasirani et al., 2013). For individual vehicles, objectives include the maximization of revenues through the participation in V2G measures (Soares et al., 2013).

A second group of objectives is related to technical factors and include the maximization of system reliability or minimization of power losses, voltage violations or peak demand (Fachrizal et al., 2020; Mohammad et al., 2020). Maximizing the utilization of electricity generated from renewable sources is another technical objective. For instance, the algorithm presented by Kam and Sark (2015) for a microgrid containing EVs, an office building and a PV-system combines a prediction of the system load and PV generation to compute a charging schedule to maximize the utilization of electricity generated by the PV system. The objective function maximizes the total electricity used, assigning a higher value to the power generated by PV.

The social i.e., vehicle owner perspective as well as ecological perspective have only seldom been considered as the sole objective of models. While CO_2 emissions are often converted to monetary units through emission certificates (Ahn et al., 2011), the study by Rangaraju et al. (2015) considers rule based charging strategies to quantify the impact of optimizing the charging process on a reduction of emissions in the use-phase of the vehicle. The study by Wen et al. (2012) considers user convenience through the SoC of the vehicles and available charging time. The objective function aims to maximize the reciprocal of the SoC and remaining available charging time of the vehicles, thus when determining a charging sequence vehicles with a lower SoC and lower remaining available charging time are preferred.

Technical or social features, or limitations, are more frequently modeled using constraints (Tan et al., 2016). Technical limitations include the consideration of an operational range of the battery e.g., the battery may not be discharged or charged below zero, a maximum threshold or predefined threshold, to minimize battery degradation (Wang and Wang, 2013), or they aim to constrain the charging power, voltage or current within certain limits (Saber and Venayagamoorthy, 2010). Social constraints account for the driving behavior of the vehicle owners and the impact on the availability (Saber and Venayagamoorthy, 2009).

Depending on the factors considered, scheduling can either employ deterministic or stochastic modeling techniques. Deterministic modeling is used for retrospective optimization, for instance, to show the effects of the feasibility of a proposed charging algorithm. When retrospective modeling is used all relevant model parameters are known *a-priori* and problems are represented in linear, integer or mixed-integer programs and solved, using commercial solvers such as Gurobi or CPLEX and implemented using methods such as dynamic programming or Benders decomposition.

Stochastic modeling is applied when uncertainties are present in the modeled system. Uncertainty can be related to several factors such as the EV e.g., individual demand of vehicles, arrival and departure time, the load caused by climatic conditions, electrical equipment, or user behavior. To model uncertainty and depending on the available data, different modeling techniques such as robust optimization, Markov chains or fuzzy logic are applied (Mohammad et al., 2020). The optimality of the solution and computational intensity differs between the applied methods. For instance, in the study by Seddig et al. (2019) the authors apply different methods to minimize charging costs in a public car park with uncertain vehicle demand and PV power. They apply a two-stage mixed integer optimization. The first stage of the model creates an optimized charging schedule based on planned vehicle arrivals and the expected PV generation pattern. The second stage aims to find recursion functions which stipulate decisions that minimize the expected costs. To assess the solution quality of their model, a mixed-integer linear programming (MILP) that assumes perfect foresight and an uncontrolled charging heuristic. The computational characteristics show how uncertainty influences the complexity of the model, as this model has over 100 times more variables and 265 times longer solution time than the benchmark that does not consider uncertainty. While a combination of factors is sometimes considered, they are usually converted to the same unit for instance, in the study by Van Der Klauw et al. (2015) where two factors are minimized in the objective function, the charging cost, and the deviation of the actual from a preferred charge, the charge preference is converted into monetary units.

The review of the electric vehicle charge scheduling problem (EVCSP) and CSPP shows that both problems are applied to strategic and operational problem contexts and have therefore been independently considered in decision models in the past. Before presenting a combined implementation, the following section provides an overview of models that implicitly consider both decision problems.

3.3 JOINT CONSIDERATIONS OF ELECTRIC VEHICLE CHARGING STATION PLACEMENT AND SCHEDULING

Table 3.1 summarizes the studies presented in the previous section regarding their objective and integration of the defined model prerequisites. As the CSPP typically supports strategic decisions while the EVCSP supports operational decisions, different cost components are typically considered in the models. While most placement problems consider infrastructure cost, these are not considered in most scheduling problems, which typically focus on variable cost and *vice-versa*. While the planning horizon of scheduling models is typically only up to a couple of hours to days, the planning horizon of placement models can take multiple years into consideration. The time resolution on the other hand is very high for scheduling models which optimize in minute to hourly intervals while in some cases placement problems aggregate data on a yearly basis.

Both the charging station placement problem and the EV charge scheduling problem are viewed as separate decision problems and only few studies touch on both problems. Chen et al. (2019) consider both CAPEX and OPEX of a charging station in the objective function. The OPEX are calculated in relation to the effort of the vehicle owner to access the station, which is related to distance to the charging stations. The model does not explicitly consider the charging schedule or individual charging activities but only requires that total demands at a station are met. Schiffer and Walther (2017) combine the routing problem of EVs with the placement decision of the charging infrastructure. Their model aims to minimize the total distance traveled by all vehicles. Their work shows, that the simultaneous consideration of both decision problems can lead shorter distances in comparison to problems that neglect the placement of charging stations. In the study by Pagani et al. (2019) a combination of an optimization and agent-based simulation are used to determine an optimal charging infrastructure focusing on the city of St. Gallen. Their model takes into account user behavior and the EV penetration level. The objective of their algorithm is to maximize the so-called load factor of charging stations which represents their utilization. The city is divided into several cells and for the initial solution one charger is allocated per cell. The solution is then analyzed using a week-long agent based mobility simulation to evaluate how charging stations are utilized. If the utilization is low in a cell, charging stations are removed from a cell, if the charging demand cannot be fully meet, additional charging stations are added to a cell. The optimization model stops, if at least 95% of all charging activities can be met by the calculated solution. The profitability of the charging infrastructure is assessed by calculating the time to break-even and net present value (NPV). While this model does include some factors related to both the CSPP and scheduling problem, they are examined separately and variable cost or profits are not explicitly considered in the termination criteria.

Table 3.1: Summary of relevant CSPPs and EVCSPs studies.

Author	Application	Objective	Mobility	Planning horizon / Time resolution	Variable Cost	Infrastructure Cost
Wang et al. (2021a)	station placement (city)	maximize captured flows	✓			✓
Jochem et al. (2019)	fast station placement (highway)	minimize number of placed stations	✓			(✓)
Chung and Kwon (2015)	fast station placement (highway)	maximize captured flows	✓	multiple periods / one year		✓
Vries and Duijzer (2017)		maximize captured flows	✓			
Li et al. (2016)	fast station placement (highway)	minimize the total cost of new charging stations	✓	multiple periods / one year		✓
Hess et al. (2012)	station placement (city)	minimize average trip time of EVs	✓	multiple periods / 120 min		
Alhazmi et al. (2017)	fast station placement (highway)	maximize number of covered drivers	✓			✓
Bouguerra and Bhar Layeb (2019)	fast station placement (city)	minimize number of placed stations / user access cost	✓	daytime charging		✓
Frade et al. (2011)	normal station placement (city)	maximize coverage	✓	day and nighttime charging	(✓)	
Binetti et al. (2015)	decentralized scheduling	minimize both the variance and peak of aggregated load profile	✓	24 h / 15 min	✓	
Aunedi and Strbac (2013)	day-ahead scheduling	minimize the system cost	✓	one year / 1 h	✓	
Sortomme and El-Sharkawi (2011)	day-ahead scheduling	maximize profit of aggregator	✓	9 h / 1 h	✓	
Chiao-Ting Li et al. (2012)	multi-level optimization	optimize schedule on multiple levels		24 h / real-time	✓	
Van Der Klauw et al. (2015)	validation of smart charging strategies	minimize electricity cost	✓	24 h /10 min	✓	
Sarker et al. (2016)	day-ahead and real-time scheduling	maximize day-ahead and real-time profits	✓	24 h / real-time	✓	
Pagani et al. (2019)	station placement (city)	maximize coverage	✓	1 week / 1 minute		✓
Chen et al. (2019)	station placement (city)	minimize cost of investment and operation	✓	1 year / 1 h	(✓)	✓
Soares et al. (2013)	station placement (city)	minimize cost of investment and operation	✓	1 year / 1 hour	(✓)	✓

3.4 THE CHARGING STATION PLACEMENT AND ELECTRIC VEHICLE CHARGE SCHEDULING PROBLEM (CSP-EVCSP)

From the literature review a clear research gap has been identified. There is currently no model for the joint consideration of the EV charging station placement and scheduling of EV charging. This problem is termed as the charging station placement and electric vehicle charge scheduling problem (CSP-EVCSP). By concurrently solving these previously separate problems in one model, the trade-offs between the scheduling of the charging process and the placement of the charging infrastructure can be assessed regarding economic or ecological parameters and and an answer to the posed research questions can be found. When considering the installation expenses of a charging network and volatile electricity procurement cost, adding charging points increases the charging availability of a vehicle while possibly reducing electricity procurement cost. A model considering both cost components allows to judge if the increased availability and associated reduction of electricity procurement cost justifies the additional expenses incurred through the installation of additional charging points. In the following section, a combined mixed-integer linear programming (MILP) model is presented. The model incorporates findings and characteristics of both the placement and scheduling problem, in order to identify the inter-dependencies of these models, both from a methodological and practical viewpoint.

The general aim of the CSP-EVCSP is to find a charging network configuration and EV charging pattern that minimizes the fixed and temporally volatile components in the objective function. The MILP model represents a set of profiles $p \in P$ and is made up of a number of potential charging locations $l \in L$. Each profile is assigned to a specific location or activity at each interval i and mobility activities are conducted using a vehicle, which moves from one location to another throughout the optimization horizon.

Charging points can be placed at locations. If a station is placed, the cost C_s for this charging station are added to the objective function. Costs are dependent on the maximum power s that can be supplied at each location l. For each profile and set of intervals $i \in I$ the variable SoC_{ip} models the SoC of a vehicle battery assigned to a profile. The variable ch_{lip} represents the supplied electricity in an interval i at location l. Next to the possibility to supply electricity at the current location l of a profile, it can also be supplied by any location that meets the requirements of Equation 3.1. Power requirements arise due to the mobility and the discharging of the state of charge of the modeled battery of a vehicle.

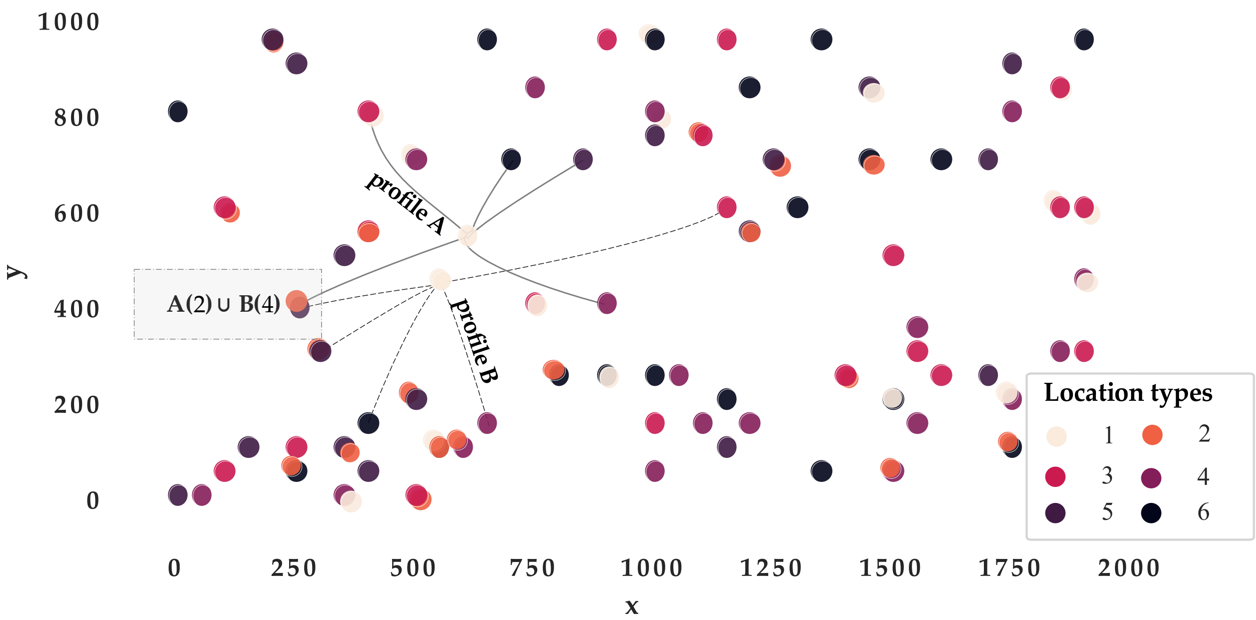


Figure 3.2: Graphical representation of the intersection between two profiles A and B at locations 2 and 4 in the CSPP.

Figure 3.2 shows an overall representation of the considered CSPP components. The model accounts for different location types, as the mobility patterns of individuals differ throughout the day and the vehicle can be located at different locations. When considering a public or semi-public charging infrastructure, it may be possible and efficient for vehicles to share charging points e.g., if parking locations are in a vicinity of a charging station. In Figure 3.2 possible charging locations for 20 profiles with six different charging locations are represented in a graph. The nodes have an x and y coordinate and the distinction between locations is represented by the different colors. Each node is assigned to one profile (e.g., in Figure 3.2 two profiles and their respective nodes are represented by the connecting edges, with location 1 as the center node). The center of each node represents the exact location, while the area of the circle represents an acceptable intersection radius between nodes. A node in profile B is considered to be covered by a node in A if

$$\sqrt[2]{(x_a - x_b)^2 + (y_a - y_b)^2} \leqslant radius_a \tag{3.1}$$

holds for any node in profile A. In the illustrated example, profile A and B intersect at location 3 (profile A) and location 6 (profile B). The intersecting nodes are considered to be eligible to supply the demand for each intersecting node.

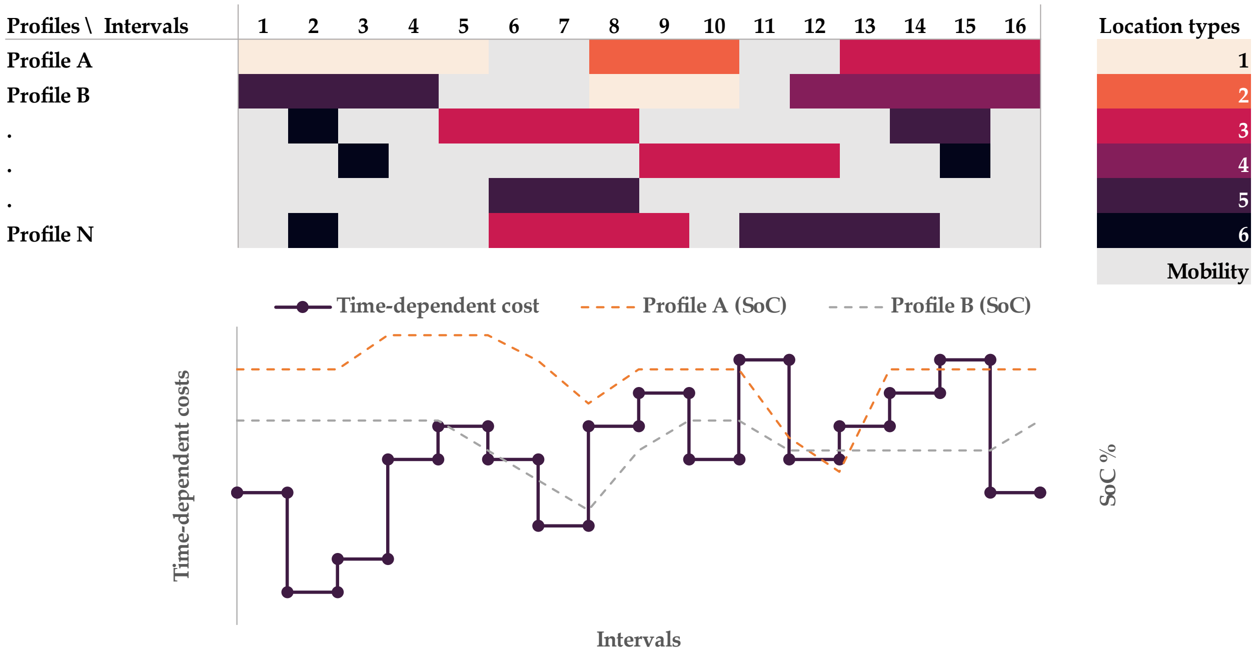


Figure 3.3: Graphical representation of the EVCSP, highlighting time and location dependence.

As highlighted in the review on scheduling literature in Section 3.2, scheduling models are used to support operational decisions such as optimizing the charging process of a vehicle battery regarding an external stimulus (e.g., price-based charging). To do so, operational, technical and economic features are modeled using constraints. Figure 3.3 shows the features that are considered in the scheduling part of the developed MILP. A profile is represented by a fixed number of intervals and each interval is assigned to a geographic location (location type) shown in Figure 3.2. If a mobility activity is conducted, the vehicle battery is discharged and if the vehicle is parked at a location, the battery can be recharged (bottom part of the figure). Time dependent costs are considered to incentivize charging activities at certain times.

$$\min \quad \alpha \sum_{p \in P} \sum_{l \in L} \sum_{i \in I} ch_{lip} O_i + \beta \sum_{s \in S} \sum_{l \in l} C_s cp_{sl} + \gamma \sum_{i \in I} \sum_{p \in P} (y_{ip} + z_{ip}) \tag{3.2}$$

The objective function of the model (3.2) consists of three terms. The model parameters are shown in Table 3.2 and the variables in Table 3.3:

- Total cost of charging the vehicle.
- Total cost of placing a charging point.
- Penalty cost for surpassing or dropping below a predetermined SoC.

Table 3.2: Model parameters of the CSP-EVCSP.

Name	Description
$i \in I$	Set of charging intervals
$l \in L$	Set of charging locations
$p \in P$	Set of profiles
$s \in S$	Set of different charging speeds
O_i	Operating expenses for a unit of charge at interval i
C_s	Capital expenses of charging station with charging power s
α, β,γ	Weighting factors for parts of the objective function
B^{max}	Maximum state of charge
B_0	State of charge of vehicle at interval 0
D_{ip}	Energy consumption in interval i by profile p
P_s	Charging energy per interval for station type s
m	Activity mobility
M	Big-M
X_{ip}	Activity/location at interval i of profile p
κ,ζ	Desired upper and lower SoC limit of the vehicle battery
L^{max}	Maximum number of charging stations

Table 3.3: Decision variables of the EVCSP.

Name	Description
ch_{lip}	Charge conducted during interval i at location l of profile p
oc_{lip}	Binary variable for each interval i and location l for profile p
cp_{ls}	Binary variable that determines if charging station with power s is available at location l
soc_{ip}	State of Charge of profile p at interval i
y_{ip}	Minimum charge undercut at interval i by profile p
z_{ip}	Maximum charge surpassed at interval i by profile p

To facilitate testing the model, the impact of the three terms on the total objective value can be modified via the weighting parameters (α, β, γ). The first part of the objective function determines the cost of charging at a given interval (i), the cost at each interval can vary and are represented by the values O_i. The variable ch_{lip} is continuous with a defined lower and upper bound dependent on the kind of charging station P_s built at a location. The cost of charging are determined by the amount of energy charged in an interval ch_{lip} multiplied by the charging costs in this interval O_i. The cost for placing a charging station are dependent on the cost of a charging points (C_s) with a charging capacity s multiplied with a binary decision variable (cp_{sl}) that is equal to 1 if a station is placed and 0 if it is not. The third term, the penalty costs, constrain the state of charge (SoC_{ip}) of the battery at each interval i through the variables (z_{ip}) and (y_{ip}).

To fulfill the practical and theoretical model requirements defined above, a number of constraints are considered. These constraints can either be motivated by the scheduling problem, or the placement problem or they are necessary to connect both problems. The following constraints are related to the scheduling problem and allow to consider the mobility behavior, the SoC of the battery and the charging and discharging process of the battery.

BATTERY CONSTRAINTS

$$soc_{0p} = B_0 \qquad \forall\, p \in P \tag{3.3}$$

$$soc_{Ip} = soc_{0p} \qquad \forall\, p \in P \tag{3.4}$$

$$0 \leqslant soc_{ip} \leqslant B^{max} \qquad \forall\, i \in I \tag{3.5}$$

$$soc_{ip} \leqslant \kappa B^{max} + z_{ip} M \qquad \forall\, t \in T \tag{3.6}$$

$$soc_{ip} \geqslant \zeta B^{max}(1 - y_{ip}) \qquad \forall\, t \in T \tag{3.7}$$

Constraints 3.3 - 3.7 model the general characteristics of the battery and its predetermined SoC at the beginning and end of the optimization horizon. As has been explained by several studies and summarized in Section 2.3.1, the SoC of the battery of an BEV is relevant both from the vehicle owner's perspective and technical perspectives. Technical factors are related to the optimal SoC of the battery in order to prolong the battery's lifetime. For fast-charging stations, there is an impact of the SoC on the available charging capacity (see Figure 2.12). Both factors are also relevant to the vehicle owner, who is concerned with retaining the battery health of the vehicle. As pointed out by Cenex (2021) and Delmonte et al. (2020), vehicle owners are interested to retain a minimum range (SoC) for emergency journeys. Therefore, the constraints 3.7 and 3.6 use the parameters κ and ζ to set this limit. As it may still be necessary to utilize the full vehicle range for certain longer trips, the constraints are modeled using soft constraints that can be violated but result in a penalty in the third part of the objective function.

CHARGING/DISCHARGING CONSTRAINTS

$$soc_{i+1p} \geqslant soc_{ip} + CD_{ip} \qquad \forall\, i \in I, p \in P \tag{3.8}$$

$$CD_{ip} = f\left(X_{ip}\right) = \begin{cases} \sum_{i\in I}\sum_{l\in L} ch_{lip} & X_{ip} \neq m \\ -D_{ip} & X_{ip} = m \end{cases} \qquad \forall\, i \in I, p \in P \tag{3.9}$$

$$ch_{lip} \leqslant oc_{lip} \cdot \max(P_s) \qquad \forall\, l \in L, i \in I, p \in P \tag{3.10}$$

$$\sum_{l\in L} oc_{lip} \leqslant 1 \qquad \forall\, p \in P, i \in I \tag{3.11}$$

$$\sum_{p\in P} oc_{lip} \leqslant 1 \qquad \forall\, l \in L, i \in I \tag{3.12}$$

The charging and discharging process of the vehicle is modeled using constraints 3.8 - 3.12. The variable soc_{i+1p} is dependent on the previous interval soc_{ip} and the charging or discharging conducted (CD_{ip}) in an interval. To determine the value of CD_{ip} the activity or location X_{ip} that is conducted in the interval is decisive. If $X_{ip} = m$, a driving activity is assumed and D_{ip} reduces the SoC of the battery. The SoC of the battery can be increased if $X_{ip} \neq m$ (Constraint 3.8). The continuous variable ch_{lip} can be set to determine the charge conducted during an interval. The binary variable oc_{lip} is constrained to 1 if a charge is conducted and 0 if it is not (Constraint 3.10). The binary variable is required to restrict charging to one charging point per interval and to ensure only one vehicle charges at one place in each interval.

$$L^{max} \geqslant \sum_{s\in S}\sum_{l\in L} cp_{ls} \qquad \forall\, p \in P \tag{3.13}$$

$$\sum_{s\in S} cp_{ls} \leqslant 1 \qquad \forall\, l \in L \tag{3.14}$$

In case of limited resources, the maximum number of installed charging points can be constrained (Constraints 3.13). The highest charging power available at a location is constrained by Constraints 3.14.

$$\sum_{s\in S} cp_{ls} P_s \geqslant \sum_{p\in P} ch_{lip} \qquad \forall\, i \in I, l \in L \tag{3.15}$$

As the capital expenses C_s of a station are dependent on the charging power the highest charge energy ch_{lip} drawn over the optimization horizon determines the value of cp_{ls}. Constraint 3.15 links the charging and scheduling model as the value of cp_{ls} is set to 1 if $ch_{lip} > 0$ at a location.

3.4.1 Computational experiments

The previous sections presented an overview of different implementations of the CSPP and EVCSP. Many of the highlighted studies formulate optimization models to reflect the inherent objectives and constraints. Scheduling problems, especially retrospective optimization models that do not consider uncertainties, can often be modeled as linear optimization problems and efficiently solved e.g., though the application of the simplex method (Dantzig, 1963). Recent studies have highlighted that the time complexity of some of these problems is comparatively low. For instance, in the implementation of the charge scheduling model for a single vehicle, Van Der Klauw et al. (2015) present an algorithm to compute the optimal schedule in quasilinear time $O(n \log n)$.

Placement problems are often modeled using MILP optimization models. The binary or integer variables are utilized to model the decision if a node (potential charging point) is considered. Variants of the problem have been shown to be NP-hard (Conrad et al., 2012; Hodgson, 1990; Lam et al., 2014). NP-hard i.e. non-deterministic polynomial time hardness, describes the algorithmic complexity of problems at least as hard as NP. The special case of integer-programming models were assigned to the category of NP-complete problems by Karp (1972) as the feasibility of solutions can be verified in polynomial time. While NP problems cannot be solved in polynomial time by a deterministic Turing machine (Arora and Barak, 2009; Kallrath, 2013), approximate solutions can be calculated. For smaller problem instances, exact solutions can be obtained using the branch-and-bound algorithm (Dakin, 1965), cutting-planes-method (Gilmore and Gomory, 1961; Land and Doig, 1960) or complete enumeration. While Horst and Tuy (1996) showed that for continuous optimization problems the branch-and-bound algorithm converges to an optimal solution, the time can be exponential in relation to the size of the problem. Therefore, time or computational effort based termination criteria are often utilized to obtain feasible but not optimal solutions.

In the following section a sensitivity analysis of the presented model concerning several parameters is conducted. The aim is to assess for which parameter configurations the CSP-EVCSP can be solved using a commercial solver for a representative problem size as specified in the introduction of this chapter. To assess this, several test-instances are created and the number of profiles, intervals and intersections between profiles is successively increased.

The model is implemented using the Python programming language (version 3.8.11) and solved using the Gurobi Optimizer (Version 9.5). There are several model parameters that have an impact on the time to solve the model. Depending on their value, the solver is either able to solve the model to optimality, to only identify a feasible solution or no solution at all within a reasonable amount of time. In the following section the impact of model parameters on the time to solve the model and model characteristics are presented. Performance testing was conducted on a computer running Windows Server 2019 with an Intel Xeon Gold 6128 central processing unit (CPU) @ 3.39 GHz with two cores and 256 GB of Random-Access Memory.

To solve the minimization problem the solver first generates a lower bound using a linear programming relaxation (Agmon, 1954) along with several pre-solve functions to reduce the size of the model. The solution of the relaxed problem is then used as the lower bound for the minimization problem. In the next step the branch-and-bound algorithm is executed. To do so, the problem is divided into sub-problems (*branching*) that are successively investigated. To avoid complete enumeration of all solutions, upper (current best solution) and lower bounds (best possible solution of sub-problems on a branch) are calculated, and the decision tree is pruned. A lower bound does not have to be associated with a feasible solution. Different pruning steps of the branches are conducted in a minimization problem, i.e. if

- the lower bound is greater than the upper bound or
- the solution of a sub-problem with a lower bound than the current upper bound is feasible, the branch can be pruned and the upper bound updated.

If the lower bound of a sub-problem is smaller than the best bound, but the current solution on a branch is infeasible, further branching of the sub-problem is necessary (Gilmore and Gomory, 1961; Nemhauser and Wolsey, 1988).

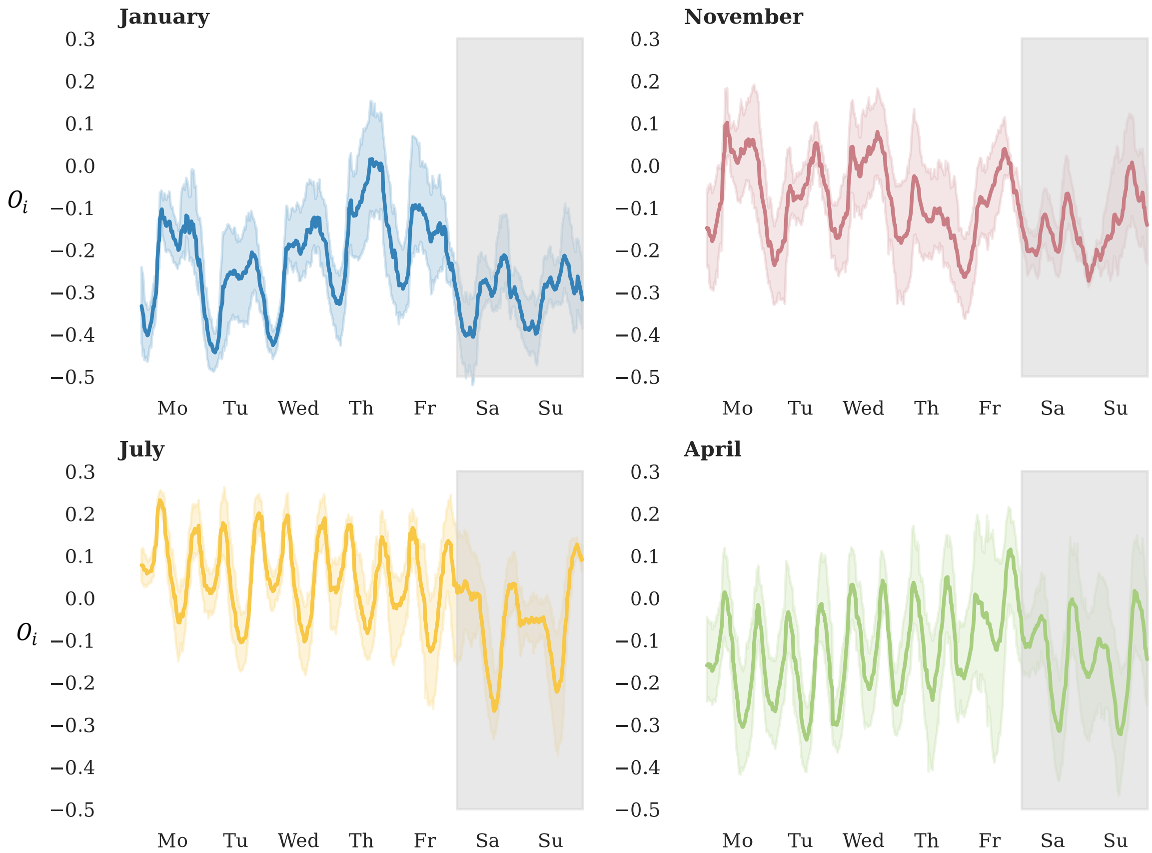


Figure 3.4: Cost for testing the model, calculated for four exemplary month using Equation 3.16.

For the computational experiments, the variations of the parameters presented in Table 3.4 are considered. To reflect the variability of electricity prices, a test instance is created using the energy generation (gen_i) and consumption (con_i) of Germany in the year 2019. To determine the cost in each interval, the electricity consumption in a time interval is deducted from the generation $s_i = con_i - gen_i$ and represented as a fraction of the span of the generation surplus or deficit over the total optimization horizon (Equation 3.16).

$$O_i = \frac{con_i - gen_i}{|min(s_i)| + |max(s_i)|} \tag{3.16}$$

To illustrate the general pattern of the O_i calculated using Equation 3.16 and used to test the developed model, Figure 3.4 shows the minimum, maximum and mean values for an exemplary week in each season. The monthly data are aggregated to one week, for a better overview of the data. Weekends are marked by a shaded gray area. The illustration shows a distinct pattern throughout the week for each month. For the winter and autumn month, cost increase in the midday, in the evening starting at about 6 p.m., and are lower on weekends. In the spring and summer, the additional generation by photovoltaic, leads to lower costs in the midday. A comparison to the real market prices of the year 2019 are not carried out in this section, as the primary purpose of the generated data, is for performance testing of the developed model. A more detailed calculation and testing of values is presented in Section 4.2.2.

The computational time was measured using the Gurobi *work* parameter. The *work* parameter is deterministic and depends on the computer hardware. It roughly equates to a second on a single thread of a CPU (Gurobi Optimization, 2022). For each test, the *work* required to achieve an optimal solution was measured, and is given in seconds or milliseconds. The parameter is further referred to as CPU-time.

3.4.1.1 Impact of the number of profiles and intervals

For the initial analysis, the number of profiles and intervals is varied. The number of intersections is set to zero, while the number of intervals and profiles is gradually increased. Figure 3.6 shows the impact of increasing the number of intervals (i) considered in the model. The assessed parameter is plotted on the abscissa, while the CPU time is plotted on the ordinate axis. The other model parameters are fixed to the values given in the plot or the *standard* values highlighted by a bold typeface in Table 3.4.

Table 3.4: Computation experiments (variations of parameters).

	I	L	P	S	O_i	P_s	C_s	α/β	B^{max}	D_i
min	100	7	1		200	2.75	−1	0.1		
				3	400	5.5			**65**	**1.9**
max	35,000	1,400	100		600	12.5	1	10		

Figure 3.5 shows the impact of the variation in the number of profiles (p). For each value depicted in the figures, three optimizations were performed with varying activity profiles. The mean total CPU time required to obtain an optimal solution is represented in the graph by the solid line, while the lowest and highest values are illustrated through the shaded area of the graph. Two additional relative metrics are presented, the mean CPU time measured in ms/per interval for the variation of intervals and s/per profile for the variation of profiles.

The results show that the marginal calculation time per added profile and interval increases. While the time to solve one profile to optimality is 0.901 s, this increases to 3.075 s for 200 profiles. On average, a model with 8,640 intervals has 8,122 binary variables (one per interval that is not occupied by a mobility activity), 16,744 continuous variables and 41,067 constraints per profile. Taking into account the modification of the intervals, a similar pattern can be observed, while the solution time per interval is equal to 0.2 ms/interval for one interval, it increases to 0.7 ms/interval for 35,040 intervals. The number of binary and continuous variables as well as the number of linear constraints increase linearly with an increasing number of intervals, e.g., there are on average 32,777 binary variables per profile for a model with 35,000 intervals.

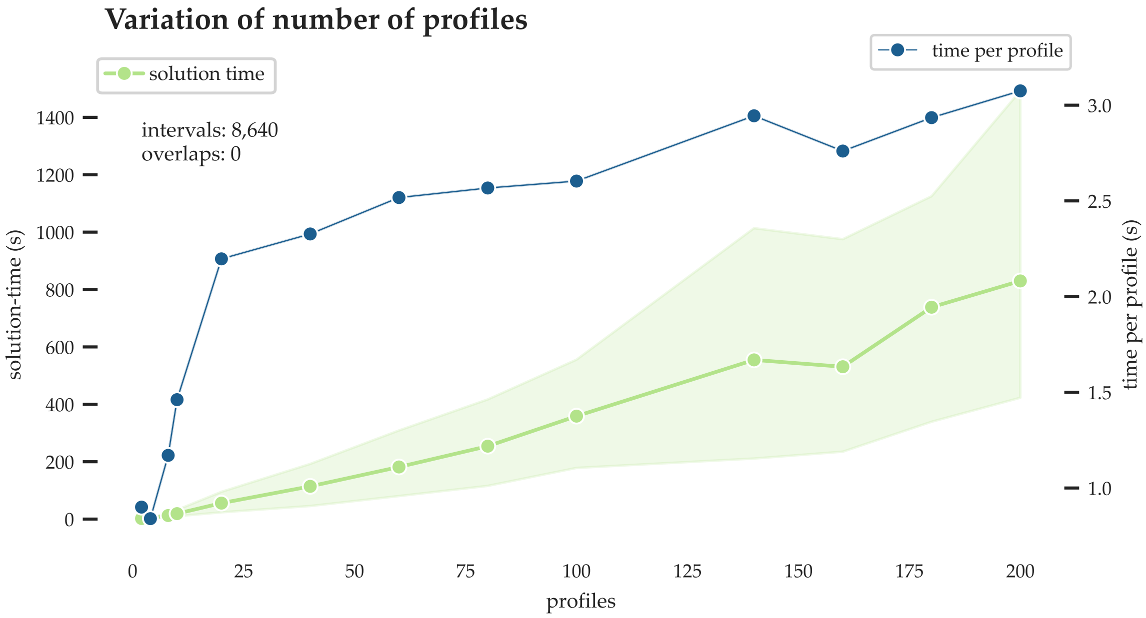


Figure 3.5: Effect of the number of driver profiles on solver runtime. The solid line represents the mean value, while the shaded area for the variation of the number of profiles represents a 95% confidence interval of the CPU time for a test-instance.

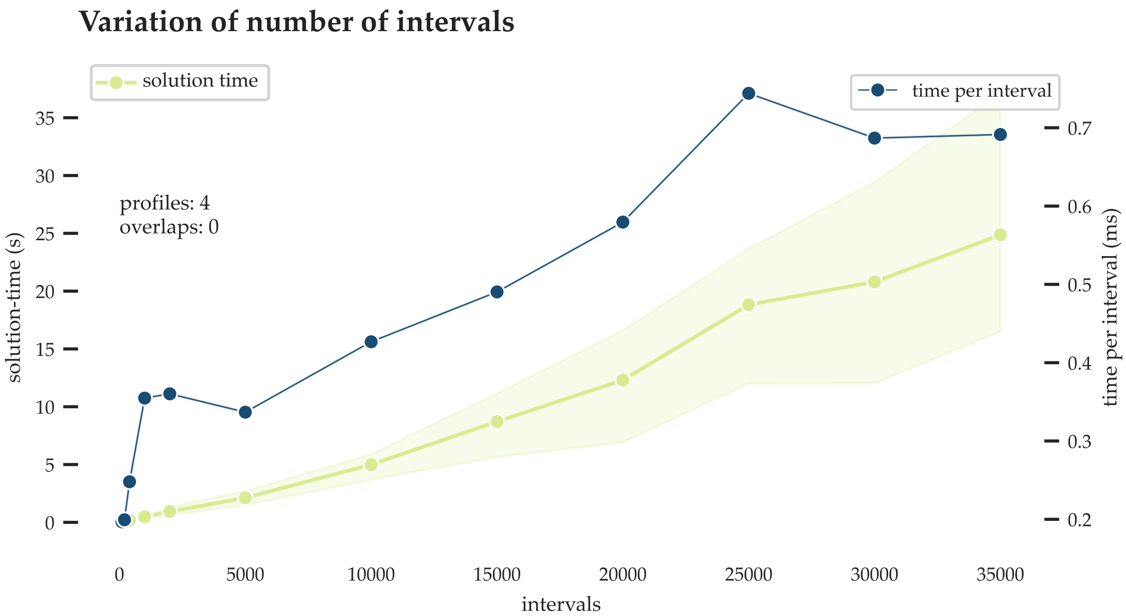
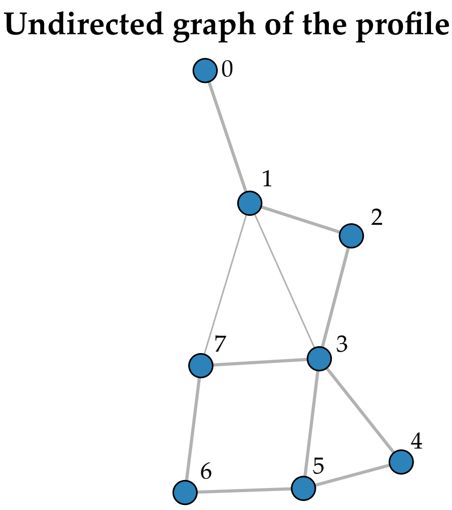


Figure 3.6: Effect of the number of intervals in the optimization horizon on solver runtime. The solid line represents the mean value, while the shaded area for the variation of the number of intervals represents a 95% confidence interval of the CPU time for a test-instance.

The impact of the interval-dependent cost is evaluated by randomizing the cost data. This change only has a minor impact on the CPU-time. For the calculation of one year and 10 profiles, the maximal deviation of the CPU time over 10 different randomized cost sets is 8.29% in contrast to the base values illustrated in Figure 3.4, a further investigation of this parameter is therefore neglected. The largest problem size tested of 1,000 profiles and 35,040 intervals can be solved optimally in 4369.3 s (CPU-time).

3.4.1.2 *Impact of the number of intersections*

The intersection between profiles, e.g., as illustrated in Figure 3.2 between Profile A and B, also have an impact on computational time. While intersections within a profile have little impact on the performance of the solver, the required solution time increases with the number of intersecting profiles. Two profiles are viewed as intersecting if they share one or more points that meet Equation 3.1. Assuming the same intersection radius of two locations, if Equation 3.1 is true for A, it must also be true for B. That is, if a point A is within the intersection radius of the point B, then B is also within the intersection radius of A. As shown in Figure 3.4.1.2, the intersections between profiles can be represented using graph theory.[3] An undirected weighted graph presents individual profiles as vertices and intersections between these profiles with the connecting edges. The weight on the edges represents the number of intersecting locations between two profiles, illustrated through the thickness of the edges in this illustration. On the right side of Figure 3.4.1.2 the corresponding adjacency matrix is presented. The symmetric matrix represents the number of intersections between two profiles i and j, through the values of the matrix element $A[i,j]$, if there is no intersection $A[i,j] = 0$. The illustrated example shows a connected graph, i.e., each profile has at least one intersecting location with another profile, and each node can be reached from another node by traversing the graph.



$$A(i,j) = \begin{pmatrix} 0 & 2 & 0 & 0 & 0 & 0 & 0 & 0 \\ 2 & 0 & 2 & 1 & 0 & 0 & 0 & 1 \\ 0 & 2 & 0 & 2 & 0 & 0 & 0 & 0 \\ 0 & 1 & 2 & 0 & 2 & 2 & 0 & 2 \\ 0 & 0 & 0 & 2 & 0 & 2 & 0 & 0 \\ 0 & 0 & 0 & 2 & 2 & 0 & 2 & 0 \\ 0 & 0 & 0 & 0 & 0 & 2 & 0 & 2 \\ 0 & 1 & 0 & 2 & 0 & 0 & 2 & 0 \end{pmatrix}$$

Figure 3.7: Undirected weighted graph and adjacency matrix for the relation between 8 profiles.

3 For a detailed introduction to graph theory, see Bondy and Murty (2008) and Diestel (2017).

To assess the effect of intersections on CPU-time, four base test instances with 25 profiles and 150 locations each were created. The test instances were gradually modified to include two intersecting locations to a total of 15 intersections between locations. An optimization horizon of 8, 064 15-min intervals (four months) was considered for the four randomized variations of the activity profiles and different values of α and β. Figure 3.8 shows the results for a variation of the number of intersections and the effect on the CPU-time. Differences in the results of the calculations are represented by the shaded area in the line plot in the box plot the whiskers represent the variation of the calculated results. All calculations were performed on the specified hardware and a cutoff criterion was defined: The parameter *WorkLimit* was set to 13, 000 units of CPU time, approximately corresponding to an average maximum runtime of the solver of 7, 200 seconds (2 h).

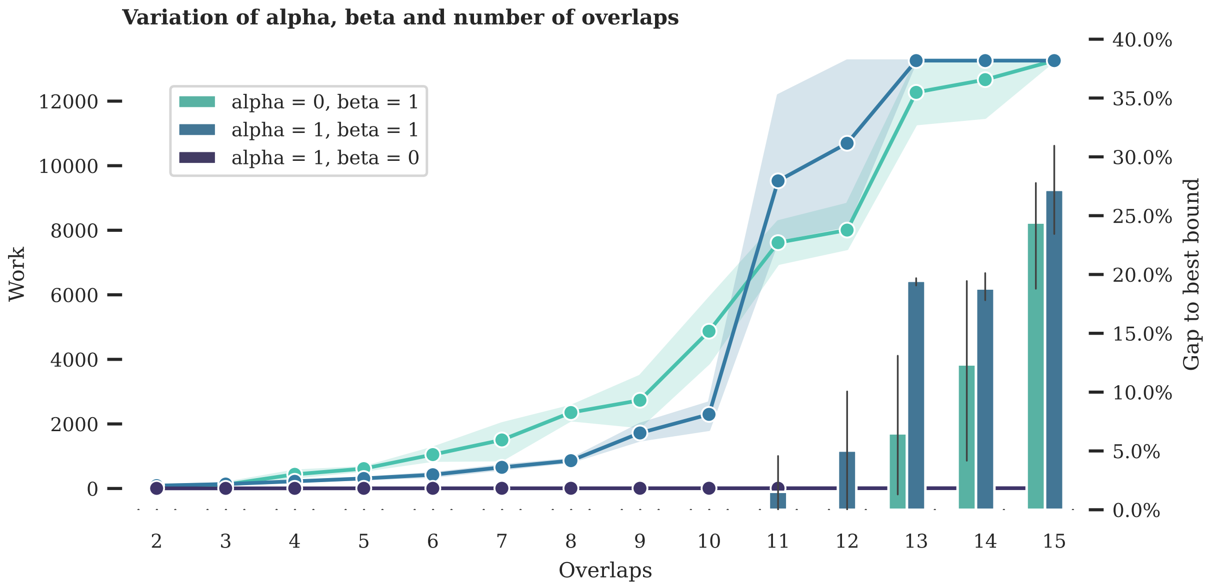


Figure 3.8: Effects of the number of profiles optimized on runtime. The solid line represents the mean value, while the shaded area represents a 95% confidence interval of a all values within the respective number of overlaps.

The values of α and β modify the objective value related to the scheduling (EVCSP) and placement (CSPP) problem in the objective function. As the value of the time bound cost function can take positive and negative values, the sum of charging costs may take negative values[4]. For $\alpha = 1$, the best values obtained range from -6, 900 to -2, 200 in the objective function. For the one-off placement cost with $\beta = 1$, the minimal results obtained range from 3, 600 to 5, 000. To analyze the impact of these factors, α and β were also alternately set to zero.

As can be observed in Figure 3.8 for the base case of $\alpha \wedge \beta = 1$, if the number of intersections increases, the CPU time to find an optimal solution also increases. If 11 locations intersect, one test instance cannot be solved to optimality, and the optimization is aborted. The respective gap from the upper bound to the best lower bound is presented as a percentage value in the bar chart

4 Variable costs can take negative values in the event of negative electricity prices or if a compensation for the provision of flexibility is considered.

and the secondary y-axis. For 12 intersections, only half of the test instances can be optimally solved within the predefined boundaries. The maximum gap between the calculated solution and the best bound increases to 11.61%. If more than 12 intersections are considered, none of the test instances can be solved optimally. The gap to the best bound increases and takes an average value of 27.19% for 15 intersections.

The results for $\alpha = 0$ are similar to those just described, except that all instances are still optimally solved within the given time for up to 12 intersections. The average gap for 15 intersections is similar with a value of 24.41%. If $\beta = 0$, all test instances can be solved optimally, and the required CPU time is shorter. It increases from 3.8 for two intersections to 9.98 for 15 location intersections. When β gradually increases from 0 to 1, the required CPU time increases from on average 48.95 units of CPU time for $\beta = 0.001$ to 453.51 units for $\beta = 0.1$ for a test instance with 15 intersections and $\alpha = 1$.

For test instances with a larger number of intersections, e.g., 100, a feasible solution is found within the *WorkLimit*, however, the gap of this solution increases to 256.84%. For 1,000 intersections, no feasible solution can be found for $\alpha \wedge \beta = 1$, within 1,200 units of CPU time for $\beta = 0$.

The computational experiments showed the different levels of computational complexity linked to the two problems combined in the presented MILP model. A higher degree of computational complexity is introduced through parts of the model related to the placement problem, where the CPU time increases exponentially with an increasing number of intersections. The parameters α and β control the impact of individual problem parts on the overall problem. For higher levels of intersections and profiles, the model does not yield an optimal solution, and the optimality gap is substantial. For problems with 1,000 overlaps, the solver could not determine a feasible solution in a reasonable time. In these cases, setting $\beta = 0$ can yield a feasible but not optimal solution.

3.4.2 Three algorithms to solve the CSP-EVCSP

As the computation experiments showed, the Gurobi solver can only find solutions to the combined CSPP and EVCSP for smaller problem sizes or in certain parameter configurations. The following section presents three different approaches, that combine different established algorithms and heuristics to solve larger instances of the CSP-EVCSP:

- *single vehicle optimization model (SVOM)*
- *successive community optimization (SCO)*
- *Set covering problem (SCP) and charge-level heuristic + EVCSP*

The general components of each strategy are summarized in Figure 3.9. Two charging strategies, the SVOM and the SCO decompose the optimization problem, by overall optimization problem into smaller sub-problems or a single sub-problem, that can be optimized optimally using the commercial solver. The third solution approach decomposes the problem by the type of problem while still considering certain prerequisites and problem-dependencies through a custom charging heuristic. Depending on the relation of C_s and O_i, the solution strategies achieve different results regarding the solution time and quality, which will be examined in the last section of this chapter.

3.4.2.1 *Single vehicle optimization model (SVOM)*

Both the single vehicle optimization model (SVOM) and the successive community optimization (SCO) approach decompose the complete problem into sub-problems that can be solved in an acceptable time. The placement and scheduling are performed iteratively for one profile at a time to build a complete solution and both approaches can be classified as constructive metaheuristics (Sörensen and Glover, 2013). The solution strategy iteratively optimizes the profiles by decomposing the overall problem into sub-problems. The goal of a sub-problem is to calculate the optimal charging locations (cp_{ls}) and charging times (ch_{il}) for a single profile. The identified charging locations and charging times are then stored, and the optimization of the next profile is performed. If one of the previously identified charging locations overlaps with a location in the optimization of the current profile, this location is considered as an alternative charging location in the optimization. No additional location costs C_s are incurred for alternative charging locations, but charges can only be carried out if no other profile is charging in the interval in question. If these conditions are met, charging can be carried out and the charging costs (O_i) are taken into account in the objective function.

3.4.2.2 *Successive community optimization (SCO)*

As shown in Section 3.4.1.2, an increasing number of intersections between profiles increases the time to find an optimal solution. At the same time, the costs associated with the placement of a charging station (C_s) can potentially be reduced. The successive community optimization solution strategy takes this into account by optimizing profiles in communities identified through a combined community detection and block modeling algorithm.

As defined in network science, a *community* is a set of nodes in a graph, where the density of edges within the community is higher than to edges outside the community (Girvan and Newman, 2002). To identify such a community structure within a network or graph, several community detection or graph partition algorithms have been developed and are applied in multiple disciplines (Clauset et al., 2004; Girvan and Newman, 2002; Javed et al., 2018). In real-world examples, it may be possible to divide the nodes of a network or graph into communities, by analyzing mobility patterns, leading to a better understanding, e.g., of the spatial structure of a city (Wang et al., 2018; Yildirimoglu and Kim, 2017).

An undirected weighted graph, as illustrated in Figure 3.4.1.2, is the basis of the algorithm. The nodes represent individual profiles, and the edges are the intersections between them. The weights on the edges are determined by the number of intersections between the profiles. The basic idea of the algorithm is to separate the graph into communities with a predetermined maximum size, while aiming to maximize the weighted intersections within a community.

Several algorithms have been proposed for community detection or graph partitioning (Clauset et al., 2004; Girvan and Newman, 2002; Zhou et al., 2017). Methods can generally be divided into agglomerative and divisive methods. Agglomerative methods successively add edges between nodes, thereby merging them into communities, while divisive methods remove edges between nodes until no further improvement of a predefined objective is possible (Javed et al., 2018). A restriction of the community size is not desirable and therefore is currently not considered in the pertinent methods.

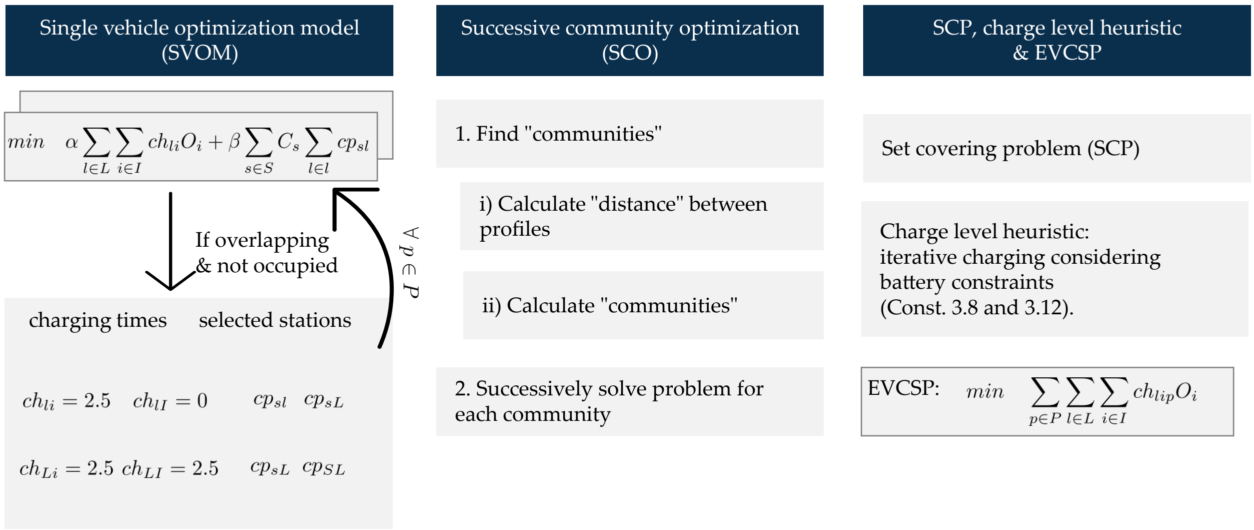


Figure 3.9: Three approaches for solving the CSP-EVCSP.

To detect communities and separate the overall graph into smaller subgraphs, an agglomerative community detection method is used in this thesis. Specifically, the Clauset-Newman-Moore greedy modularity maximization algorithm, as implemented in the networkx Python package, is applied (Clauset et al., 2004; NetworkX Developers, 2022). The aim of the algorithm is to maximize *modularity* as defined by Newman (2010). The calculation of the modularity (Q) of a network is shown in Equation 3.17 and differs for a weighted and unweighted network. For an unweighted network, m represents all edges of the network, while m is equal to the sum of all edge weights in a weighted network (as is the case with the problem at hand). A_{ij} is a weighted or unweighted adjacency matrix of the network with nodes i and j, while k_i represents the degree of node i in the network (i.e., the number of connections it has with other nodes). $\delta(c_i, c_j)$ is a *Kronecker delta function* that is equal to 1 if nodes i and j are in the same network and 0 if not.

The modularity score can be calculated for different community structures within a network. In a weighted undirected network, the number range of modality can range from -0.5 to 1 (Brandes et al., 2008). However, the upper bound is dependent on the general network structure and may be well below a value of 1 in certain networks (Newman, 2010). A modularity score of 0 indicates that the created community structure is not better than randomly generated communities. Positive values generally indicate a community structure that is better than a random allocation (Newman, 2004).

$$Q = \frac{1}{2m} \sum_{ij} \left(A_{ij} - \frac{k_i k_j}{2m} \right) \delta \left(c_i, c_j \right) \tag{3.17}$$

The solution of the Clauset-Newman-Moore greedy modularity maximization algorithm can result in large communities. These communities may be to large to be optimally solved within a reasonable timeframe. In a second step, the resulting communities are therefore broken up into *sub-communities* of a predefined size and sorted using a greedy swap algorithm. To achieve this, a weighted adjacency matrix is calculated for each community determined by the Clauset-Newman-Moore algorithm. Within these communities, *sub-communities* of a predetermined size are defined. Swaps are executed between profiles of sub-communities. To determine whether a swap is executed or not, a weighted intersection score, as presented in Equation 3.18 is calculated for each sub-community. A swap of two profiles is executed if the total intersection score of both considered sub-communities is increased. The algorithm terminates if no further swaps can be found to improve the intersection score I.

$$I = \sum_{ij} (A_{ij})\, \delta\, (c_i, c_j) \tag{3.18}$$

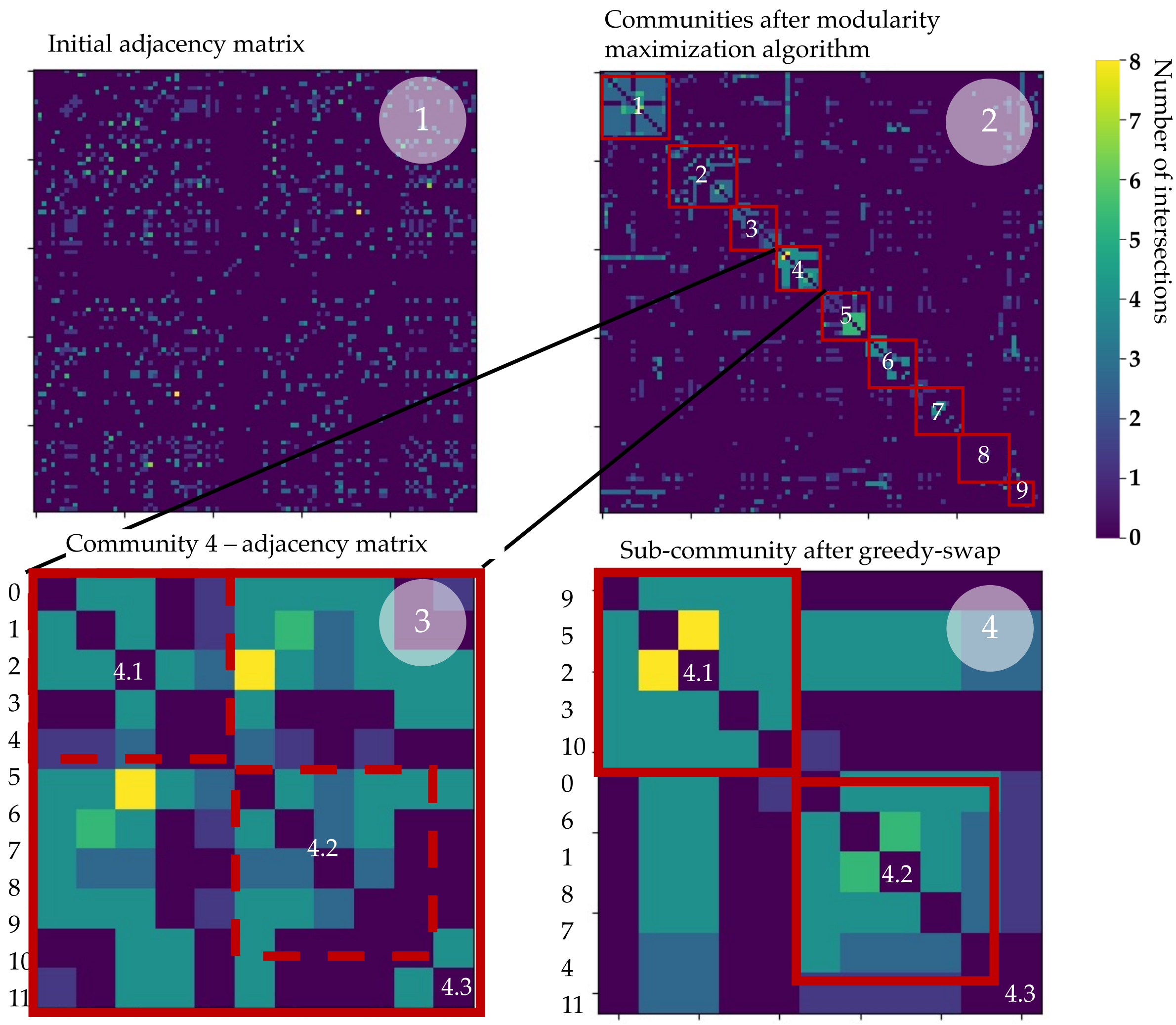


Figure 3.10: Community creation process for 100 profiles and a maximum community size of 5 using the SCO solution strategy.

An example with 100 profiles and a required maximum community size of 5 profiles is presented in Figure 3.10 and shows how the previously described community detection algorithm is able to cluster intersecting activity profiles. The numbers in the upper right corner of the adjacency matrix indicate the steps of the complete algorithm. The first adjacency matrix is not sorted. The number of intersections between profiles is highlighted by different color codes. The Clauset-Newman-Moore algorithm yields ten different communities of different sizes (see the second adjacency matrix in Figure 3.10). Most communities have a size that exceeds the predefined community size of 5. Therefore, the communities need to be further divided. For example, as illustrated in the third step, the fourth community is further divided into 3 sub-communities. These sub-communities are then optimized using the greedy-swap method. For instance, when comparing sub-community 4.1 before the greedy-swap heuristic and after, it can be observed that profiles 2 and 5 have the highest number of overlaps and are swapped into the same sub-community.

The results for an example with 100 nodes and varying community sizes is presented in Figure 3.11. In the upper left corner, the unsorted weighted adjacency matrix is given, with weights representing the overall number of intersections between two profiles. The other matrices show the results for maximum community sizes of two, five and ten. The matrices are sorted according to the affiliation with a sub-community, e.g., in the top-right corner, for a maximum community size of two, the intersection of the first two values of rows and columns one and two belong to the same sub-community. The results of the algorithm are evaluated regarding their weighted modularity and weighted intersection score. The results are calculated for the algorithmically generated communities as well as for randomly generated communities and summarized in Table 3.5. While Newman (2004) suggests a modularity value above 0.3 to be attainable to represent satisfactory communities, this bound is not directly applicable to the results of the presented algorithm, as communities found by the Clauset-Newman-Moore algorithm need to be further separated, to reach the attainable community size decreasing the modularity score. Nevertheless, in the example presented, the algorithm performs better than a random assignment of nodes to communities concerning both performance measures.

In the final step, the optimization model proposed in Section 3.4 is used to optimize the placement and charge process within each community. Similarly as for the SVOM, the solution concerning the stations placed and their availability is passed on to communities that are optimized downstream of the current optimization.

Table 3.5: Modularity and intersection score in relation to detection algorithm and community size.

size	Community composition	Modularity	Intersection Score
2	random communities	-0.012	3,558
	community detection algorithm	0.021	5,602
5	random communities	-0.013	1,372
	community detection algorithm	0.085	2,808
10	random communities	-0.015	614
	community detection algorithm	0.142	1,930

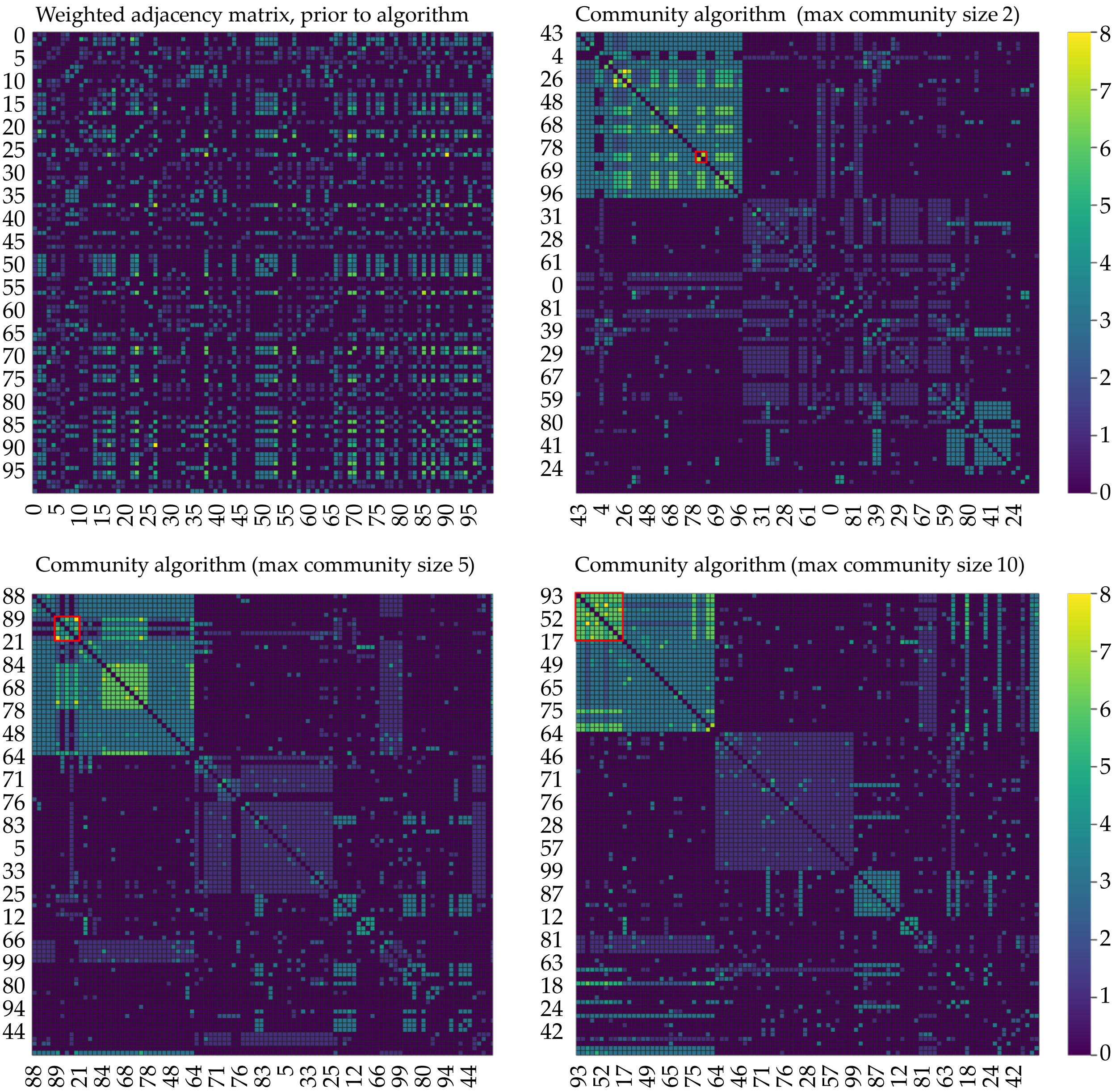


Figure 3.11: Adjacency matrices sorted according to the results of the community detection algorithm.

3.4.2.3 *Set covering problem (SCP) and charge-level heuristic*

Finally, a third solution method is presented, taking into account the solution approaches that have been applied to solve CSPP in previous studies. In a first step, a set covering problem is solved. To calculate a solution, for the entire CSP-EVCSP, a heuristic is applied to supplement the solution of the initial solution, and finally, the charging process is re-optimized using a commercial solver.

The set covering and charge-level heuristic approach is based on set covering problem. As it is not possible to explicitly consider the SoC of vehicles in this type of problem formulation, the resulting stations are used as a starting solution for a charging heuristic. The set covering problem (SCP) is one of Karp (1972) 21 NP-complete problems. It assumes a finite set A and a collection B of subsets $s \in S$. Each element of the set can be covered by at least one subset (Cormen et al., 2017).

$$A = \bigcup_{S \in B} S \tag{3.19}$$

The aim of the model is to determine the minimal number of subsets that cover every element in the finite set A. The problem can be implemented as an integer optimization problem (Konjevod et al., 2002). If the costs of adding a subset to the solution are equal for all subsets, the problem is referenced as unweighted SCP, while the weighted SCP assumes varying costs over the subsets, and the overall costs are minimized, as illustrated in Equations 3.20 to 3.22.

$$\min \quad \sum_{b \in B} c_b x_b \tag{3.20}$$

$$\sum_{b \in B} y_{ab} x_b \geqslant 1 \qquad \forall\, a \in A \tag{3.21}$$

$$x_b \in \{0, 1\}, b \in B \tag{3.22}$$

In this model, x_b is a binary variable that determines whether the subset b is considered in the solution or not, while c_b denotes the cost of including this subset in the solution. The parameter y_{ab} is equal to one, if the subset b covers the element a. The Constraints 3.21 ensure that each element a of the finite set A is covered by the solution.

SCPs can be found in several research fields and problem types (Cormode et al., 2010). For example, Kritter et al. (2021) apply a SCP to optimize surveillance camera placement, while Li and Huang (2014) optimize refueling station placement, and Hosseini and MirHassani (2015) use a SCP in their capacitated recharge station location model with queueing. While Hosseini and MirHassani (2015) apply a greedy heuristic to solve the model, several other algorithms have been developed to solve the weighted and unweighted SCP (Bilal et al., 2013; Rosenbauer et al., 2020; Wang et al., 2021b; Zhu, 2016).

In the application of the SCP in this thesis, it is assumed that the finite set A contains all profiles, while the subset B represents the charging locations. y_{ab} is equal to 1 if a profile a is covered by the subset (station) b. The cost c_b of including a station (set) b in the solution can represent infrastructure investments (e.g., the variable C_s in the model shown in Section 3.4). This can also account for the amount of electricity a charging station can deliver or its potential profitability.

To solve this SCP, the algorithm developed by Zhu (2016) was applied. It combines a greedy algorithm and the Lagrangian Relaxation Approximation Method. The author shows that the heuristic can solve test instances from Beasley's OR Library (Beasley, 1990) efficiently and, on average, can find an optimal solution for 99% of the SCP test instances in the library.

The initial solution to the SCP is not necessarily a feasible solution to the complete problem, as the constraints related to the EVCSP are not considered (e.g., feasible values of SoC or restrictions on simultaneous charging). Although all profiles may be covered by the calculated solution, the available charging times may not be sufficient to meet the energy requirements of the BEVs. Constraints 3.8 to 3.12 are not considered and can be violated by the solution of the SCP. Therefore, two additional steps are necessary to verify the feasibility of the determined solution and restore feasibility in cases where constraints of the EVCSP are violated.

The battery of a vehicle is discharged by mobility activities modeled through constraint 3.8. The SoC may not drop below 0 or above B^{max}. To ensure that the SCP solution can meet the charging requirements of the vehicles, a validation check of the solution is conducted. To achieve this, the battery is charged by the maximum possible value at each charging location given in the solution of the SCP. If the battery of a vehicle cannot be sufficiently charged, when considering the determined solution, the SCP is re-executed with modified cost factors. For infeasible profiles, the charging places (b) currently intended in SCP solution are identified and the costs c_b of the place b, which does not adequately cover the charging requirements of the profile a, are increased. The SCP is then solved again. This procedure is repeated until a feasible solution, to this part of the problem, is found.

The solution calculated by the iterative application of the SCP allows simultaneous charging of vehicles at one charging station and therefore can possibly violate the Constraints 3.12. To consider this circumstance, the potential charging nodes determined by the SCP are added to the preliminary solution set Y and passed to a charging heuristic.

The basic idea of this part of the algorithm (the charging heuristic) is to supplement the solution set Y by additional stations to ensure that all of the EVCSP constraints, not considered in the SCP are met. The heuristic tracks the SoC of each vehicle and the occupation of the charging stations. To determine the order in which to check individual profiles, the urgency of a charge is determined for each vehicle. For this purpose, the interval i is determined at which the SoC of each vehicle (profile) would be depleted by mobility activities without charging. The profile with the earliest interval i is considered to have the most urgent charging needs and is thus selected. The charging activities of this profile are optimized until the interval of battery depletion i, adheres to the charging constraints. This is achieved by considering all possible charging locations in the set Y that are visited by the vehicle up to the interval i. If battery limitations are violated after charging the vehicle at all possible stations in Y, all other stations that are visited (and are not in set Y) are additionally considered. If multiple stations are visited, two parameters are used to select from the potential stations. The first parameter is the fraction of the total charge required by the profile that can be supplied by a charging station not in the set Y. If two stations have the same fraction of charge they can supply to a vehicle, a second parameter is used as a reference, that is, the charge that can be delivered to all other profiles over all intervals. The best station is added to the solution set Y. If the charging requirements of a vehicle are met, the next urgent profile/vehicle is considered. The selected intervals are saved for subsequent executions of this part of the algorithm. The selected time intervals are discarded from the feasible set of charging intervals for the stations for other profiles. These steps are repeated until the charge of all vehicles has been met.

The results of the algorithm present a feasible solution to the CSP-EVCSP. However, since variable costs are not considered, the solution can be improved by solving only the EVCSP. To do so, the cp_{ls} variable is set to 1 for the charging places determined by the SCP and heuristic (in the solution set Y) while for any places not considered in Y, cp_{ls} is set to 0. As illustrated in Section 3.4.1.2, this reduced problem can be solved in a fraction of the time compared to the complete CSP-EVCSP.

3.4.2.4 *Evaluation of the identified solution strategies*

The solution methods yield different results with respect to the computing time and the quality of the results. Therefore, the methods are compared using a test instance regarding their computational time and solution quality. To evaluate the performance of the three solution approaches presented, a test instance with 100 profiles, 35,040 intervals and 600 different charging places was solved using each strategy with respect to different parameters. The goal of these calculations is to determine whether a solution strategy performs better with certain parameter configurations, i.e, leading to a lower objective value.

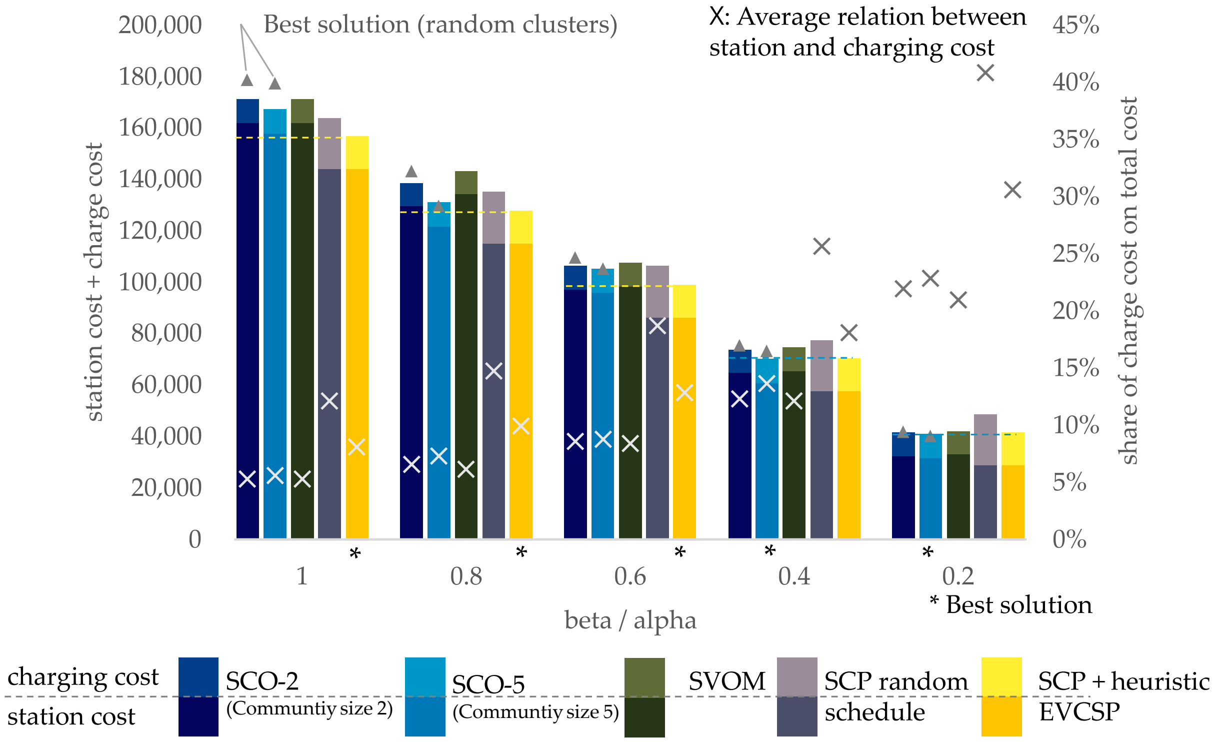


Figure 3.12: Calculation results for the different solution methods on exemplary test instances.

Figure 3.12 shows an overview of the station, charging, and total cost for five different solution strategies. Furthermore, five different relations between the charging cost ($\beta ch_{lip} O_i$) and the station cost ($\beta\ C_s$) are differentiated and simulated by modifying the relationship between α β. Station costs gradually decrease as β (the parameter multiplied with the station cost) decreases. If $\beta/\alpha = 1$, the station (one-off) costs are dominant in the total cost. If $\beta/\alpha = 0.2$, the share of the volatile cost component of the total cost increases. The secondary ordinate axis represents the share of the charging costs in relation to the total costs.

Communities of sizes two and five were created by applying the Clauset-Newman-Moore algorithm and the greedy heuristic presented in the previous section. To evaluate the performance of the algorithm, communities were also randomly generated (and the calculation results are represented by the top tip of the triangle in Figure 3.12). The other three solutions strategies assessed are the individual solution approach, and the solution by problem type approach, with two different calculations of the charging cost: In one case, the costs are calculated under consideration of the volatile charging profile (EVCSP), in the other case, the costs are not considered. To assess the impact of neglecting this part of the optimization problem, charging costs are calculated ex post according to the unoptimized charging pattern.

The results show that the base scheduling model minimizes total costs until the charging cost accounts for approximately 16% of the total cost. If this value is exceeded, the SCO solution method with a community (of size five) performs best. The communities generated using the Clauset-Newman-Moore algorithm also reduce total costs by 2% - 6% for the communities of size two and of size five, when comparing these costs with those achieved through randomized communities. This advantage decreases with an increasing share of the charging costs of the total costs. The problem instance with a community of size five cannot be solved to optimality in each instance, which also leads to higher total costs. In general, the results suggest that the developed solution strategies perform differently depending on the model configuration. For different model configurations and costs of charging the vehicles and placing charging points one solution strategy can lead to a lower overall objective value in comparison to the others.

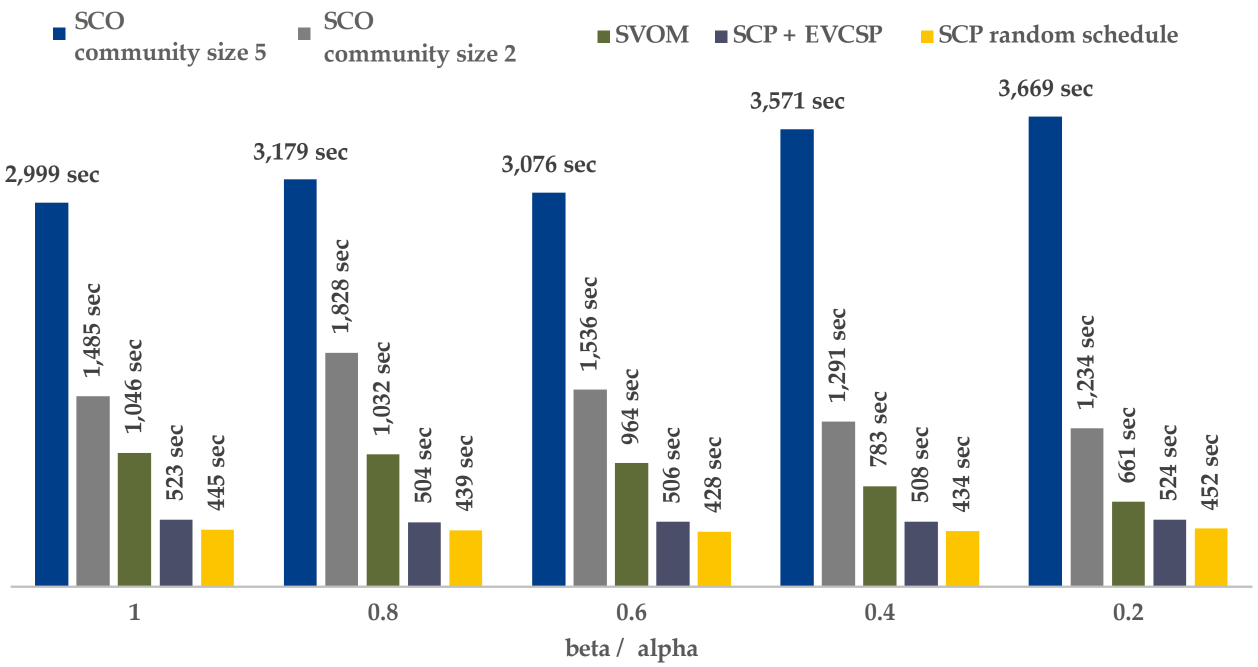


Figure 3.13: Solution time for different solution methods on exemplary test instances.

Figure 3.13 shows the calculation time of the different solution methods. For calculations with different community sizes, it can be observed that the calculation time is on average longer for a community size of 5 compared to a community of size 2. The SVOM strategy is faster than the random community solution of size 2, however, the SCP solution is by far the fastest solution, taking only about 500 seconds.

3.5 SUMMARY

This chapter provides an overview of the current scientific literature on the planning of EV charging stations and the scheduling of EV charges. In contrast to previous approaches, in which the location and charge scheduling of charging stations and vehicles are treated separately, an approach is presented that allows for a concurrent consideration of both components in an optimization model.

First, a mixed-integer linear optimization model is formulated that simultaneously minimizes volatile charging costs and location costs. The model is then solved using the Gurobi solver. A computational study shows that exact solutions using the solver are not possible for any problem configuration and size. In particular, overlapping charging locations by several profiles can lead to unsolvable problem instances. As these overlaps are an essential factor in the CSPP and can significantly reduce the number of required charging station and to be able to consider a representative number of profiles, three different solution strategies are developed and presented. These strategies divide the overall problem in different ways into solvable sub-problems. The first two constructive metaheuristic approaches iteratively solve the problem for single profiles or groups of profiles, the third approach first minimizes the number of charging locations and then adjusts the solution to satisfy all constraints of the mixed-integer optimization model. The application of the three solution strategies to an exemplary data set shows that the quality of the solution differs depending on the solution strategy. While the single vehicle optimization model and successive community optimization identify good solutions for problems in which volatile charging costs and OPEX dominate and the SCP and charge-level heuristic solution strategy leads to better solutions in cases where location costs (e.g., CAPEX) dominate. In cases where the cost of a charging point outweigh those for charging a vehicle, the SCP and charge level heuristic can be expected to perform well, while for instances with low costs for placing charging points, the SCO solution strategy should be preferred. Generally, a larger community size leads to a better objective value. However, depending on the number of intersections between profiles, the community sizes may be limited to 2-10 profiles if the model is to be solved optimally.

While the solution strategies in this chapter were applied to fictitious test instances, the next chapter discusses how the required model parameters can be derived from real mobility and GIS data and how variable costs and emissions can be estimated. In Chapter 5, the developed model is used to plan the charging infrastructure and charging of EVs in the city of Essen with the help of the solution strategies.

4 DERIVATION OF DRIVING AND ELECTRICITY PATTERNS

The decision on where to place a charging station can be based on various factors. A common assumption is that locations with a high dwell time have the potential to provide more electricity to vehicles and are therefore preferable from an economic perspective. Different approaches have been used to model the mobility behavior of individuals in the scientific literature. The CSP-EVCSP model developed in this thesis and presented in Chapter 3, requires geographically and temporally resolved driving patterns that were obtained in a multi-step process, described in the following section.

In addition to deciding where to place a charging station, the optimization model takes into account the decision of when to charge a vehicle. This decision is based on several factors, such as the location of the vehicle and the volatile charging costs. Charging costs are calculated on the basis of an additional linear optimization model. The model is used to approximate current and future energy generation patterns and calculate volatile prices and emissions, and is presented in the second part of this chapter.

4.1 DERIVATION OF GEOGRAPHICALLY AND TIME-RESOLVED DRIVING PATTERNS

In this section, the derivation of time-resolved driving patterns is described. First, an overview of existing studies and databases that have been used to generate mobility profiles for EVs is presented, before a multi-step process for generating the required driving patterns is developed.

4.1.1 Existing approaches for the derivation of travel data

The travel data of individuals can be collected, aggregated, analyzed, and published in different ways, depending on the intended use. For modeling the use of EVs Daina et al. (2017) classify the current research by the resolution of the mobility data and the applied modeling techniques used. Concerning the time resolution, they distinguish between annual mileage and daily pattern models. The data used in annual mileage or vehicle ownership models are highly aggregated over a yearly or longer time horizon. The resulting annual kilometers driven can be classified by transport mode or vehicle characteristics and allow quantifying changes in the composition of the vehicle fleet (Papu Carrone and Rich, 2021) or the relationship with other factors, for example, the effects of the COVID-19 pandemic on mobility behavior (Bhaduri et al., 2020; Wu et al., 2021). The results of these studies may be of interest to several decision makers. Car manufacturers can use the data to quantify the changing interests of consumers, while energy companies can use the data to forecast future energy consumption or the required energy mix in the mobility sector.

For scenario planners, these studies can also help to assess the energy consumption attributed to the transport sector when switching to an electricity-based power train (Quaschning, 2016) or to estimate the general ecological impacts of the mobility sector (Rolim et al., 2012; Schwarzinger et al., 2019).

Annual mileage models can support decisions on a longer time-scale; however, most decision support models involving the coordination of the charging of EVs require a higher resolution. Daily pattern models capture travel information on an hourly scale or even finer. The data are not represented on an aggregated yearly scale as in the annual mileage models, but by individual activities or trips. These models estimate travel behavior based on travel surveys or simulate travel behavior within a city or in a geographic region. For example, Hartmann and Özdemir (2011) use a national travel survey to create different travel schedules on an hourly basis. They use this information to create different scenarios of the use of EVs and assess their impact on the power grid. Waraich et al. (2013) apply an agent-based transport simulation to derive the mobility pattern of EVs. This approach allows for a more detailed assessment of different types of integration between the electricity system and the mobility sector. Only a limited number of studies consider an interaction between charging behavior and travel patterns. Unlike the studies by Döge et al. (2016), Kullman et al. (2021), and Soares et al. (2016), in most studies published in the past no additional trips or detours are considered, for example, to accommodate different characteristics, such as the lower range or charging times of EVs.

Table 4.1: Overview of national activity surveys in Germany.

	KiD Kraftfahrzeuge in Deutschland	MiD Mobilität in Deutschland	REM Regional Eco Mobility	MoP Mobilitätspanel Deutschland	ZVE Zeitverwendungs- erhebung
Years	2002,2010	2002,2008, 2017	annually since 2011	annually since 1994	2012/2013
Vehicles(trips)	50,928 (117,377)	34,601 (193,290)	630 (91,422)	3,100 (70,000)	11,000 individuals
Trip Distances	✓	✓	✓	✓	
Trip Purpose	✓	✓		✓	✓
Parking Location	✓	✓			
Vehicle Type	private and commercial	private	commercial	private	private
BEV study	Döge et al. (2016) and Hacker et al. (2015)	Hartmann and Özdemir (2011) and Linssen (2019)	Plötz et al. (2014)	Gnann et al. (2012) and Plötz et al. (2014)	Nebel-Wenner et al. (2019)

Due to the current early stage of market penetration and the limited diversity of BEVs no systematic surveys for EVs are available for Germany at this stage. However, a selection of national mobility and activity surveys is presented in Table 4.1. Data acquisition for these surveys has been conducted for specific years and/or annually. The "Kraftfahrzeugverkehr in Deutschland" (KiD) survey is conducted annually. The operators of commercial and private vehicle vehicles must document all journeys they made on a specified day. Most of the travel data recorded corresponds to commercial users. This survey has been used mainly to model the use of commercial EVs, for example, in studies by Döge et al. (2016) and Hacker et al. (2015). The Mobility in Germany *(ger. Mobilität in Deutschland)* (MiD) study is the most recent study conducted in Germany. Samweber et al. (2016) develop a methodology to generate coherent and, in terms of statistical totality, correct annual driving profiles of individual EVs from the single-day driving profiles collected in the study "Mobility in Germany 2008". The 'REM 2030 Fahrprofile' documents the trips of 630 commercial vehicles over a three-week period, which in total results in 91,422 trips. However, the schedules do not contain information on destinations and travel purposes. The 'Deutsches Mobilitätspanel' (MoP) documents various types of mobility activities for private purposes regardless of the underlying transport mode, and therefore, also documents walking trips or public transportation trips. Every year, the mobility activities of 3,100 individuals are documented for 7 days, resulting in 70,000 trips. Schedules contain not only information about travel distances, but also travel purposes. Finally, the 'Zeitverwendungserhebung' *(engl. time use survey)* (ZVE) has been conducted three times in the years 1991/92, 2001/02, and 2012/13 by the German Federal Statistical Office. In total, 5,040 households and more than 11,000 individuals participated in the survey (Statistisches Bundesamt 2015). As the study provides not only travel information, but also the utilization of household appliances, Blaufuß et al. (2019), Nebel-Wenner et al. (2019), and Reinhold et al. (2018) used this data for empirical and synthetic load forecasts of user-dependent appliances, without explicit consideration of driving profiles, as in the studies mentioned above.

4.1.2 Geographically and time resolved driving patterns

To build on the work documented in previous studies and to allow the creation of geographically and time-resolved driving patterns, the developed process builds on the data of the "Zeitverwendungserhebung" (ZVE), and the database developed by Blaufuß et al. (2019), Nebel-Wenner et al. (2019), and Reinhold et al. (2018). The process of generating these mobility profiles is documented in the following sections. First, the general makeup of the database is presented. The database is extended by assigning different types of location to activities. This information enables the modeling of travel profiles by applying an algorithm. The daily vehicle movement profiles generated in this way are assigned to geographic locations to create geographically and time-resolved driving patterns.

4.1.2.1 Activity database

The developed multi-stage process relies on the activity database created in the research project *NEDS – Nachhaltige Energieversorgung Niedersachsen'* (Blaufuß et al., 2019). The activity database created by Reinhold et al. (2018) shows 231 different activities of individuals throughout the day with a resolution of 10 minutes. The authors clustered these data and conducted an exploratory cluster analysis. The cluster analysis leads to three clusters for weekdays and six clusters for the weekend. A more detailed analysis of each cluster can be found in Blaufuß et al. (2019). The 231 activities where assigned to 22 broad categories according to their similarity, e.g., work activities (main occupation), work (part-time), work (main/part-time) are all assigned to the occupational activities category.

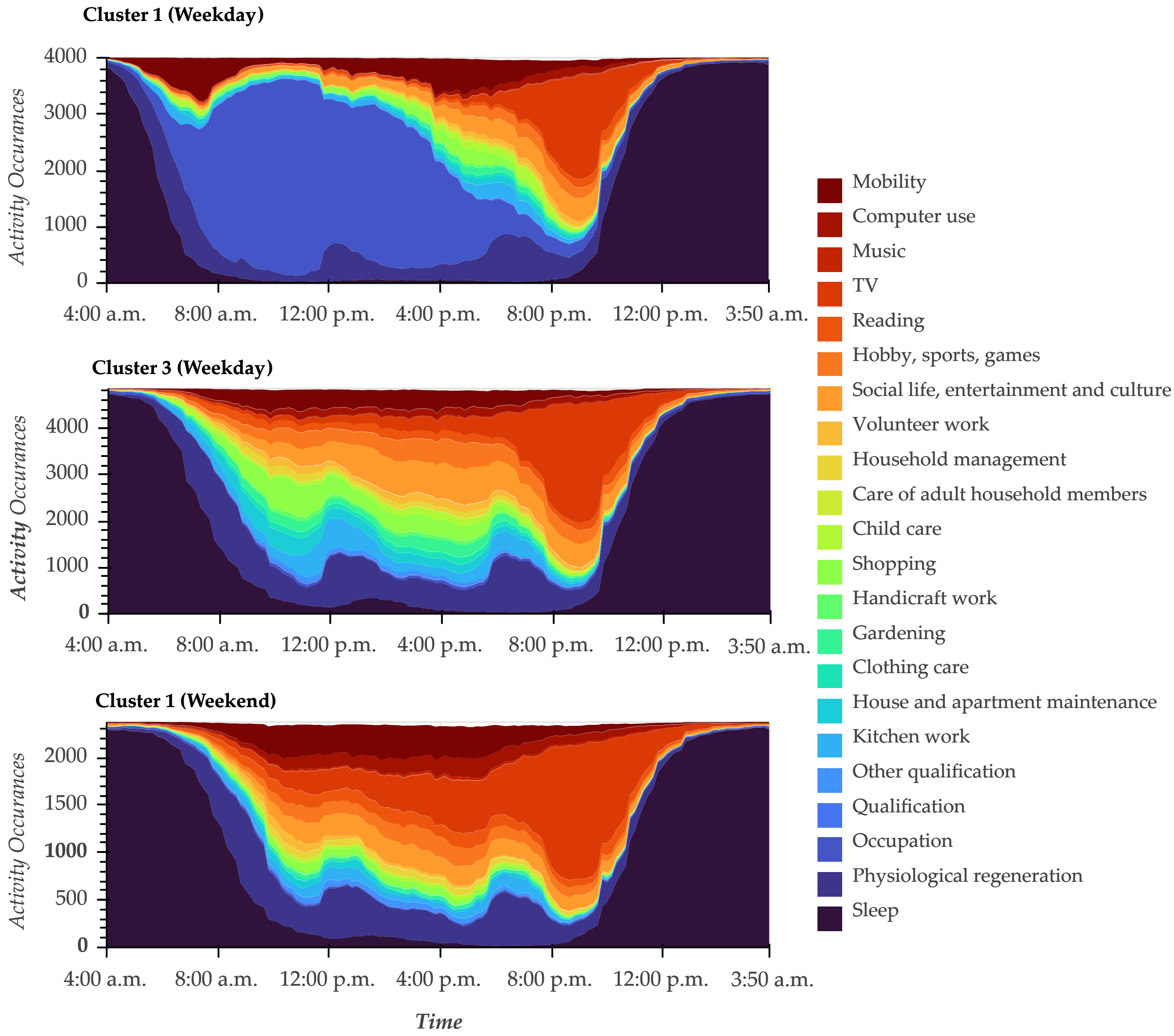


Figure 4.1: Exemplary depiction of three activity clusters, grouped by the 22 different activity categories, based on the clusters and database developed by Reinhold et al. (2018).

Figure 4.1 shows the occurrence of the 22 different activity categories throughout the week or a weekend day for Cluster 1 and Cluster 3. Cluster 1 is characterized by occupational activities from 6 a.m. to approximately 7 p.m. on weekdays. The peak of mobility activities can be observed shortly before the peak of the occupational activities, indicating that mobility activities end at the workplace. Cluster 3 is characterized by television-related activities beginning at 8 p.m., with shopping and childcare activities distributed throughout the day. The second cluster (not depicted in Figure 4.1) can be characterized by a variety of qualification activities throughout the day. For the six weekend clusters, all but Cluster 4 show the same frequency of television-related activities in the evening hours with different activities such as shopping and TV (Cluster 1), social life (Clusters 3 and 4), occupational activities (Cluster 6) or hobby, sports, games (Cluster 5) throughout the day.

To be able to assign a geographic location to each activity, the first six different locations (home, work, university/school, shopping location, entertainment venue, authorities/places of assembly) and two attributes (unknown, mobility) are added to the database. The 231 activities are assigned to one of these six locations or the two attributes. If an assignment is ambiguous, it is assigned the attribute *unknown*. If the activity constitutes a mobility activity, the mobility attribute is assigned. As shown in Table 4.2, 45% of the activities are assigned to these two attributes. The highest number of activities assigned to the locations *Home* followed by activities of the category *University/School*.

Table 4.2: Overview of the location assignments

location attribute	Activities assigned to location	location appearances	Share of location appearances
Home	52	216,832	46%
Mobility	41	51,576	11%
Work	14	13,541	3%
University/ School	28	9,573	2%
Shopping Location	3	11,488	2%
Entertainment Venue	8	3,537	1%
Authorities/ Places of assembly	7	6,072	1%
Unknown	78	158,281	34%

4.1.2.2 Generation of profiles

The activity data, attribute, and location assignments presented above are used as input for a structured process to generate mobility profiles for weekdays and weekends. A mobility profile for a year consists of 365 daily profiles that are generated successively. Each activity in the database has a predefined start time and end time and can be assigned to a cluster, month, and weekday, allowing to define daily subsets of activities over all activities in the database. After the definition of the type of day (weekend[1]/weekday), month, and cluster, a profile can be defined for a single day. The algorithm to achieve this is presented in the flow chart in Figure 4.2. The process has several functions that are used to draw an activity from the subset of the database (GET: Activity), save a feasible activity (SAVE), or keep track of the current stage and attributes of the generated profile (UPDATE). In each step of the algorithm, the current time, location, and previous activity are tracked.

The sequence to generate a daily driving profile starts by creating a subset of the database that meets the month, the cluster and the type of day of the current position of the algorithm. The algorithm successively concatenates activities to create the daily profile. To select a daily activity, the subset of the database is filtered according to the current "temporal" position of the algorithm. For example, for the first day in the year that is, the first execution of the algorithm, the start time of the first activity is set to 00:00 a.m. As no previous activity has been extracted from the database, the algorithm randomly selects an activity that meets the corresponding starting time and adds it to the daily profile. The current "temporal" position of the profile is updated to the time the selected activity ends and serves as the starting time for the next activity drawn from the subset. To create a realistic mobility and travel profile, activities are selected according to a number of predefined conditions and parameters. As each activity is assigned to one of six locations or assigned the attribute *mobility* or *unknown*, this information can be used to influence the algorithm. The main assumption of the algorithm is that the location of a profile can only change if a mobility activity is conducted, otherwise the activity has to be located at the same location as the previous activity. Two further parameters are used to shape mobility profiles. The parameter $MaxTrips$ restricts how many activities assigned to the mobility attribute can be considered by the algorithm per day. The parameter $MaxMobility$ restricts the total mobility time of a profile per day. If the activity selected from the subset of the database is assigned the unknown attribute, the location of the previous or following activity (if the previous activity is a mobility activity) is adopted. The process continues until the end time of the last activity is greater than 00:00 a.m., that is part of the next day. The end time of this activity and the respective activity are passed as the starting activity for the next execution of the daily mobility generation algorithm presented in Figure 4.2.

1 Public holidays are treated as weekend days.

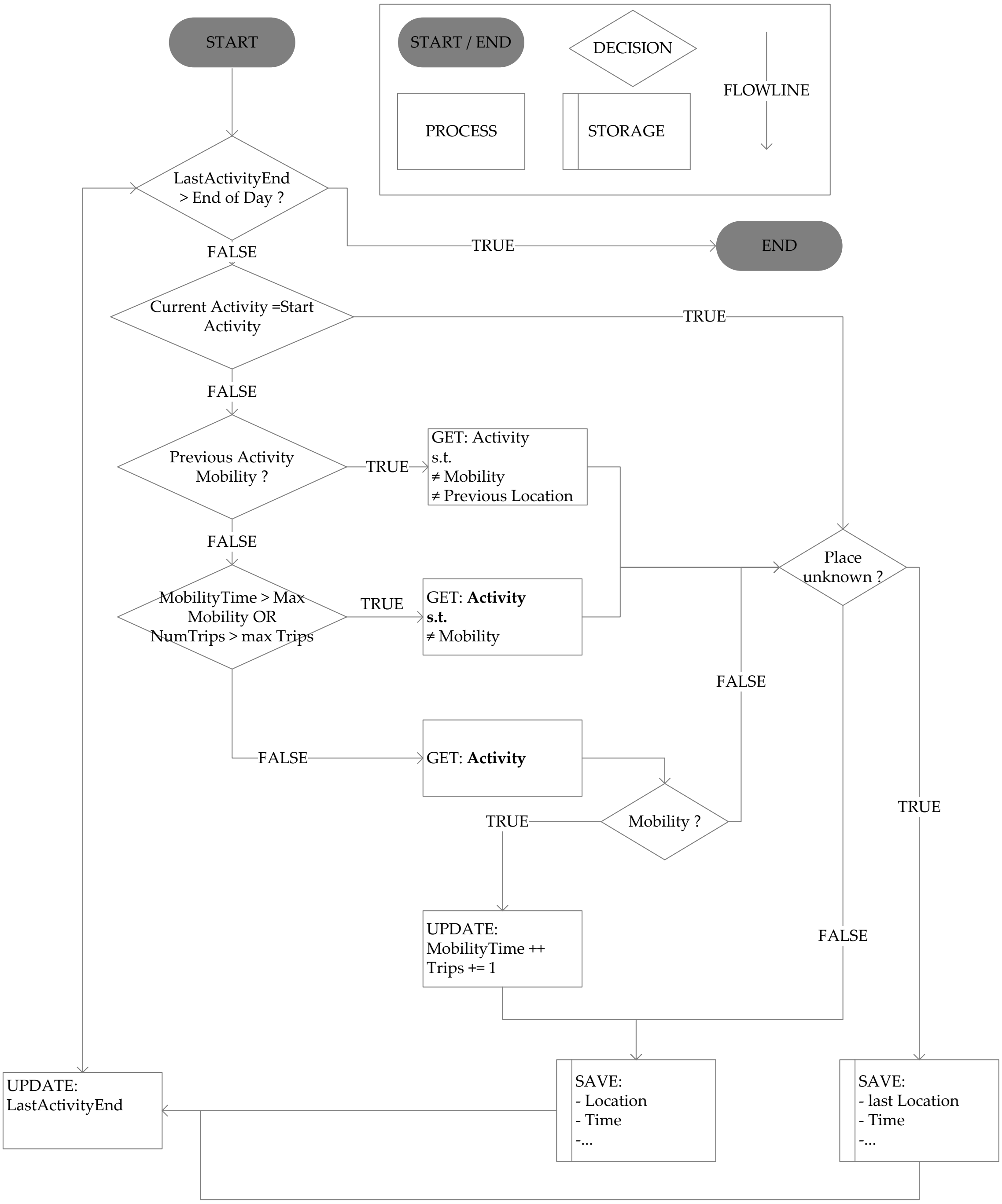


Figure 4.2: Process for the generation of profile for a specific day and cluster type

Figure 4.3 shows an exemplary result for a weekday profile in Cluster 1. Locations and mobility activities are highlighted in different colors. As can be seen, location changes are connected by mobility activities (marked pink). The location of the activity *Fitness - dancing* is ambiguous, and therefore the unknown attribute is assigned. Consequently, the activity is assigned to the next location, in this case a shopping location. In real life, this can mean that the place where this activity is carried out is near or in a shopping center.

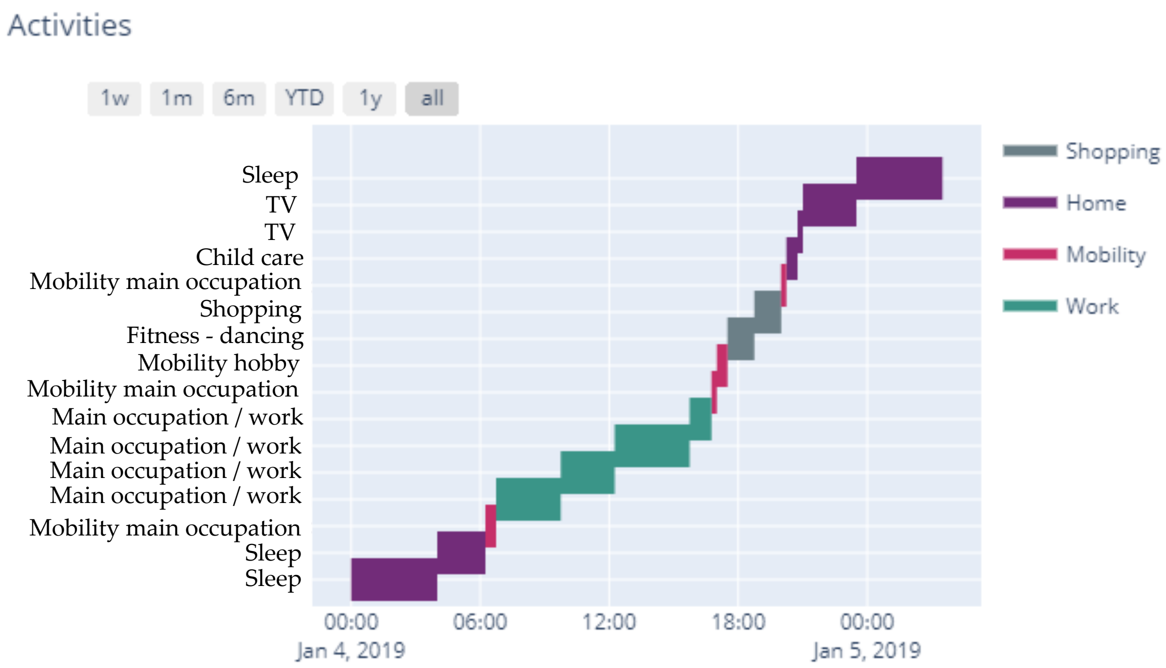


Figure 4.3: Exemplary activity profile for a weekday and cluster 1.

The resulting (average) trips per weekday and (average) driving time per day vary depending on the selection of the parameters $MaxMobility$ and $MaxTrips$. In Figure 4.4 the results of multiple executions of the algorithm for varying weekdays and parameters $MaxMobility$ and $MaxTrips$ are presented. The two figures on the left show the impact of the variation of the parameter $MaxTrips$ when setting $MaxMobility$ at a value of 24 hours. The resulting travel profiles can be compared with existing studies using metrics such as the average number of daily trips, the average daily driving time, or the average kilometers of driving.

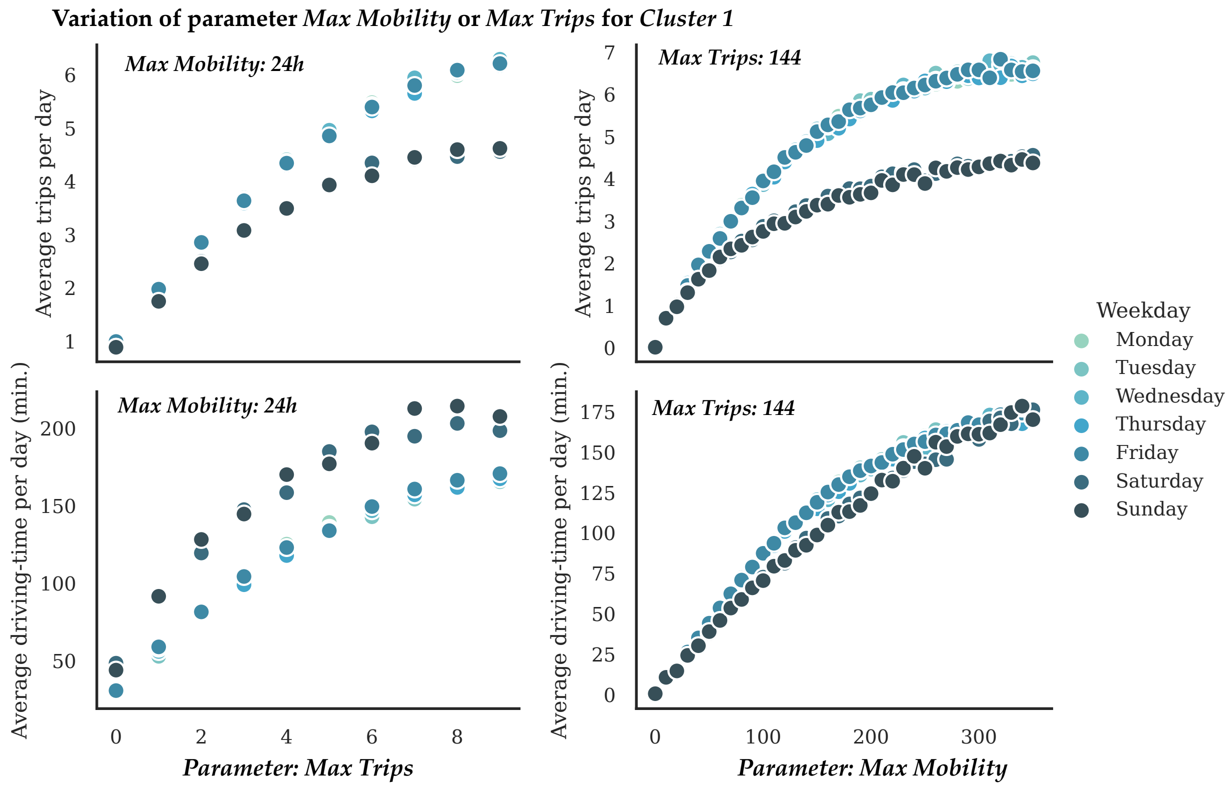


Figure 4.4: Effect of the variation of the parameter MaxMobility and MaxTrip to determine the effect on average driving time and trips per day. Algorithm conducted for 365 days and 25 profiles.

As the activities in the database have a resolution of 10 minutes, the same applies to the resolution of the total duration of the activities. However, the time convention considered in the model is 15 minutes, since this is the standard in the German electricity market and many other major markets around the world (IRENA, 2019c). Therefore, the following algorithm was applied to approximate the 15 minute resolution of the profiles. The time conversion (algorithm 1) rounds the obtained time intervals up or down to the nearest multiple of 15.

Algorithm 1 Time Conversion

```
for activity ∈ activityList do
    tenMinuteInt ← activityDuration.seconds/600
    if tenMinuteInt/600 mod 2 = 0 then
        fifteenMinuteInt ← ⌊tenMinuteInt/1.5⌋
    else
        fifteenMinuteInt ← ⌈tenMinuteInt/1.5⌉
    end if
    convertedActivityList ← fifteenMinuteInt
end for
return convertedActivityList
```

4.1.2.3 *Geographically resolved mobility patterns*

Finally, the generated activity profiles are assigned to real-world geographic locations. Various data sources, such as census data, travel data, surveys, and simulations, have been used to spatially locate charging stations (Pagany et al., 2019). To obtain a list of geographic places that can be assigned to the locations of the mobility profiles, data from the OpenStreetMap database are used (Haklay and Weber, 2008; Jokar Arsanjani et al., 2015). In April 2021, the database had 7,423,982 worldwide users and 8,904,999 relations. As of November 2022, the database has 9,522,245 users and 10,428,335 relations (OpenStreetMap, 2022). As the database is user-generated and maintained, several studies have tried to quantify the quality of the data provided (Basiri et al., 2019; Degrossi et al., 2018) with respect to the precision of the names assigned to places (Antoniou et al., 2016), or points of interest (Jackson et al., 2013). The data quality has been shown to differ between countries and mapped objects, with the map of Germany showing good data quality (Barrington-Leigh and Millard-Ball, 2017). To further improve data quality, several methods have been proposed (Basiri et al., 2019; Li et al., 2020).

The OSM data consist of elements, that is, relations, ways, and nodes used to model real word objects. Elements can be assigned keys and values that describe the modeled object. Various tags have been defined, while tags that use the keys *building* and *amenity* are the most important when identifying locations (OpenStreetMap, 2021). To generate a list of possible geographic locations and assign them to locations, the database is searched for all entries with the keys *building* and *amenity*. The key building can have different values, such as apartments or detached (for detached housing), while the key amenity has values such as a bar or library assigned to it. As presented in Table 4.3, the identified values are assigned to one of the six activity locations in the mobility data. For the derivation of potential charging locations, activity locations are assumed to be potential charging locations with the possibility of constructing multiple charging points (one for each profile) at the location.

The model considers the joint utilization of the charging infrastructure if two geographic locations are within a specified distance from each other. To calculate the distance between two locations, there are several distance measures. For example, the distances between two points can be calculated using the Euclidean distance method, the Manhattan norm, or the Haversine

Table 4.3: Assignment of OpenStreetMap (OSM) attributes to activity locations.

Activity Location	OSM: keys and values
Home	apartment, detached
Work	industrial, commercial, office
University/ School	college, university, civic
Shopping/ Location	retail, supermarket
Entertainment Venue	bar, biergarten, cafe, fast-food, pub, restaurant, arts-centre, casino, cinema, nightclub, theater
Places of /Assembly	government

formula (Purbaningtyas and Arizal, 2019). To estimate the distance between the two locations of the activities, and as has been done in other studies (Maria et al., 2020; Vial and Schmidt, 2019), the Haversine formula is applied and the geographical distance calculated. The formula shown in Equation 4.1 calculates the distance between two points on a sphere. To do so, it takes the longitudinal (λ_i) and latitudinal (φ_i) values of the two points as the radiance and radius (r) of the sphere ($\approx 6,371\,km$ mean radius of the Earth) (Wagner et al., 2013).

$$d_{1,2} = 2r \arcsin\left(\sqrt{\sin^2\left(\frac{\varphi_2 - \varphi_1}{2}\right) + \cos\varphi_1 \cdot \cos\varphi_2 \cdot \sin^2\left(\frac{\lambda_2 - \lambda_1}{2}\right)}\right) \tag{4.1}$$

The resulting activity profiles are geographically and temporally resolved and can be applied in the model. Various further steps could be considered to improve the accuracy of the geographic data, for instance, by ruling out no-parking zones or by considering the number of available parking spaces or general parking area, and the set of potential parking solutions could be reduced.

4.2 CALCULATION OF COST AND EMISSIONS BASED ON ENERGY SCENARIOS

The developed CSP-EVCSP considers one-time and time-dependent factors in the objective function. These factors can be expressed in different units, such as costs or emissions. For historical years, it is possible to use real-world electricity prices and energy generation to calculate emissions. For future energy systems, the share of electricity generation based on renewable primary energy is expected to change substantially, and therefore electricity generation patterns, emissions, and prices of electricity generation can also change. These changes can be considered when planning a future charging network. This consideration is possible using the developed CSP-EVCSP. The integration of CSP-EVCSP into an existing energy system model is beyond the scope of this thesis and would require a different solution approach to consider the interdependence between these models. As cost and emission factors are only an input for CSP-EVCSP, a simplified linear optimization model was used to approximate the prices of electricity and emissions. The model takes advantage of the results of existing energy scenarios for Germany and calculates feasible electricity generation and consumption patterns.

4.2.1 An overview of existing approaches to model energy systems

As highlighted in Section 2.1.4, in addition to the renewable expansion targets set by the German government, several studies have published energy system scenarios for Germany with the aim of presenting possible energy system pathways. Although the legislature provides guidelines for the year 2030, no path to a fully renewable energy system is predefined until the year 2050. Several factors influence the decisions in this context, including technological development. To model and assess uncertainties, energy system analysis and scenario planning are often applied (Witt et al., 2020). To improve understanding of the requirements and functionalities of a future energy system, different energy system models are applied in energy system analysis (Cao et al., 2016; Möst and

Fichtner, 2008). The results of these models can be used to support political decisions and differ in the level of detail of the systematic illustration. Energy system models can be differentiated according to their planning horizon (short- and medium- to long-term planning models) or their level in the decision-making hierarchy (e.g., strategic, tactical, operational) (Möst and Fichtner, 2008; Ringkjøb et al., 2018; Subramanian et al., 2018).

Short-term models that support operational decisions consider a temporal scale of seconds to hours and model the operation of power plant or plant components. By applying Computational Fluid Dynamics or mass and energy balances, operational strategies are modeled and analyzed (Grossmann et al., 1983). Medium-term models consider a scope of days to weeks, e.g., the planning and scheduling of generation or production through the application of mathematical or computational models. Finally, long-term models have a temporal scale of several years. These models are applied to support strategic decisions, for example, for long-term energy forecasting, energy policy support, or supply chain design. To support strategic decisions, top-down or bottom-up models are applied. Macroeconomic top-down models have a high level of aggregation and make use of readily available data, for example, in general equilibrium models (Van Regemorter et al., 2013) or input-output models (Miller and Blair, 2009). Unlike top-down models, bottom-up models have a higher level of technical detail and tend to be limited to the energy sector (Subramanian et al., 2018). For example, electricity market models depict specific areas of the energy system using simulation or optimization approaches. By providing a higher level of detail, they can be used to model the energy system and to enhance the understanding of connections within. Ringkjøb et al. (2018) present an overview of different modeling tools to analyze energy and electrical systems. Energy system models with a long time horizon are difficult to validate, and their results are highly sensitive to the assumptions made.

4.2.2 Derivation of electricity cost and emissions

There are several high-resolution electricity system models for modeling a (future) energy system Misconel et al. (2022). An overview of bottom-up open source energy system models is collected by Openmod (2022). Adapting open-source energy models (for example, the open energy system model of Atabay (2017) or Glismann (2021)) would be beyond the scope of this thesis, as the main focus is on the placement and scheduling of charging infrastructure, and flexible energy prices are only considered as input to the model. To calculate representative costs, emissions, and energy generation in quarter-hour resolution for specific energy systems, a linear optimization model was implemented with the aim of scaling up or down past electricity generation and consumption according to the values specified in energy scenarios to validate the developed CSP-EVCSP.

The linear optimization model for the approximation of electricity costs and emissions is based on published energy system scenarios and the stipulated installed capacities, electricity generation, as well as historical electricity generation and consumption patterns. Figure 4.5 shows the general setup and components of the linear optimization model. The parameters and variables of the model are shown in Tables 4.4 and 4.5.

For electricity generation, two types of technologies are distinguished. Uncontrollable renewable electricity (based on wind and solar) and controllable generation. Uncontrollable electricity

Table 4.4: Electricity system model: Parameters.

NAME	DESCRIPTION
$t \in T$	Set of time intervals
$e \in E$	Set of electricity generators
$s \in S$	Set of different storage types
$LCOE_e$	LCOE per kWh for each power generator
$\psi_{p \cup s}$	Emissions per kWh for each power generator or storage technology
C_s	Capital expenses for storage type s and electricity generators e
G_{et}	Electricity generation of volatile power plant e in time interval t
P_e^{max} ,P_e^{min}	Maximum and minimum power of power capacity generator of type e
K_s^{max} ,K_s^{min}	Maximum and minimum power capacity that can be added to storage of type s
B_s^{max} ,B_s^{min}	Maximum and minimum electrical energy that can be stored by storage of type s
L_e	Total electricity generated by power generators of type e over all intervals t
C_t	Energy consumption in interval t
η_s	Energy conversion efficiency of storage type s
$\zeta_{e \cup s}$	Smoothing factor for power generated by generator e or stored and fed in by storage type s
A_t^{norm}	Normalized value of the curtailed electricity at t

generation is extrapolated from historical data of a base year (e.g., as published by SMARD (2022)) to the generation specified in the considered energy scenario.

This increased generation of electricity is passed to the model as a parameter (G_{et}). The generation of electricity by controllable power generators such as biomass and conventional power generators is considered a variable (p_{et}) that must be set for each interval (t) and technology (e). The aim of the model is to find a feasible electricity generation pattern for controllable electricity generators such that the demand for electricity (C_t) is met in every time interval t. The total electricity generation of each controllable electricity generator must be equal to the value specified in the scenario. In particular, in scenarios that consider a fully renewable electricity mix, electricity generation can deviate from electricity demand, without the possibility to increase electricity generation any further. Therefore, electricity storage ($s_{st}^{+/-}$) and the curtailment of generated electricity (a_t) are considered. Imports (h_t^+) and exports (h_t^-) are only implicitly considered, without modeling volatile prices or availability over time.

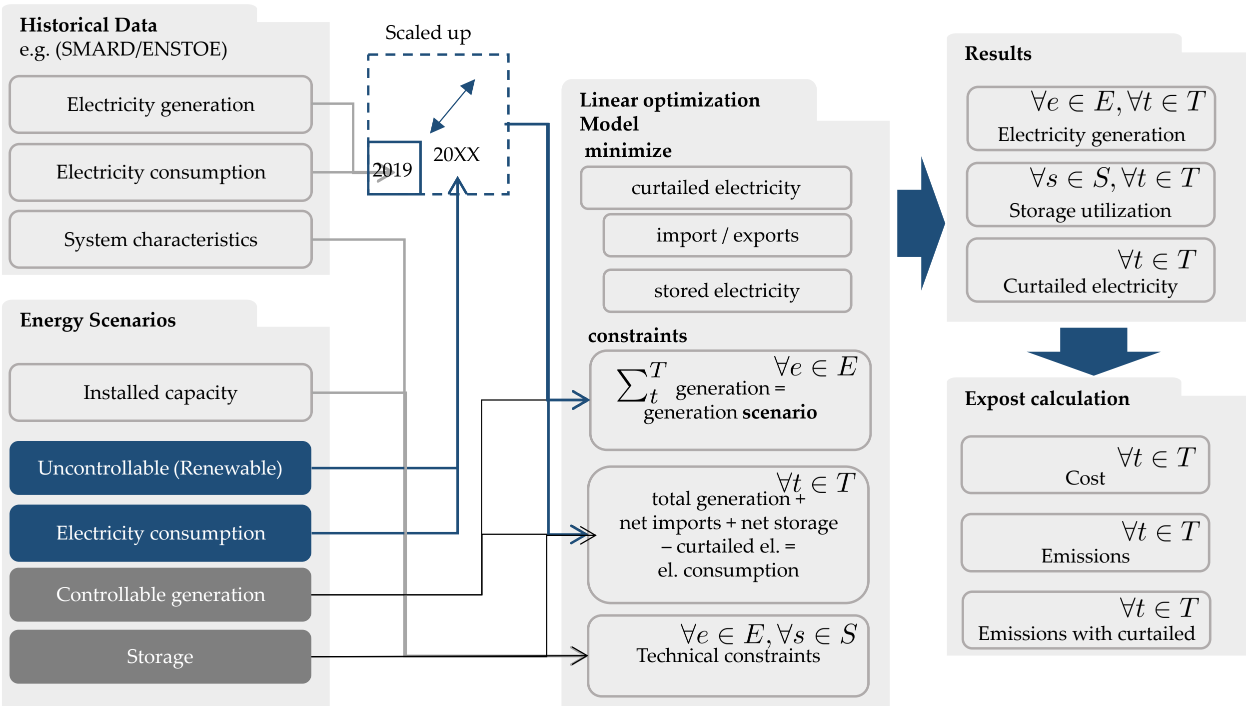


Figure 4.5: Overview of the of the model components.

As the total electricity generation by each generation technology and consumption is specified by the input data of an energy scenario, consideration of the electricity generation costs in the objective function would not affect the solution, as the total electricity to be generated is predefined by the values of existing scenarios. Instead, the objective function is formulated to minimize the use of storage (s_{st}), electricity export (h_t^-), and curtailed electricity (a_t). To avoid electricity curtailment, it is penalized in the objective function (Equation 4.2) by multiplying the cost factor (big) M. It is therefore preferable to export or store electricity to the maximum available capacity, i.e., to use the generated electricity efficiently.

Table 4.5: Electricity system model: Decision variables.

NAME	DESCRIPTION
$p_{e,t}$	Generated electricity of power generator or type e in time interval t
$s^{-}_{s,t}$	Electricity stored in time interval t by storage type s
$s^{+}_{s,t}$	Electricity feed back to the power system in time interval t by storage type s
h^{+}_{t}	Electricity imported to the power system in time interval t
h^{-}_{t}	Electricity exported from the power system in time interval t
a_t	Electricity curtailed in time interval t
$b_{s,t}$	Storage level of storage type s at interval t

$$\min \sum_{t \in T} (h^{-}_{t} + a_t M + \sum_{s \in S} s^{+}_{st}) \tag{4.2}$$

Constraints 4.3 - 4.8 model the technical parameters of electricity generators or storage technologies, as well as the general logical prerequisites. The total power that an electrical generator can provide in each time interval t, is limited by constraints 4.4 and by the parameters P^{max}_{e} and P^{min}_{e}. Furthermore, the total electricity generated over all time intervals is restricted by Constraints 4.3.

$$\sum_{t \in T} p_{et} = L_e \qquad \forall e \in E \tag{4.3}$$

$$P^{min}_{e} \leqslant p_{et} \leqslant P^{max}_{e} \qquad \forall e \in E \tag{4.4}$$

For electricity storage, the electricity that can be added or drawn from an electricity storage system (K^{min}_{s} and K^{max}_{s}) is established by the constraints 4.5 to 4.6.

$$K^{min}_{s} \leqslant S^{+}_{st} \leqslant K^{max}_{s} \qquad \forall s \in S \tag{4.5}$$

$$K^{min}_{s} \leqslant S^{-}_{st} \leqslant K^{max}_{s} \qquad \forall s \in S \tag{4.6}$$

The smoothing factor $\zeta_{e \cup s}$ can be defined to restrict fluctuations in electricity generation or storage from one time interval to the next. Although strong fluctuations in the output of pumped hydro storage can be cost-optimal in the model, they do not have to be so in reality. Furthermore, thermal power stations, such as nuclear power plants, cannot arbitrarily increase or decrease their power generation due to technical or economic constraints (IRENA, 2019d). Constraints 4.7 to 4.8 restrict the power level of the following interval $(t+1)$ to only deviate a fraction of the total available power (P_e) of the generator.

$$p_{e(t+1)} \leqslant p_{et} + \zeta_e P_e \qquad \forall e \in E, t \in T \tag{4.7}$$

$$p_{e(t+1)} \geqslant p_{et} - \zeta_e P_e \qquad \forall e \in E, t \in T \tag{4.8}$$

Finally, the constraints 4.9 and 4.10 restrict the values of the variables to meet the required power consumption in each time interval. If insufficient power is available from volatile power generators (G_{et}) and all controllable generators ($\sum_{e \in E} p_{et}$), additional electricity can be drawn from electricity storage or imported. In contrast, if too much electricity is generated by volatile power generators, excess electricity can be exported, stored, or curtailed (dumped). Constraints 4.10 stipulate that stored electrical energy increases or decreases when electricity is fed to the grid or stored taking into account storage efficiency and minimum and maximum storage levels.

$$\sum_{e \in E} p_{et} + \sum_{e \in E} G_{et} + \sum_{s \in s} (s_{st}^{+} - s_{st}^{-}) + h_t^{+} - h_t^{-} - a_t = C_t \qquad \forall t \in T \tag{4.9}$$

$$b_{s(t+1)} = b_{st} + s_t^{-} \eta_s - s_t^{+} \qquad \forall t \in T \tag{4.10}$$

$$B_s^{min} \leqslant b_{st} \leqslant B_s^{max} \qquad \forall t \in T \tag{4.11}$$

The model is implemented using the Python programming language (version 3.8.11) and solved using the Gurobi Optimizer (version 9.5). The model calculates a feasible electricity generation schedule, within the defined constraints. In addition, it provides information on the necessary curtailment of electricity and the utilization of storage. To calculate volatile costs and emissions, electricity generation costs are derived using the shares of electricity generated in each interval. For the calculation of the electricity procurement cost, the levelized cost of energy (LCOE) are used as a reference. The calculated electricity costs are intended to correspond to the volatility of electricity generation and represent a projected wholesale market price. The detailed calculation is presented in Equation 4.12. As imports and exports are only considered implicitly in the model, without considering volatile electricity costs or availability in non-domestic markets, a fixed value is assumed, and electricity imports and exports are valued with the average LCOE of the domestic system, while curtailed electricity is valued with the maximum LCOE of all conventional (p_{et}) power generators in the system.

$$PWMP[t] = \frac{\sum_{e \in E} (p_{et} LCOE_e + G_{et} LCOE_e) + h_t^{+} LCOE_{mean} - h_t^{-} LCOE_{mean} - a_t LCOE_{max}}{\sum_{e \in E} (G_{et} + p_{et}) + h_t^{+} - h_t^{-}} \tag{4.12}$$

To evaluate the degree to which the developed model can represent the volatility of real-word electricity prices, it was used to calculate the electricity prices for the year 2019 ex post. As a basis, the model uses information published in existing energy scenarios or data from the electricity system, for example, published by governmental institutions such as the German Federal Network Agency in their annual *Monitoringbericht (Monitoring Report)* (Bundesnetzagentur, 2020). A full description of the input data used, such as the total power and energy capacity of the technologies, is presented in Table 6.1 in the Appendix. The results are compared with the market data obtained for the hourly wholesale market price (WMP) for the German electricity market (SMARD, 2022).[2] Figure 4.6 shows projected wholesale market prices (PWMP), the prices calculated by the model, and the emissions obtained. The volatility of the costs derived by the application of the model is lower than those of the actual WMP. The visualization shows that the calculated PWMP cannot

2 Used reference price: Day-Ahead BZN | DE-LU traded at EPEX SPOT, EXAA or over the counter.

predict the extreme price movements present in WMP, for example, at the end of January or in the middle of April and June. This can be explained by the simplifications made; e.g., the model does not consider strategic behavior, uncertainties, or variability in the cost of primary energy carriers that can cause these price fluctuations. The calculated prices PWMP show an overall pattern similar to the WMP. This is also confirmed by examining the statistical coefficients presented in Table 4.6. The standard deviation of the costs calculated by the model is lower than the actual WMP for 2019. This can be attributed to the above-mentioned extreme price deviations, which are not represented by the model. The LCOE are given for newly constructed power generators and therefore can be higher or lower than the costs currently incurred by the operating plants. The calculated PWMP have a high correlation with WMP for the year 2019. The mean WMP is approximately half as high as the calculated PWMP. As volatile electricity prices are included in CSP-EVCSP and are valued against the one-time cost, the model price is corrected by the difference between WMP and PWMP. When comparing the parameters presented in Table 4.6 with the values calculated in other studies (for other years), they are within a similar range (Ladwig, 2018; Schubert, 2016). Unfortunately, no values could be found for 2019, therefore, a direct comparison is not possible.

In addition to the time-dependent electricity cost, volatile emission factors are also calculated for the generated electricity. Although the calculation of hourly emission factors is a relatively new phenomenon in carbon accounting, research has pointed to the fact that it can be a more exact way of quantifying emissions, compared to an annual summation of emissions (Miller et al., 2022; Müller and Wörner, 2019). Other studies calculate marginal emission factors to assess the environmental performance of electricity systems (Peters et al., 2022; Seckinger and Radgen, 2021).

Based on the electricity generation patterns, two emission factors are calculated:

- EMIS[t]: Average emissions of electricity generated and stored at time t (see Equation 4.13).
- EMIS_{A_t}[t]: Average emissions of electricity generated and stored, taking into account curtailed electricity at time t (see Equation 4.14).

Both calculation schemes are similar to the one presented by Frommann and Divalentino (2012) and Kono et al. (2017) and do not take into account the electricity trade balance, thus representing a domestic emission factor. Different calculation schemes are possible for instance, Rüdisüli et al. (2022) and Tranberg et al. (2019) assess how emissions can be traced in an interconnected electricity system and highlight the importance of considering electricity imports and exports to quantify greenhouse gas emissions. As this type of data was not openly accessible, domestic CO_2e emissions are calulated.

Equation 4.13 shows how the average hourly emissions are calculated. The calculation takes into account the emissions from volatile power generators (G_{et}) and flexible electricity generators (p_{et}) as well as electricity storage technologies ($s^+_{s,t}$). The CO_2e emissions where calculated for the year 2019 using Equation 4.13, the resulting average emissions (361.98 kg CO_2e/MWh) are lower than the average CO_2e emissions found in other publications for this year (e.g., (UBA, 2021) 401 kg CO_2e/MWh). This difference can be explained by differences in the calculation scheme (Miller et al., 2022) or the simplified representation of the emission factors of the power generators.

$$\mathrm{EMIS}[t] = \frac{\sum_{e\in E}(p_{et}\psi_e + G_{et}\psi_e) + \sum_{s\in S} s^+_{st}\psi_s}{\sum_{e\in E}(p_{et} + G_{et}) + \sum_{s\in S} s^+_{st}} \tag{4.13}$$

Table 4.6: Statistical values for the normalized costs generated by the model and values of 2019.

	mean	standard deviation	median	max	min
	€/MWh				
WMP	37.66	15.51	38.06	121.46	-90.01
PWMP	62.37	11.77	64.0	87.28	26.6
(no mean correction)					
PWMP	37.66	11.77	39.29	62.57	1.89
	kg CO_{2e}/MWh				
EMIS	361.98	78.76	365.91	528.43	175.53
Correlation (WMP, PWMP)					81.24%
Mean Absolute Error WMP, PWMP (mean corrected)					6.11 €/MWh
Root Mean Square Error WMP, PWMP (mean corrected)					9.08 €/MWh

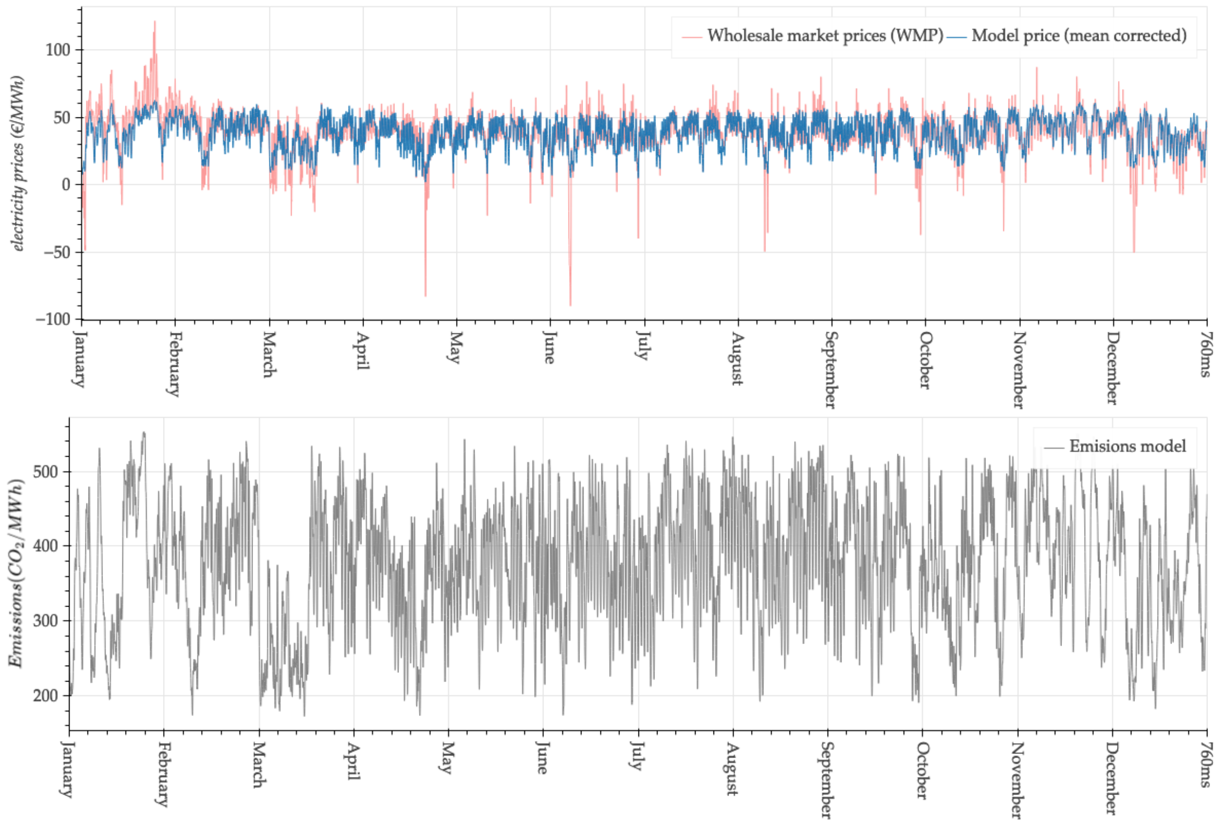


Figure 4.6: Comparison of the normalized cost of the year 2019 WMP and the cost calculated by the model PWMP and the associated emissions (EMIS[t]).

A second emission factor $\mathrm{EMIS}_{A_t}[t]$ was calculated to take into account the supply and demand of electricity in the form of curtailed electricity at a given interval t. The optimal solution reduces the curtailed electricity to the minimum required to obtain a feasible solution to the model. Shares of curtailed electricity in a solution are necessary to retain feasibility and cannot be reduced any further (e.g., by increasing exports and decreasing the generation of other power generators or storage).

$$\mathrm{EMIS}_{A_t}[t] = \frac{\sum_{e \in E}(p_{et}\psi_e + G_{et}\psi_e) + \sum_{s \in S} s^+_{st}\psi_s - A^{norm}_t \mathrm{EMIS}[t]}{\sum_{e \in E}(p_{et} + G_{et}) + \sum_{s \in S} s^+_{st}} \tag{4.14}$$

Equation 4.14 takes the curtailment into account by subtracting a proportion of $\mathrm{EMIS}[t]$ from each time interval t where the curtailment is conducted. To calculate the proportion of $\mathrm{EMIS}[t]$, which is credited, the normalized value (A^{norm}_t) of the curtailed electricity in each time interval is considered. The curtailed electricity is normalized using a min-max normalization i.e., $A^{norm}_t = 0$ when the minimal amount of electricity is curtailed and $A^{norm}_t = 1$ when a_t reaches the maximum values.

$$A^{norm}_t = \frac{A_t - A_{min}}{A_{max} - A_{min}}$$

By taking into account the normalized value of curtailed electricity, the emissions factor used in the objective function of an optimization model can be used to incentivize electricity consumption during periods of oversupply. This is because the emissions factor is multiplied by the amount of electricity used in each time-step, and curtailed electricity is subtracted from the emissions associated with the generated and stored electricity. This means that the emissions factor will have less of an impact on the objective function during periods of oversupply, creating an incentive for electricity consumers to increase their consumption during these times. If the maximum amount of electricity is curtailed, the emissions will be zero, reflecting the fact that curtailed electricity does not contribute to emissions. Conversely, if there is no curtailment, there will be no reduction in emissions. Therefore, the emissions factor can be seen as representing an incentive to utilize curtailed electricity, as the more electricity is curtailed in an interval, the lower the emissions and the higher the incentive to utilize electricity in that interval.

4.3 SUMMARY

This chapter presents a summary of the current state of the art in determining site-specific activity profiles. Most of the existing approaches are based on surveys and mobility studies. The most comprehensive and often referenced study is the "Mobility in Germany MiD" survey. These studies indicate that the derivation of real-world mobility profiles for BEVs is impeded by the comparably low diffusion of these vehicles in Germany, as well as by data protection issues.

To overcome these data acquisition problems and to test the CSP-EVCSP and developed solution approaches, synthetic mobility profiles were generated. Based on the work of Reinhold et al. (2018) and on the basis of open source geographical data, a process is developed to generate temporally and geographically resolved mobility profiles for arbitrary geographic regions.

Due to the focus of the thesis and for testing the CSP-EVCSP, a simplified model for the derivation of future electricity generation based on a linear optimization model was presented in the second section of this chapter. An ex post calculation of the model is conducted for the year 2019. Electricity prices and emissions generated by the model are found to be consistent with the real-world values to a reasonable degree.

The developed methods are applied in the following chapter to derive mobility patterns for Essen, Germany, and electricity generation patterns, quarter-hourly emissions and costs for Germany for different years. Based on these temporally and geographically resolved activity patterns and different energy costs, the planning of the charging infrastructure in the city of Essen is optimized and the results are presented.

5 A CASE STUDY ON OPTIMIZING EV CHARGING NETWORKS BASED ON ELECTRICITY PRICES AND EMISSIONS

In this chapter, the developed charging station placement and electric vehicle charge scheduling problem (CSP-EVCSP) is applied to optimize the charging infrastructure and charging of EVs in the city of Essen. The purpose of the case study is to answer the question of how the developed model can support real-world decision making and assist in locating EV charging stations while considering the charging process of BEVs. Furthermore, the evaluation aims to show how different configurations of the electrical system and the objective of decision makers can influence the decision-making process, the resulting infrastructure configurations, and the charging of EVs. Four different configurations of the electricity system are considered, based on the mix of energy generation presented by the scenario *Klimaneutrales Deutschland* 2045 (Prognos AG et al., 2021). The electricity mix is modeled for four exemplary years (2019, 2025, 2035, 2045) by applying the optimization model developed in Section 4.2. Using the resulting shares of electricity generation, electricity prices, and CO_2e emissions are calculated subsequently and used as input parameters for the objective function of the model. The objective function distinguishes between a fixed component (emissions or expenses associated with the investment in the infrastructure) and a variable component (costs or emissions associated with charged electricity). As highlighted in Section 2.1, the distribution between fixed and volatile components can deviate for the costs (fixed expenses dominate, in contrast to the procurement cost) and CO_2e emissions (emissions from the charged electricity are greater than the emissions related to the production and construction of the charging infrastructure). This circumstance also requires the application of two different solution approaches. The model also incorporates the possibility to consider joint use of the charging infrastructure. Therefore, the exemplary application is restricted to a fixed geographical location, the city of Essen, Germany. The changes of electricity prices and CO_2e emissions and their impact on the optimization problem and its results, are viewed from two perspectives. First, the charging infrastructure expansion of a charging point operator (CPO) within the city of Essen, with the objective of cost minimization and second, the ecological assessment for minimizing CO_2e emissions. To present the case study and the results, this chapter is structured as presented in Figure 5.1. First, the mobility data is derived using the process described in Section 4.1.2.2, thereafter different energy system configurations and resulting electricity prices and CO_2e emissions are derived using the application of the linear optimization model presented in Section 4.2.2. The data derived in this way are used in the optimization model to minimize expenses and CO_2e emissions, and enable a combined assessment of both factors. To highlight the effects of the different solution strategies and parameter configurations, seven different cases are presented and analyzed. Finally, an assessment of the results, a summary, and outlook are given.

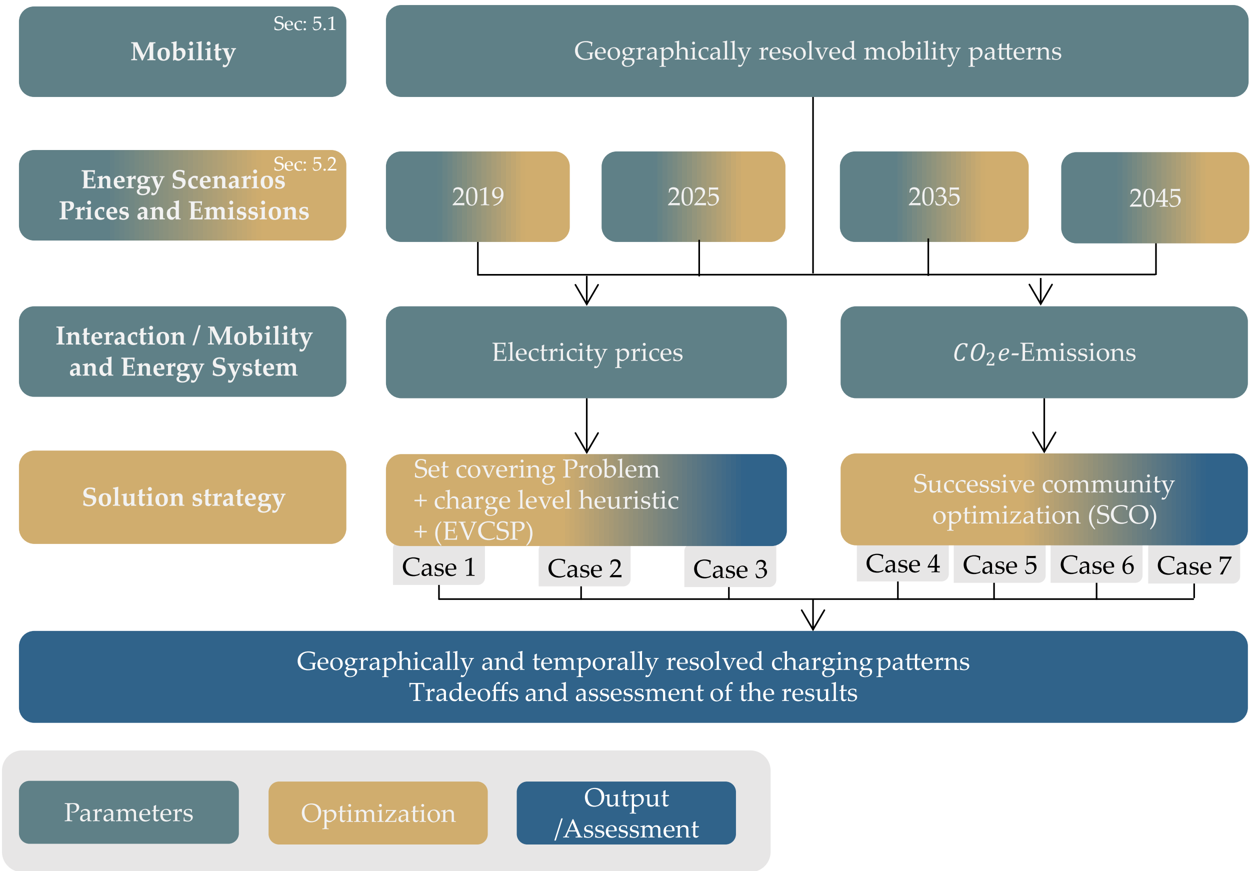


Figure 5.1: Structure and contents of the case study.

5.1 MOBILITY USER AND VEHICLE PARAMETERS

Essen is located in the Ruhr region and is the fourth largest city in North Rhine-Westphalia with 582, 760 inhabitants in 2019. Essen's electrical grid is owned by Westnetz GmbH, but operated jointly by Stadtwerke Essen and Westnetz GmbH. As part of the Rhine-Ruhr metropolitan region in Germany, Essen is connected to other cities in the region by a dense road network. The main mode of transportation is by private automobile (52% of all trips) (Melkonyan et al., 2020; Schwarze et al., 2017). Essen is one of the urban centers of the region with a high proportion of commuters. As the analysis of Volgmann (2014) shows, employees commute between metropolitan areas of the region, and in general, commute distances have increased in recent years.

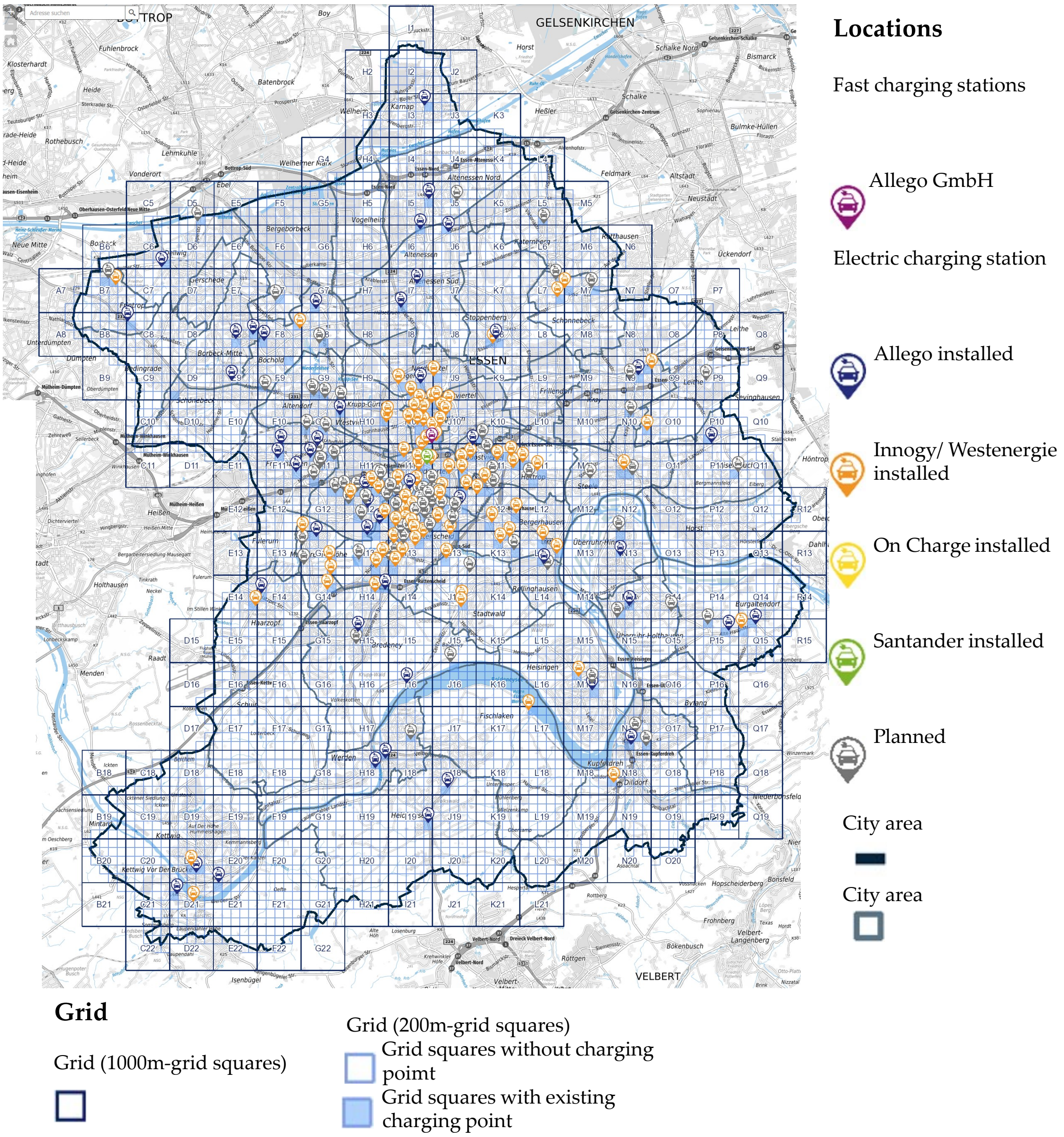


Figure 5.2: Current "grid-approach" and expansion of the charging infrastructure in the city of Essen (Stadt Essen, 2022a).

There are currently 518 charging points in Essen, 65% of which are public and 35% semipublic. They are operated by different private CPOs. The current expansion of the charging infrastructure in the city is influenced by the municipal administration (Stadt Essen, 2022b). To regulate the expansion of the charging infrastructure, a so-called 'grid approach' is applied. The approach shown in Figure 5.2 covers the city in quadrilaterals with a length of 200 m. The resulting grid is used as a basis for charging infrastructure planning activities. For each quadrilateral, a special use permit can be granted for the installation of up to two charging points. The approach stipulates that additional charging stations will only be approved in a square once a certain utilization limit of existing charging stations has been reached. As can be seen in Figure 5.2, there are currently four CPOs who operate the charging infrastructure within the city. Four CPOs operate normal charging points, while Allego GmbH also operates fast charging points.

To derive the temporally and geographically resolved driving patterns, the process presented in Section 4.1.2 is applied. For the application of the process, several case-specific parameters related to the generation of activity profiles are required. The algorithm requires the selection of a cluster, *maximum mobility time per day*, and *maximum trips per day*. For the exemplary application of the developed model, Cluster 1 was selected, representing a cluster that corresponds to a full-time employee (Reinhold et al., 2018). All mobility activities in the profile are assumed to be carried out using a BEV. For the parameters *mobility time per day* and *max trips per day*, the information published in the study MiD is used as reference (Infas, 2019a). In the MiD study, there is a differentiation between different regional types. In the greatest aggregation of two regional types, the "urban" and "rural" regions are distinguished. The data for an urban region are taken as a reference. To accommodate the higher number of commuters, the value of *maximum mobility time per day* was allowed to be 10% higher than the value provided in the study MiD for Germany. 500 different profiles were generated for the case study. The resulting parameters of the generated data, that is, trips per day and driving time, are shown in Table 5.1 along with the data published in the study MiD.

Table 5.1: Comparison of mobility data

	Trips per day	driving time in minutes	MiD trips per day	MiD driving time in minutes
Monday	1.96	51.06	2.00	44.50
Tuesday	1.96	51.63	2.10	54.70
Wednesday	1.97	50.13	2.10	48.80
Thursday	1,94	51.15	2.00	46.40
Friday	1.95	50.11	2.20	57.80
Saturday	1.60	50.13	1.50	35.40
Sunday	1.63	49.90	1.00	32.80
Average	1.86	50.59	1.84	45.77
Sum	13.00	354.11	12.90	320.40

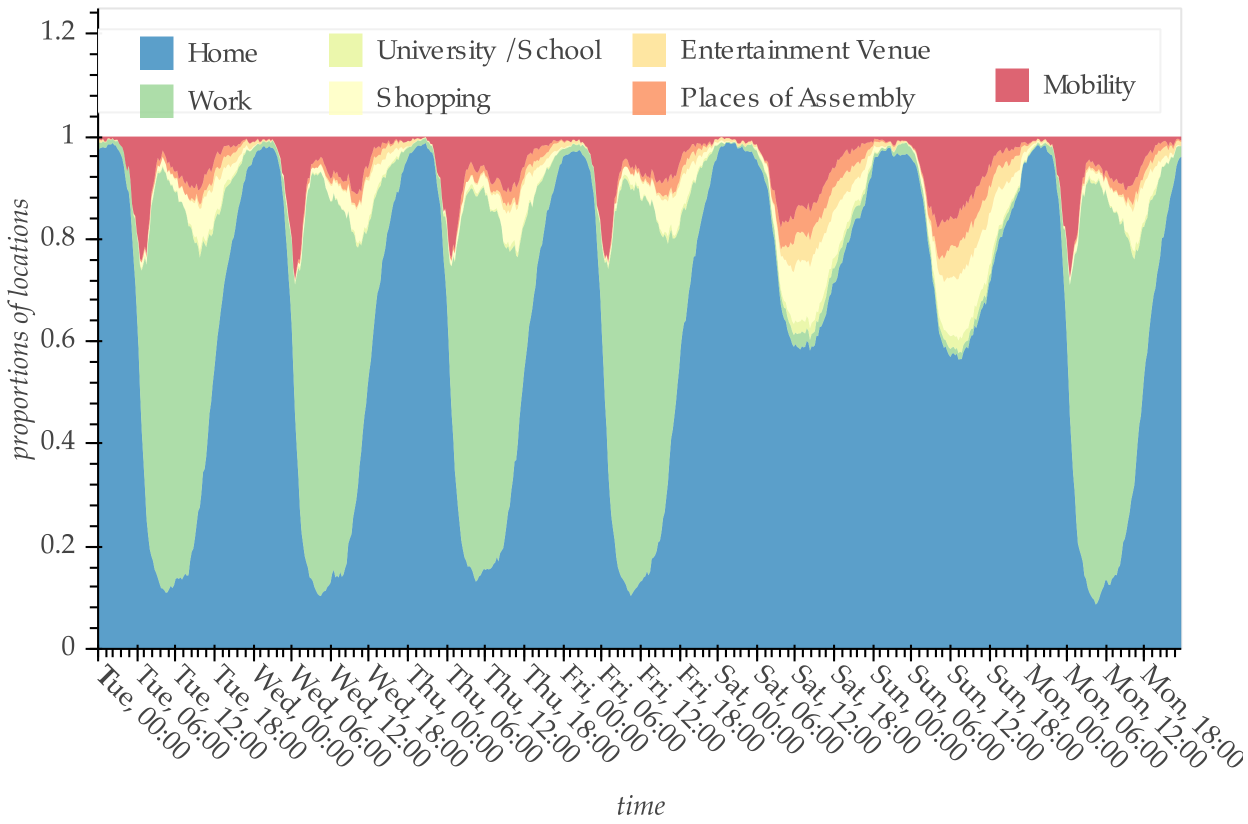


Figure 5.3: Aggregated values for 500 profiles from cluster 1.

Figure 5.3 shows an aggregated view of the 500 yearly profiles of the cluster 1. As can be seen, vehicles are parked at home most of the time. Throughout the week, the second most visited location is the workplace, where on average a vehicle is parked for 8 hours and 25 minutes.

A more aggregated view of the activities is shown in Figure 5.4, where the activities are averaged by type of day (weekend / weekday) and for each hour. To allow for a more detailed evaluation, the location home is excluded from this graph. During the week, the profiles are characterized by a peak of mobility activities at 6:30 a.m. with an average of 19.9% of all activities falling into this category, the proportion of activities located at the workplace increases subsequently to a maximum of 81.9% of all activities at 10:15 a.m. The utilization of this location continuously decreases throughout the rest of the day, dropping below a share of 50% at 04:30 p.m. Most activities that can be assigned to places that do not fall into the home or work category are carried out during the week from 05:00 p.m. to 05:30 p.m., with activities assigned to shopping locations making up the highest share of 7.9% of all activities. On weekends, activities outside the home on average start after 8:30 a.m. reaching their maximum 12:15 p.m. to 3:45 p.m. where activities can be assigned to shopping locations (9.3%) followed by places of assembly (5.0%) and entertainment venues (4.6%).

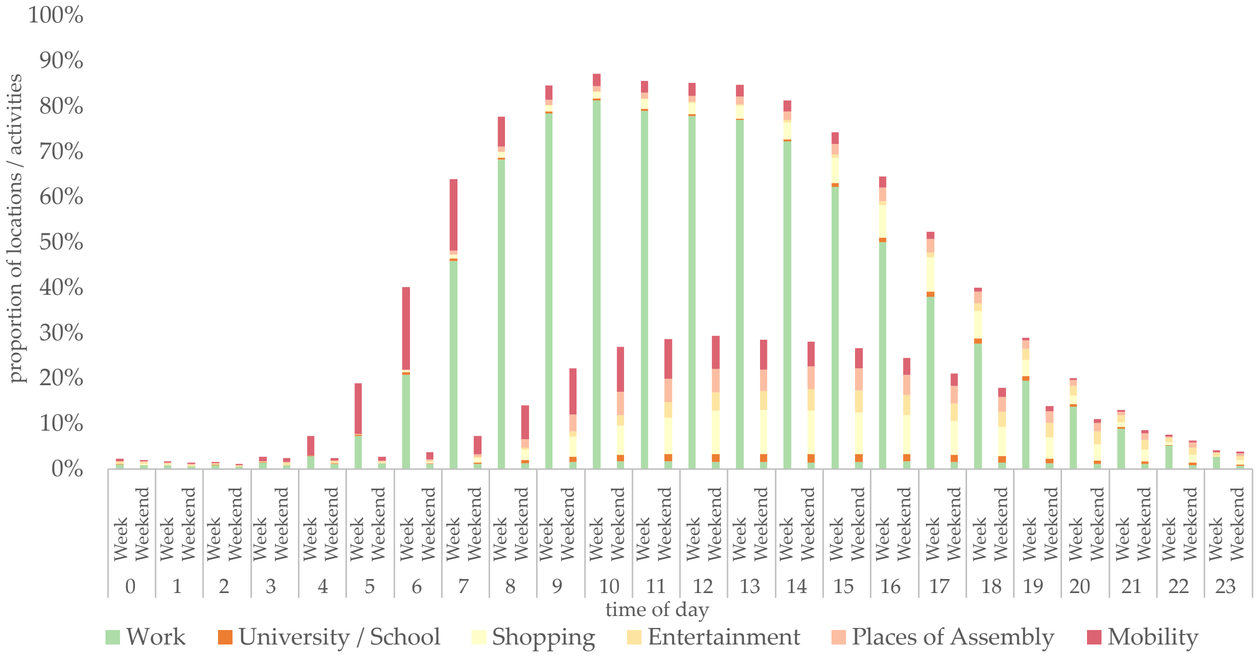


Figure 5.4: Activity locations for 500 vehicles generated from Cluster 1 aggregated by type of day and hour. For a better representation, the location home is excluded in this graph.

Mobility activities directly influence how many kilometers a car covers per day and year and for BEVs the corresponding required electricity. To calculate the kilometers covered, the average driving speed published in the study MiD for the urban region is considered. The study calculated an average driving distance of 29.4 km per day. In addition to the average driving time of 45.9 minutes, the average driving speed for the study MiD is equivalent to 38.43 km/h for urban areas. This leads to an annual driving distance of 10,731 km in the study MiD and 11,889 km for the mobility profiles generated. Taking into account the high share of commuters in the city, the 10% higher annual mobility is considered reasonable. The electricity required for mobility activities is set at 19 kWh/100 km, which leads to an average electricity requirement of 2,259 kW/a for each mobility profile. The usable battery capacity considered is 65 kWh.

To link driving patterns with geographic charging locations, data were obtained from OSM for Essen and assigned to one of the six activity categories. The resulting locations are shown in Figure 5.5. In total, more than 150,000 building objects were extracted from OSM using the attributes presented in Section 4.3. A total of 156,514 different buildings and their respective locations can be assigned to homes, 739 to work sites, 41 to education centers, 276 to shopping sites, 1259 to authorities, and 23 to entertainment centers. For each activity category, the corresponding places are randomly assigned one of the extracted OSM locations.

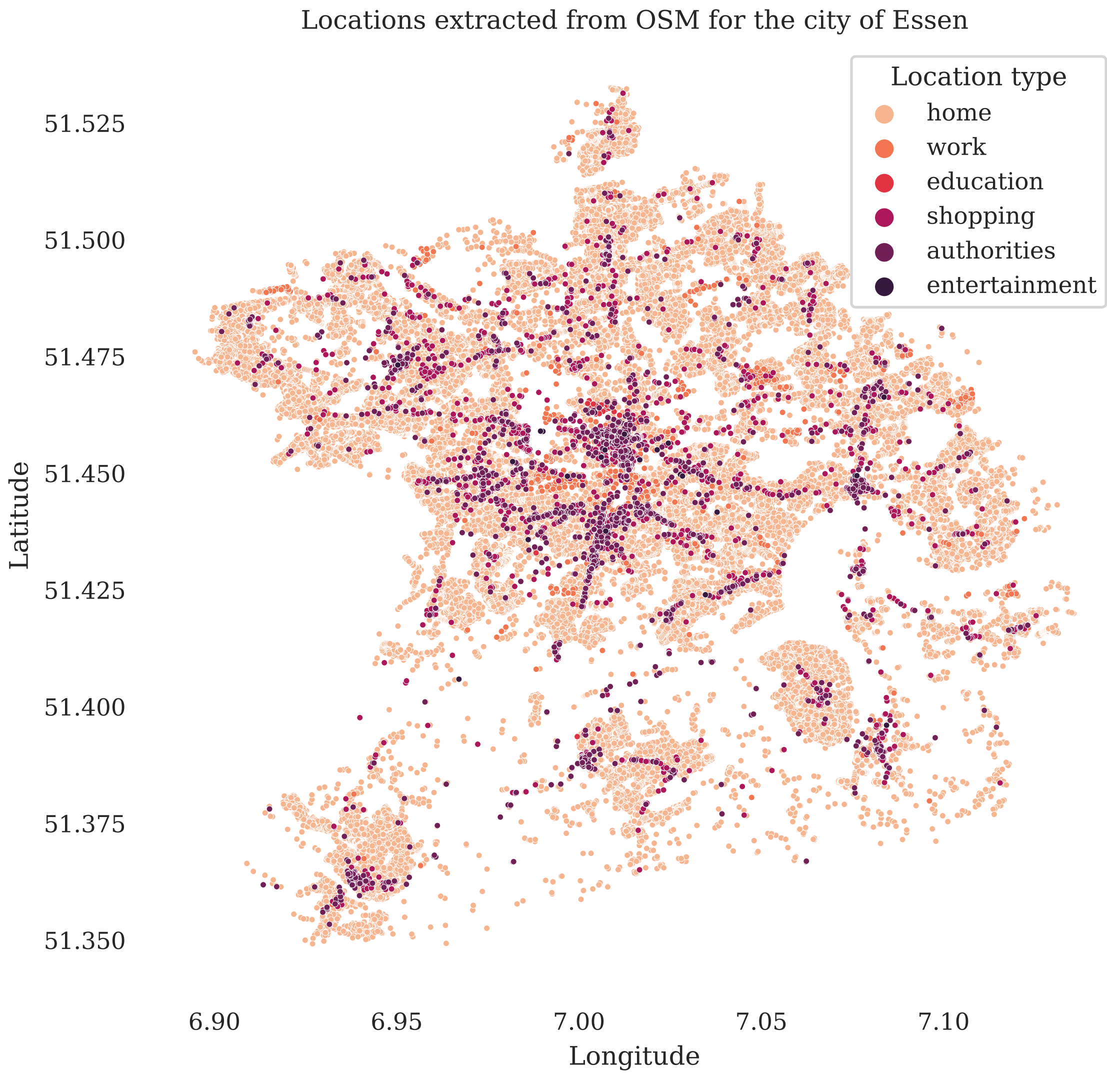


Figure 5.5: Locations extracted from OSM for the city of Essen, Germany.

To identify intersections between places, an intersection radius must be defined. Within the model, this value can be changed for each potential charging location or depending on the duration of the activity carried out. The maximum distance to walk from an activity location to a parking location was analyzed in several studies (Adenaw and Krapf, 2022; Waerden et al., 2017). Among other parameters, such as the cost of parking or the maximum possible parking duration, the distance to the final destination was shown to influence the choice of parking (Khaliq et al., 2018). A study by Waerden et al. (2017) for the city of Eindhoven with the aim of investigating the willingness of car drivers to walk between a parking location and the final destination showed that the maximum distance people are willing to walk also depends on the type of activity carried out. In cities, a distance below 500 m is preferred. For activities carried out very frequently, participants prefer a distance below 50 m (Waerden et al., 2017). As no clear values could be identified for each type of location defined in this study and several other factors affect the walking distance, which are not included in the model, a value of 250 m is uniformly considered for all locations in the case study. The selected locations are visualized in Figure 5.6, highlighting the different types of location with different colors.

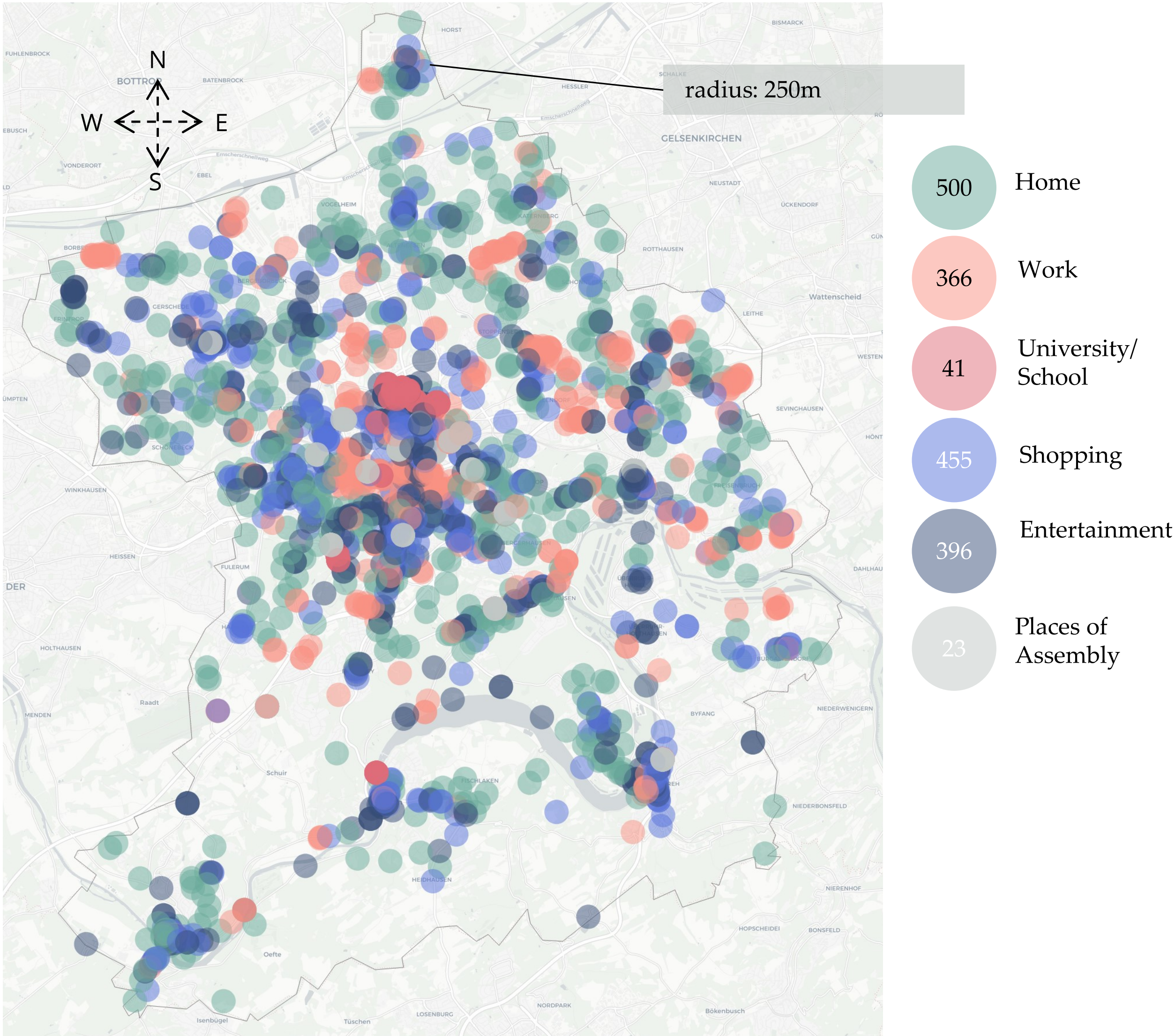


Figure 5.6: Possible charging locations for the city of Essen for 500 profiles and a radius of 250 m.

5.2 ELECTRICITY SYSTEM SCENARIOS

The calculation of emissions and costs is based on the energy systems described in the *Klimaneutrales Deutschland* 2045 study (Prognos AG et al., 2021), which presents a German energy system in the year 2045 that is carbon neutral. The study takes into account all sectors, as well as energy imports and exports. Figure 5.7 presents the installed renewable power generation capacity and the net renewable power generation for the six years calculated in the study. For the case study, the year 2019 is used as a reference year, and the energy mix for the years 2025, 2035, and 2045 is considered as presented in that study.

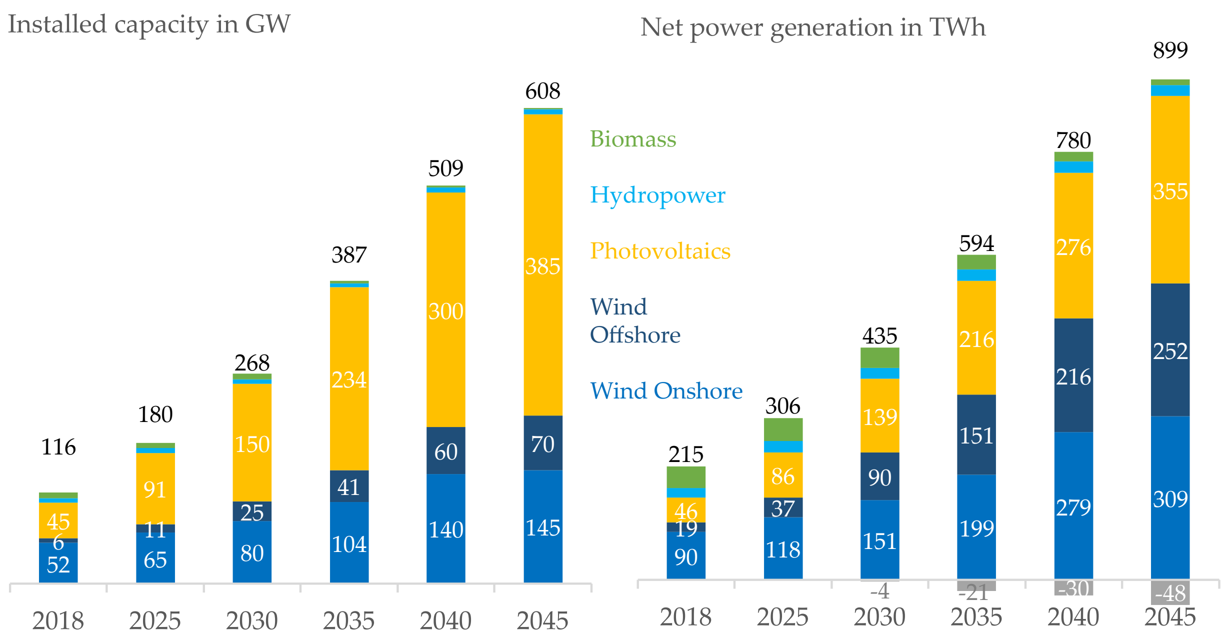


Figure 5.7: Installed renewable capacity and renewable net power generation in the *Klimaneutrales Deutschland* 2045 scenarios (Prognos AG et al., 2021).

The following mix of electricity generation was calculated by applying the linear optimization model presented in Section 4.2.2. The values required as input for the model, such as maximum generation capacities, maximum power, minimum or maximum load, are documented in the appendix (Table 6.1) and by the openly available values of the original study. For values that have not been published by the authors, other literature values were considered and are referenced. For 2019, the values published by the federal network agency in *Monitoringbericht* 2020 and other sources were used to supplement the study data (for 2018) *Klimaneutrales Deutschland* 2045. As a reference for the remaining years, the study values were used. The resulting electricity generation, consumption, energy imports and exports, as well as curtailed electricity can be found in Table 5.2. To simplify and improve the presentation and allow comparability between years, the same sequence of weekdays and holidays is assumed for the years 2025, 2035 and 2045 as in 2019.

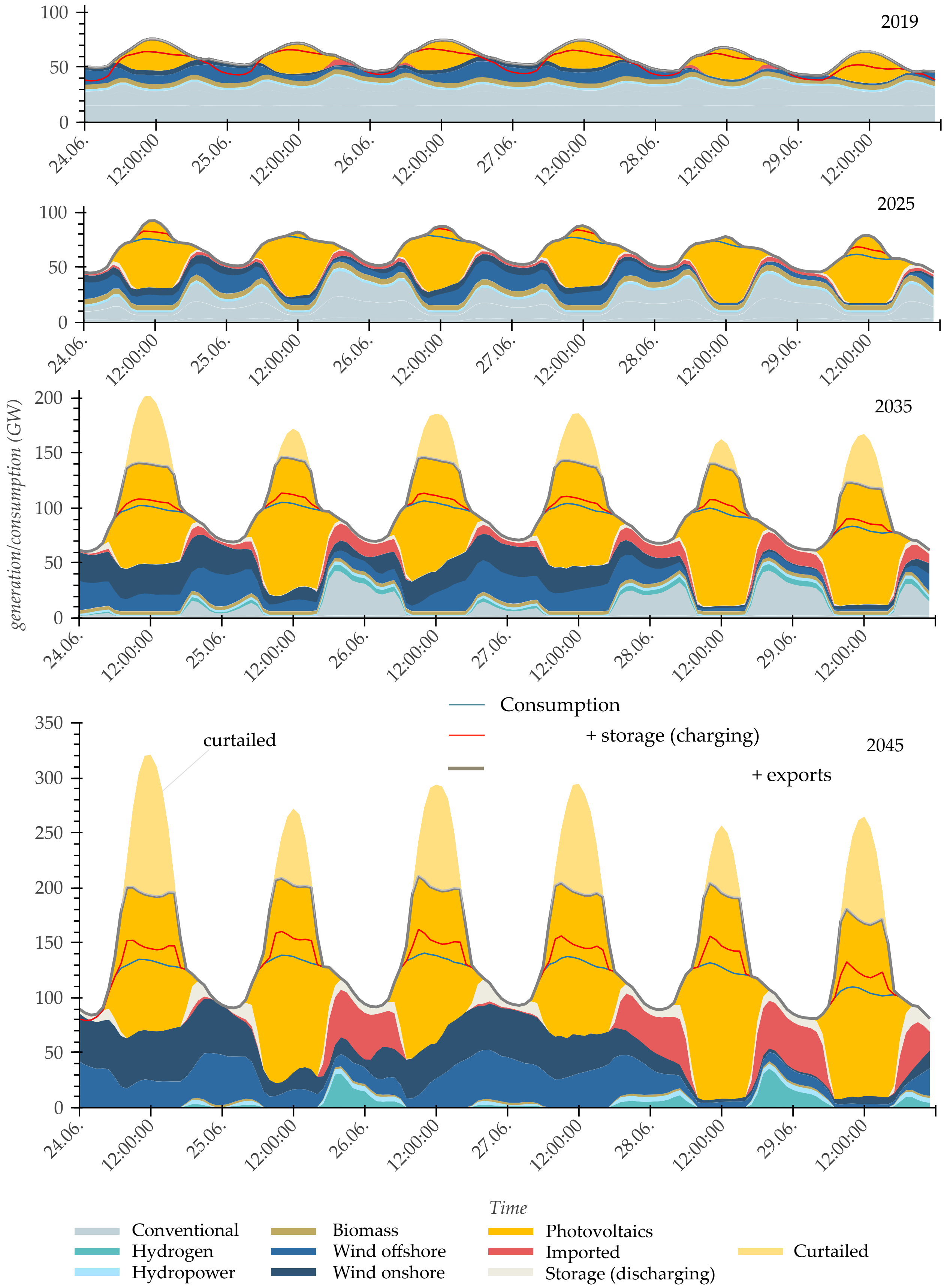


Figure 5.8: Representative summer week in every scenario year.

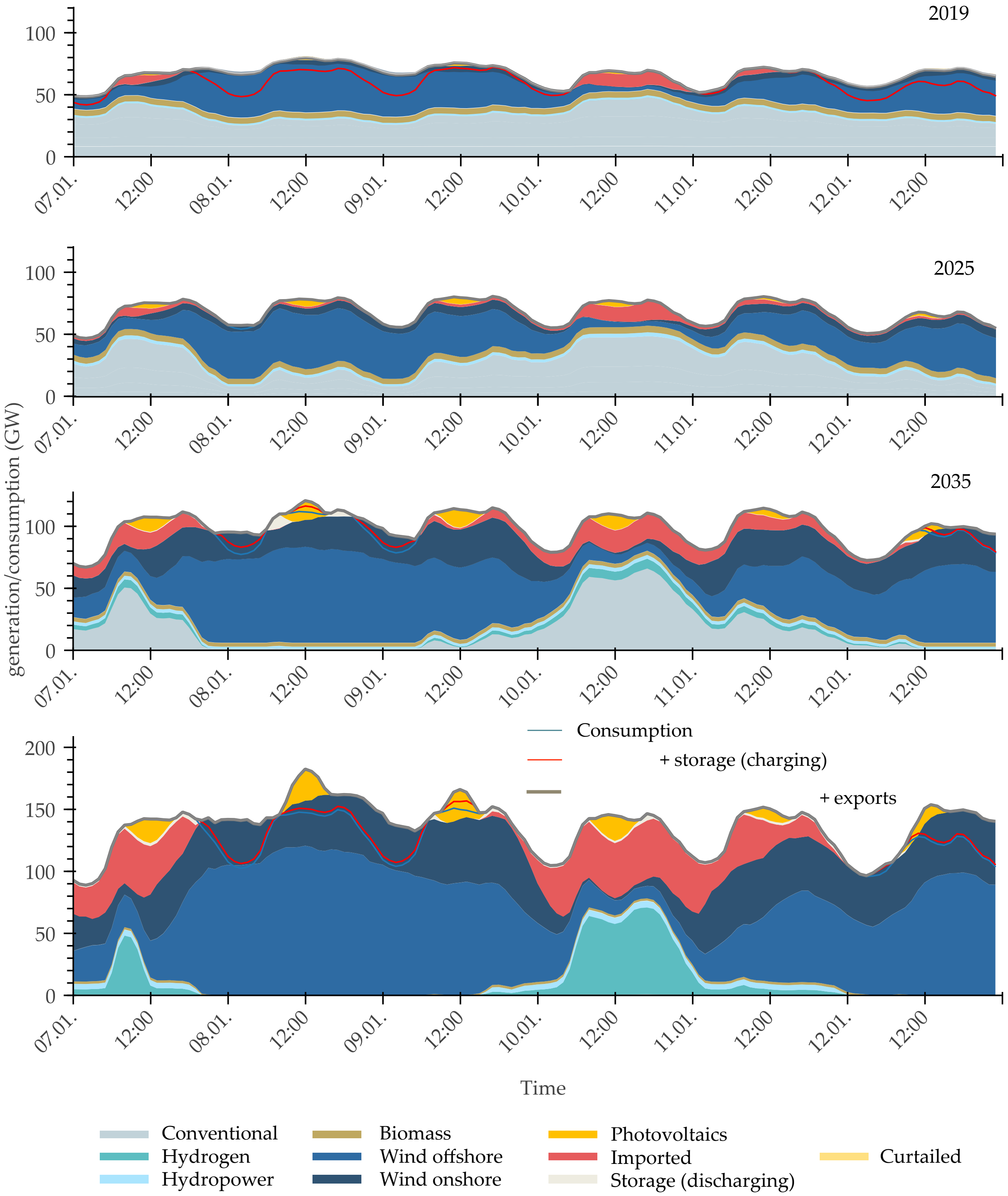


Figure 5.9: Representative winter week in every scenario year.

The expansion of renewable energy, the reduction of the capacity of conventional power plants, and the net generation of electricity are assumed according to the values documented in Figure

5.7 and for non-renewable generators, as documented in the study (Prognos AG et al., 2021). To illustrate the results of the model, Figures 5.8 and 5.9 show a summer and a winter week in the year 2019, 2025, 2035, and 2045.

Table 5.2: Total generation and consumption calculated by the model.

	2019	2025	2035	2045
Wind Onshore	99.88 TWh	118.40 TWh	199.37 TWh	308.74 TWh
Wind Offshore	24.39 TWh	37.40 TWh	151.16 TWh	252.38 TWh
Photovoltaic	41.92 TWh	85.80 TWh	216.13 TWh	354.88 TWh
Hydrogen	-	-	22.00 TWh	60.00 TWh
Hydropower	15.83 TWh	20.70 TWh	20.67 TWh	20.67 TWh
Biomass	40.39 TWh	43.70 TWh	27.61 TWh	10.13 TWh
Conventional and other	289.67 TWh	232.70 TWh	127.00 TWh	2.00 TWh
Import	43.45 TWh	20.17 TWh	55.24 TWh	137.18 TWh
Export	76.78 TWh	5.53 TWh	54.62 TWh	111.48 TWh
Curtailed	4.31 TWh	0.23 TWh	19.34 TWh	49.15 TWh
Electricity Consumption	467.50 TWh	553.10 TWh	745.05 TWh	986.37 TWh

Renewable energy generation made up 43% of total electricity generation in 2019, which gradually increases to 100% by 2045. As can be observed in Figures 5.8 and 5.9, until 2035 conventional power generators still provide most of the base load. In 2025, 50% conventional power generators use hard and lignite coal, while the remaining electricity from conventional energy is provided by natural gas electricity generators. From 2019 to 2045, electricity consumption more than doubles. Although Germany was a net electricity exporter in 2019, it is assumed that electricity imports increase until 2045, making Germany a net electricity importer in the years 2025, 2035 and 2045.

The combined electric power of all energy generators reached a peak generation of 85.61 GW for the calculation of 2019. The highest power is provided by onshore wind power generators (40.32 GW), followed by photovoltaics with 30.03 GW. Wind onshore also contributes the second highest mean power capacity in the year 2019 with 11.40 GW, and only plants powered by natural gas exceed this value with 11.73 GW. The highest amount of electricity curtailed per hour is 6.95 GWh. The highest amount of electricity imported in the course of one hour is 15.49 GWh, while the maximum exported electricity is equal to 21.81 GWh.

For 2025, the electricity generated by renewable energy generators increases and represents 57%. Due to restrictions on the total generation of electricity per technology, conventional power generation is shifted from nuclear and lignite and anthracite coal-based electricity generation to natural gas-based generation, which constitutes 49% of the total generation of electricity in 2025. The peak electric power of all electric generators is provided by photovoltaics (61.47 GW), followed by wind onshore (47.80 GW). Although the total curtailed electricity is reduced to less than 1 TWh, the maximum curtailed electricity within one hour increases to 4.79 GWh.

In 2035, all conventional power generators except natural gas are phased out in the *Klimaneutrales Deutschland* 2045 study. Consequently, only 17% of electricity is generated from conventional sources; however, as electricity consumption increases to 745.05 TWh, the total electricity generated from natural gas increases by 14 TWh compared to 2025. The peak photovoltaic power generation capacity more than doubles to 154.84 GW, and the peak offshore wind generation increases more than three times to 42.65 GW. The maximum amount of electricity curtailed in a one-hour interval increases to 95.26 GWh.

In 2045, the maximum power of renewable generators increases to 124.64 GW for wind onshore, 71.21 GW for wind offshore, and 254.23 GW for photovoltaics. The maximum electricity generated in a one-hour interval increases to 173 GWh. Hydrogen is considered a replacement for natural gas power plants starting in 2035 and is not modeled as energy storage, but rather as a power generator in the model as also done in the *Klimaneutrales Deutschland* 2045 study.

In terms of the seasonal difference between electricity generation, the patterns visible in Figures 5.8 and 5.9 are representative of the differences between seasons. In general, 66% of photovoltaic electricity is generated in spring and summer. Although photovoltaic power generators in 2019 only contribute 13% of total power generation in spring and summer, they contribute 44% in 2035 and 53% in 2045. As is to be expected after considering Figure 5.9, in the autumn and winter months, photovoltaics contribute only 5% in 2025 and 21% in 2045. In these months, electricity generation is heavily dominated by offshore and onshore wind power plants, which contribute 63% of total electricity generation in the fall and 74% in the winter of the year 2045. The pattern of electricity imports remains largely unchanged in the scenarios, with most of the electricity imports occurring in the winter and fall months (61%), and the exports are relatively evenly distributed throughout the year. While in 2019 more electricity is curtailed in the fall and winter (58% of curtailed electricity), this is shifted to the summer and spring in the years 2025, 2035, 2045 (76%-93% of curtailed electricity). The generation of electricity by hydrogen fuel cells, which is only considered in the years 2035 and 2045, is mainly used in the winter months (36%-40%).

The electricity prices and CO_2e emissions are calculated according to Equations 4.12 and 4.13 and using the LCOE and CO_2e emission factors presented in Table 6.1 in the appendix. The mean correction factor calculated for the year 2019 is applied to the prices calculated for each year.

Figure 5.10 shows the aggregated results for the summer and winter months. For the base year (2019), the values are presented in Table 4.6. Detailed statistical values for each season can be found in Table 6.2 for the cost and Table 6.3 for emissions in the appendix. The mean electricity prices vary over the four considered years. Costs increase from 37.66€/MWh in 2019 to 57.34€/MWh in 2025 and decrease to 37.55 €/MWh in 2045. Although, the mean costs are similar over the seasons in 2019 and 2025, seasonal differences increase in 2045 and the average summer and spring prices are 12.65 to 15.07 €/MWh lower than in autumn/winter. As can be seen in Figure 5.10, the overall volatility of prices increases from 2019 to 2045. The standard deviation in 2019 is equal to 11.8 €/MWh, increases to 14.18 €/MWh in 2025, 28.51 €/MWh in 2035, and reaches its maximum value in 2045 with a standard deviation of 37.56 €/MWh. The price range in 2019 is between 1.08 €/MWh and 62.72€/MWh and continuously increases to values of -84.06 €/MWh and 147.52 €/MWh by 2045. Negative prices can be mainly attributed to increases in curtailed electricity, especially during the middle of the day, while increasing costs are caused by increased electricity imports and electricity generation by hydrogen power plants.

As highlighted in Section 2.1.1.4, negative prices can occur in situations of oversupply, when the marginal generator would prefer to pay a price rather than reduce its output (Seel et al., 2021). Several factors can induce this situation Bajwa and Cavicchi (2017) and other studies have also shown that with the current market scheme, the occurrence of negative prices and volatility of prices (e.g., measured using the standard deviation) could increase with higher shares of renewables in the electricity mix (Winkler et al., 2016). However, as these studies also suggest, restructuring or redesigning electricity markets and subsidies for renewable power generators could reduce these effects. This effect is not considered in the calculation of electricity prices and emissions.

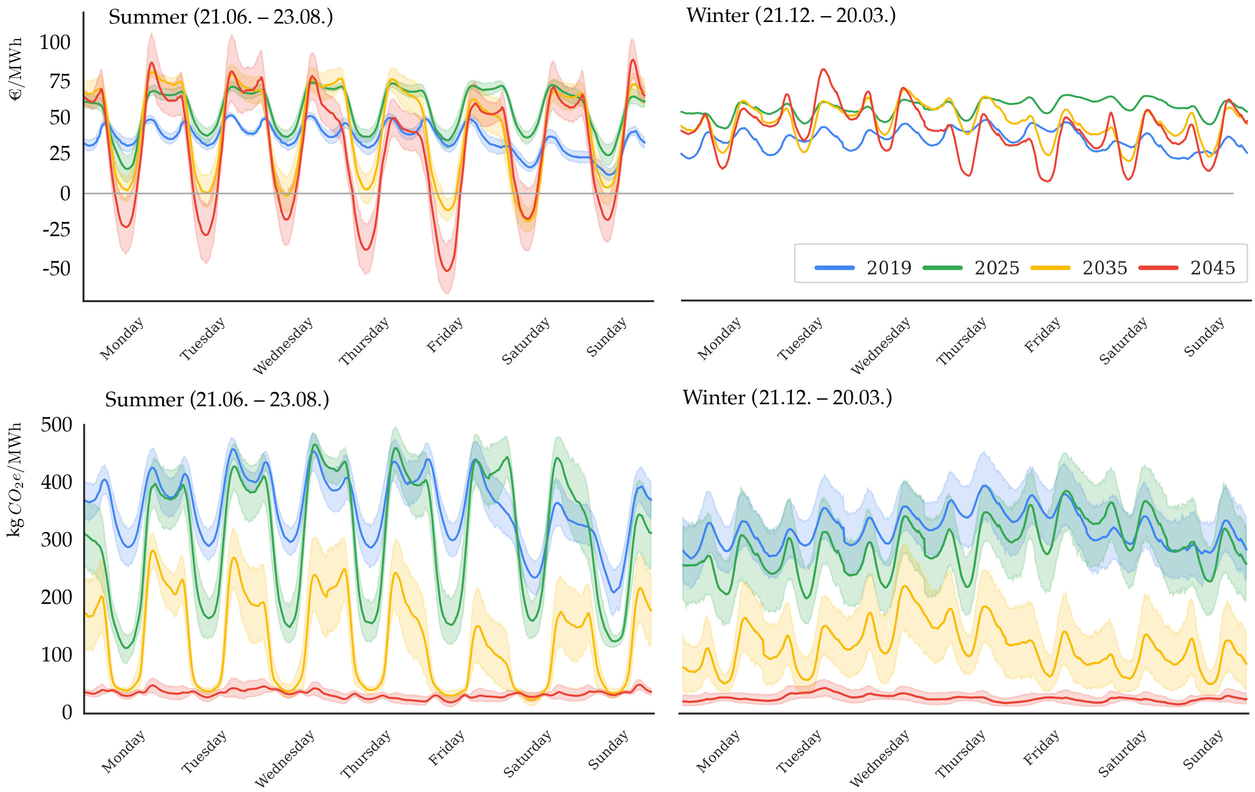


Figure 5.10: Cost and CO_2e emissions for a summer and winter week in every calculated year. The solid line represents mean, while the shaded area represents a 95% confidence interval of all values within the respective season. CO_2e emissions are shown under consideration of curtailed electricity (Equation 4.14). The confidence interval is not plotted for the cost graph in the winter, to allow for a better representation.

The time-bound CO_2e emissions were calculated according to Equations 4.13, without the consideration of electricity curtailment ($\mathrm{EMIS}[t]$) and according to Equation 4.14 with the consideration of curtailed electricity ($\mathrm{EMIS}_{A_t}[t]$). In contrast to the electricity prices, the average CO_2e decrease from 2019 until the year 2045 for both indicators by 90.6%-90.8% and CO_2e/MWh reach a value of 32.05 - 33.26 kg CO_2e/MWh in 2045. Generally, average emissions per MWh are lower in the autumn and winter months, due to a higher share of wind onshore and offshore electricity generation, which has the lowest CO_2e emissions of all considered technologies. Starting from the year 2019, the minimum emissions CO_2e/MWh (in a time interval) decrease constantly in the years 2025, 2035 and 2045. The standard deviation of the emission values increases until 2035 and decreases significantly in the year 2045 as carbon-intensive conventional power generators are no longer part of the energy mix. These effects can be observed for both emission factors ($\text{EMIS}[t]$ and $\text{EMIS}_{A_t}[t]$). The pattern of the average CO_2e/MWh emissions do not differ between the seasons for both emission factors. However, curtailed electricity has an effect on the time the minimum emissions occur. While these occur in the winter months when no curtailment is considered, they occur in the spring when it is considered.

In general, the calculated emissions and costs show a distinct pattern. The mean emissions decrease until 2045; however, the mean costs remain similar to the values calculated for 2019. The emission range is lowest in 2045, whereas the price range is highest in this year. Controlled charging is most effective if high fluctuations in prices or emissions can be exploited.

The two emission factors also show a deviating pattern. When curtailing electricity is considered ($\text{EMIS}_{A_t}[t]$), the emissions during the day are lower, while they are lower at night and in the evening when curtailing electricity is not considered ($\text{EMIS}[t]$). To explore these discrepancies, the cost and emission factors will be used as input and the resulting charging patterns and charging network configurations will be analyzed.

5.3 OPTIMIZED PLACEMENT AND SCHEDULING OF EV CHARGING STATIONS UNDER ECONOMIC CONSIDERATIONS

After the preparation and derivation of temporally and geographically distributed driving profiles and electricity data, this section presents the results of the CSP-EVCSP. The general results and economic evaluation for a charging point operator are presented, before presenting the results of the emissions reduction in the next section.

The simplified decision problem represents a greenfield expansion problem. 500 vehicles and their mobility profile are considered over a period of one year (35, 040 intervals of 15 minutes). This number of vehicles allows to efficiently solve the CSP-EVCSP and to efficiently assess different cases over the four considered years. Moreover, other studies have indicated that this number of vehicles can provide a sufficient trading volume for the intraday or day-ahead market and results may therefore be suitable for a more detailed analysis in other studies (IRENA, 2019b; Kempton et al., 2001). Vehicles are assumed to park only in publicly accessible locations. The case study therefore optimizes the on-street parking situation within the city of Essen. The charging requirements for all vehicles must be met for all vehicles at all times. A charging point can supply only one vehicle at a time; however, several charging points can be considered at each location. The aim of the decision maker, the CPO, is to minimize the total cost of the charging infrastructure while meeting the charging demand of all vehicles. The total expenses are made up of OPEX, CAPEX, and the cost of electricity procurement. The calculation is carried out for the period of one year. To make expenses comparable to the cost of electricity procurement, CAPEX are annualized using the annuity factor (see Equation 2.3). The weighted average cost of capital (WACC) are used for the cost of capital (WACC = 6%). Two types of stations are considered, with a capacity of 11 kw and 22 kw. With annualized total expenses of €660 per year for a charging point of 11 kW and

€1,051 for a charging point of 22 kW. The WMP are equal to the costs calculated using Equation 4.12 (PWMP) and as presented in Figure 4.6. As the annualized operating expenses of the charging infrastructure currently outweigh the cost of PWMP and their potential reduction through the coordinated charging process, the *SCP and charge level heuristic* solution approach is applied to this problem following the analysis presented in Section 3.4.2.4 on page 84. To assess the impact of the controlled charging strategy, three different cases are differentiated.

Table 5.3: Overview of the considered cost minimization cases.

Problem	Case 1: CSP-EVCSP	Case 2: Full coverage	Case 3: Uncontrolled
One-off cost	CAPEX, OPEX	none	CAPEX, OPEX
Variable cost	PWMP	PWMP	none
Problem type	CSP-EVCSP	EVCSP	CSPP
Solution method	SCP, heuristic and exact charging	exact charging	SCP, heuristic

Table 5.3 presents an overview of the main prerequisites of the three cases.

- Case 1: CSP-EVCSP (min cost)

The CSP-EVCSP charging case with total cost minimization applies the SCP and charge level heuristic solution approach. In this approach, a charging network configuration is first calculated that minimizes the number of charging points while adhering to the constraints of the optimization model (that is, SoC of the vehicle must be considered, and only a single vehicle can charge at a charging point in each time interval). In the second step, the resulting configuration of the charging network is treated as a EVCSP that minimizes the cost of electricity procurement while considering only the charging solution obtained in the first step.

- Case 2: Full coverage controlled charging (11 kW)

The full coverage and uncontrolled charging approaches are used as a reference to the case of the optimized charging infrastructure (Case 1). The *full coverage (11 kW)* solution assumes that charging is possible whenever the vehicle is parked. It is a best-case for the EVCSP, minimizing only the cost of electricity procurement.

- Case 3: Uncontrolled charging

In the uncontrolled charging case, the charging network is optimized as a CSPP, through the application of the *SCP + charge level heuristic*. The resulting charging network is the same as in Case 1. However, the PWMPs are not considered and there is no incentive to control charging. The charging pattern for this strategy is uncontrolled and remains the same over all examined years and only meets the constraints specified by the CSP-EVCSP.

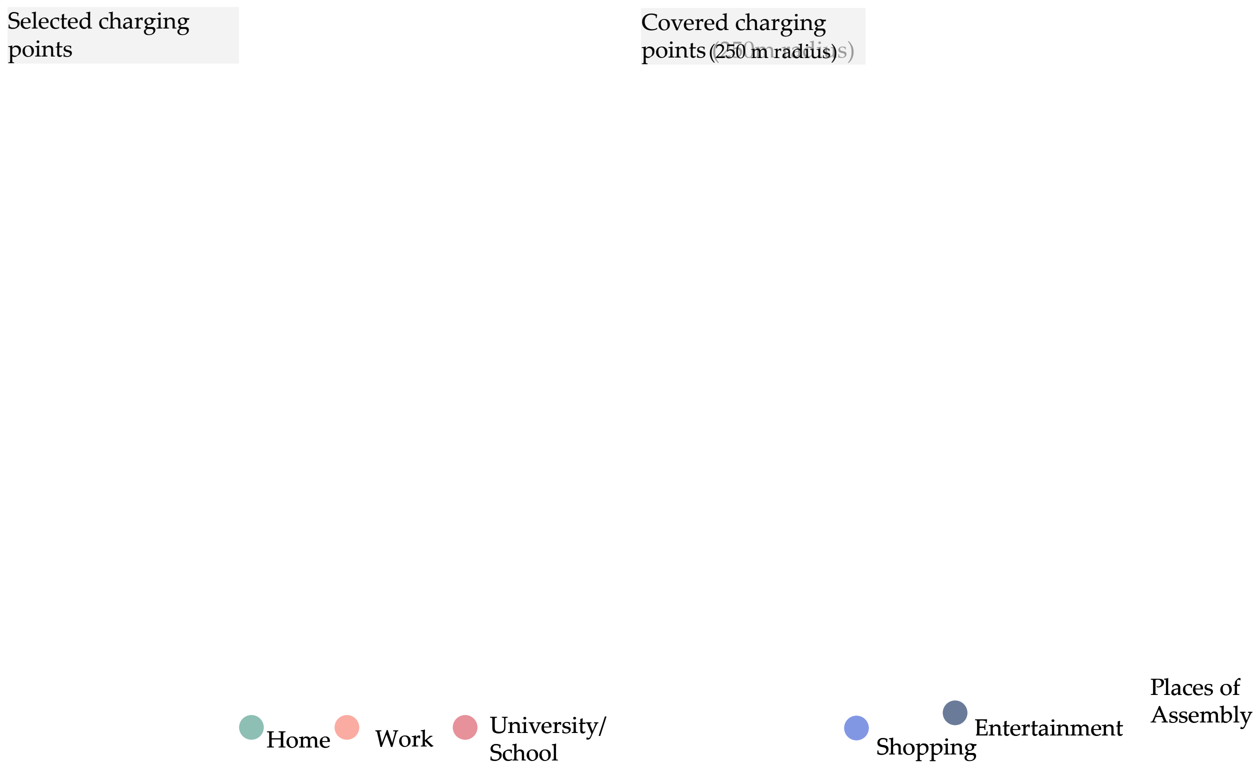


Figure 5.11: Result of the set covering problem (SCP) and charging heuristic. The left side shows only the selected charging points, while the right side of the figure also highlights the charging points within a radius of 250 m of the selected locations. In both figures, all possible charging points that are not part of the calculated solution are depicted in light gray.

The application of the SCP algorithm finds that a minimum number of 113 locations is sufficient to cover all vehicle charging requirements. After applying the charging heuristic that considers the required electricity in each interval and the exclusion of simultaneous charging, the final number of stations that results in a feasible scheduling solution is 118 charging points. The total annual expenses of the 118 charging points with a capacity 11 kW are equal to €77,880 per year and €124,018 per year if 22 kW charging points are considered. The resulting charging network is shown in Figure 5.11. As highlighted by the different colors in Figure 5.11 and summarized in Table 5.4, the selected charging points can be assigned to different types of locations. Most of the selected charging points are added at work (44) and near home locations (43).

The overall solution covers 776 of the 1,781 possible locations and 1,245 of the 3,000 potential charging points.[1] Assuming that any vehicle parking within 250 m of a charging point is *covered* by it, it is possible to calculate the total surface area of the city that is covered by the charging network. 12% of the city (25,518,756 m^2) is covered by at least one charging point, while 1,970,179 m^2 are covered by multiple charging points.

Figure 5.12 shows the average charging capacity of the 500 vehicles and 118 (11 kW) charging points, available throughout the day, on weekends and on weekdays. The capacity at a charging

1 More charging points than locations are covered, as several charging points can be assigned to one location, as for instance for workplace locations or especially for places of assembly, where the 500 profiles are assigned to one of the 23 assembly locations.

Table 5.4: Overview of charging point by location type.

	Possible locations	Selected charging points	Covered locations	Covered charging points
Home	500	43	186	186
Work	366	44	299	423
University /School	41	1	7	92
Shopping	455	12	154	171
Entertainment	396	15	120	154
Places of assembly	23	3	10	219

point in an interval is considered to be available if at least one BEV is parked at or near the charging location. The aggregation of vehicle charge, based on the type of day (weekend or weekday) shows that the total available charging power is approximately 10.2% (93.08 kW) less on weekends. On weekends, there is a smaller standard deviation (σ = 9.06 kW) of the average available power, compared to a higher standard deviation throughout the week (σ = 65.30 kW). On average, the highest share of connected vehicles on weekdays is between 6:15 p.m. and 7:45 p.m., and the maximum charging power on average is available in the 15 minute time interval starting at 6:30 p.m.

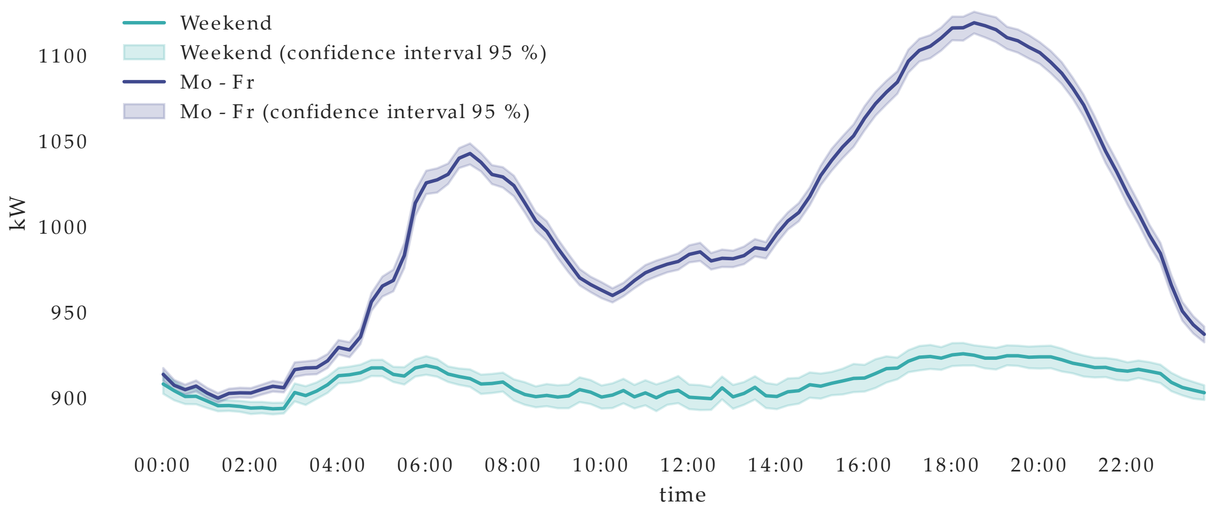


Figure 5.12: Average available power for the solution of the set covering problem and charging heuristic (500 vehicles and 118 (11 kW) charging points).

5.3.1 Analysis of the charging patterns

In this section, the results related to charging activities are presented and analyzed. Before presenting the detailed charging results, the two reference cases, that is, full coverage (11 kW) and uncontrolled charging, are presented. In the full coverage solution, the parameter β is set to 0, and annualized expenses are not taken into account in the objective function. In the case of the uncontrolled charging solution, the parameter α is set to 0, thus neglecting the PWMP. The charging solution only needs to meet the charging constraints of the model, taking into account the charging network resulting from the application of SCP and the heuristic.

In total, 1, 129, 860 kWh per year is charged by the 500 vehicles. On average, a vehicle charges 2, 259.72 kW. Table 5.5 summarizes the overall results for the different scheduling procedures. The station costs account for the majority (on average 76%) of all costs. For the case of full coverage, the total station cost can only be estimated, as they are neglected in the objective function. This can lead to inefficient solutions, as multiple charging points cover one location, while only one charging point would be necessary. When considering only one charging point for each location and aggregating any charging points that are overlapping, the number of charging points required would range from 1764 to 1776, leading to annual station cost of 1, 164, 240 to 1, 172, 160 €.

As Table 5.5 shows, the average costs increase for the uncontrolled charging case and the years 2025 and 2035 before decreasing for the year 2045. For the CSP-EVCSP and full coverage solution, the average costs increase for the year 2025 compared to 2019 and decrease in the years 2035 and 2045. When considering the cost of electricity procurement (PWMP) for each strategy, in contrast to the average electricity prices calculated based on Equation 4.12 for the years 2019 - 2045 (37.66, 57.33, 46.20, 37.55 €/MWh), the deviation from the average cost can be calculated. The PWMP for the uncontrolled charging strategy only deviates by 1.77 €/MWh from the average calculated market prices over all years. For the CSP-EVCSP charging solution, they are on average 32.01 €/MWh lower, and for the case of full coverage 47.52 €/MWh lower for all years.

On a more detailed examination of the individual years for the CSP-EVCSP and full coverage case, the savings of the procured electricity compared to the average market prices increase. For the CSP-EVCSP charging solution, the average charging costs are 52.73 €/MWh lower in 2045 than the average market cost, while for the full coverage charging solution, average savings of 76.05 €/MWh result for 2045 compared to the average market prices. Negative prices occur more frequently in the years 2035 and 2045, as they are induced by curtailed electricity in the calculation, which increases in these years. In these situations, CPO would be remunerated for purchasing electricity during these times. In the fully renewable energy system in 2045, this can even lead to negative average charging prices. For all charging patterns, the standard deviation of the charging costs is similar to that of electricity market prices. The minimum charging costs presented in the model are calculated for each vehicle and charging strategy, and the minimum prices for all charging events are reported in Table 5.5. The minimum PWMP calculated by the model occurs in September at 11:45 a.m. in each of the years evaluated. In every charging solution, at least one vehicle is charging at this time; however, there are significant differences of the number of vehicles actively charging. For the full coverage solution, all vehicles are charging during this time in each examined year, while in the CSP-EVCSP charging case, 95 vehicles are charging using 97.6% of the total charging energy available during this time interval.

Table 5.5: Results of the three cost minimization charging strategies for 2019 to 2045.

	charging cost				total cost	
	mean	std	min	max	charging cost	station cost
	€/MWh				€/ a	
2019						
Case 1: CSP-EVCSP	23.87	9.54	1.08	61.88	26,822.02	77,880
Case 2: Full Coverage (11 kw)	13.49	5.16	1.08	44.52	15,101.49	n/a
Case 3: Uncontrolled Charging	40.06	11.28	1.08	62.72	45,398.76	77,880
2025						
Case 1: CSP-EVCSP	36.42	13.55	-8.63	78.19	40,957.65	77,880
Case 2: Full Coverage (11 kw)	22.83	14.60	-8.63	57.48	25,508.60	n/a
Case 3: Uncontrolled Charging	56.67	14.13	-8.63	78.63	64,152.64	77,880
2035						
Case 1: CSP-EVCSP	5.59	20.62	-34.64	94.11	6,017.38	77,880
Case 2: Full Coverage (11 kw)	-9.18	17.59	-34.64	43.19	-10,588.38	n/a
Case 3: Uncontrolled Charging	44.13	28.83	-34.64	94.20	50,114.91	77,880
2045						
Case 1: CSP-EVCSP	-15.18	31.42	-84.06	144.29	-17,625.71	77,880
Case 2: Full Coverage (11 kw)	-38.50	30.68	-84.06	33.50	-44,075.84	n/a
Case 3: Uncontrolled Charging	35.58	39.73	-84.06	147.51	40,610.35	77,880

For the full coverage solution, the charging location and charging point cannot be differentiated. For the other two solution strategies (CSP-EVCSP and uncontrolled charging), charging activities can be categorized according to the location of a charging point, or the activity carried out while the vehicle is charging. If overlaps between charging locations are considered, the charging location does not have to correspond to the type of activity conducted, e.g., a vehicle might be parked and charging at a shopping location while the activity carried out is assigned to a work location.

In the case of the **CSP-EVCSP** charging solution (case 1), the charging results differ over the four representative years. However, in all years, most charging activities are carried out at work locations (41.6%) followed by home locations (25.4%) and shopping locations (6.6%). The highest share of electricity is charged at work in 2045 (42.5%). The distribution of charges by type remains largely unchanged, with an average deviation of 0.6% over the total electricity charged at each type of station. For the controlled charging solution, the difference between the charging location and the activity conducted is also notable. There is a positive discrepancy for charges carried out at work and home, for example, while 42.5% of electricity is charged at work locations, 53.3% of the total charged electricity is charged during work activities. The opposite is the case for charging conducted in shopping and entertainment locations, where 7.2% and 3% of the total electricity are charged during shopping and entertainment activities, while 12.6% of total electricity are charged at charging points located at shopping locations and 15.9% at entertainment locations.

For the **full coverage** charging solution (case 2), 84.6% of charging activities in 2019 are carried out at a charging point located at home followed by charging points located at shopping locations (5.6%), entertainment (2.9%), assembly places (2.9%), work (2.6%) and university/school (1.29%) locations. In 2025 the second highest share of charging in the full coverage charging solution is carried out at work locations (8.4%), while the order of the remaining places remains unchanged. The charge at home decreases to 64.8% in 2045, while the charge at work sites represents a share of 16.6% in 2045.

For the **uncontrolled charging** case (3), most charging activities are carried out at stations located at the workplace (45.7%) or while performing work-related activities (59.3%). The electricity charged at home represents 23.09% and 30.4% of the total electricity consumed during activities assigned to the location home. For all other locations, there is a stronger deviation between the charging location and the activity carried out. For example, 14.95% of the charging activities are carried out at charging points located at entertainment locations; however, only 2% of the activities carried out during this time are activities assigned to the entertainment category. On average, the charging points are occupied with charging activities 14.6% of the total possible times. The charging points at work have the highest utilization (19.4%)[2] while the charging points at home and the assembly sites have the lowest utilization.

The utilization of charging places deviates for the six different types of location in the CSP-EVCSP solution. Over all years, charging points located at places of assembly have the highest utilization (18.7%) followed by charging points at work (17.9%). The use of charging points at universities / schools, shopping, and entertainment locations varies between 13.7 and 15.1%, while those located at home have the lowest utilization (8.5%). Charge point utilization remains similar over all of the considered years, with the greatest difference in utilization occurring for university/school locations, where utilization decreases from 14.6% in 2019 to 13.5% in 2045.

2 Calculated as the share of charged electricity at the workplace charging point divided by the total electricity that could be charged by all vehicles at workplace charging points.

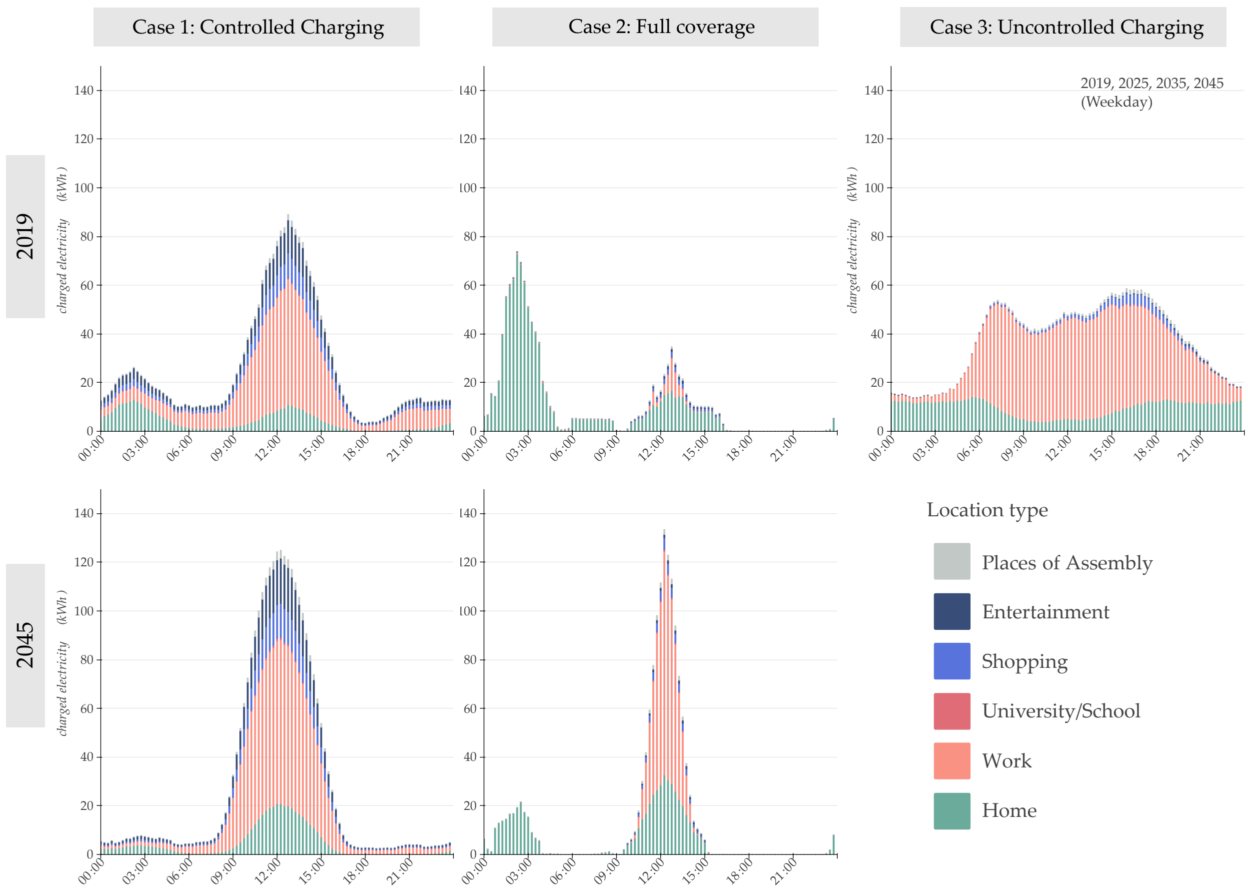


Figure 5.13: Average electricity charged for each charging solution (by charging location), for an average weekday (Mon.- Fri.) in 2019 and 2045. For the uncontrolled charging case, the charging pattern remains the same over all considered years.

Although the overall utilization of charging stations remains similar over all years, the charging pattern differs in several dimensions. The most noticeable differences in charged electricity per day occur between weekdays and weekends, and charging also varies over the weekday depending on the type of day, year, and charging strategy. Figure 5.13 shows the charging patterns for the three charging strategies and the years 2019 and 2045 on a weekday.

For the CSP-EVCSP charging case, most electricity is charged from 12:00 p.m. to 6:00 p.m., with the share increasing from 45.1% in 2019 to 52.2% in 2045. In 2019, the interval with the highest charge occurs from 12:45 p.m. to 13:00 p.m. where 88.06 kWh are charged. In 2045 the average peak charging interval is 30 min. earlier and on average 123.54 kWh are charged in the 15 minute interval.

The average weekday in 2019 for the full coverage solution can be characterized by a charging peak at 2:15 a.m. to 2:30 a.m. where 73.1 kWh within a 15-minute interval are charged (equivalent to an average peak charging power of 292.3 kW). 62.6% of electricity is charged until 6:00 am, while 24.7% is charged from 12 p.m. to 6 p.m. For 2045, the maximum electricity consumption is shifted to the interval from 12:00 p.m. to 12:15 p.m. and increases to 131.94 kWh (527.76 kW). The share of electricity consumption at night continuously decreases, accounting for 46.2% in 2025 and 18.7% in 2035. In 2045 59.3% of electricity is charged from 12:00 p.m. to 6:00 p.m. during the week.

For the uncontrolled charging case, the weekday charging pattern remains unchanged for the considered years, as there is no incentive to charge during a certain time-period as long as the constraints of the model are met. The majority of charging is conducted from 12 p.m. to 6 p.m. (35.3%), the maximum electricity consumption occurs between 4:30 p.m. and 4:45 p.m., where 57.6 kWh are charged. In general, the charge is distributed throughout the day more evenly than for the two cases previously described.

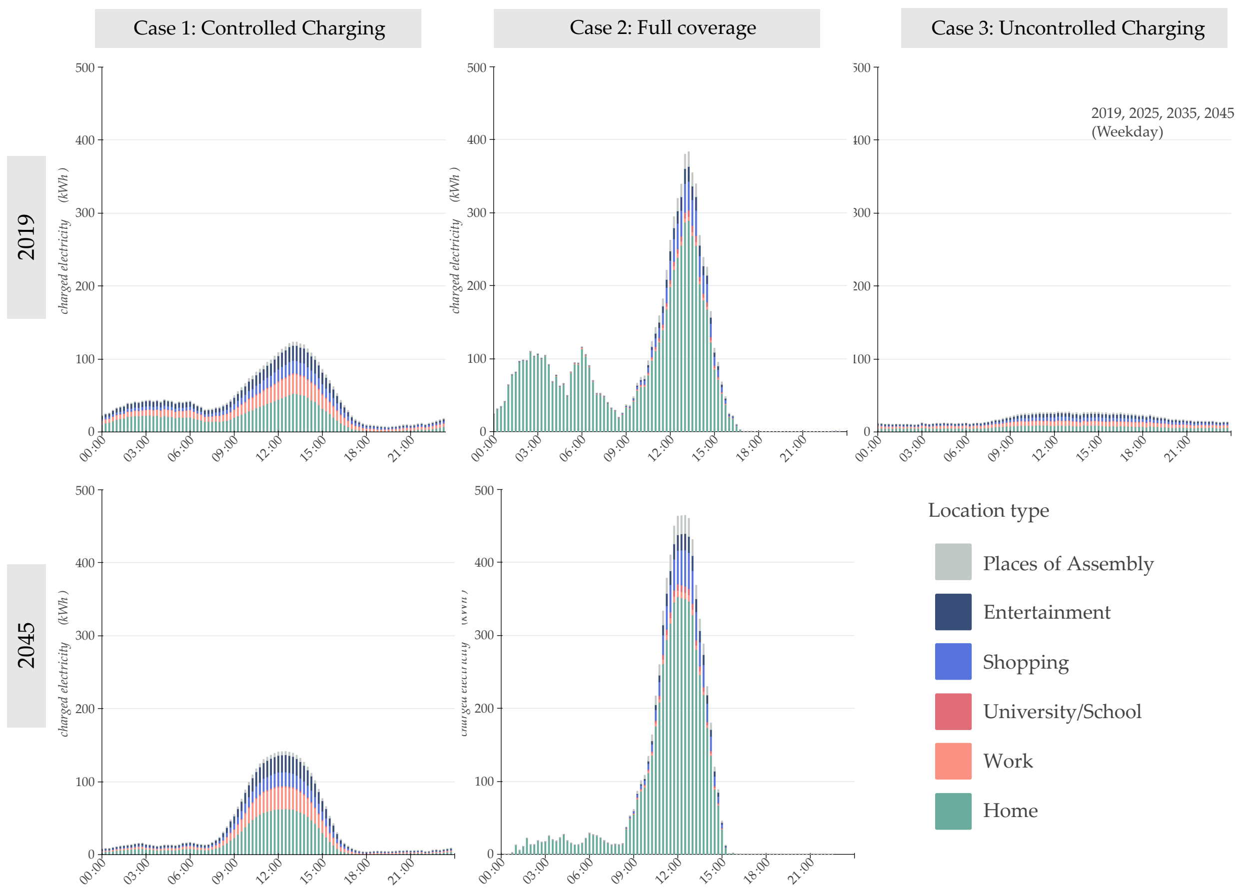


Figure 5.14: Average electricity charged (by charging location) for each charging solution, for an average weekend (Sat.- Sun.) day in 2019 and 2045. For the uncontrolled charging case, the charging pattern remains the same over all considered years.

Figure 5.14 shows the average results of weekend charging for the three charging strategies and the years 2019 and 2045. When comparing the results with Figure 5.13, it should be noted that the axis has been adapted to represent the higher maximum power charged in the full coverage case. Generally, the patterns described in the previous paragraphs for weekday charging can also be observed for weekends. The biggest differences exist in the full coverage charging solution. Most of the electricity is charged from 12 p.m. to 6 p.m. in 2019 (51%), further increasing to 54.2% of all charges carried out during this time in 2045. This corresponds to the lower electricity prices on weekends. This also leads to more electricity being charged on weekends, where 68.9% of the total electricity is charged in 2019, and 73.7% in 2045. During the two weekend days, a higher average charging power is consequently also required, in contrast to the five weekdays. During the peak charging interval in 2019 from 1:15 p.m. to 1:30 p.m., 394.55 kWh are charged, corresponding to a charging power of 1578.20 kW. In 2045, the average peak interval is shifted 45 min. earlier and increases to 477.9 kWh or 1,911.8 kW. For the controlled charging strategy, the peak charging interval increases from 126.9 kWh in 2019 to 145.5 kWh in 2045.

5.3.2 Economic and geographic assessment

The financial evaluation for the uncontrolled and CSP-EVCSP solution is presented in Table 5.6. The total costs include the annuity for the CAPEX and OPEX of the charging points, the expected yield embodied in the equity cost of the considered WACC, as well as volatile electricity costs to acquire the required charging electricity. Costs can be distributed between individual charging points. In doing so, the total costs per kWh for the uncontrolled charging strategy are 1.6 cents higher than the costs per kWh for the CSP-EVCSP solution in 2019. This difference increases to 5.1 cents per kWh for the year 2045. Therefore, the revenue required to break-even in 2019 is 17.7% higher for the uncontrolled strategy, in contrast to the CSP-EVCSP solution and 96.6% higher for 2045. To achieve the required revenue to break-even, for the CSP-EVCSP solution charging strategy, an electricity price of 9.3 cents/kWh (without taxes and levies) is necessary in 2019.

Table 5.6: Break-even revenue and cost per MWh (incl. expected return on equity).

	Total cost €	specific cost €/MWh	per charging point €/charging point
2019			
Case 1 : CSP-EVCSP	104,702.02	92.67	887.31
Case 3: Uncontrolled	123,278.76	109.11	1,044.74
2025			
Case 1: CSP-EVCSP	118,837.65	105.18	1,007.10
Case 3: Uncontrolled	142,032.64	125.71	1,203.67
2035			
Case 1: CSP-EVCSP	83,897.38	74.25	710.99
Case 3: Uncontrolled	127,994.91	113.28	1,084.70
2045			
Case 1: CSP-EVCSP	60,254.29	53.33	510.63
Case 3: Uncontrolled	118,490.35	104.87	1,004.16

Assuming the specific costs to break-even shown in Table 5.6 are paid per kWh by all customers, the revenue of each charging point can be calculated. For 2019, the revenue from the electricity charged at each charging point ranges from €200.10 to €2,458.88 for the CSP-EVCSP case (considering a flat electricity price of 9.26 cents/kWh) and €225.82 to €3, 331.60 for the uncontrolled charging strategy (considering a flat electricity price of 10.91 cents/kWh). The total cost resulting from the infrastructure expansion and electricity procurement are higher for the uncontrolled charging strategy, this also results in a higher electricity price and revenue required to break-even.

The average electricity procurement costs per charging point influenced by the PWMPs range from 16.67 to 31.54 €/MWh for the CSP-EVCSP solution, while the costs of the uncontrolled charging solution range from 33.75 to 42.82 €/MWh in 2019. The full coverage solution achieves the lowest procurement costs per charging point in this year, which range from 12.81 €/MWh to 14.39 €/MWh in 2019. For the year 2045 the cost spread between the minimum and maximum charging procurement cost per charging point increase. For the CSP-EVCSP solution, the procurement costs decrease to a minimum value of -36.38 and maximum to 2.47 €/MWh, while they are negative for every charging point in the full coverage solution (-43.32 to -32.97 €/MWh) for the uncontrolled solution; however, the average procurement costs remain close to the 2019 costs, with the minimum value reaching 27.18 €/MWh and maximum 52.39 €/MWh for all charging points.

The difference between the procurement cost of the different strategies arises due to the timing of the charging activities described above and depicted, for example, in Figure 5.13. Therefore, this also leads to different distributions of charging activities throughout the city. Figure 5.15 shows the geographic concentration of charging activities for the three charging strategies in 2019. The map data is visualized using hexagonal shapes due to their advantages in accuracy and superior visual appeal in contrast to the grid structure used by the city of Essen (Birch et al., 2007; Carr et al., 1992).

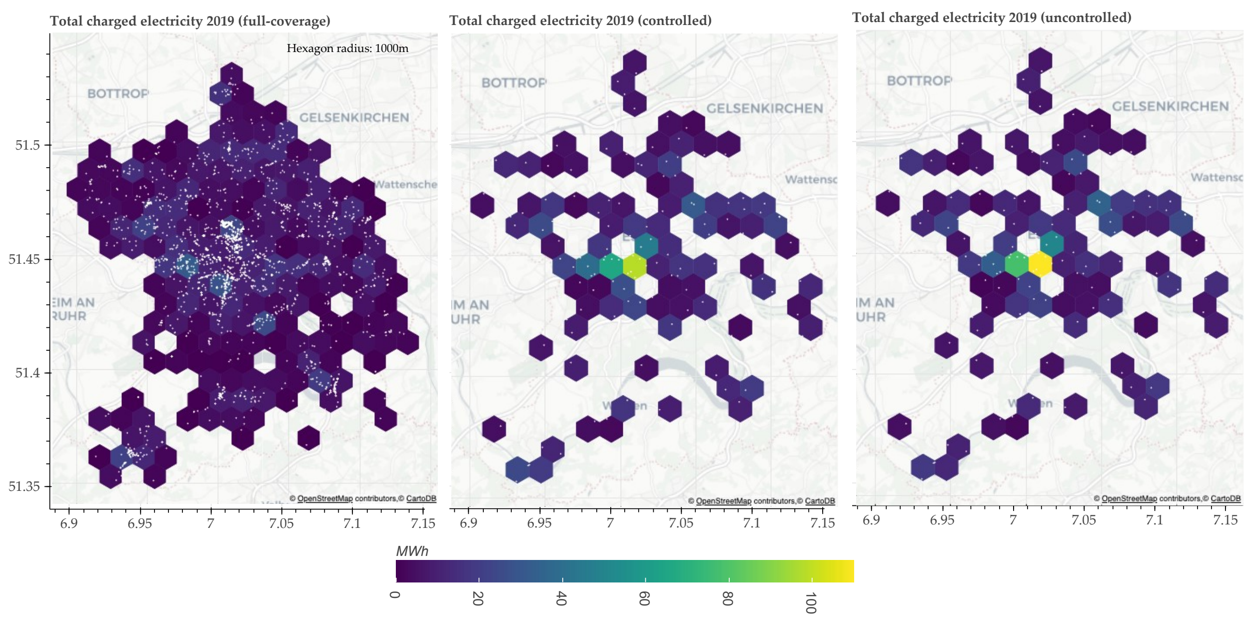


Figure 5.15: Total electricity charged for each charging point in 2019 for the three charging strategies.

The radius of the hexagons is set to 1,000 m when measured in the circumcircle (center to vertex). The fill color corresponds to the total charge carried out at the charging points over a year. The charging points are depicted using white dots. When comparing the geographical concentration of charged electricity for geographic areas, it can be observed that for the full coverage strategy, the total charged electricity is distributed throughout the city in 184 hexagons. The hexagons with the highest total charge are located in the city center with a total charge of 31.85 MWh over the year, while the average charge on the 184 hexagons is equal to 6.14 MWh in 2019. Charging is less distributed for the other two solution strategies. For the CSP-EVCSP solution and uncontrolled charging solution, the charging is concentrated on a total of 86 hexagons. The maximum charge for a single hexagon is carried out in the city center ("51.455°, 7.15°") and equal to 98.33 MWh for the CSP-EVCSP solution and 114.31 MWh for the uncontrolled charging strategy. The minimum total charge in a hexagon on the northern outskirts is equal to 2.07 MWh and 2.16 MWh ("51.437°, 6.96°"). More electricity is charged in the center of the city, when comparing the solution of 2019 and 2045. The installed capacity directly impacts the charged electricity per hexagon. In both the uncontrolled and CSP-EVCSP solution, the hexagon that has the highest cumulative charging capacity also has the highest total electricity consumption. Although this distribution is similar for the uncontrolled and CSP-EVCSP charging cases, there are differences in the overall distribution of charging and on average, the total charge per hexagon deviates for both solutions by 1.91 MWh for the year 2019.

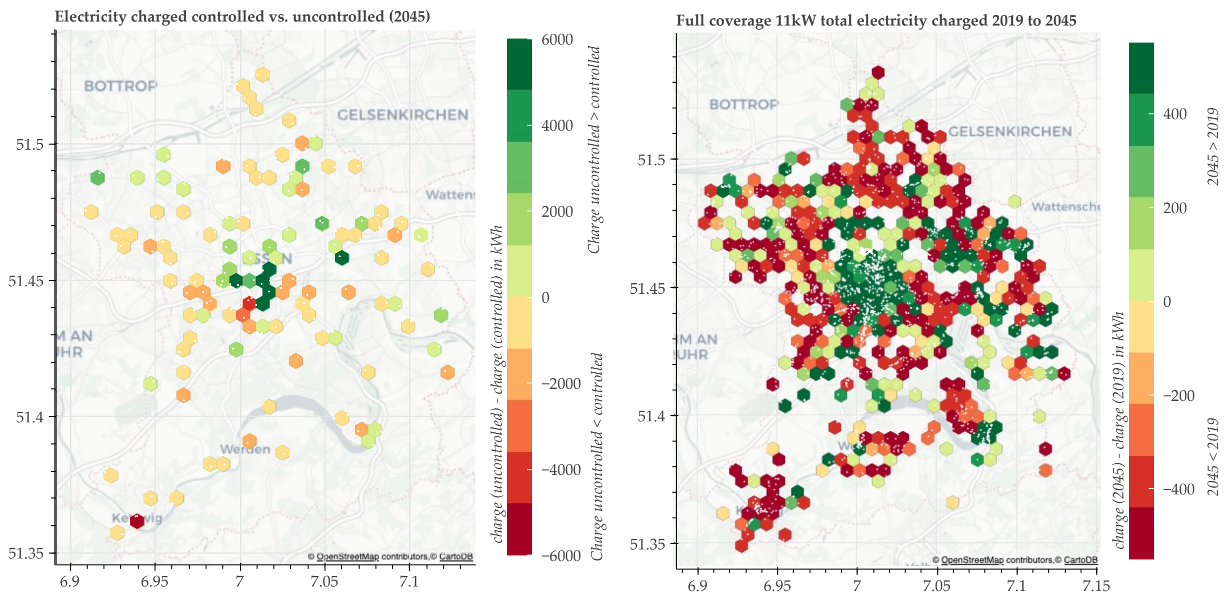


Figure 5.16: Differences in geographic charging patterns. Left: uncontrolled charging vs controlled charging in 2045. Right: Full coverage case differences in the geographic distribution of charging in 2019 vs. 2045.

Figure 5.16 shows the geographic distribution of the total charging in 2045 for the CSP-EVCSP charging strategy and uncontrolled charging (left side), as well as difference between the full-coverage charging solutions for the years 2019 and 2045 (right side). To allow for a finer differentiation, the radius of the hexagons is reduced to 500 m when measured in the circumcircle (center to vertex). Therefore, 109 hexagons are considered with only 6 hexagons encompassing two charging points of the total 118 considered charging points. Consequently, the total electricity charged per year for each hexagon is also only about half as high with 39.24 MWh to 48.71 MWh

Both depictions of the results show that more electricity is charged within the center of the city. This finding is in line with the insights regarding the temporal distribution and distribution by charging location and activity conducted while a vehicle is charging presented in the previous section. As can be observed in Figure 5.11 that presents the selected and covered charging points by type of location, there is a large overlap between places with a high output and the places of work. The highest discrepancy between the total electricity charged in two hexagons is 9.49 MWh, between the uncontrolled and the CSP-EVCSP solution.

In general, the minimization of the charging costs in cases 1 to 3 allows to derive several general and case study specific results. Firstly, considering the temporal distribution of charging activities through the charge level heuristic increases the number of charging points by 4.5% in contrast to the exclusive application of the SCP. As previous CSPP problems do not consider temporally resolved charging patterns, these studies can overestimate the ability of a charging network to meet the electricity demand of vehicles. When comparing the possible saving of the charging procurement cost of the controlled (case 1) in contrast to the uncontrolled (case 3) strategy, the results show, that a higher volatility of electricity prices also increases the savings of the controlled in contrast to the uncontrolled charging strategy. Between the years 2019 and 2045, the potential savings through the controlled charging strategy in contrast to the uncontrolled strategy more than triple. When comparing the charging cost in the full coverage (case 2) and controlled charging (case 1) solution, the cost savings also increase from 2019 to 2045. Although charging costs decrease if more charging stations are considered, higher infrastructure costs do not justify additional infrastructure expansion.

5.4 ECOLOGICAL CONSIDERATIONS

In this section, the optimization model is applied with the aim of minimizing the CO_2e emissions of the charging infrastructure (i.e., the emissions that can be attributed to the manufacturing and installation of the infrastructure) as well as emissions attributed to charged electricity. Infrastructure emissions are based on the values calculated in the study by Zhang et al. (2018). In this thesis, the values of CO_2e emissions of the charging infrastructure are annualized and it is assumed that the emissions are equal to 26 kg/CO_2e (per year) for a 11 kW charger and 36 kg/CO_2e (per year) for a 22 kW charger. Emissions of charged electricity are calculated as presented in Equations 4.13 and 4.14 and using the results of the energy scenarios presented above.

The emissions calculated according to Equation 4.13 explicitly consider curtailed electricity, while the emissions factor calculated using Equation 4.14 only includes the emissions attributed to the German energy mix (without considering curtailed electricity).

In contrast to the electricity procurement and infrastructure cost previously considered, the share of emissions in the use phase, i.e, the emissions related to the charged electricity, are greater than the emissions attributed to the construction and installation of the infrastructure. As highlighted in Section 3.4.2.4, in these cases, a generation of communities and step-wise optimization (successive community optimization (SCO)) yields better results than minimizing charging points and subsequent optimization of the charging schedule. As the solution procedure does not guarantee an optimal result, a best-case charging solution is calculated assuming full coverage of all charging points. Four different results are presented in this section.

- Case 4: CSP-EVCSP (curtailed - $EMIS_{A_t}[t]$)
- Case 5: CSP-EVCSP (no curtailment - $EMIS[t]$)
- Case 6: Full coverage (22 kW) (curtailed - $EMIS_{A_t}[t]$)
- Case 7: Full coverage (22 kW) (no curtailment - $EMIS[t]$)

In the previous assessment (cost minimization), the consideration of charging points with a higher charging capacity was not justified, as expenses increase between a charging station of 11 kW and 22 kW, and this investment cannot be recovered through electricity procurement cost savings. If CO_2e emissions are taken into account, the consideration of a charging infrastructure with a higher capacity appears to be reasonable. Therefore, the optimization model considers both the possibility of charging points with a capacity of 11 kW and 22 kW. A complete overview of the four additional cases is presented in Table 5.7.

In contrast to the results of the cost minimization (cases 1-3) presented in the previous section, the locations and number of charging stations vary over the years 2019, 2025, 2035 and 2045 for the cases 4 to 5. Additionally, also 22 kW charging stations are considered in the solutions of the years 2019 and 2025.

On average, 321 charging points are used in the calculated solutions. These charging points cover 45.4% of all possible charging points and 58.8% of possible charging locations. The highest number of charging points are selected in the year 2019 (355 curtailed/ 357 without curtailment) and the lowest in the year 2045 (288 curtailed/ 296 without curtailment). Overall more charging points are considered when CO_2e emissions are calculated without the consideration of curtailed electricity ($EMIS[t]$). On average 4.75 additional charging points are included in the calculated solution compared to the solution if curtailed electricity is included in the cost calculation ($EMIS_{A_t}[t]$). In all solutions, home charging points make up more than 97% of all charging points. As shown in Table 5.8 and Figure 5.17, the number of charging points depend on the potential CO_2e savings per kWh from the charging strategies. The number of planned charging stations decreases as the ratio of infrastructure emissions to operational emissions decreases. Furthermore, 22 kW charging stations are not selected in the years 2035 and 2045. Consequently, the number of charging points decreases and reaches the smallest value in 2045.

The decreasing average emissions per kWh also have an impact on the capacity of the charging points. The annualized emissions for a charging point with 11 kW and 22 kW are assumed to

Table 5.7: Overview of the considered cases.

Problem	Case 4: CSP-EVCSP $\min(EMIS_{A_t}[t])$	Case 5: CSP-EVCSP $\min(EMIS[t])$	Case 6: Full coverage (22 kW) $\min(EMIS_{A_t}[t])$	Case 7: Full coverage (22 kW) $\min(EMIS[t])$
One-off emissions	Infrastructure Emissions		none	
Variable emissions	$EMIS_{A_t}[t]$	$EMIS[t]$	$EMIS_{A_t}[t]$	$EMIS[t]$
Problem type	CSP-EVCSP		EVCSP	
Solution method	SCO (community size: 2)		exact charging	

differ by 10 kg CO_2e annually. This consideration leads to different charging point capacities over the years 2019, 2025, 2035 2045. For the emission factor that considers curtailed electricity, all but one charging point have a charging capacity of 22 kW in 2019. The share of 11 kW charging points is higher when curtailed electricity is not considered in the emissions factor, and 19.3% of charging stations have a lower capacity of 11 kW in the solution for 2019. For the emission factor EMIS[t], all but one charging station in the year 2025 have a capacity of 11 kW, while 47.2% of charging stations have a charging capacity of 22 kW when considering electricity curtailment. For the years 2035 and 2045 all charging stations have a capacity of 11 kW for both emission factors.

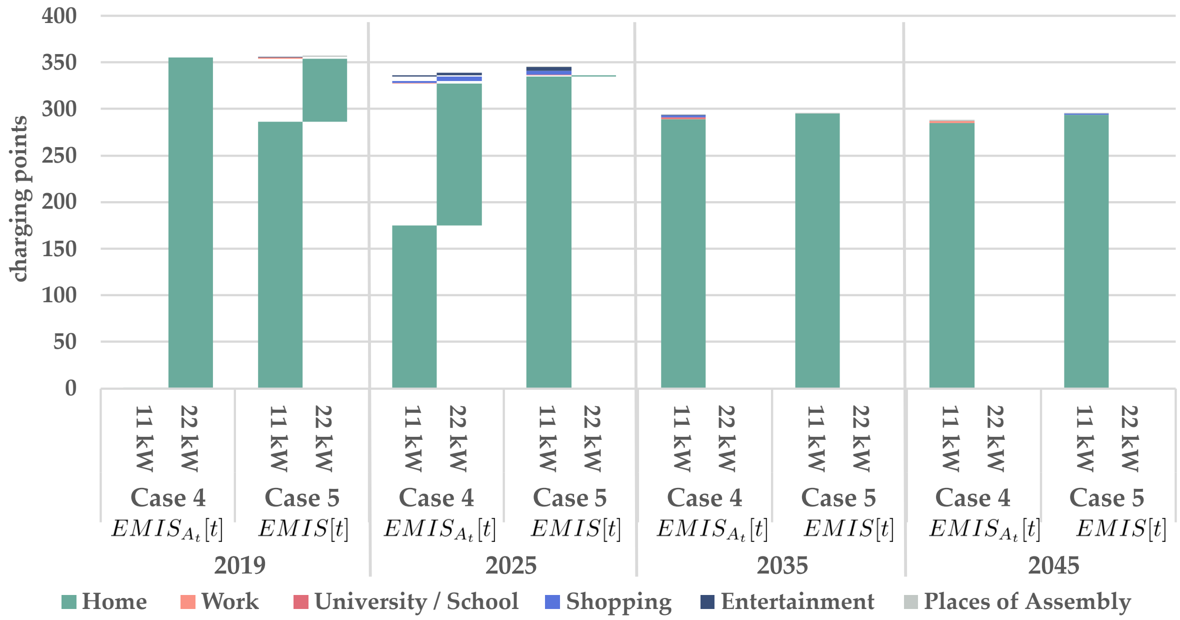


Figure 5.17: Considered locations in the optimization based on emissions.

When comparing a location solution with the one previously presented for the cost optimization case (e.g., cases 1 and 3), it can be observed that the type of locations and the overall covered area differ for both solutions. The example presented in Figure 5.18 shows the selected and covered

Table 5.8: Overview of charging point by location type.

	Possible locations	Selected charging points	Covered locations	Covered charging points
Home	500	285-355	462-500	462-500
Work	366	0-2	93-113	118-147
University /School	41	0-1	3-7	46-92
Shopping	455	0-7	220-253	242-279
Entertainment	396	0-4	188-217	234-268
Places of assembly	23	0-1	4-9	79-187

charging points for the year 2019, taking into account the emission factor that considers curtailed emissions ($EMIS_{A_t}[t]$). More area is covered by the selected charging stations and specifically in the outskirts of the city.

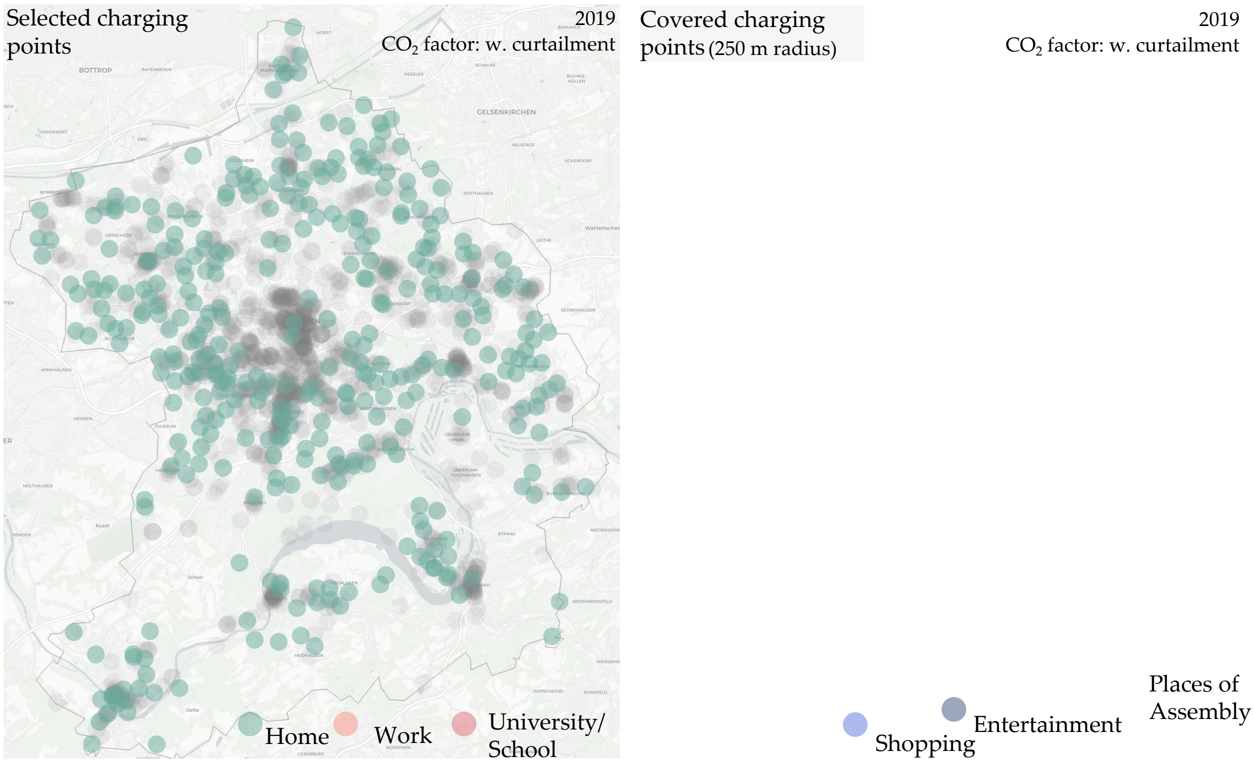


Figure 5.18: Selected charging locations for the minimization of emissions. The left side shows only the selected charging points, while the right side of the figure also highlights the charging points within a radius of 250 m of the selected station. In both figures, all possible but not considered charging points are depicted in light gray.

Table 5.9 shows the statistical values that represent the changes in the average and total emissions for each of the optimization strategies. Emissions decrease at each time step, as is the case for the emissions of the electricity mix (see Table 6.3 in the appendix).

The average emissions in the electricity system decreased by 90.7% ($EMIS_{A_t}[t]$) and 90.8% ($EMIS[t]$) for the two emission factors between the years 2019 and 2045. The overall charging emissions decrease by 92.9% ($EMIS_{A_t}[t]$) and by 94.1% ($EMIS[t]$). The proportion of emissions attributed to the infrastructure, of total emissions increases from 3.7% ($EMIS_{A_t}[t]$) and 5.7% ($EMIS[t]$) in 2019 to more than 33.5% in 2045 for both emission factors, due to lower emissions from the energy mix, while emissions of charging points remain unchanged over the assessed years.

To calculate the full coverage (22 kW) charging solution, it is assumed that charging can be conducted at all charging points i.e., carried out if a vehicle is not driving (i.e., parked). To determine the necessary charging points for this solution, all charging points that are not utilized are excluded, and only one charging point per location is considered. This means that multiple charging activities can be carried out at one charging point; therefore, the full coverage solution

Table 5.9: Emissions emissions minimization cases.

	charging emissions				total CO_2e	
	mean	std	min	max	charging	station
	kg CO_2e/MWh				kg CO_2e/ a	
2019						
Case 4: CSP-EVCSP (curtail)	187.72	48.86	0.00	397.10	209,544.72	12,770
Case 5: CSP-EVCSP (no curtail)	229.71	32.47	174.63	411.02	258,383.48	9,972
Case 6: Full Coverage (22 kW) (curtail)	180.66	49.79	0.00	390.25	201,028.35	20,268
Case 7: Full Coverage (22 kW) (no curtail)	221.02	30.4	174.63	398.04	247,865.52	20,412
2025						
Case 4: CSP-EVCSP (curtail)	116.42	29.29	0.00	364.25	130,038.10	10,414
Case 5: CSP-EVCSP (no curtail)	122.62	23.07	93.64	385.96	137,945.31	9,006
Case 6: Full Coverage (22 kW) (curtail)	107.61	30.46	0.00	336.63	120,233.03	20,268
Case 7: Full Coverage (22 kW) (no curtail)	114.54	20.28	93.64	336.63	128,565.19	20,160
2035						
Case 4: CSP-EVCSP (curtail)	23.12	7.36	0.00	168.25	25,953.43	7,644
Case 5: CSP-EVCSP (no curtail)	27.04	7.90	19.13	168.25	30,388.52	7,696
Case 6: Full Coverage (22 kW) (curtail)	19.38	6.54	0.00	84.02	21,557.00	20,412
Case 7: Full Coverage (22 kW) (no curtail)	25.25	6.25	19.13	84.02	28,149.81	20,052
2045						
Case 4: CSP-EVCSP (curtail)	13.20	4.26	0.00	51.19	14,825.22	7,488
Case 5: CSP-EVCSP (no curtail)	13.55	4.10	11.13	44.03	15,219.97	7,696
Case 6: Full Coverage (22 kW) (curtail)	11.58	3.65	0.00	35.13	12,900.40	20,088
Case 7: Full Coverage (22 kW) (no curtail)	12.63	2.97	11.13	39.38	14,135.72	19,368

(22 kW) and the respective station emissions should only be considered as a general reference point as the considered stations may not present a feasible solution to the CSP-EVCSP.

Optimization of the charging process (cases 4 and 5) leads to 60% lower emissions compared to the average electrical mix in the assessed years. The highest difference between the average emissions in the electricity system and the emissions to charge the vehicles is achieved in 2035, where the emissions are on average 79.5% lower than the mean emission factors for the year. This is due to the high fluctuation and difference between the minimum and maximum emissions induced by a high share of renewable electricity generation with considerable shares of power production from non-renewable natural gas powered electricity generators.

For all solutions to CSP-EVCSP (with and without consideration of curtailment), more than 87% of electricity is charged at home. In 2019, 35%-36% of total electricity is charged on weekdays for both emission factors. The proportion of electricity charged on weekends gradually decreases over time. In the solution of the year 2045, 58.5% of electricity is charged on weekdays when considering curtailment (case 4) and 62.7% without consideration (case 5). Consequently, the share of charging during work activities on weekdays increases from 4.3% in 2019 to 14.5% in

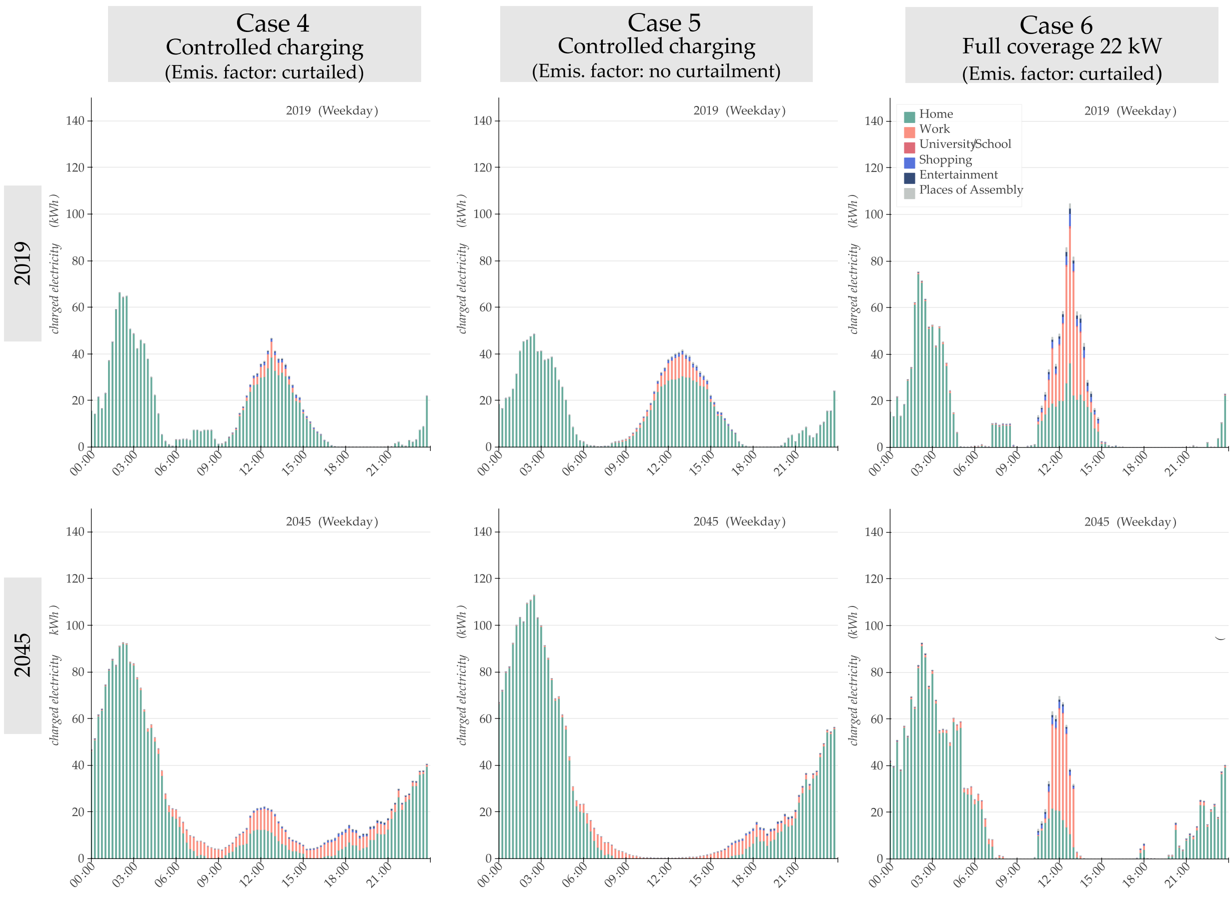


Figure 5.19: Average electricity charged during different activities for each charging solution, for an average weekday (Mon.- Fri.) in 2019 and 2045. For the uncontrolled charging case, the charging pattern remains the same over all considered years.

2045 when considering the emission factor with curtailment and from 7.1% to 7.6% when no curtailment is considered.

If the charging activities are classified by the activity conducted while the vehicle is charging, the pattern also changes from the year 2019 to the year 2045. These changes are illustrated for the cases 4,5 and 6 and for the years 2019 and 2045 in Figure 5.19. The charging activities are distinguished according to the activities carried out while the vehicle is charging (in Figures 5.14 and 5.13, the results are distinguished by the location of the vehicle regardless of the activity carried out).

For case 5 where curtailment is not considered, the charging times deviate between the years 2019 and 2045. In 2019, 48% of electricity is charged between 6 a.m. and 6 p.m. However, for the year 2045, only 7% of electricity is charged in this time interval, and the majority of electricity is charged throughout the night. For cases 4 and 6, under consideration of curtailed electricity in the calculation of the emissions factor, the general distribution of charging activities is less strongly shifted to the night and 20% to 33% of electricity is charged throughout the day (6 a.m. to 6 p.m.). The general shift of charging to the nighttime is induced by large shares of electricity generated by wind turbines which entails lower CO_2e emissions than other technologies. In the cases where curtailed electricity is considered, large shares of electricity generation from solar energy lead to electricity curtailment at noon, which decreases emissions in these hours.

Figure 5.20 shows the maximum charge possible for different solutions. For this depiction, the same assumptions are made as for the analysis presented in Figure 5.12, that is, the charging power is considered available if a vehicle is parked near a charging point at a certain interval. The plot shows the potential charging power available for four different infrastructure expansions:

- Case 6,7: Full coverage (22 kW)
- Full coverage (11 kW)
- Case 4: CSP-EVCSP solution **2019** (curtailed - $\mathrm{EMIS}_{A_t}[t]$)
- Case 4: CSP-EVCSP solution **2045** (curtailed - $\mathrm{EMIS}_{A_t}[t]$)

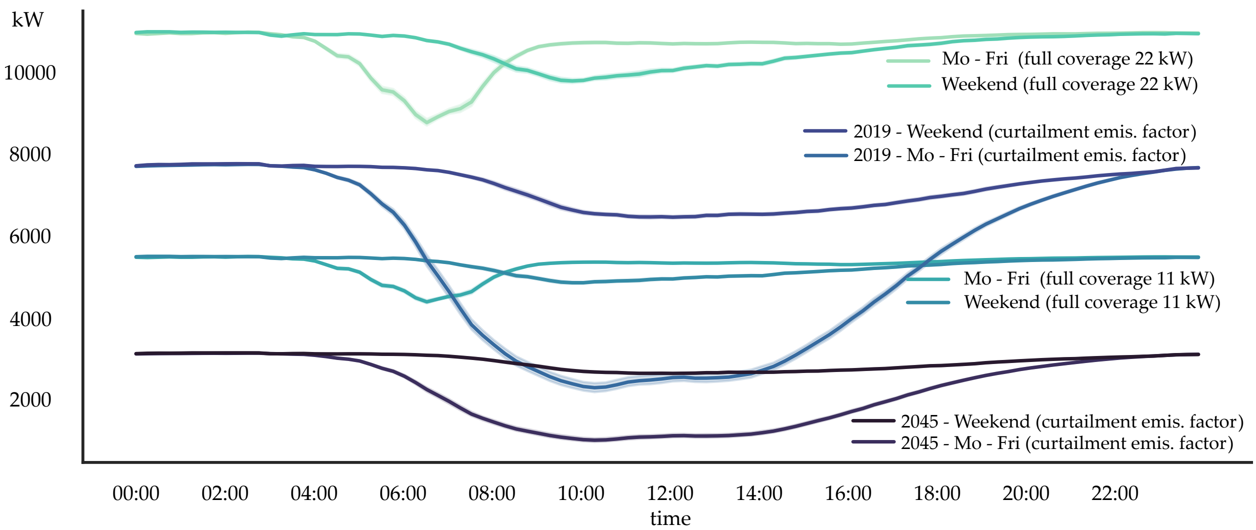


Figure 5.20: Maximum available power for different charging network configurations resulting from a minimization of emissions. The shaded area represents a 95% confidence interval of all values within the year.

For the two full coverage solutions, a uniform 22 kW charging capacity and 11 kW are assumed. For these cases, the maximum charge only decreases during mobility activities; consequently, the maximum decrease in charging power on weekdays occurs on average at 06:30 a.m. and on average drops by 2,238 kW for the case of 22 kW and by 1,119 kW for the case of 11 kW, from the maximum values, where all vehicles are connected. On weekends, the maximum drop is about half as high (1,196 kW and 597.17 kW) and occurs in the interval from 09:45 a.m. to 10:00 a.m.

The two other cases (case 4 (2019) and case 4 (2045)) show the potential charging capacity of an optimized charging network based on the emission factors for 2019 and 2045. Although the considered charging infrastructure differs between both years, the general patterns of the available charging capacity of both are similar. On weekdays, the potential charging power decreases according to the full coverage cases induced by increasing mobility activities starting at 06:30

a.m., however, since fewer charging points are considered in or near work locations, it sharply decreases and only 32.8% (2019) and 34.3% of the maximum potential charging capacity (7,799 kW/ 3,157 kW) of all vehicles is available between 09:00 a.m. and 02:00 p.m. On weekends, a similar pattern can be observed; the average available charging power is approximately 22.49 - 23.8% higher on weekends than on weekdays.

5.5 THE TRADE-OFF BETWEEN COST MINIMIZATION AND EMISSION MINIMIZATION IN THE ENERGY SYSTEM

In this section, the trade-off between the results obtained for the case of cost minimization and emission minimization is discussed. Furthermore, the results are also evaluated in light of the presented energy system configurations. To do so, the charging solutions obtained from the cost minimization model are weighed with the prevailing emissions. This makes it possible to present an answer to the question of how much higher emissions would result from the optimization based on cost in contrast to the optimization with regard to emissions. In the same manner, the additional cost of the emissions minimization solution in contrast to the cost minimization solution can be calculated. In an assessment of the entire energy system, the charging patterns and the charging point configurations obtained are extrapolated to a larger vehicle fleet to calculate the effects of additional electricity consumption on the electricity system.

Table 5.10 shows a comparison of cost and emissions for of all presented charging strategies and assessed indicators. The cost and emission values per MWh of electricity charged per vehicle include the one-off emissions or cost as well as running cost / emissions. Over all years, costs per MWh are on average 1.83 to 2.7 times higher for emission minimization cases in contrast to the total cost of the cost minimization solution. The cost minimization solution leads to 25% to 39% higher CO_2e emissions for the factor that considers curtailment and 15% to 71% higher emissions in contrast to the case that does not consider electricity curtailment. The uncontrolled charging solution leads to 79% to 311% higher emissions ($\mathrm{EMIS}_{A_t}[t]$) and 55% to 265% for the $\mathrm{EMIS}[t]$ emissions factor.

The total costs are broken down into annualized expenses and charging cost in Figure 5.21. The higher cost of solutions that minimize emissions can be attributed to annual charging station expenses that comprise more than 91% of total costs in the case of minimizing emissions. For years 2019 and 2025, the costs are the highest, as the largest number of and the most expensive charging points (22 kW), with a higher charging capacity, are considered. Therefore, charging cost are 65% lower for the optimization under consideration of emission factors than for the charging cost minimization solution. Figure 5.21 also highlights additional expenses and electricity procurement costs, in contrast to the best solution found in each year. Total costs are mostly caused by the high annualized expenses that make up 66% to 129% for the cost minimization solution[3] and 89% to 96% for the ex post calculated cost of the emissions solutions. The comparison of the two emission factors reveals that the annualized expenses of the solution based on the factor $\mathrm{EMIS}_{A_t}[t]$ (curtailment) are higher (20% to 40%) than the emissions that do not consider this

3 Annualized expenses make up more than 100% as PWMP are negative for the year 2045.

Table 5.10: Comparison of cost and emissions minimization solutions.

year	solution type	Cost (€/MWh)	% to best	$EMIS_{A_t}[t]$ $kgCO_2/MWh$	% to best	$EMIS[t]$ $kgCO_2/MWh$	% to best
2019	Case 1: CSP-EVCSP (cost)	92.67	0%	245.46	25%	272.00	15%
	Case 3: Uncontrolled Charging	109.11	18%	352.46	79%	369.05	55%
	Case 4: CSP-EVCSP (curtail)	344.28	272%	196.76	0%	-	-
	Case 5: CSP-EVCSP (no curtail)	248.21	168%	-	-	237.51	0%
2025	Case 1: CSP-EVCSP (cost)	105.18	0%	154.17	24%	155.33	19%
	Case 3: Uncontrolled Charging	125.71	20%	304.19	145%	304.33	134%
	Case 4: CSP-EVCSP (curtail)	281.59	168%	124.31	0%	-	-
	Case 5: CSP-EVCSP (no curtail)	232.09	121%	-	-	130.06	0%
2035	Case 1: CSP-EVCSP (cost)	74.25	0%	37.16	25%	43.38	29%
	Case 3: Uncontrolled Charging	113.28	53%	122.09	311%	123.19	265%
	Case 4: CSP-EVCSP (curtail)	180.28	143%	29.74	0%	-	-
	Case 5: CSP-EVCSP (no curtail)	199.95	169%	-	-	33.71	0%
2045	Case 1: CSP-EVCSP (cost)	53.33	0%	27.45	39%	34.73	71%
	Case 3: Uncontrolled Charging	104.87	97%	36.54	85%	37.92	87%
	Case 4: CSP-EVCSP (curtail)	180.20	238%	19.75	0%	-	-
	Case 5: CSP-EVCSP (no curtail)	198.97	273%	-	-	20.28	0%

factor in the years 2019 and 2025, while they are slightly lower (0.68% to 2.70%) for $EMIS_{A_t}[t]$ in 2035 and 2045.

The results presented in Figure 5.21 also show that even though PWMPs are not considered in the objective function of emission minimization, the ex post calculated procurement costs of the solutions that minimize emissions are 5% to 65% lower than the solution that minimizes procurement costs and expenses in the years 2019 and 2025. A probable explanation is the high correlation between the calculated emissions and the cost factors (90% - 92%) in these years, paired with a higher charging capacity and a greater distribution of charging stations in the city. In 2035, the correlation decreases to about 83% and 43%-59% in 2045, depending on the compared emissions factor. This explanation is further reinforced by the similar distribution of the proportion of primary energy sources of the charged electricity in the year 2025 and stronger deviation in 2035 and 2045 as illustrated in Figure 5.22. While the emissions reduction solution considers twice as many charging points as the cost minimization in 2035 and 2045, the shift in the electricity generation and lower electricity prices in the midday lead to lower PWMP for the cost minimization case.

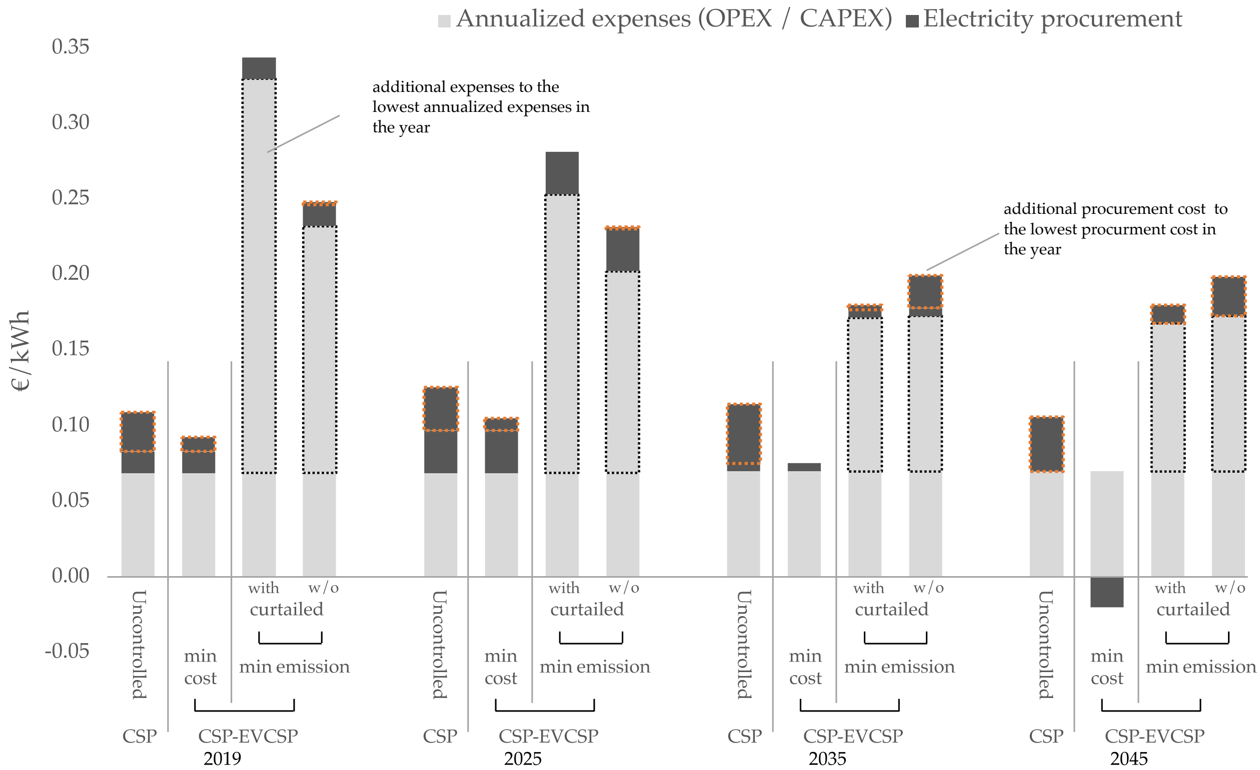


Figure 5.21: Cost per kWh for charged electricity in the different cases and years. The cost include the infrastructure cost as well as the electricity procurement cost.

In the same way, it is also possible to (ex post) calculate the emissions of the cost minimization and uncontrolled charging solution. In contrast to the total cost, CO_2e emissions for the $\mathrm{EMIS}_{A_t}[t]$ and $\mathrm{EMIS}[t]$ impact factors are distributed vice versa. Emissions for manufacturing and installation of the charging infrastructure only comprise 1% in 2019 and 6% in 2025 and 2% to 33% in the years 2035 and 2045. The emissions attributed to the charged electricity account for most of the emissions.

On average, over all years, the cost minimization strategy leads to 50% higher emissions in all years compared to ($\mathrm{EMIS}_{A_t}[t]$) and performs 33% worse than the minimization strategy for the emissions factor that does not consider electricity curtailment. Charging cost are only 15% to 31% higher than the minimum value calculated for both emission factors, in the first two years, while they are 29% to 88% higher in 2035 and 2045.

With a larger share of renewables in the electricity mix, the differences between cost and emissions become more pronounced because of the higher emissions from photovoltaics in contrast to electricity generated by wind turbines and the higher cost of wind energy, especially offshore in contrast to photovoltaic. On average, the charging and infrastructure expansion strategy calculated for the minimization of emissions under consideration of curtailed electricity (case 4) would lead to €373.38 higher cost per year and vehicle, leading to an increase of on average by 0.17 €/kWh and the solution emissions factor, which does not consider curtailed electricity (case 5) on average, would lead to €312.9 (0.14 €/kWh) higher cost per vehicle. The solutions that minimize CO_2e emissions on average lead to 26.462 t lower emissions when considering $\mathrm{EMIS}_{A_t}[t]$

and 23.695 t lower emissions when considering EMIS[t] for the case study of Essen. In contrast to the uncontrolled charging case, emissions are 125.622 t (case 4) and 116.641 t (case 6) lower.

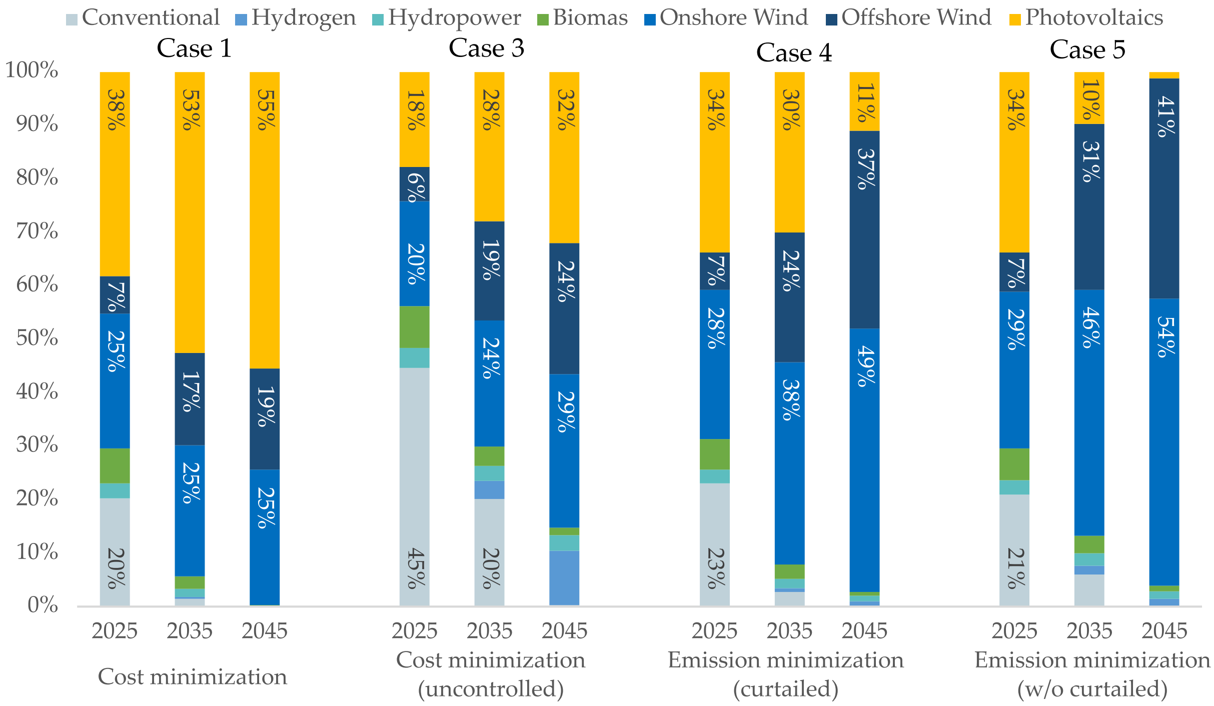


Figure 5.22: Proportion of primary energy sources of charged electricity in different charging scenarios and energy system configurations.

The proportion of primary energy sources also changes with the different charging strategies and with changes in the electricity generation patterns. These changes are shown in Figure 5.22. As can be observed, most of the electricity in the case of the cost optimization strategy that is charged comes from photovoltaics. This is influenced by curtailed electricity, which occurs mainly in times with a high penetration of photovoltaic electricity generation. When only considering the emissions associated with electricity generation (EMIS[t]), high electricity shares are charged during times of high penetration of offshore and onshore wind.

To evaluate the effects of the proposed charging strategies on a larger scale, the charging pattern was extrapolated to a larger number of vehicles. Following the data published in the study MiD, 49% of the vehicles in metropolitan areas park in the public street space parking at home. Assuming that 10.4 million vehicles are registered with inhabitants of metropolitan areas, this would be equal to a share of more than 5 million vehicles parked in public spaces (Infas, 2019b). To assess the large-scale effects of the proposed charging strategies, the results obtained for the city of Essen are upscaled to a larger vehicle fleet and it is assumed that 5 million vehicles follow the calculated charging pattern. These vehicles add 11.29 TWh to the total electricity consumption in each year. To evaluate the effects of the calculated charging strategies based on emissions and cost (case 1 to case 4) the charging patterns of 500 vehicles are extrapolated by the factor 10,000 to represent the larger vehicle fleet of five million BEVs. The charging pattern and the corresponding electricity consumption are considered as additional consumption in the linear energy system model for the years 2025, 2035 and 2045. To allow a clearer examination of the results, the electricity imports and exports, as well as the generation capacities, are restricted to the total generated electricity determined for the original cost calculations (see Table 5.2). This means that the total electricity generation remains the same; however, for all electricity generators and storage, except wind and solar, the electricity generation and storage pattern can be modified. To obtain a feasible solution, any additional required electricity that exceeds the total capacity generated by all power generators is provided by an additional "back-up" generator, at the highest cost. This calculation scheme allows to evaluate how much of the required charging electricity can be met by previously curtailed electricity and at which times additional power plant capacities would be needed to meet the requirements of the proposed charging strategy.

To summarize, the additionally required electricity can be supplied from three sources:

- The utilization of previously curtailed electricity,
- the reduction of storage losses through decreasing storage requirements or the use of more efficient storage, or DSM or
- the back-up power generator.

Figure 5.23 shows the exemplary results for the two charging solutions for cost and emission minimization and a summer day in 2045. Two examples of increases in electricity demand through BEVs are highlighted. The figure on the top is based on the solution of cost minimization. In the highlighted case, additional electricity is provided through electricity that is curtailed in the case without consideration of BEVs (see Figure 5.8). In the second case, for the minimization of emissions demand, demand is increased during the night, where in the original calculation the majority of electricity was generated using onshore and offshore wind. In the re-optimization of the electricity generation, the increased demand leads to increased power generation by hydropower, hydrogen electricity imports and the depleting of thebattery storage. However, the curtailed electri city is not utilized during the day. In the example, 0.33 TWh are charged throughout the week in the cost minimization case, while only 0.19 TWh are charged in the emissions minimization case. For the cost minimization, 100% of electricity is charged during the time from 7:00 a.m. to 5:30 p.m. (when electricity is generated from photovoltaic). For the emission minimization case, on the other hand, 95% of electricity is charged during hours, the photovoltaic electricity generators do not generate any electricity.

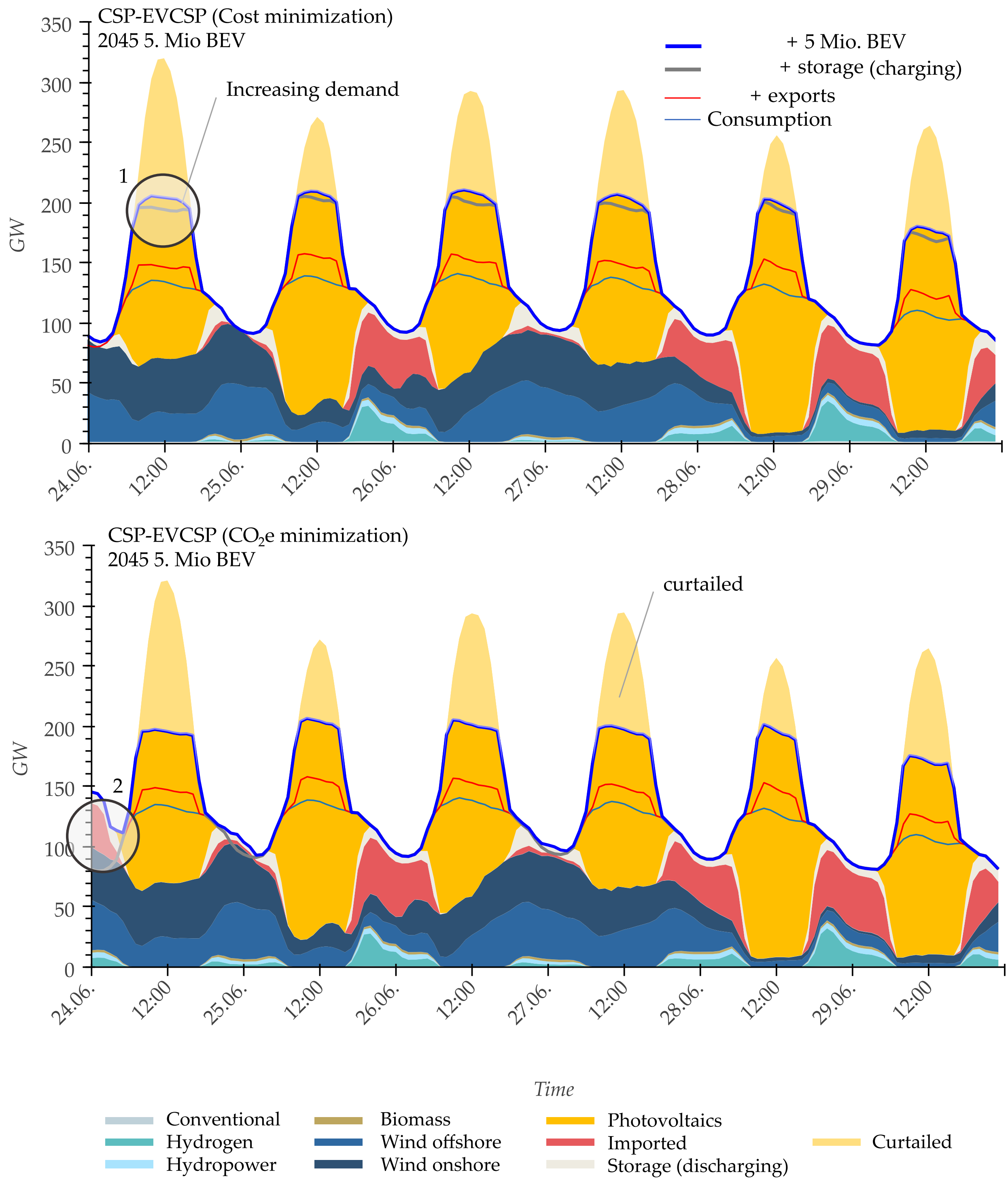


Figure 5.23: Increased electricity demand from 5 million BEV charging, considering two different optimization solutions. Two examples are highlighted. 1: curtailed electricity is utilized by BEVs; 2: Additional electricity consumption from BEV induces additional electricity generation from hydropower and Hydrogen as well as imports.

Table 5.11 shows the summarized results of the re-optimization considering the additional electricity consumption of BEVs. As the total electricity generation for each type of generation remains the same, as in the original calculation (see Table 5.2) over the years assessed, only the curtailed electricity and the required backup capacity values are presented for the three optimization strategies. The amount of curtailed electricity increases in the data without considering the additional demand from the BEVs. In 2025, all of the previously curtailed electricity is utilized in every re-optimization, considering the additional demand from the vehicles.

Table 5.11: Additional curtailed electricity and backup capacity required.

	No BEV		CSP-EVCSP		CSPP
		Case 1	Case 4	Case 5	Case 3
		PWMP	$EMIS_{A_t}[t]$	EMIS[t]	Uncontrolled
	TWh	TWh	TWh	TWh	TWh
2025					
Curtailed Generation	0.23	0.00	0.00	0.00	0.00
Backup Capacity		10.60	10.57	10.58	11.08
2035					
Curtailed Generation	19.34	13.92	14.76	18.90	18.15
Backup Capacity		5.26	6.19	10.20	9.75
2045					
Curtailed Generation	49.16	41.98	46.81	48.94	47.27
Backup Capacity		3.39	8.08	10.16	8.72

Even though the total electricity generation is fixed, the required backup capacity may still differ in each solution, as different storage technologies (with different efficiencies) can be used in the re-optimization, leading to a lower or higher required backup capacity. Curtailed electricity increases in 2035 and 2045 with a greater expansion of electricity generation from wind and solar. The optimization based on curtailed emission allows for greater utilization of the curtailed electricity than the uncontrolled (case 3) and emissions minimization that do not consider curtailment (case 5). Only the minimization of total cost (case 1) leads to better use of curtailed electricity and a lower required backup capacity. For 2035, 40.6% of additional electricity required by vehicles can be supplied using curtailed electricity for the controlled charging case based on emissions and 48% for the case where the scheduling is based on cost. For 2045, 63.50% of the 11.29 TWh required can be covered using curtailed electricity for controlled charging based on electricity prices. All other controlled charging strategies result in lower usage of curtailed electricity compared to the cost-controlled charging strategy. The emissions-based controlled charging strategy, without considering electricity curtailment, can only use 1.9% of the curtailed electricity to meet vehicle charging demands.

To assess the effect of a higher utilization of previously curtailed electricity and the required backup capacity, the average marginal emissions and cost can be calculated. To determine these values, the additional backup energy is used as a reference. To determine marginal cost and emissions, the average emissions (EMIS[t]) and the electricity procurement cost (PWMP) are multiplied by the required backup capacity in the years 2025, 2035 and 2045. The results that include the average cost and emissions of the infrastructure per year are shown in Figure 5.24. As cost minimization and uncontrolled charging solutions have the lowest number of charging stations, the total cost are also the lowest for these two approaches over all years. In 2045, the total cost of the CSP-EVCSP solution are 22% lower than the required backup electricity cost in the uncontrolled solution and about a third of the additional cost required by the emission minimization solutions. When only backup electricity and infrastructure emissions are considered to calculate the average emissions, the cost solution also has the lowest total marginal emissions, which are less than half of the emissions in the emissions minimization case.

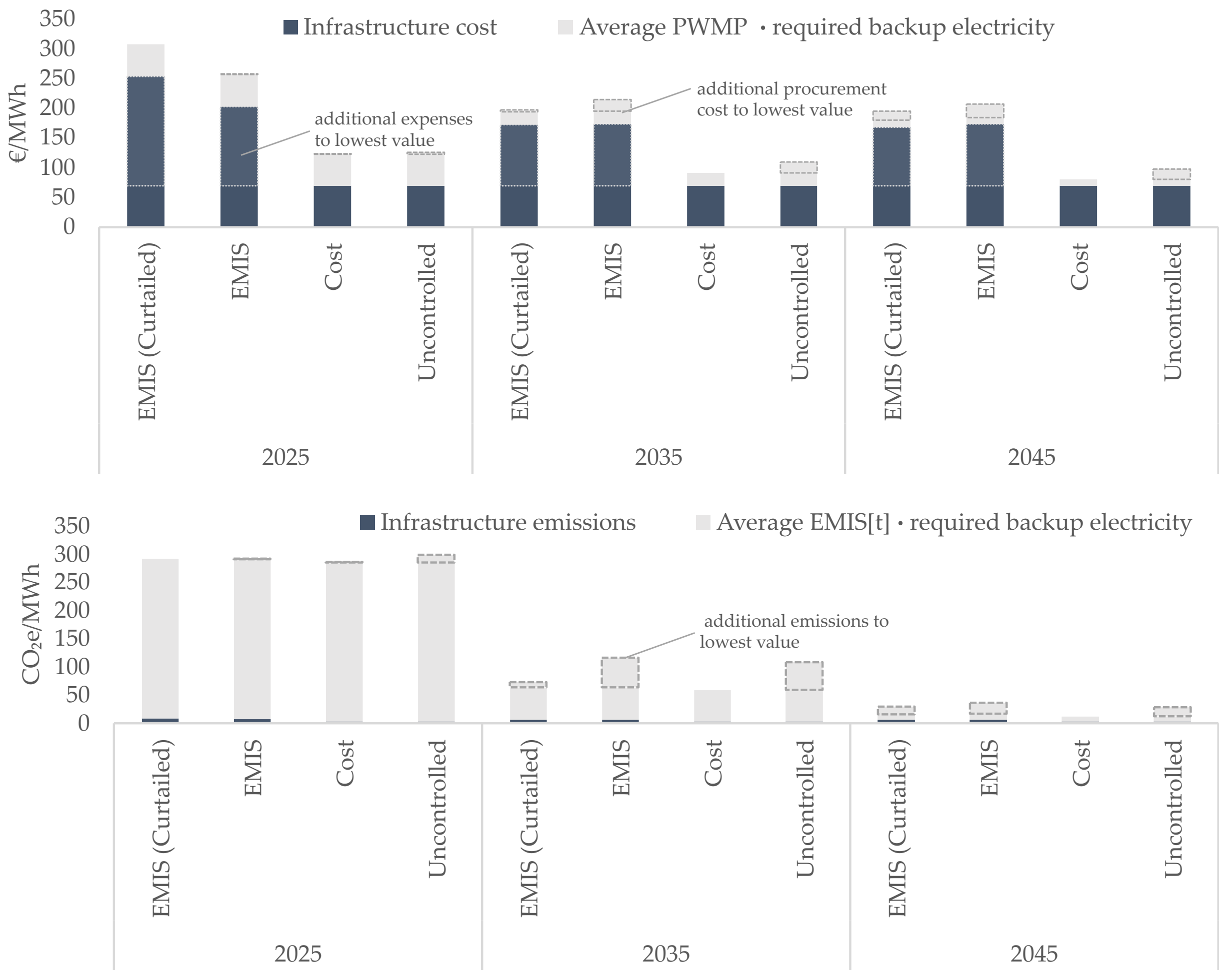


Figure 5.24: Additional cost and emissions from the required backup capacity, due to the additional demand of 5 million BEVs.

Overall the results show, that the controlled charging solutions are able to achieve the highest reduction in charging cost and emissions if the volatility of the electricity prices and emissions are high, and there is a large gap between the highest and lowest emission or cost value. The projected cost and emissions lead to a countervailing trend for the emissions and cost and the impact of the fixed and variable cost and emissions. While the impact of one-off costs increases for the emissions, it decreases for the costs. The extrapolation of the results to a larger vehicle fleet shows that rebound effects need to be considered when optimizing the charging behavior of a larger fleet of vehicles, in the case study this was especially relevant for the optimization based on emissions.

5.6 DISCUSSION AND OUTLOOK

The results presented in the previous section on the optimization of the charging infrastructure of Essen, are influenced by several factors and uncertainties. Some of these factors can be addressed through further analysis of the case study. The results of this chapter are assessed and discussed in order to evaluate the suitability and ability to transfer results to support real life decisions.

5.6.1 Assessment of the results

The calculation of the model depends on several simplifications and assumptions. Therefore, the results should be classified in the context of a real decision-making situation in order to derive practical implications.

The objective function of the optimization model only considers expenses and costs that can be influenced by the decision maker. However, as shown in Section 2.3, other stakeholders are involved in the charging process. An important stakeholder to consider is the vehicle owner, who needs an incentive to participate in controlled charging initiatives. However, as described in Section 2.1.1, the electricity procurement costs only represent a small part of the total cost incurred by the end customer, since taxes, levies, and the cost of electricity distribution make up a large share. Figure 5.25 highlights that, depending on the year considered and the optimization strategy applied, 16% - 42% of the total charging costs paid by an end customer can be attributed to annualized expenses and the electricity procurement cost. If the total possible savings of the controlled charging strategy in contrast to the uncontrolled strategy were passed on to the customer, this would lead to a reduction of overall charging cost of 4.3% to 13.7%. As highlighted in several practical trials (Delmonte et al., 2020), overall cost savings would need to be higher, to encourage participation in controlled charging initiatives. Vehicle owners might also be incentivized by the additional benefits of the controlled charging strategy discussed in Section 5.5, that is, the cost minimization strategy could lead to a higher utilization of curtailed electricity and reduce CO_2e emissions.

Figure 5.25 also presents the ex post calculated costs of the solution based on minimizing emissions. In contrast to the cost-optimal solution, the charging cost are 30 - 42% higher if the additional cost were fully passed on to the end customer.

Similarly, emission can also be considered in terms of vehicle total emissions. A common metric evaluated in literature is the life-cycle emissions of BEVs (see Table 2.3). For a vehicle manufactured in China, with a similar battery capacity as the vehicle in the case-study, 62.13 g CO_2e/km incur in the manufacturing phase of the vehicle (Tesla, 2022). Depending on the year and the objective function, the emissions of the charged electricity and the charging infrastructure can range from 3.85 g CO_2e/km to 70.11 g CO_2e / km and represent 5.8% to 53% of total emissions. For the years 2019 and 2025, between 25.01 and 33.12 g CO_2e/km can be saved through the CSP-EVCSP solution in comparison to the uncontrolled charging solution. In the years 2035 and 2045 this is reduced to 17.01 g CO_2e/km and 3.35 g CO_2e/km. This indicates that the emission reduction through the controlled charging strategy has a higher impact in the years that still consider non-renewable power generators. However, in the years with high surplus electricity, this factor is an important reference.

According to the Federal Government plan, on average 14 vehicles are supplied by a public charging point (NPE, 2018). Taking into account the obtained results, on average 4.2 BEVs are supplied by one charging point. However, since the entire electricity of all vehicles is supplied by the public charging infrastructure and no private charging infrastructure is considered, this ratio may not be suitable as a reference. When also considering private charging points, the national platform on electric mobility estimates that 1 million BEVs should be supplied by 70,000 public AC charging points and 1 million private charging points (NPE, 2018). It could be argued that the second ratio, i.e., more than one charging point per vehicle, is more suitable for a comparison of the vehicle to charger ratio, as both configurations of the system can fully meet the charge of all BEVs.

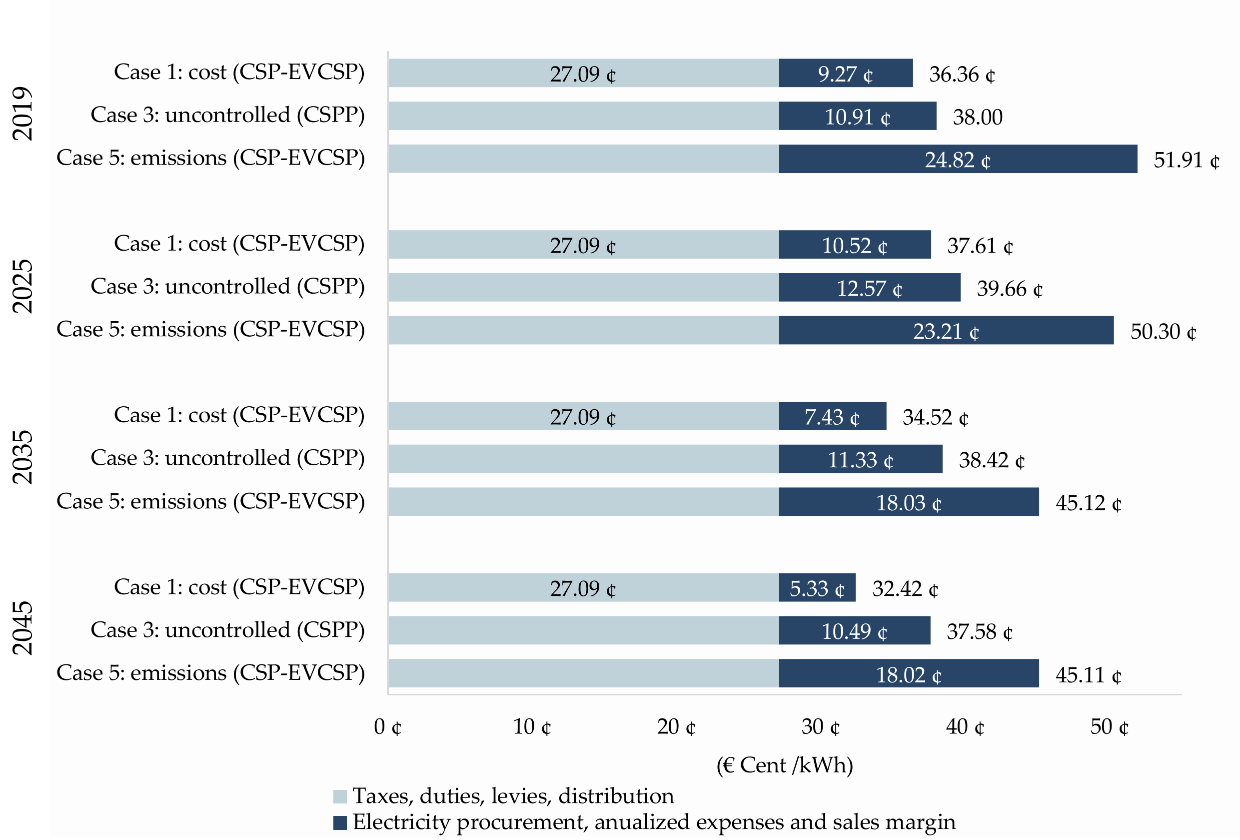


Figure 5.25: Charging cost per kWh for the end-customer for the assessed charging solutions.

The cost savings in the years 2035 and 2045 can be attributed to the negative electricity prices, especially in the noon hours. Although volatility and the range of prices for electricity could increase in a fully renewable energy system, the low electricity prices calculated by the model need to be further examined (Gabrielli et al., 2022). As mentioned in Section 2.1.1.4, negative electricity prices can occur due to regulation, contractual obligations, or technical reasons, however it is questionable if these prices would occur in a regular and predictable pattern as presented in the model.

5.6.2 Possibilities for expansion of the case study

"All models are wrong, but some are useful" (Skogen et al., 2021). This quote alludes to the fact that models can only represent reality to a certain degree; nevertheless, they can help uncover certain relationships within the modeled system and their implications. The results of the application of the developed model to the planning of the charging infrastructure and the controlled and uncontrolled charging of EVs in Essen showed the effects of different infrastructure configurations.

The scope of this thesis limits the degree of detail to which the analysis can be performed. Therefore, in addition to the general avenues for future research presented in Section 6.2, further evaluations, possibilities for expansion, and sensitivity analysis are highlighted in this section.

The costs of constructing charging points are assumed to be constant for all locations. However, as shown in Figure 2.14, there can be significant differences in the required investments in building and operating a charging point. In particular, construction and electricity network-related costs show a wide variation in studies. A large part of the cost depend on the characteristics of the location, e.g., the distance to the nearest grid connection point, the exposure of the charging equipment to the elements or if grid expansion is necessary. While these factors are very site-dependent it may be possible to derive location-dependent cost factors if enough data is available. For instance, through a cooperation with network operators or by linking the model with network planning models, it is possible to identify locations that have additional grid capacity available and those that do not, thus reducing installation expenses for upgrading the power grid. The same is also true for the CO_2e emissions attributed to the installation and construction of the charging infrastructure. Only a few studies could be identified that conducted a detailed LCA on the installation of public charging infrastructure. A detailed analysis of emissions, by stages of the life-cycle, could help to identify which factors contribute to higher or lower emissions.

A further refinement of the temporally and geographically resolved charging patterns could also lead to more accurate results. To achieve this, the developed geographic data and information and mobility patterns could be supplemented. This could be achieved at several levels. First, different clusters of the activity database could be considered to model additional mobility patterns and vehicle parking locations. As Reinhold et al. (2018) point out, other clusters are characterized by more activities that are conducted at home. The application of the developed method to generate geographically and temporally resolved mobility patterns from these clusters would lead to different parking locations of vehicles. Second, the assignment of mobility profiles to geographic locations could be supported by additional data, for example from customer surveys or commercial data providers, such as popular times, wait times, and visit duration data from Google (2022), which would allow the distribution of mobility profiles throughout the city. Lastly, it is possible to restrict the charging at certain locations to specific profiles, this makes it possible to consider an expansion of the public and private charging infrastructure simultaneously. For instance, to assess the impact of private charging points at work or detached houses on the charging network design. Data protection issues however, can be an obstacle in obtaining a higher degree of detail and more realistic mobility patterns.

The focus of the case study was to illustrate how consideration of CSPP and EVCSP affects the design of the charging network and the scheduling of the charging activities. A critical stakeholder in this context is the vehicle owner. Several operational questions could be further assessed using the developed model. Studies have shown that vehicle owners are discouraged from participating in smart charging projects due to the fear that their vehicle will not be sufficiently charged (Delmonte et al., 2020). Therefore, a detailed analysis of SoC and charging from the point of view of the vehicle owner can also provide valuable information. Although SoC is included in the optimization model through constraints, this factor is not evaluated in detail. Direct consideration and restriction of the SoC to a certain interval is possible through the third term in the objective function of the CSP-EVCSP.

Electricity prices were calculated using a simplified model of the electricity system. Although other models cannot either accurately forecast electricity prices over a time horizon of decades, since electricity prices are influenced by many factors and unforeseen events, such as geopolitical conflicts, war, or supply chain disruptions, and can alter the decision field dramatically. Nevertheless, these models take into account a number of different factors such as the detailed examination of exports and imports, electricity storage, or the interdependencies with other sectors (such as heating or industry). These factors can alter the shape of the WMP and therefore have a significant impact on the charging results. By considering the results of the calculation of different energy system models, a sensitivity analysis of this factor could be possible.

5.6.3 Managerial and policy implications

The results of the model can be used to facilitate management and policy decisions on a municipal and state or on a country-wide level. For example, the city of Essen is pursuing a joint initiative with businesses as part of the mobility partnership and thereby promoting efficient and environmentally friendly mobility. A goal of this initiative is to promote a charging infrastructure in workplaces (Stadt Essen, 2018). The city and participating employers are interested in quantifying the economic, environmental, or technical impact of installing charging infrastructure. In this context, the model can support stakeholders by integrating case- or company-specific data and assessing the effects of proposed measures before their implementation. For example, by quantifying the share of electricity that can be charged in the workplace, the electricity mix and associated emissions. This data can help to facilitate further participation in the program. In addition to the generic cost function of Germany, company or site-specific knowledge can also be considered. For instance, if a corporate PV-system is available that generates excess electricity, the model can be used to assess how much of this electricity can be charged by vehicles.

The model can support the decisions of network operators at different levels. Using the geographically and temporally resolved charging profiles, load profiles can be calculated for specific inner-city locations. The results of the geographic assessment show that the charging infrastructure in the center of the city is highly utilized in all energy mixes and infrastructure configurations. This result is also consistent with the findings of other studies and the current development of the charging infrastructure in the city. The geographically distributed load profiles help to determine the impact of different expansions of infrastructure on the distribution of loads throughout the city. Grid operators currently bill charging stations according to standard load profile *(ger. Standardlastprofile)* (SLP), in part due to the still small number of BEVs. However, analysis show that the charging profiles of BEVs can greatly deviate from these profiles (Hashemifarzad et al., 2019). The model can be applied to further enhance this analysis and derive location specific deviations from the SLP. For the TSOs and DSOs in Germany, the simulation and optimization according to different future energy generation and mobility scenarios can support decisions concerned with upgrading the grid infrastructure. The case study and previous research results show that vehicles may be applicable to deeper integration with electric girds. For example, in both network configurations, the average available charging capacity in the emissions optimization case is above a capacity of 2 MW in most solutions. In this case, ancillary network services could be a viable business model.

As of January 1, 2022, there are 590 companies registered in North-Rhine Westphalia that operate charging infrastructure for EVs. By applying the model, potential charging locations can be selected more efficiently, leading to economic benefits for charging infrastructure operators. For CPOs, comparisons between an optimized and their current charging infrastructure could reveal bottlenecks in the charging infrastructure and help in the expansion or refinement of their charging network or to identify frequently visited locations. For highly integrated CPOs that generate electricity from volatile renewable energy sources, the model can be applied to coordinate the planning of their charging infrastructure to match the generation patterns of their power plants and thereby increase electricity self-consumption. For a complete coverage of the 500 vehicles as assumed in the case study, some stations generate more revenue than others, due to a lower utilization of the charging infrastructure. By considering the utilization of the charging infrastructure within the city, the model can also be used to define spatially variable charging tariffs throughout the city, to stimulate the charging at certain locations and achieve a more uniform utilization of the infrastructure.

5.7 SUMMARY

In this chapter, the developed decision model and solution approaches were applied to the planning of the charging infrastructure in Essen. To investigate the impact of a changing power system, the model was applied based on costs and emissions of possible future power system configurations. The different configurations of the objective functions and the distribution between the costs related to CSPP and EVCSP, require the application of different solution approaches for each problem instance. This section presents a case study of a charging station expansion problem and BEV charging scheduling problem. The purpose of the case study is to answer how the developed model can support real-world decision making in placing EV charging stations and scheduling the charging process of BEVs. First, the mobility data and electricity prices and emissions are derived using the processes described in the previous section. Then, the resulting charging network configuration is used in a scheduling model that minimizes the cost of electricity procurement. The results show that the optimized charging process can lead to lower costs and emissions compared to the average electrical mix in the assessed years. A deeper analysis of the results shows that the results can have an impact on multiple levels.

6 CONCLUSIONS AND OUTLOOK

The use of renewable energy is critical for achieving global greenhouse-gas-reduction targets. This shift from fossil primary energy sources to renewable sources, such as solar and wind, provides the potential to drastically reduce CO_2 emissions from power generation. The primary underlying goal and motivation for reducing CO_2 emissions is to limit anthropogenic climate change. A CO_2 budget for each country can be calculated. For Germany, massive efforts and efficient use of energy and infrastructure are required to limit global warming to 2° C degrees (SRU, 2022).

In the mobility sector, this reduction can be achieved, among other things, by replacing ICE vehicles by BEVs. Compared to other technologies, such as vehicles that are propelled by hydrogen or synthetic-fuel BEVs demonstrate the highest well-to-wheel efficiency. At the same time, most studies have shown that these vehicles emit less CO_2 throughout their life cycle. A crucial element in reducing emissions throughout the life cycle of a vehicle is the emission related to the electrical mix used to charge these vehicles. Therefore, if the overall emissions in the transportation sector are to be reduced, charging vehicles at times when there is an excess in renewable power generation is available is sensible. Because personal vehicles are parked 95% in a day, on average, their charging process can be controlled to obtain electricity from volatile renewables. The integration of electricity and transportation sectors requires collaboration of the actors along a new value chain from the primary energy sources of solar and wind to marketing, distribution, and provision of electrical energy to the charging stations. To optimize the application of electric-vehicle charging to meet the demands of an electricity system, considering the geographical and temporal distribution of vehicles throughout the day is important. Therefore, a suitable method is needed to identify and analyze this interdependence. Thus, in this study, an approach is presented to simultaneously locate electric-vehicle charging stations and control their charging behavior.

Charging station operators, strife for minimizing costs while maintaining revenue. Two methods are available to reduce costs in terms of controlled charging for a given set of EVs. First, by reducing the number of charging stations required to supply their customers. Second, is to purchase electricity when it is abundant and the price is low. When considering these expenses and cost components, a charging network that considers more charging points can lead to better exploitation of fluctuations in energy prices, while at the same time it leads to higher expenses (for the construction and operation of the infrastructure). From the perspective of CO_2 reduction, expansion of the charging infrastructure results in additional emissions, which can possibly be offset by charging electricity with a lower CO_2 footprint.

In previous studies, the decision on the controlled charging of vehicles and the location planning of the charging infrastructure has been considered in separate models. In this thesis, both factors are considered simultaneously with the aim of uncovering the trade-offs between both of these factors.

The application of the model requires geographically and temporally resolved mobility patterns, which are generally not widely available for EVs. The use of these data can also be restricted for legal reasons (data protection). Therefore, in the present work, geographically distributed activity patterns are derived using an activity database. The developed methodology allows generation of these profiles for different groups of people and arbitrary geographical locations. From the production-management perspective, location planning of electric-vehicle charging stations is a tactical or strategic problem because a charging infrastructure has a projected lifespan of 15–20 years. In this time horizon, electricity generation is projected to change and can vary depending on the geographical location or scope of the considered electricity generation. To identify the possible effects of incorporating volatile electricity generation costs and emissions in the decision making, different energy system configurations are considered.

To illustrate the effect of taking these data into consideration in the optimization model, the model is applied to a case study on planning and controlled charging of 500 vehicles in the city of Essen, Germany. The decision problem is considered from a cost- and emission-reduction perspective, and an outlook is given on how the developed decision support model can support the decisions of the charging infrastructure planners and policy makers.

6.1 ADDRESSING THE RESEARCH QUESTIONS

The objective of this thesis is to develop a model that can be used to identify the relationships between different configurations of charging networks and to plan the charging activities of EVs in future configurations of energy systems. The research questions posed at the beginning of this thesis can be answered as follows.

1. What are the projected changes in electricity generation and how will these changes affect future planning of the layout of the charging infrastructure and charging patterns of electric vehicles?

The shift toward electricity generation based on renewable primary energy sources can increase the volatility of electricity generation. Several energy system scenarios feature different system configurations and highlight the need for additional storage and for flexible electricity demand.

The current setup and regulation of the energy system only consider these changes to a limited extent. Actors such as DSOs and TSOs face new challenges such as more decentralized electricity generation and consumption, which can lead to a shift in responsibilities to local entities (DSOs). The charging of BEVs poses a further challenge in this context because they increase the overall electricity demand and can induce spikes in electricity demand and geographic bottlenecks in the electrical grid. To fully electrify the entire fleet of vehicles in Germany, approximately 108 - 139 TWh of electrical energy is needed, which increases the total demand for electricity by up to 25% . Simultaneously, the corresponding number of BEVs has a storage capacity that is larger than that of all pumped hydro storage plants in Germany. Regarding the charging points of normal speed, the estimated charging power is also similar to that of pumped hydro storage and exceeds it when fast-charging stations are included in the consideration (Hecht et al., 2022; Heimerl and Kohler, 2017). These facts highlight the interconnection and importance of joint planning of the electricity and transportation sectors.

In addition to the ability of the charging infrastructure to meet the requirements caused by the mobility needs and charging of individuals, including electricity generation and consumption in the optimization of the charging infrastructure, can lead to a better integration of the electricity sector and the mobility sector. The integrative model can help achieve efficient electricity use. To assess this relationship, a proxy for the temporal utilization (overall demand and generation) of the electricity system should therefore be included in an optimization model. As previously highlighted, the installation of a charging infrastructure can affect multiple factors, e.g., costs or CO_2e emissions. Simultaneously, the generation and consumption in the electricity sector are volatile and can influence costs or emissions. On the cost side, CAPEX and OPEX, and volatile electricity procurement costs can be considered to represent this problem. Emissions occur in the manufacturing and installation of the charging infrastructure and in the use phase. The emissions of the use phase depend on the electricity mix and can represent a volatile factor to consider in an optimization model.

2. How can geographically resolved travel and charging profiles for electric vehicles, as well as factors associated with the electricity system, be combined into a model that simultaneously considers the planning of the charging infrastructure of electric vehicles and the timing of charging?

The effect of increased vehicle electrification is believed to be affected by two major factors: First, the design of the charging infrastructure, i.e. the locations of charging stations and second by the timing of charging activities. As highlighted in the insights on the first research question, two decisions are important for the assessment of the charging infrastructure: where the charging stations are located and when the vehicles are charged. Both these questions have been evaluated in different streams of literature and are addressed by charging station placement problem (CSPP) and electric vehicle charge scheduling problem (EVCSP). Whereas CSPP address the issue on where to locate the charging infrastructure, the majority of the factors considered are the mobility behavior of individuals and the aggregated demand in representative geographic locations. These models rarely consider temporal factors aside from the charging demand. On the other hand, EVCSP is concerned with more operational questions and attempts to provide an answer to the question, when a vehicle should be charged. It models a closer interaction with the electricity system and associated uncertainties such as volatile electricity prices or uncertain arrival or departure of BEVs. Most of these studies consider a fixed charging network. Currently, a combined approach that considers both location of charging stations and controlled charging of vehicles in a single decision-support model cannot be found in the pertinent literature.

To integrate both problems, a mixed-integer linear-programming model is formulated. The developed CSP-EVCSP model accounts for the fixed and variable components related to the problem, as well as the mobility behavior and the geographical location of vehicles and their interaction. The model is solved using a commercial solver, and several computational experiments are presented. The results of these calculations show that specific factors related to the CSPP increase the computational complexity and do not allow the model to be optimally solved.

Three different solution methods are implemented to solve CSP-EVCSP. The developed approaches realize different solutions, depending on the distribution of fixed and volatile cost components. All approaches allow solving the model for a time of one year (35,040 15-minute intervals) while considering up to 500 different vehicle profiles and 3,000 potential charging locations.

3. How can the geographically and time-resolved mobility patterns of electric vehicles, as well as the costs and emissions of prospective energy systems, be derived?

To apply the developed model and support the placement and charging process of EVs, factors related to the electricity and mobility sectors must be considered. For real-world applications within a city, geographic information is required. Section 4.1.2 presents an overview of the current approaches related to the derivation of mobility profiles. Although several mobility surveys have been conducted in Germany, which are continuously updated, particularities exist when EVs and their charging behavior are considered. For example, since there are currently still only a small number of BEVs, detailed real-world mobility data are often not available. The model requires highly temporally and geographically resolved activity patterns that are not available in current surveys, often because of concerns about data protection. To overcome this drawback, a new approach is developed within the scope of this thesis and based on the activity database developed by Reinhold et al. (2018). It uses a set of logical instructions to derive the mobility patterns. The resulting data are supplemented with open source geographical information to generate a geographically and temporally distributed mobility profile. These data can be generated for arbitrary geographic locations and contain information that allows to model the interaction between mobility profiles at multiple (temporal and geographic) levels.

To derive the cost and emissions of the prospective energy systems, several different approaches and models are found in the literature. Energy system analysis and, energy system modeling can be used to improve understanding of the operational principles of the energy system. Energy scenarios are used to illustrate possible developments in the energy system of the future. When both approaches are combined, modeling the characteristics of future energy systems can be made possible. Several scenarios have been published for the potential developments of the future energy system and energy system models have been used to model and assess the characteristics of these energy systems.

To calculate a feasible electricity generation pattern of a potential energy system (e.g., found in published energy scenarios), a linear optimization model is implemented in this thesis. The optimization model presents the distribution of electricity generation from the generation technology at each time step (e.g., in 15 min intervals). The results of the model are used to calculate a cost and two CO_2e emission factors to be deployed in the CSP-EVCSP.

4. What are the possible benefits and effects of optimizing the placement of electric vehicle charging stations on the electricity demand and the renewable electricity consumption on the local and countrywide scale? How can these factors be quantified?

To assess the benefits and effects of the application of the developed model to a real-world planning situation, a case study is conducted. The model is applied to minimize the total emissions and costs in different potential future energy systems in the city of Essen. The costs include OPEX and CAPEX for the installation and operation of charging stations, as well as the cost of electricity procurement. Emissions include those that occur during the building and installation phases of the infrastructure and those related to the charged electricity. Among other factors, these are used to quantify the overall effects of the model. The results of the model are compared with those of other infrastructure expansions, such as a complete infrastructure expansion that allows charging at every location and uncontrolled charging case.

Depending on whether emissions or costs are considered in the objective function, different charging system configurations and charging patterns are realized. The cost minimization solution minimizes the number of charging points within the city, taking advantage of overlapping geographic locations. In contrast to other models found in the literature, the solution approach developed in this thesis supplements the results of a SCP using a charging heuristic that considers the charging and location of the vehicles. The results of the application the SCP only without considering the heuristic reveal that a SCP solution can overestimate the potential to satisfy the temporal charging demand of vehicles. In the calculated case, five additional charging points would be required to satisfy the charging demands of all 500 vehicles. The number of charging stations considered by the model further increases when the tradeoffs between the fixed and variable emissions are considered. Different optimized network configurations are determined depending on the electricity system configuration. When the overall CO_2e emissions in the electricity system decrease over the considered years, fewer charging stations with lower charging power are included in the charging network.

Other factors that are used to assess the effect of the model are the charging patterns and charging location of the vehicles when costs or emissions are considered. In highly renewable energy systems, most of the cost-optimized charging is conducted during midday, which takes advantage of the high surplus of electricity generation from photovoltaics. For the solution of the model that minimizes emissions, a significant amount of electricity is also charged at night. If curtailed electricity is not considered in the calculation of the CO_2e emissions, more electricity charging is performed at night, especially at times with high shares of renewables because of the lower CO_2e emissions of wind energy. To assess the effect of the charging strategies on the entire electricity system, the different charging patterns are upscaled and considered in the linear optimization model as additional electricity consumption (11.29 TWh). Subsequently, the shares of electricity that can be delivered from previously curtailed electricity and those that would be supplied by other sources can be determined. The main advantage of the optimization strategy is the reduction in additional electricity required in a fully renewable electricity system where 63% of the additional electricity required by vehicles can be supplied by previously curtailed electricity.

6.2 DISCUSSION AND EXTENSION POSSIBILITIES

The developed model that simultaneously optimizes the location of the charging stations and the charging of EVs is the first approach that considers both the EVCSP and the CSPP. Multiple avenues are available for further research. In addition to the extensions of the case study and to the application of the model to other cities, regions, or countries, several extensions of the developed method are possible, e.g., to improve the developed solution approach or to incorporate relevant components for other decision makers or decision problems.

To determine whether the composition of a city affects the distribution of the charging infrastructure and the charging of vehicles, the model can be applied to other cities or regions. For example, the results of the application to the city of Duisburg, Germany demonstrate that the charging infrastructure is more distributed, which indicates that the urban structure of cities can potentially affect the results of the model (Dumeier and Geldermann, 2023). Application of the model to a rural region can also lead to different results because more vehicles are parked in a dedicated parking spot or garage, which can lead to lower infrastructure costs. In addition, on average, people who live in rural regions travel a longer annual distance with their vehicles (Infas, 2019b). Similarly, application of the model to different activity clusters of the database affects the location of vehicles. In Cluster 3, most activities are carried out at home; therefore, the vehicle is parked at this location throughout the day, which also leads to a different configuration of the charging network.

As highlighted in Chapter 2, sustainability can be measured in many different ways. By considering other emission factors as also demonstrated by other studies as well as the application of a similar charging model, the hourly emission factors can differ depending on what emission factor is considered. The results of the study by Zacharopoulos et al. (2023) show that the CO_2e emissions and material-resource-depletion emission categories have an inverse emission pattern throughout the day. Their study neglected the location problem, including the emissions of the charging infrastructure, which could lead to different results. More research is needed to assess the emissions of different types of charging infrastructures. Moreover, emissions can be considered in different ways in optimization models. For an electricity system with conventional power generators, which can adapt to changes in electricity demand, additional charging of BEVs could be compensated. It can be assumed that flexible power generators, such as gas-fired power plants can supply the additional electricity requirement, which increases emissions through the additional use of primary energy sources. In many studies, this issue has been addressed using a marginal emission factor (Peters et al., 2022; Seckinger and Radgen, 2021). However, for a fully renewable electricity system, additional demand must be met by electricity storage or additional renewable power generators. The questions of which emissions and how these emissions are credited to additional electricity demand remain an open question in this context.

To allow a direct comparison of the results presented in the optimization model for the assessed years, the emissions and cost of electricity generators for a future energy system, are considered to be equal to those in the year 2019. Several methods, such as the prospective LCA method, have been proposed in the literature that also consider the effect of changes in the electricity system on the emissions of different electricity generators (Volkart et al., 2018). Several models can be found in the literature that model and forecast electricity prices. However, unforeseen events, such as geopolitical conflicts can lead to electricity price increases or changes in the cost of primary energy carriers. For instance, the average wholesale electricity price in the year 2022 (until November) was 239.90 €/MWh, which was six times higher than the value of the average price in the year 2019. The standard deviation of electricity prices in the year 2022 was more than nine times higher than that in the year 2019 and reached a value of 143.76 €/MWh (SMARD, 2022). Both of these values were significantly higher than those calculated in this thesis. In particular, the high fluctuation in the electricity prices indicated by the high standard deviation could be exploited in the controlled charging solution approach, to generate additional revenue.

For long-period forecasts, several uncertain factors exist. To explore how uncertainty can influence the decision problem presented in this thesis, the application of scenario planning methods can be beneficial. For example, the structured process defined by Gausemeier et al. (1998) has been shown to support the development of energy scenarios (Witt et al., 2020). For instance, the recent changes in the mobility patterns induced by the COVID-19 pandemic, e.g., more work at home instead of the office Flüter-Hoffmann and Stettes (2022), influences the parking and charging location of EVs. To explore potential future changes in mobility, several guiding scenarios can be developed using the process described by Gausemeier et al. (1998) and evaluated using the developed model.

On a more operational problem level, i.e., in the vehicle charging process, uncertainty can arise based on the vehicle arrival and departure times. However, these factors can also influence the location of charging stations because the uncertain arrival and departure times of vehicles can require considering more charging stations to meet the charging demand in a satisfactory manner. This type of uncertainty can be considered in the current model by considering a larger buffer for the vehicle battery that is available for controlled charging or the uncertainty intervals on the required electricity and arrival or departure times of a vehicle. As has been highlighted in Section 3.2, this problem has been studied in many scheduling problems, and is solved using various methods. Several studies indicate that modeling this uncertainty can increase computational intensity. In the model presented in this thesis, robust optimization could be applied to find a network configuration that meets the charging demand of a defined worst case or to calculate and minimize the overall *regret* cost over a set of different scenarios (Laporte et al., 2019).

Several further extensions of the proposed model are possible, which allow consideration of other real-world factors in the decision problem and can help to assess their effect on the overall decision problem. As highlighted in the study by Nelder and Rogers (2019), constructing several charging points in a single location can reduce hardware and installation costs. These factors can be included in the optimization problem by considering additional types of charging stations that consider multiple charging points. In these charging stations, the model constraint that restricts simultaneous charging at the charging stations (Constraints 3.12) would have to be eased by increasing the maximum number of vehicles that can simultaneously charge at the charging point. Furthermore, more geographic constraints can be added to the model to restrict the possible total charge in a geographical region. For example, in the case study, most of the charging is performed in the center of Essen.If information on the utilization of the capacity of the grid can be obtained, the maximum cumulative charging for each time interval can be restricted.

As highlighted in the summary of real-world smart-charging applications, many studies have indicated that by providing grid services, the flexibility of EVs may receive higher remuneration. The model can be applied to assess the ability of vehicles to provide secondary or tertiary control reserve by decreasing or increasing their electricity consumption. By assuming a derivation of the capacity and energy prices for provision of these services, these factors can be included in the model by adding additional revenue to the objective function. Modeling the V2G capability of the vehicle battery can be beneficial. Although this process can be achieved by introducing a discharge variable, modification of SCP and the charging heuristic-solution approach is also required, whereas the other two solution approaches can be applied without the need for extensive modification.

Most of the aforementioned additions to the model require data of the energy system at further levels of detail in addition to the data derived in this thesis. Therefore, integration with an energy system model can lead to benefits on multiple levels. Because these models consider changes to electricity consumption or induced by additional electricity consumption in other sectors such as the heating or industry sector, as well as electricity imports and exports, the electricity generation pattern of an electricity system model can deviate from the simplified calculation used in this thesis, which only intends to obtain a feasible energy-generation schedule. For example, consumption could adapt to surplus electricity generation, and novel technologies such as hydrogen electrolysis, direct air capture of CO_2e or electrical heating can provide additional flexible electricity demand (Prognos AG et al., 2021), leading to changes in consumption throughout the day and year that were not considered in the model used in this thesis.

Finally, the presented solution approaches can be improved to speed up calculation times. When the SCP and charging heuristic approach is considered, the heuristic offers a feasible solution for the EVCSP. However, to optimize the charging patterns, the EVCSP is solved using a commercial solver. As shown by Van Der Klauw et al. (2015), formulating an exact algorithm to solve this problem that can lead to fast calculation times may be possible. Moreover, a combined version of the problem can be solved through a customized metaheuristic.

The general results of this thesis demonstrate that the problem of charging station location and scheduling is a multifaceted problem with several influencing factors. Overall, it can be stated that the present thesis has advanced the state of the art in the planning of EV charging stations by enabling the simultaneous planning of charging locations and charging of EVs for the first time, taking into account location factors and mobility patterns.

APPENDIX

Table 6.1: Electricity prices, emission factors and general model parameters used for calculation. Values are presented for 2019, for the years 2025,2035 and 2045 see the openly available information in the Klimaneutrales Deutschland Study.

Technology	Power[1,2] MW	Energy[1,2] MWh	Storable energy[1,3,4] MWh	LCOE/LCOS[6] €/ MWh	Flexibility[5] %	Min power[5] %	CO_2e[7] kg CO_2e / MWh
Nuclear energy	9,500.00	71,044,587.00	0.00	62.00	13.47	84.37	55.36
Hard coal	24,500.00	47,819,697.00	0.00	110.00	22.06	21.28	854.36
Lignite coal	19,700.00	102,732,654.75	0.00	100.00	19.32	20.32	1,046.61
Gas	23,800.00	54,624,090.00	0.00	120.00	16.45	10.03	490.00
Hydrogen Power	0.00	0.00	0.00	259.52	0.00	0.00	93.49
Other	6,400.00	13,445,213.00	0.00	103.30	10.52	22.98	292.40
Import balance	0.00	-38,100,000.00	0.00	0.00	0.00	0.00	0.00
Wind Onshore	52,400.00	99,883,328.00	0.00	62.64	100.00	0.00	11.00
Wind Offshore	6,400.00	24,387,353.00	0.00	68.17	100.00	0.00	12.00
Photovoltaic	45,200.00	41,917,037.00	0.00	47.55	100.00	0.00	93.19
Hydropower	5,600.00	15,832,965.75	0.00	53.00	11.41	31.28	38.00
Curtailed	100,000.00	6,482,000.00	0.00	120.00	100.00	0.00	1,046.61
Biomass	7,500.00	40,391,936.00	0.00	85.00	5.88	60.48	230.00
Pumped-Hydro Storage	6,600.00	0.00	37,400.00	260.00	100.00	0.00	24.00
Battery Storage	0.00	0.00	0.00	300.00	100.00	0.00	39.50
Demand Side Management	3,000.00	0.00	3,000.00	450.00	100.00	0.00	0.00

1: Bundesnetzagentur (2020), 2: Prognos AG et al. (2021), 3: Heimerl and Kohler (2017), 4: Ladwig (2021), 5: SMARD (2022), 6: Fraunhofer ISE (2021), 7: UBA, 2022

Table 6.2: Statistical values for the costs calculated by the model for the year 2019, 2025, 2035, 2045 in €/MWh.

year	season	mean	standard deviation	median	max	min
2019		37.66	11.80	39.28	62.72	1.08
	0	36.17	11.29	37.65	58.72	1.08
	1	37.30	10.48	38.75	55.66	4.66
	2	39.26	11.69	41.17	61.05	8.00
	3	37.31	13.04	39.03	62.72	6.96
2025		57.33	14.18	60.38	78.63	-8.63
	0	54.61	16.47	58.99	77.50	-8.63
	1	55.83	16.21	59.44	78.63	-3.88
	2	59.71	12.13	61.95	78.54	6.31
	3	58.04	11.82	59.77	78.23	13.28
2035		46.20	28.51	51.16	94.20	-34.64
	0	41.05	31.44	47.22	91.39	-34.64
	1	42.04	32.88	47.63	92.59	-32.62
	2	50.59	25.58	54.37	94.20	-27.70
	3	48.63	24.11	51.33	93.88	-20.32
2045		37.55	38.12	41.39	147.51	-84.06
	0	29.05	39.80	39.18	137.23	-84.06
	1	30.16	41.98	37.84	133.17	-80.32
	2	44.12	35.44	43.82	147.51	-71.52
	3	42.81	34.12	41.71	145.24	-61.72

0 - spring, 1 - summer, 2 autumn, 3 - winter

Table 6.3: Statistical values for the emissions $EMIS_{A_t}[t]$ (incl. curtailment) calculated using equation 4.14 and based on the electricity generation pattern generated by the model for the year 2019, 2025, 2035, 2045 in kg CO_{2e}/MWh.

year	season	mean	standard deviation	median	max	min
2019		342.94	84.30	347.16	527.90	0.00
	0	343.50	73.31	346.03	513.38	0.00
	1	357.37	74.97	362.72	511.83	85.38
	2	349.87	84.61	356.48	523.65	143.81
	3	322.79	96.35	323.58	527.90	56.55
2025		302.60	120.95	313.58	536.42	0.00
	0	292.32	116.83	303.17	525.85	0.00
	1	304.75	126.47	314.02	531.72	26.84
	2	317.74	117.21	329.01	532.02	88.32
	3	291.40	123.87	299.28	536.42	96.23
2035		120.92	99.78	80.36	397.37	0.00
	0	112.26	89.63	66.61	368.45	0.00
	1	124.12	100.18	74.47	379.56	2.20
	2	129.73	103.83	94.87	397.37	11.10
	3	115.84	102.86	75.49	395.65	15.68
2045		32.05	16.00	29.85	89.56	0.00
	0	32.52	12.56	32.89	78.84	0.00
	1	35.74	14.21	34.97	84.59	1.98
	2	32.33	17.39	28.52	89.56	9.21
	3	28.56	17.68	22.79	89.25	10.41

0 - spring, 1 - summer, 2 autumn, 3 - winter

Table 6.4: Statistical values for the emissions (w/o. curtailment) calculated using equation 4.13 and based on the electricity generation pattern generated by the model for the year 2019, 2025, 2035, 2045 in kg CO_{2e}/MWh.

year	season	mean	standard deviation	median	max	min
2019		361.99	78.89	366.03	528.54	174.63
	0	364.31	66.95	365.64	520.33	178.96
	1	377.5	70.73	381.35	521.82	194.71
	2	367.58	79.66	372.99	526.07	179.77
	3	341.03	89.95	342.52	528.54	174.63
2025		302.77	120.64	313.58	536.42	93.64
	0	292.78	115.98	303.17	525.85	93.64
	1	305.01	126.02	314.02	531.72	105.07
	2	317.76	117.18	329.01	532.02	94.87
	3	291.40	123.87	299.28	536.42	96.23
2035		121.91	98.91	80.36	397.37	19.13
	0	114.18	87.92	66.61	368.45	20.55
	1	125.95	98.51	74.47	379.56	24.11
	2	130.17	103.43	94.87	397.37	19.18
	3	115.98	102.74	75.49	395.65	19.13
2045		33.25	15.81	32.25	89.56	11.13
	0	34.74	11.97	35.76	78.84	11.41
	1	37.99	13.19	37.96	84.59	11.45
	2	32.92	17.31	29.83	89.56	11.20
	3	28.80	17.62	23.30	89.25	11.13

0 - spring, 1 - summer, 2 autumn, 3 - winter

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SCIENTIFIC CONFERENCE PRESENTATIONS

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