Commercial EV fleet smart charging for cost reduction and renewables integration – A case study in Germany

André Corsetti

Thesis to obtain the Bologna Master Degree in

Energy Engineering and Management

Supervisors: Prof. Rui Castro and Prof. Carlos Santos Silva

Examination Committee

Chairperson: Prof. Name

Supervisor: Prof. Rui Castro

Members of Committee: Prof. Name

: Prof. Name

October 2023

I declare that this document is an original work of my own authorship and that it fulfils all the requirements of the Code of Conduct and Good Practices of the *Universidade de Lisboa*.

To...

Acknowledgements

Abstract

The transition towards electric mobility reduces transportation carbon emissions but imposes challenges to integrate a growing electricity demand with renewable electricity generation and power systems. Smart charging arises as a key technology to minimize operational costs and support higher usage of green electricity for EVs. Market analysis indicates a trend towards dynamic electricity tariffs, incentivizing EV charging at times favourable to the electricity grid. This thesis studies, for a commercial EV fleet in Germany, different smart charging strategies considering a Real-Time-Pricing (RTP) tariff indexed to day-ahead market prices, and renewable electricity integrations. HOMER Grid is used to model such smart charging strategies and generate new EV load profiles. A dynamic model is used to calculate project economics and carbon impact using the generated smart charging EV load profiles and varying solar PV and batteries capacities. Direct and indirect CO2 emissions and renewable electricity usage ratios are calculated based on granular electricity grid and self-consumption data. The resulting Levelized Cost of Energy (LCOE) is minimized using Microsoft Excel's Solver with GRG Non-linear solving method, varying solar PV and batteries capacities. The adoption of an RTP tariff decreases LCOE from € 0.530 to € 0.314 per kWh. A smart charging strategy designed to reduce peak demand and schedule charging at times of lower prices reduces LCOE further to € 0.283 per kWh. The lowest LCOE of € 0.281 per kWh is obtained with 34.4 kWp of solar PV capacity and no batteries. Carbon impact is minimized with larger solar PV and batteries capacities.

Keywords

Electric vehicles, smart charging, renewables integration, carbon impact, dynamic electricity tariffs, commercial fleets.

Resumo

A transição para a mobilidade eléctrica reduz as emissões de carbono do setor de transporte, mas impõe desafios para integrar uma crescente demanda de eletricidade com eletricidade de fontes renováveis e sistemas de energia. O carregamento inteligente surge como uma tecnologia chave para minimizar os custos operacionais e apoiar uma maior utilização de eletricidade verde para VEs. O mercado de energia indica uma tendência para tarifas de eletricidade dinâmicas, incentivando o carregamento de VEs em momentos favoráveis à rede eléctrica. Esta tese estuda, para uma frota comercial de VEs na Alemanha, diferentes estratégias de carregamento inteligente considerando uma tarifa de Preços em Tempo Real (RTP) indexada aos preços do mercado grossista, e integração de eletricidade renovável. HOMER Grid é utilizado para modelar as estratégias de carregamento inteligente e gerar novos perfis de carregamento de VEs. Um modelo dinâmico permite calcular os custos do projeto e o impacto do carbono, utilizando os perfis de carregamento inteligente gerados e variando a capacidade de produção solar fotovoltaica e baterias. As emissões diretas e indiretas de CO_2 e as frações de utilização de eletricidade renovável são calculados com base em dados granulares da rede eléctrica, e de autoconsumo. O Custo Nivelado de Energia (LCOE) resultante é minimizado utilizando o Solver do Microsoft Excel com o método de resolução não linear GRG, variando as capacidades de energia solar fotovoltaica e das baterias. A adoção de uma tarifa RTP diminui o LCOE de € 0.530 para 0.314 euros por kWh. Uma estratégia de carregamento inteligente, concebida para reduzir os picos e programar o carregamento para períodos de preços mais baixos, reduz ainda mais o LCOE para € 0.283 euros por kWh. O LCOE mais baixo, de € 0.281 euros por kWh, é obtido com 34,4 kWp de capacidade solar PV e sem baterias. O impacto do carbono é minimizado com maiores capacidades de energia solar fotovoltaica e de baterias.

Palavras-chave

Veículos eléctricos, carregamento inteligente, integração das energias renováveis, impacto de carbono, tarifas dinâmicas de eletricidade, frotas comerciais.

Table of Contents

List of Figures

List of Tables

List of Abbreviations

Enter your text	Enter your text (without dot at the end)

List of Symbols

Enter your text	Enter your text (without dot at the end)

List of Software

Enter your text	Programmes Abstract

Chapter 1

Introduction

Section 1.1 presents an overview of this thesis topic: the adoption of Electric Vehicles (EVs) to decarbonize the transportation sector. Global trends are highlighted and indicate the need for widespread smart charging technology adoption, increasing the synergies between EVs and electricity grids and leading to reduced operational costs and carbon impact. Section 1.2 presents the motivation and a short description of the thesis content. Section 1.3 describes the thesis research questions and objective. Finally, Section 1.4 indicates the scientific contribution this thesis aims to provide.

1.1 Overview

The fight against climate change relies on successfully decarbonizing different sectors, such as industries, electricity and heat generation, and transportation. The transportation sector, alone, is responsible for 25% of total European CO_2 emissions (Barman et al., 2023). The transition towards electric vehicles (EVs) has emerged as a pivotal solution to support this sector's decarbonization. EVs prices have been steadily decreasing in the last years, driven by lower battery costs and higher production volumes. In Europe, EV sales rose by 15% from 2021 to 2022, reaching a 2.7 million EV fleet. Worldwide, in 2022 more than 25 million EVs were actively registered and operational. EV adoption rates are a positive signal towards reaching decarbonization goals, and by 2030 it is expected that overall electricity demand will be increased by 4% because of EVs (International Energy Agency, 2023). Even though EVs technology emits no tail-pipe CO_2 emissions, the source of electricity used to charge them defines the actual environmental impact for transportation people and goods within electric mobility (Beaufils & Pineau, 2019).

The electricity sector is decarbonizing quickly. By 2030, solar and wind energy are expected to represent 25% of global electricity production (Barman et al., 2023). However, renewable energy resources, a critical component of reducing emissions, are inherently volatile, subject to fluctuations in weather conditions. This volatility, in turn, poses significant challenges to power system operators, particularly in meeting peak demand while integrating a growing share of renewables. The expansion of decentralized photovoltaic (PV) installations on residential and commercial/industrial buildings has been on the rise, further complicating the scenario. Electricity generated from these PV installations can be consumed on-site, stored locally, or even fed back into the grid, depending on demand and storage availability. Power system operators find themselves facing a dual challenge: incorporating EVs into the complex dynamics of the power grid and simultaneously accommodating the growing generation of renewable energy (Beaufils & Pineau, 2019).

To accelerate decarbonization in the transporation sector, the European Union (EU) recently announced its integration with the EU Emission Trading System (EU-ETS), starting in 2025. A mechanism to trade carbon allowances from fossil fuels purchasing will be put in place, and an emissions cap will be reduced on a yearly basis to restrict the availability of carbon credits and reduce total emissions (European Parliament, 2022). However, (Heinrichs et al., 2014) and (Haywood & Jakob, 2023) indicate that, in the short-term, individuals and firms have little alternatives to reduce their demand for transportation fuels. Adopting more efficient ICE cars or EVs becomes a longer-term alternative to replace this demand, as it is restricted by investment capabilities and other factors. As a result, given the open carbon credits market across different segments, it is expected that carbon credits will be purchased in other markets, where decarbonization is cheaper, to cover the demand for transportation. According to the authors, the electricity market is going to be directly affected by the inclusion of the transportation sector in the EU-

ETS, encouraging a faster decarbonization process.

Thus, the transition towards electric mobility brings its own set of challenges, especially in the context of power systems and electricity distribution. If EV charging is not performed with zero or low emissions electricity, it increases electricity demand in peak hours, and transfers fossil-fuels burning in internal combustion engine vehicles to coal or gas power plants (Beaufils & Pineau, 2019). Smart charging technologies emerge as a solution to manage EV charging in cheaper, more sustainable ways. Charging is automated to minimize its impact on electricity grids and increase renewable electricity integrations according to different strategies (Sadeghian et al., 2022). Maximizing grid integrations with EVs and RE can be done with unidirectional (V1G) or bi-directional flow (V2X) of energy. In V1G, dynamic control EV charging occurs unidirectionally and in sync with grid needs. In V2X, bi-directional flow of power between EVs and power systems become a reality, and EVs' batteries can be used in the same way stationary batteries are when connected to grids and buildings. Nevertheless, bi-directional charging requires vehicles and chargers technical compatibility, and market regulation, and is still not a common industrial solution (Barman et al., 2023).

With V1G smart charging, locally EV charging adapts to renewable energy production rates, local loads, charging infrastructure usage (real-time and forecasted EV demand), maximizing electricity-self consumption. On a power system levels, smart charging can react to electricity prices signals, demand-response programs, and grid ancillary services via EV aggregators. These for-profit entities intermediate the communication between power systems and EVs, managing various distributed generation resources or flexible loads (like EVs) to provide ancillary services for the power network (Barman et al., 2023). Accurately modelling and forecasting EV loads is crucial to enable smart charging services, as it allows aggregators to plan ahead and control EV charging sessions according to grid requirements (Sadeghian et al., 2022).

To make smart charging more appealing for EV owners, financial incentives must be put in place to encourage charging profiles matching the electricity grid needs. The ongoing roll-out of smart meters provides real-time information on electricity consumption. This leads the way for utilities to offer more complex tariffs, using real-time electricity consumption data (Beaufils & Pineau, 2019). The work of (Hildermeier et al., 2022) investigated the European energy market, measuring the availability of EV tariffs and services. They identified dynamic Time-of-Use (ToU) tariffs as the most frequent tariff structure for EV charging, especially in Northern European countries like Sweden. Lower prices are offered at time intervals following electricity spot market prices variations, and results in reduced operational costs for EV owners and grids operations.

The adoption of EVs by commercial fleet has been facilitated not only by lower EVs prices, but also by vehicles batteries range increasing over the past years. Most companies owning EVs charge at their private infrastructure to minimize costs and ensure maximum vehicles availability (International Energy Agency, 2023). A large fleet adds a significant amount of electricity to a building's base load, and it must be delivered according to vehicle's presence on the site, charging infrastructure capacities and buildings constraints. Not only is the connection to electricity grids limited to the connection point capacity, but higher demand peaks also lead to higher grid power costs. The integration of local renewable electricity assets, such as solar PV and batteries, reduces the demand for electricity and reduces operational costs. However, installing such systems is capital intensive, and the trade-off between operational cost reduction and capital expenditures depends on proper system design and operations. This context imposes challenges on EV adoption and charging infrastructure design and operation for commercial fleets. Once again, smart charging technology becomes crucial to enable a successful transition towards EVs in an affordable and sustainable way (Simolin et al., 2021). Proper understanding of EV charging loads, local renewable electricity generation, storage and consumption, and systems integrations is essential to deliver EV smart charging solutions beneficial for electricity systems and EV owners.

1.2 Motivation and Contents

This thesis addresses the topic of EV smart charging and renewable electricity integration for a commercial fleet case study, in Germany. The baseline scenario considers 65 EVs charging on-demand at the company's own charging infrastructure at fixed electricity prices. No smart charging is in place, and nor are renewable electricity integrations. The adoption of different smart charging strategies and solar PV and batteries are investigated, aiming to identify cost savings and carbon emissions reduction opportunities.

This thesis is conducted in collaboration with RiDERgy GmbH, an energy management and EV fleet aggregator company located in Berlin, Germany. RiDERgy offers efficient fleet electrification consulting services and a smart charging and energy management software to reduce operational costs and maximize green electricity usage. The company is interested in investigating this thesis topic to enhance its solution offering.

The work is divided as follows:

Chapter 2 presents a comprehensive literature review on the topic of EVs smart charging, grid integrations with renewable electricity and EVs, road transportation decarbonization, and showcases different EV smart charging case studies. It identifies research gaps and indicates how this work fulfils them.

Chapter 3 describes the case study and elaborates on the project methodology. EV smart charging strategies are proposed and modelled using HOMER Grid Software. Dynamic energy balances are generated to estimate operational costs, CO2 emissions and renewable electricity usage for different solar PV and batteries capacities.

Chapter 4 presents this thesis results. It shows the impact of adopting a Real-Time-Tariff, different smart charging strategies and solar PV and batteries integrations from an economic and environmental perspective. Several analyses are made, as well as a sensitivity analysis on electricity prices, solar PV and batteries costs and project interest rates.

Chapter 5 concludes the work summarizing the main findings and identified benefits, opportunities and challenges for EV smart charging, and renewable electricity integrations for a commercial EV fleet use case and others. It also suggests future research opportunities to expand the knowledge on the topic approached by this thesis.

1.3 Objective

Three research questions guide the development of this thesis:

- What are the economic and environmental benefits from adopting smart charging strategies, aiming to shave charging peaks and shift demand according to charging schedules?
- What are the economic and environmental benefits from integrating solar PV and batteries with EV smart charging?
- What is the ideal system architecture to minimize project costs over its lifetime?

This thesis objective is to propose a methodology to investigate smart charging strategies and renewable electricity integration based on a Real-Time-Pricing electricity tariffs. A tool to estimate cost and carbon impact emissions reduction is created to evaluate different scenarios for a commercial EV fleet case study in Germany, supporting the investment decision making process.

1.4 Scientific Contribution

This thesis covers an existing literature gap, expanding knowledge on EV smart charging and renewable electricity integration for a commercial fleet use case. It proposes a methodology to model and analyse smart charging strategies based on granular, dynamic electricity prices from the day-ahead-market, and local renewable electricity integrations. HOMER Grid is used to generate smart EV charging load profiles and energy balances considering variable solar PV panels and batteries integrations are modelled. The work investigates the impact of adopting a Real-Time-Pricing (RTP) tariff indexed to the day-ahead market, and the proposed methodology identifies the optimum system configuration that leads to lowest costs under different scenarios. In addition, the carbon impact of such systems is assessed, quantifying direct and indirect emissions from electricity purchases from the grid, as well as self-generated solar PV electricity. The work provides background to support the ongoing development of RTP tariffs and decentralized renewable electricity assets in Europe for a commercial EV fleet use case, sharing the knowledge with the scientific community, EV and energy market players and supporting the transition towards greener electric mobility.

Chapter 2

Literature Review

In this literature review, a structured exploration of Electric Vehicles (EVs) Smart Charging with a dual focus on operational cost reduction for fleet owners and carbon emissions reduction by integrating renewable energy resources. Fundamental concepts are presented in Section 2.1, offering an overview of EV charging technology and renewable electricity integrations with grids. Building upon this foundation, Section 2.2 explores the challenges and opportunities to integrate RE and EVs in profitable grid operations. An overview of the existing EV smart charging approaches is presented, and the market alternatives in Europe is presented in detail. Section 2.3 focuses on the impact of policies and smart charging technology to reduce the environmental impact of road transportation. The European Union Emission Trading System II, which will be implemented in the coming years, is presented along on some studies held aiming to measure its effectiveness. In Section 2.4, specific studies proposing smart charging strategies or considering EV smart charging to reduce costs and CO_2 emissions are presented, showcasing the diverse approach taken by the scientific community. Finally, Section 2.5 concludes the chapter identifying research strategies and gaps that serve as the guideline for this work.

2.1 Overview of Electric Vehicles and Smart Charging

EVs have a central role in the road to decarbonize the transportation sector, but require appropriate energy management strategies to ensure vehicles are charged with green electricity. This section presents an overview of EV charging, renewable electricity integration with grids and within mini-grids, and different EV smart charging approaches.

2.1.1 Existing renewable resources for Electric Vehicle charging and grids integration

(Barman et al., 2023) discuss the pros and cons of different renewable resources for EVs and grids integration. Hydropower (44% of global renewable power installed capacity) presents itself as a great alternative for EV charging and grids integration, because of its high power capacity, natural abundance, and technology maturity. Major drawbacks are related to the environmental impact of construction and operation of hydro-power plants. Wind power (25% of global renewable power installed capacity) is another mature technology, that can be built over land and sea safely and offer high power capacity. The volatility of wind across hours, days and seasons brings about great challenges for grid integrations. Solar PV electricity (24% of global renewable power installed capacity) allows decentralized and central generation, with easy installation and Operation & Maintenance processes. In addition, it requires low maintenance and panels currently have a long lifespan. On the other hand, PV panels have low efficiency, and their manufacturing, transportation and installation processes create carbon footprint. This technology is also highly volatile requiring more complex technology to integrate with. Solar thermal power (0.24% of global renewable power installed capacity) is potentially a good alternative resource for EV charging and grids integration. This technology leads to efficient, continuous electricity generation, requiring low maintenance in larger stationary power plants. Nonetheless, it is capital intensive during construction, uses greats amount of water and requires large energy storage systems using molten salts, which increases the solar thermal's carbon footprint (Barman et al., 2023).

(Barman et al., 2023) highlight the potential of EVs supporting solar and wind power integration with grids. Because of the large energy storage capacity in Lithium-ion batteries and demand flexibility, EVs can be charged directly with solar and wind electricity but also integrate with grids to react to forecasted and real-time wind and solar generation volatility. That, as previously mentioned, is enabled by a complex technology infrastructure, and their work focuses on explaining those. The technological infrastructure for EV integration with RE resources is depicted in Figure 1.

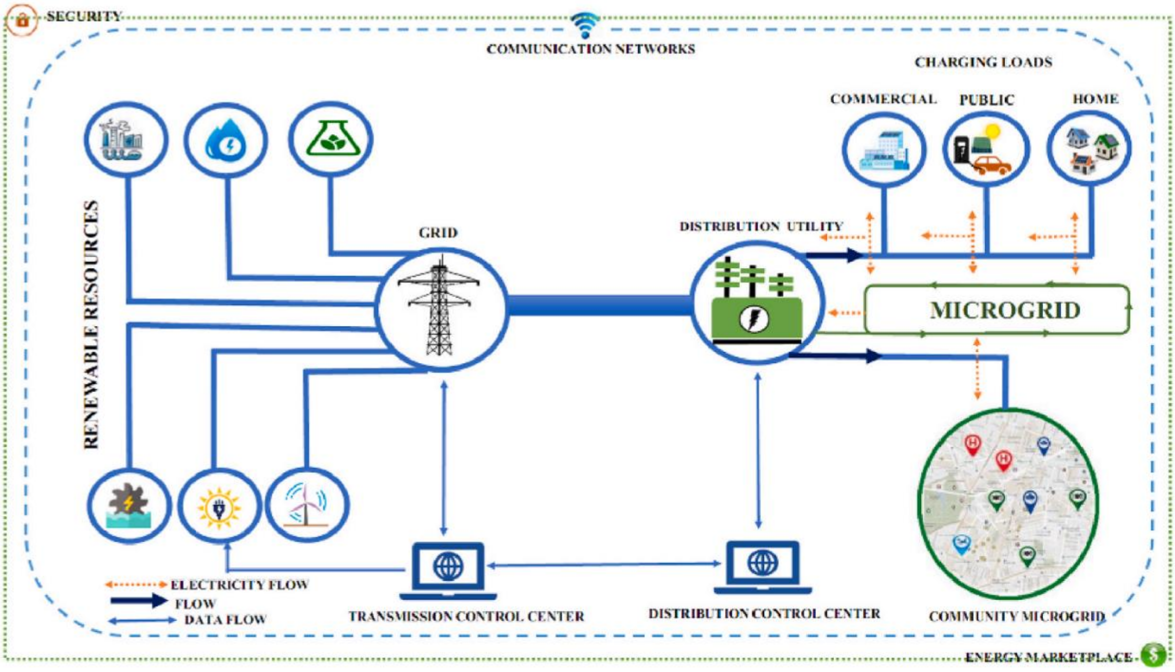
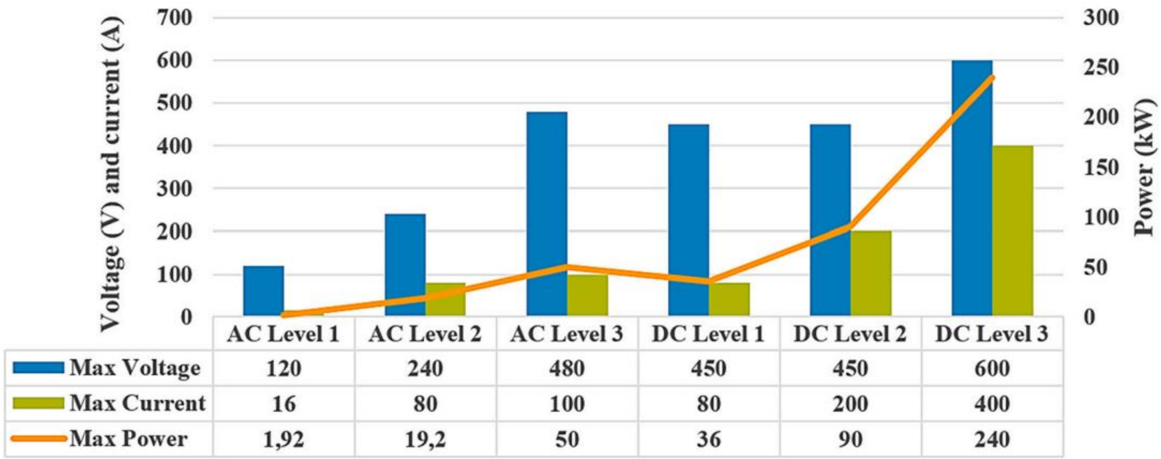


Figure 1: Technological infrastructure for EV integration with RE resources (Barman et al., 2023)

2.1.2 Electric Vehicle charging and Renewable Electricity

EV chargers receive AC electricity from grids or local systems. Renewable electricity is oftentimes produced in DC (e.g. solar PV), which requires external inverters before feeding any EV charger or connecting with grids. In addition, RE output voltage is usually too low to feed EV chargers, so power electronics located outside the vehicle need to step the voltage up to allow timely sessions (Barman et al., 2023).

(Sadeghian et al., 2022) present an overview of usual power, current and voltage rates employed by different AC and DC charging technology according to their charging levels, which is shown in Figure 2:



	AC Level 1	AC Level 2	AC Level 3	DC Level 1	DC Level 2	DC Level 3
Max Voltage	120	240	480	450	450	600
Max Current	16	80	100	80	200	400
Max Power	1,92	19,2	50	36	90	240

Figure 2: AC and DC charging levels according to power, current and voltage (Sadeghian et al., 2022)

Charging at the residential and workplace levels predominantly involves AC Level 1 and Level 2 charging. These methods are most frequently employed for overnight charging at home and at various commercial sites. In contrast, DC fast chargers take a different approach by using off-board chargers, typically integrated directly into the charging station infrastructure. These chargers play a pivotal role in optimizing the charging process by correcting power factor through rectifiers and precisely controlling voltage using DC/DC converters. DC fast chargers are primarily used in public or semi-public charging locations, where time is key for EV owners. Several charging specifications exist, such as the Society of Automotive engineers (SAE) and International Electrotechnical Comission (IEC) (Barman et al., 2023).

2.1.3 Power Electronics

At the core of this complex charging ecosystem are power electronics, serving essential functions. They facilitate the seamless conversion of electricity between AC and DC while simultaneously correcting power factors (PFC). Furthermore, a crucial DC/DC conversion stage is employed to regulate voltage and current, directly influencing the charging power delivered to the EV. To achieve the delicate balance between rapid charging and extended driving range, an array of communication devices is indispensable, ensuring efficient and coordinated operation within the EV charging system (Barman et al., 2023).

2.1.4 Energy storage technology

To prevent RE power losses, electricity must be consumed immediately or stored. Stationary storage systems accommodate surplus renewables, as well as stabilize EV charging processes. Storage must provide both large energy storage and power capacity, which requires a mix of different technologies. While physical storage systems such as flywheels and pumped storage offer great power quality, they lack high storage capacity. Similarly, electromagnetic energy storage systems such as super- and ultra-capacitors have high power density, but a high rate of charging/discharging cycles. Chemical storage systems, or batteries, offer high energy storage capacity and for many applications enough power. The most common type of batteries are lithium-ion (76% of installed capacity), followed by sodium-sulfur batteries (13%), lead batteries (7%) and redox flow batteries (3%) (Barman et al., 2023).

2.1.5 Smart charging technology and Electric Vehicle aggregators

(Barman et al., 2023) define smart charging as the EV charging ecosystem composed of EV, charging infrastructure, network and charging operator. Connectivity is obtained via the internet, and chargers and EVs data are managed in a cloud-based back-end known as Virtual-Power-Plant (VPP) that can be managed by EV aggregators. A VPP aggregates the flexibility of various EVs to allow better network management, lower costs and higher RE usage. Charging can be controlled based on different signals, such as energy production, local loads, number of online EVs (real-time and forecasted EV demand), or other market signals.

(Sadeghian et al., 2022) also highlight the role of EV aggregators to enable and maximize smart charging benefits. These for-profit entities intermediate the communication between power systems and EVs, managing various distributed generation resources or flexible loads (like EVs) to provide ancillary services for the power network. EV aggregators participate in day-ahead and intraday electricity markets (participating in wholesale markets), bidding flexibility obtained via the pool of EVs under their portfolio (participating in retail markets). Although the definition of EV aggregators differs throughout the literature, their purpose is to aggregate distributed EV demand and turn them into flexible energy resources. To achieve so, aggregators must ensure EV owners are rewarded for offering their vehicle's flexibility, while guaranteeing a minimum SoC, dealing with market prices uncertainty, power supply reliability, among other challenges.

To ensure a secure and effective coordination across charging stations, EV and charging station management system (CSMS), a standard communication protocol called Open Charge Point Protocol (OCPP) has been established. OCPP is currently present in almost 150 nations and more than 65,000 charging stations are compatible to it. CSMS may be part of VPPs or independent, and effectively controls the charging process by exchanging demand response messages with charging stations via a local proxy or local controller. For example, a third-party DSO can send signals indicating grid limits for a CSMS to consider these constraints in their smart-charging algorithms. The same could happen with a third-party VPP or aggregators exchanging different signals. This complex cloud architecture, presented in Figure 3 is crucial to enable widespread smart charging, and to ensure smart grids and EV owners remain protected from cyber-attacks and hackers (Barman et al., 2023).

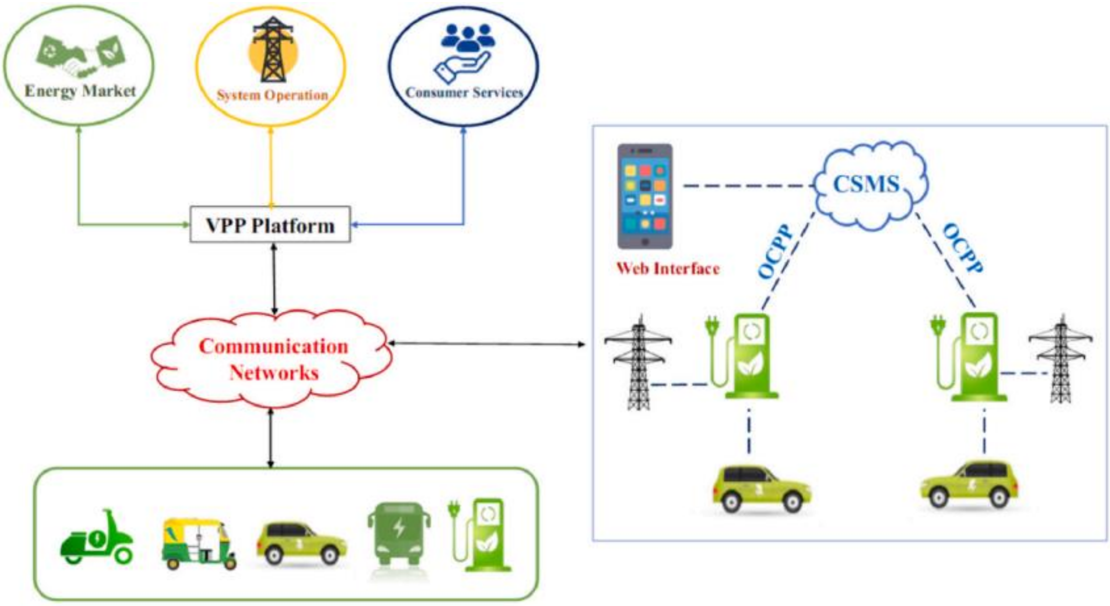


Figure 3: VPP platform for smart charging using OCPP (Barman et al., 2023).

2.2 Grid integrations with Renewable Electricity and

Electric Vehicles via smart charging

(Beaufils & Pineau, 2019) discuss the possibility of distribution utilities facing a *death spiral* because of overall deployment of decentralized solar PV and storage. These customers become producers and consumers, the so-called *prosumers,* of their own electricity, decreasing the demand (and revenues) from the utility. However, because of the solar PV generation profile, demand at peak hours remains (almost) unchanged. Since most utilities charge their customers based on overall energy consumed, rather than power peak demand, this decreases utilities' revenues and forces them to rise prices. Therefore, more customers see the benefit of investing in self-generation solutions and the problems is worsened – thus the term death spiral.

The increased demand for electricity from EVs charging could help offset revenue losses from PV self-consumption, however if charging is not properly managed it will most likely increase the demand for electricity in evening peak hours. In 2017, in the USA, 59% of electricity costs were related to generation, 23% to transmission and 13% to distribution. While varying energy demand has a marginal effect on operational costs, transmission and distribution are sunk costs related to the physical grid infrastructure. It needs to be maintained and enhanced to deal with peak electricity demand, thus strongly affected by electricity consumption profiles (Beaufils & Pineau, 2019).

(Barman et al., 2023) highlight that optimizing the usage of the existing infrastructure over a whole day is more cost-effective than upgrading it to deal with peak hours of demand. Maximizing grid integrations with EVs and RE can be done with unidirectional (V1G) or bi-directional flow (V2G) of energy. These allow the exchange of power between electricity systems and vehicles batteries, and require data communication from charging infrastructure, EVs and, grids.

In V1G, dynamic control EV charging occurs unidirectionally and in sync with grid needs. EV charging times and power are adjusted according to grid or energy market signals, dynamically. In V2G, bi-directional flow of power between EVs and power systems become a reality, and EVs' batteries can be used in the same way stationary batteries are when connected to grids. It requires vehicles and chargers technical compatibility, and market regulation. With bi-directional flow of energy, other smart charging approaches such as vehicle-to-building (V2B), vehicle-to-home (V2H) and vehicle-to-everything (V2X) expand the opportunities to leverage on idle EV batteries, facilitates the adoption of decentralized RE. These still require vehicles compatibility, but are done behind-the-meter so less regulations are involved (Barman et al., 2023).

From a grid operator perspective, EV smart charging could help maintain and improve grid stability while providing ancillary services, such as power quality services, grid loss reduction, voltage and frequency regulation, and grid congestion management (Sadeghian et al., 2022).

2.2.1 Utility pricing structures

(Beaufils & Pineau, 2019) highlight the importance of electricity tariffs reflecting grid operational costs. The ongoing roll-out of smart meters provides real-time information on electricity consumption. This leads the way for utilities to offer more complex tariffs, using real-time electricity consumption data. They are divided into:

- Time-of-Use (ToU) tariffs: pre-defines peak and off-peak hours, with higher prices per kWh during peak hours and lower prices during off-peak to encourage consumption.
- Critical peak (CPP) tariffs: follows the same peak/off-peak structure of ToU tariffs. In addition, during a few (10 to 12) extreme weather days per year the electricity price during peak hours is increased significantly.
- Real-Time Pricing (RTP) tariffs: the price per kWh is dynamically adjusted, according to market conditions. This is the most granular and cost-reflective tariff structure.

In addition, smart meters allow utilities to charge households, commercial and industries a fee proportional to their real power demand. Demand-based charges, also known as capacity charges, are usually defined based on peak kW consumed or contracted over a period (month or year). They may, or not, be only applicable if peaks are coincident with system peak demand hours. Since capacity charges are meant to help utilities recover their network fixed costs, experts argue that customers should only pay higher tariffs if their peak consumption occurred at the same time as overall system peak.

According to (Beaufils & Pineau, 2019), utility pricing structures are summarized into 5 principles: economic efficiency, equity, revenue adequacy and stability, bill stability and customer satisfaction. Combining them all into one single rate is complex and oftentimes not feasible. For example, RTP tariffs are efficient and equal, since customers are charged according to their behaviour and utilities can proportionally recover their costs. However, inherent market prices fluctuations lead unstable and unpredictable bills. The authors conclude that the need to keep electricity tariffs low hinders the acceleration of cost-reflective tariffs. In Europe, many utilities charge customers based on a ToU and/or demand charge by default, which is not the case in North America. They highlight fixed ToU tariffs can encourage EV owners to charge during off-peak hours, which reduces energy-related revenues but can lead to a new peak demand time. Moreover, fixed volumetric tariffs tend to increase peak demand during systemic peak hours, increasing distribution costs significantly. Combining demand charges and time-variant energy prices to compensate for increased DER's is crucial to help utilities fight their death spiral, in an equitable way for customers.

2.2.2 Smart charging strategies

As mentioned, to achieve EV charging in sync with grids and RE needs, either with uni- or bi-directional flow of power, a complex system architecture must be in place to ensure proper data exchange and control within vehicles, chargers, local energy assets, grid operators and flexibility aggregators. Smart charging strategies differ according to the application, but it will always aim to minimize costs for EV owners and power system operators, maximize the use of renewable electricity, while prioritizing vehicles mobility.

(Barman et al., 2023) segment the existing approaches into:

Network charging: enables EV owners to contract a fixed amount of green energy, which is guaranteed to be generated from renewables. Charging is encouraged to occur at times that are beneficial to the grids, or when there is surplus of RE generation. Commonly, these occur overnight on weekdays, and during the day on weekends. Time-of-Use (ToU) tariffs are usually the preferred utility tariff because of their simplicity and capacity to influence customer behaviour.

Shift charging: discounted rates for off-peak hours and when RE generation exceeds demand. Green energy premium is offset by the discounted prices. This demand shift benefits utilities and users, leading to higher RE usage and lower costs for both. Such programs offer ToU combined with RE enablers, meaning the off-peak hours can be adjusted to reflect the balance between RE production and demand.

Charging with excess renewables: EV charging occurs at times of higher availability of RE, helping with RE grid integration directly. This is signalled to EV owners with dynamic electricity prices, with are indirectly proportional to renewables generation. Again, ToU tariffs are a common way for utilities to offer a simple enough signal to their customers.

On-site renewables: EV charging is typically achieved using locally generated solar PV electricity in residential and commercial sites. To maximize RE usage, charging is managed, and stationary storage systems are commonly integrated. Authors highlight the challenge to manage several vehicles charging process at once.

Managed charging: EV charging flexibility is leveraged with direct control over charging times and power. With unidirectional (V1G) charging, charging times, power and duration are adjusted and managed according to utility signals, representing the status of the grid and RE availability. With bi-directional (V2G) charging, the vehicle's battery is also discharged when there is not enough RE in the grid. Level 1 and Level 2 AC chargers are preferred since they allow reaction to utility signals. Fast DC chargers are less suitable given their intrinsic high power. The managed charging is the enabler for fully integrating EVs, RE, power systems operators, aggregators and e-Mobility Service Providers (eMSP). Price of tariffs fluctuates in real-time according to demand-supply, requiring accurate forecasting, and EV owners are able to charge automatically with lower prices.

(Sadeghian et al., 2022) highlight the importance of accurately forecasting EV loads to enable smart charging services, as it allows aggregators to plan ahead and control EV charging sessions (number of EVs, power rates, charging locations) according to grid requirements. Driving patterns influence on vehicles arrival and departure times, and EV types directly impact energy consumption and demand. Grid data indicate demand side flexibility requirements and are the driving force of flexibility scheduling and activation. Data handling mechanisms include clustering, forecasting and scheduling processes, and various researchers and industries study methods to predict the load profile of EVs. Section 2.4 presents some approaches.

(Barman et al., 2023) mention that, in the USA, utilities and governments have initiatives to offer green procurement of electricity via green tariffs, solar community projects, direct PPAs with RE producers, and green pricing structures. These, however, don't focus on EV load management, and prevent the fully capture of EVs' demand flexibility. New smart charging services address that, with focus on light duty vehicles and offering innovative pricing structures to maximize the usage of RE for EVs charging.

One example of network smart charging in the US is obtained from Austin Energy's "Plug-in Everywhere" tariff:

- Off-peak throughout the day on weekends, from 7pm to 2pm on weekdays.
- For off-peak residential charging, $30/month for >10kW, and $50/month if >10kW.
- No energy consumption-related fee, except if charging occurs during peak hours. During summer, costs $0.40 / kWh and during winter $0.14 / kWh.
- Requires a dedicated meter for EV charging infrastructure, since this tariff is applicable exclusively to EV demand.

2.2.3 Smart charging tariffs and services in Europe

(Hildermeier et al., 2022) performed a thorough market analysis of EV smart charging tariffs and services in Europe. They identified 139 offers for EV owners, considering only those that were exclusively offered to EV smart charging via devices integrations. The authors highlight the existence of generic Time-of-Use tariffs that encourage users to consume electricity at grid-friendly hours, which can be done via EVs charging, but also via heat pumps and other appliances. Figure 4, below, presents the number of smart charging tariffs in European countries, and the colour code represents how advanced the offering of generic dynamic tariffs, i.e. not exclusive to EV smart charging.

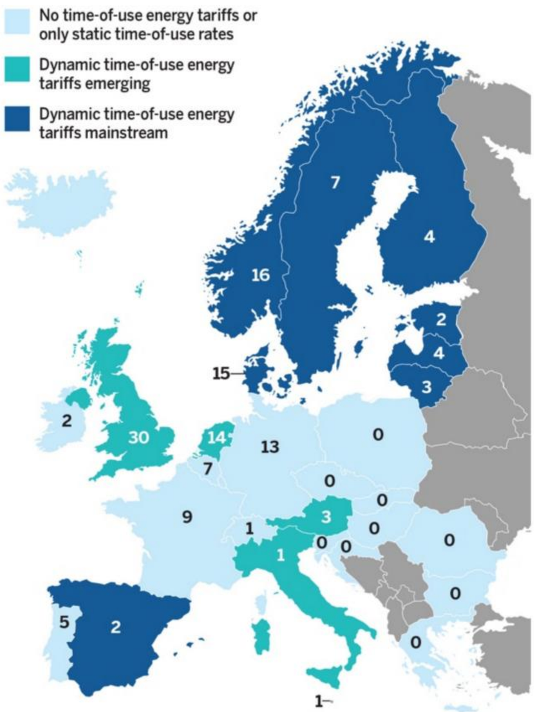


Figure 4: Smart charging tariffs in Europe (Hildermeier et al., 2022)

This study aimed to understand industry trends and opportunities and propose strategies to ensure EVs are integrated with electricity grids sustainably and with low costs of EV owners and grid operators. Thus, focus on tariffs and services offered exclusively to EV smart charging is given. They are divided into five categories, which are described below along with an indication of the number of services provided in Europe (Hildermeier et al., 2022):

- **Dynamic ToU pricing (77 occurrences):** day-ahead wholesale energy market tariffs are directly offered to charge EVs at lower prices every day. Most of the identified tariffs were present in Nordic countries, where smart meters and generic dynamic tariffs are more commonly available as well. They highlight these are ideal conditions for smart charging offering to exist. Services usually offer EV charging automatic to charge optimally within users' preferences.
- **Other dynamic inputs (44 occurrences):** for smart charging based on inputs such as electrical grids real-time carbon intensity or renewable electricity availability. These services are based on renewables production forecasts, either on a national level or more commonly in a local level (PV self-consumption).
- **Static ToU pricing (38 occurrences):** lower prices are offered during historical off-peak hours, i.e. period of the day during which demand for energy or power are historically lower. This type offers great price transparency.
- **Grid balancing mechanisms (28 occurrences):** EV owners offer their demand flexibility to help balance supply and demand of electricity within a market zone (often a country). These balancing services are offered directly via real-time market signals, or via aggregators that procure demand flexibility from TSOs and other market participants. Users can choose to participate, and the system's activation depends on real-time energy market conditions, as well as EVs availability.
- **Distribution network management (13 occurrences):** DSOs send price signals or other inputs that reflect the distribution network condition, historical or in real-time. This helps grid operators minimize costs related to peak demand times, reduce energy losses when surplus feed-in electricity is available. The study suggests that since EVs are exchanging power in a decentralized way at distribution grid level (lower voltage), there is great room for exploring further services in this area.

The authors highlight that 38 services combine more than one category, for example demand-response programmes combined with dynamic day-ahead market prices. This approach can increase the benefits for EV owners, who are encouraged to charge their vehicles at the times most beneficial for the electricity system. Finally, 10 of the services offered combined TSOs and DSOs demand-response signals, thus rewarding EV owners for offering their vehicles to support grid operations in a nationwide and local distribution levels. The distribution of such tariffs and services in European countries is shown in Figure 5.

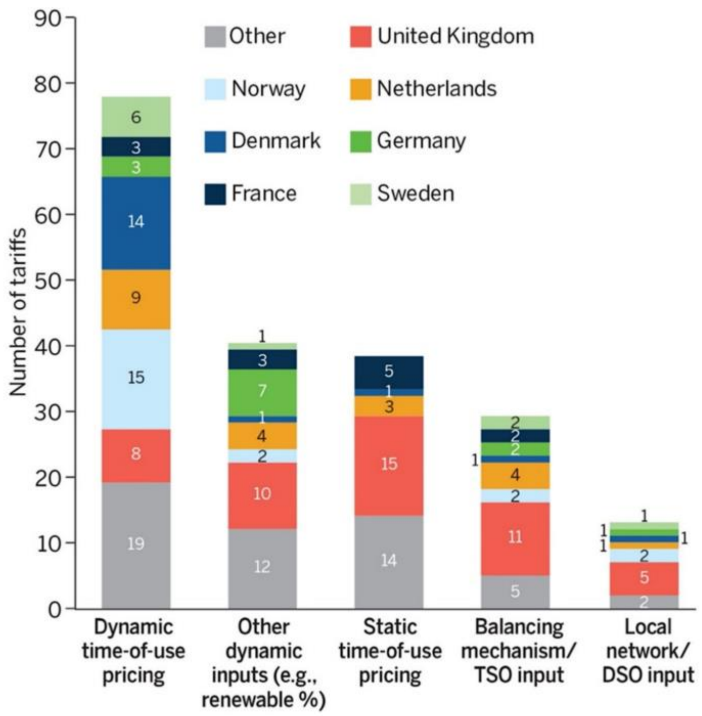


Figure 5: Distribution of smart charging services in Europe (Hildermeier et al., 2022).

In Germany, dynamic ToU tariffs are not commonly present. However, a specific regulatory framework allows grid operators to offer a controllable load network tariff, and gain control over loads at certain times of the day in exchange for a reduced network fee. According to the authors, this approach discourages transparency and innovation, and limits the benefits from smart charging for users (Hildermeier et al., 2022).

The article is finished with a detailed discussion on six strategies the authors propose to increase the availability and use of smart charging in Europe.

- **Smart EV charging as default:** lack of consistent regulation throughout Europe makes it more complicated for market actors. A good example is in the UK, where the Smart Charge Points Regulations (2021) establishes that home chargers with smart charging features must be configured during installation to charge, by default, during off-peak hours. Although users can change this, it helps with customer awareness on smart charging.
- **Public smart charging as default:** higher public charging costs significantly hinder EV adoption for citizens and businesses that are unable to install a private charging infrastructure. Smart charging at public sites can reduce charging costs and support on-street charging for public fleet users, and lower-income groups.
- **Customer awareness:** increased information on smart charging services and their benefits for EV owners and energy systems are likely to accelerate the synergies between EV charging and the electricity system needs. They suggest service providers should further highlight the benefits for customers and develop user friendly interfaces to encourage their use. In addition, policy makers should encourage educational campaigns, and provide backing to innovative pilots testing new EV charging services with real consumers.

- **Rewards for consumer flexibility**: smart charging services can be enhanced via specifically designed tariffs and also through generic smart-charging tariffs. In both cases, the value of EV charging flexibility in energy systems must be rewarded to EV owners. Nonetheless, existing regulation barriers such as minimum bidding size, metering requirements and interoperability constraints fail to allow market participants to easily reward their customers.
- **Multiple system benefits:** it will be important to stack up optimization and cost savings opportunities. For example, adjusting charging aiming for minimum environmental impact from electricity used, while offering balancing services opportunities. Or, alternatively, optimizing charging for maximum locally generated electricity consumption, lower costs from wholesale electricity markets, while improving load management in multi-dwelling or commercial buildings.
- **Improved local grid utilization:** EV smart charging biggest potential for electricity grids stability lies at distribution grid levels, given their decentralized and granular energy consumption behaviour. To increase the use of grid data in real-time, regulators should create a framework that supports grids digitalization and smart management. This would require DSOs to share grid data with aggregators, that can offer smart charging services to reduce grid congestion. In addition, flexibility markets must be created at a local level to EV owners to participate.

Despite all the identified trends and market opportunities, the authors suggest further studies to quantify the value of smart EV charging with such services are required, focusing on avoided investment to reinforce power grids, grids operation costs and renewables curtailment. They also highlight that the described services can also be combined with V2G technology and stationary energy storage systems, with great opportunity to enhance savings and benefits of smart charging.

(Ensslen et al., 2016) conducted a study to analyse the interest and willingness to pay (WTP) from companies to services related to charging and operation of EV commercial fleets. The authors surveyed fleet managers of 109 small and medium-sized companies, in Germany, that were part of the Get eReady program. This program offered (partial) subsidies for companies to adopt e-mobility (i.e. acquire vehicles, chargers, setup private charging infrastructure, e-mobility consultancy, among others). All participants had acquired EVs through the program and they were asked to respond two surveys. The first aimed at identifying services which were interesting for fleet managers, and the second survey quantified their WTP for such services. The most interesting service from a fleet manager perspective was related to offering the company's charging infrastructure to others (and monetizing on it), followed by having access to "basic connected charging services", which are related to real-time data on public charging infrastructure, with the possibility to make reservations. Smart charging services were the next in terms of fleet managers interest, and low-cost smart charging had a higher rank in comparison to charging optimization for lower CO_2 direct emissions. It must be highlighted that all services received similar grades as the survey's output, being considered "relevant". In terms of willingness to pay, fleet managers showed they expect lower electricity prices if an aggregator is charging their vehicles "optimally", i.e. they expect lower tariffs in comparison to the reference. However, when it comes to smart charging services to reduce the CO_2 emissions related to electricity consumption, fleet managers are willing to pay higher tariffs than the reference. The authors suggest future work to analyse costs and benefits of e-mobility services at commercial EV charging sites, aiming to understand if those can help EV adoption.

2.3 Road transportation CO_2 emissions reduction

In 2022, the European Parliament targeted the decarbonization of fuels for road transport and buildings by including it in a parallel EU ETS system, the so-called EU ETS II, that should start in 2025. Fuel distributors, who are the regulated entities, will need to report the amount of supplied fuel into the market on a yearly basis, starting from 2024. A cap on the emissions allowances will be stablished in 2026, and after that the cap would gradually decrease to reach 43% reduction by 2030 compared to 2005. To incentivize decarbonization, all allowances will be auctioned, and none will be free. A Social Climate Fund is created to buffer social implications of rising fuel prices in these sectors. From the revenues collected in this new ETS sector, the fund will provide €72.2 billion between 2025-2032 for the EU to support European citizens affected or at risk of energy or mobility poverty, followed by the implementation of the ETS in road transport and buildings (European Parliament, 2022).

(Haywood & Jakob, 2023) analyse the role of the EU ETS II to decarbonize road transport from a policy perspective. They emphasize including road transport in the EU carbon trading system is part of a broad European Union policy mix and assess the possible outcomes of such. The authors highlight the small elasticity between fuel prices and demand for fuel for transportation. According to their study, in the short-term, individuals and firms have little alternatives to reduce their demand for fuel, such as adopting public transportation or reducing driving distances. Adopting more efficient ICE or EVs is a long-term alternative. The authors acknowledge the likely effective decrease in total CO_2 emissions across the EU, and highlight other existing policies in place. For example, the Energy Tax Directive (ETD) establishes different taxation for different fuels, being higher for more polluting fuels. The authors suggest that lower taxes for electricity in comparison to fossil fuels would help accelerate the transition towards EVs.

The conclusion reached by (Haywood & Jakob, 2023) is similar to the one found by (Heinrichs et al., 2014). This study aims to aims to understand if this is a cost-effective approach to support the sector's decarbonization process. The authors focused on the German market and coupled two parallel models: road transport needs for households and commercial fleets COMIT model, and the European electricity system PERSEUS-EU model. In addition, they simulated scenarios with low and high penetration of EVs, and simulated how the emissions trading system would impact fuel prices and lead to transport and electricity system decarbonization by 2030. The methodology followed by the authors is explained below:

COMIT's model to simulate the EU ETS mechanism for road transport includes several stakeholders: private households (that purchase vehicles and fuel to drive them), freight forwarders (that purchase vehicles and fuel to drive them), vehicle manufacturers (that produce or import and sell vehicles), and oil companies (that produce or import and sell fuels). Oil companies are the ones trading emissions allowances, relative to their fuels' carbon impact. Since the EU ETS is an open trading system, if the cap of emissions within the road transportation sector is not enough the cover the demand, market players can purchase carbon allowances from other industries. Thus, carbon emissions from road transportation are not necessarily directly reduced, but this higher demand for carbon credits in other markets pushes the carbon cost up, which reflects in gasoline, diesel and other fuel prices. The model considers this behaviour, identifying the point of equilibrium between CO_2 allowances price and demand for fossil fuels for transportation, as well as the CO_2 emission trading requirements for oil companies (Heinrichs et al., 2014).

Germany's electricity sector is simulated using PERSEUS-EU. Being the principal sectors within the EU ETS system, electricity costs are directly impacted by CO_2 allowance prices. To simulate the impact of carbon allowances trading on electricity price and decarbonization, the authors use PERSEUS-EU's database to model fuel supply, and electricity, and heat generation and final demand in 22 countries. Heat is included to correctly measure the need for combined heat and power generation. The objective function of PERSEUS-EU is to minimize system expenditures from energy flows (transmission and distribution), power-plant operation, power-plant capacities as well as carbon allowances prices. Their approach simplifies the emissions allowances allocation. In real conditions individual companies trade allowances. For simplicity, however, the authors allocate them according to transmission line capacities thus still impacting electricity prices (Heinrichs et al., 2014).

To couple both models, the authors iterate simulations between COMIT and PERSEUS-EU. Starting with a simulated CO_2 allowance price from PERSEUS-EU, COMIT calculates the need for CO_2 allowances trading in road transportation. The additional demand is reflected in PERSEUS-EU's overall CO_2 emission cap, and a new simulation calculates a new CO_2 price. To simulate different EV penetration scenarios, the increased electricity demand for EV charging is calculated in COMIT, for Germany, and extrapolated to the European fleet. Since the focus of this work is not on EV charging demand, a standard load profile is considered. The authors are able to analyse the cost-effective decarbonization balance between the electricity sector and road transportation fossil fuels, and the impact of CO_2 allowance prices on it (Heinrichs et al., 2014).

Their results indicated an inelastic relationship between increased fuel prices and demand for fossil fuels. An allowance price of €50 per ton of CO_2 leads to a 7% price increase in fuels in 20 years, which is comparable to historical fuel price increase in Germany. In a low penetration EV scenario (10% of the fleet), 6% reduction in CO_2 emissions is achieved in the transportation sector, and in the high penetration scenario (44% of the fleet), that increases to 20%. The electricity sector is impacted by the increased demand, and generation capacity is expanded considering renewables but also gas power plants, especially because of their flexibility. Results indicated a requirement for 19%-37% greater (compared to 2010) gas power plant generation capacity.

With lower demand for fossil fuel, CO_2 allowances are traded with fossil-fuel based electricity producers that are needed to cover the electricity demand. Nonetheless, fossil fuel prices, which are paid for by transportation users (people and businesses) will always cover a carbon cost that supports decarbonizing the electric sector. The work concluded that given the EU ETS market regulation strategy, decreasing the overall carbon allowances available across all industries, to include road transportation helps decrease overall CO_2 emissions in the EU. The work, nonetheless, does not explore smart charging approaches, and the authors recognize its impact in generating a more flexible EV load profile, likely to decrease the demand for flexible gas power plants (Heinrichs et al., 2014).

(Xu et al., 2020) perform an in-depth analysis of the environmental impact of fleet electrification in Europe, considering different smart charging strategies. They not only account for direct CO_2 emissions from fossil fuel-based electricity, based on the increased demand for EV charging, but also for indirect emissions from new power plants assets manufacturing and construction, and from vehicles and batteries manufacturing processes. To do so, the authors couple Life Cycle Analysis (LCA) with electricity system model obtained from their proposed methodology to include flexible EV charging demand in PERSEUS-EU.

Four different scenarios for the electricity system in 2050 are modelled. The baseline is set based on a hypothetical reference scenario with no EVs by 2050. The EV fleet estimated by 2050 is considered, and a scenario considering all demand is inflexible is simulated. Unidirectional EV smart charging, for which EVs have a 12h-window per charging session, is included in the model to generate the third scenario. Finally, it is assumed that during the 12h all EVs have bi-directional charging capability, providing a higher degree of flexibility to the energy system via V2G services.

(Xu et al., 2020) results indicate a 15% increase in total demand for electricity for the growing EV fleet by 2050, in comparison to a scenario with no EVs. Even though this increased demand leads to a higher production from gas-fired power plants than in the baseline scenario, massively adopting EVs in Europe leads to a 36% decrease in overall GHG emissions because of the avoided CO_2 emissions from fossil fuels burned in ICE vehicles. When unidirectional smart charging is considered, EVs help with RE grid integration and a total reduction of 40% in GHG emissions is obtained. V2G expands the benefits of EVs and reduces gas-powered electricity demand significantly, achieving a total of 47% in GHG emissions in comparison to the baseline scenario. The authors breakdown the indirect emissions from PV panels and other power generation manufacturing processes, as well as vehicles' batteries influenced by faster degradation from V2G. They conclude that, based on the proposed methodology and assumptions, EV smart charging is always beneficial to support RE production, especially PV, and reduces the environmental impact of EVs and energy systems. Furthermore, V2G outperforms uni-directional smart charging even when battery degradation is considered. Finally, the authors acknowledge the limitation of their smart charging modelling, as no individual EV is modelled but rather an overall EV load and flexibility per country is. Also, battery degradation behaviour is simplified.

2.4 EVs smart charging case studies

This section presents different case studies related to smart charging and renewables integration that are available in the literature. Focus is given on studies analysing the potential for cost and CO_2

emissions reduction from smart charging, and the researcher's approach to quantify those are explained as well as main results and conclusions obtained.

2.4.1 Residential Electric Vehicle charging with solar PV integration – no dynamic tariffs

(Beaufils & Pineau, 2019) studied a household use case with solar PV and EV charging integrations. They used data from a typical house located in Chicago, USA, with average daily consumption of 24.5 kWh and a standard load profile, installed solar PV capacity of 4.4 kWp, and an EV daily demand of 10.4 kWh being supplied via a Level 2 AC charger (3.6 kW). Different scenarios were simulated, integrating (or not) PV self-consumption and/or EV charging, and varying EV charging to start at 19h (standard, unmanned charging) or at 1:00 am (optimized, off-peak smart charging). A scenario with lower charging power (1.4 kW) is also simulated to assess this variable's impact on peak demand. Tariff structures based on varying maximum power demand, total energy consumption and time of use rates were created to assess the impact on distribution utilities costs, revenues and expenses.

Figure 6 shows the household load profile and the impact of solar PV and EV charging (standard and optimized) integration.

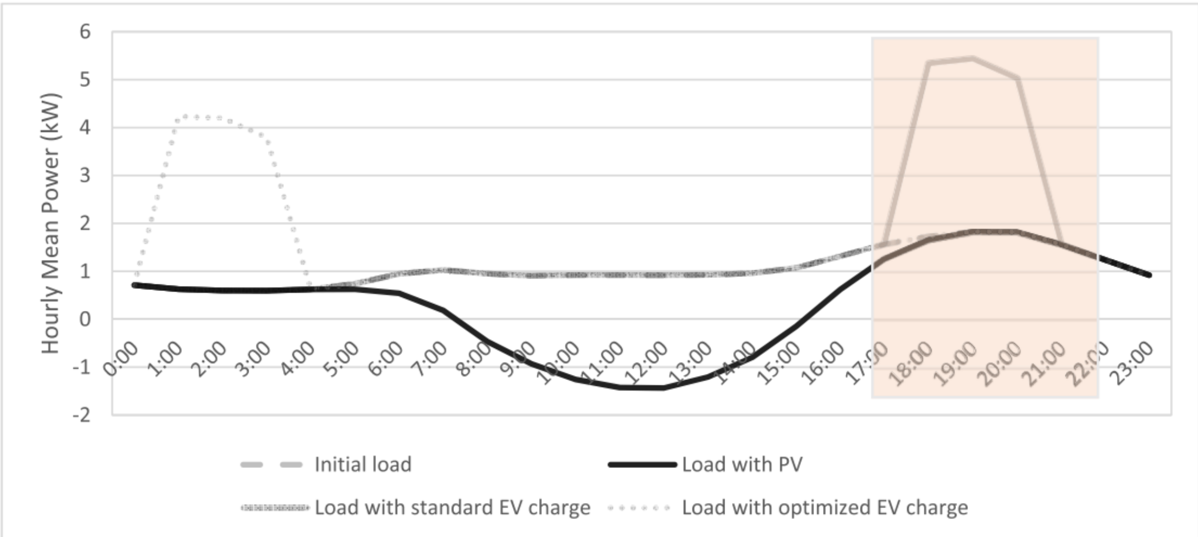


Figure 6: Impact of PV and EV integration at a residence in Chicago (Beaufils & Pineau, 2019).

Their results indicate that, although PV production always reduces total energy consumption and costs from energy purchase, it does not impact maximum power demand. Thus, distribution costs for utilities are not reduced. Net metering worsens the problem since it encourages people and businesses to install larger PV systems. EV charging, on the other hand, increases overall energy consumption and peak demand. Even when time of charging is shifted to 1h, a new peak occurs during nighttime. This new peak, however, is smaller and occurs during the electric grid system's off-peak hours, thus leading to lower operational costs for utilities. When PV panels are integrated with EV charging, the total energy demand is decreased, and a higher peak of power consumption occurs. In the lower charging power scenario combined with smart charging, the increase in peak demand becomes insignificant. In addition, the introduction of ToU tariffs increased electricity costs in the standard EV charging scenario, and had little impact in the smart charging scenario. Thus, the authors conclude that with higher charging flexibility, utility distribution costs and electricity costs for EV owners are minimized. Furthermore, the introduction of demand-related charges leads to more cost-reflective electricity tariffs.

2.4.2 Residential Electric Vehicle charging with solar PV and battery integration – no dynamic tariffs

(Boonrach et al., 2021) study the optimal design for a mini-grid residential system in Bangkok, using Homer Grid as the modelling and optimization tool. A residential base load of 150 kWh per month is considered, based on data from more than 119 residences made available from the Metropolitan Electricity Authority of Thailand. In addition, an EV demand of 16 kWh per day is assumed, which is provided with a maximum power of 50 kW. The mini-grid comprises a PV panel system with DC/AC converter, energy storage system (ESS) using lithium iron phosphate batteries, and a DC/DC converter to control the battery charging/discharging voltage. The system architecture assumes EV charging electricity always comes from the battery storage system.

Homer Grid is used to simulate different configurations and find the optimal mini-grid design. In their design, PV electricity will charge the ESS, between 8:00 and 16:00, whenever generation is greater than the base load. ESS will supply electricity to the EV in the evening. Excess electricity is sold to the grid. The design objective is to minimize the system operational costs, aiming for near 0% of electricity curtailment and minimum grid purchases. Homer simulates different system sizes and provides the optimal design based for the proposed mini-grid.

The optimum design indicated a 12.4 kWp solar PV capacity, using 345 W panels, and 14 kWh of storage. Total electricity produced over the year (2020) is 17,081 kWh. This electricity is distributed to the primary load (35%), sold back to the grid (27%) and for the EV load through the storage system (38%). A negligible amount of electricity is purchased from the grid (0.345% of the total electricity demand). The study concludes that the proposed methodology supports the deployment of renewable energy residential mini-grids in Thailand, avoiding fossil fuels usage for EV charging by maximizing self-consumption and self-sufficiency. Nonetheless, the study does not evaluate the cost-effectiveness of such system, as it does not analyse scenarios with electricity purchases from the grid (which could consider dynamic prices).

2.4.3 Electric Vehicle charging with solar PV and storage – no dynamic tariffs

(Pavan et al., 2019) propose a smart charging strategy to maximize solar PV self-consumption usage and calculate the resulting electricity cost and the vehicle's Total Cost of Ownership. The case study is a micro-grid system located at the University of Trieste, Italy. It consists of 3.9 kWp PV capacity, 4.6

kVA inverter capacity and 10 kWh storage capacity using lithium iron phosphate batteries. The batteries are only charged with surplus electricity from PV panels. A charging station with up to 22 kW is used to charge a Nissan Leaf, which is shared across different university employees.

In their study, the authors model the energy demand for the vehicle based on vehicle data and different mobility patterns. Based on that, it is assumed that the vehicle is driven for 18,000 km / year, demanding a total of 3,524 kWh / year. The model considers a fixed cost per kWh for the PV system (LCOE = €0.076 per kWh), and for the storage system (LCOS = € 0.094 per kWh). Since the batteries are only charged with electricity from the PV system, when discharged the authors consider a total cost of €0.170 per kWh (LCOE + LCOS). The cost for electricity purchased from the grid is 0.197 €/kWh. The smart charging strategy considers that the cheapest electricity will be used to charge the vehicle. Thus, PV generated electricity has first priority, electricity from the storage system has second priority and electricity purchase from the grid has last priority. The vehicle's TCO calculation considers all upfront and annual operational costs, and residual value at the time of sales. An interest rate is considered to correct the annual operation costs over the vehicle's lifetime.

Results indicated that, for that case study, 72% of charging needs are provided from self-generated electricity and 60% of it flows through the batteries. The final calculated LCOE for EV charging is € 0.166 per kWh, 15% cheaper than the grid tariff. The vehicles TCO per km is € 0.34, which is marginally smaller than for a compared ICE vehicle (TCO/km = € 0.35).

A sensitivity analysis is done to assess the impact of varying storage capacity and capital cost on the price of energy used for charging, presented in Figure 7. The green coloured boxes indicate the threshold to which the EV's TCO/km result becomes greater than the ICE's. It evidences the importance of identifying the cost-effective energy storage design to keep EV's costs low.

	Battery Price [€/kWh]							
Battery Size [kW]	150	200	250	300	350	400	450	500
1	0.16	0.16	0.16	0.16	0.16	0.16	0.16	0.16
5	0.14	0.15	0.15	0.15	0.16	0.16	0.16	0.17
10	0.13	0.14	0.14	0.15	0.16	0.17	0.17	0.18
15	0.13	0.14	0.15	0.16	0.17	0.18	0.19	0.20
20	0.14	0.15	0.17	0.18	0.19	0.21	0.22	0.24
25	0.14	0.16	0.18	0.20	0.22	0.23	0.25	0.27
30	0.15	0.17	0.20	0.22	0.24	0.26	0.28	0.30
35	0.16	0.19	0.21	0.24	0.26	0.29	0.31	0.33
40	0.17	0.20	0.23	0.26	0.28	0.31	0.34	0.37

Figure 7: Impact of storage capacity and cost on price of charged energy (€/kWh) (Pavan et al., 2019).

(Pavan et al., 2019) are able to indicate, for a fixed charging schedule and fixed electricity costs, the cost of energy and percentage of self-generated electricity used to charge the vehicle. A high percentage of self-consumption is achieved because of the storage system. However, no scenario with PV panels only (i.e. no batteries) is considered. In addition, authors do not explore the possible impact of dynamic tariffs or other smart charging strategies that could help with renewables integration with grids. Rather, the work focuses on the TCO calculation for that specific use case. As further work, authors suggest investigating optimal sizing of PV and storage systems, for different fleets and sizes, as well as performing economic feasibility analyses of such microgrid projects integrating renewable electricity and EVs.

2.4.4 Public Electric Vehicle charging integration with Renewable Electricity using Homer Grid

(Ghatak et al., 2021) use Homer Grid to analyse the integration of renewable resources solar PV or wind generation for a public fast EV charging station in India. The authors leverage on Homer Grid's capability to analyse two different utility tariffs schemes. A demand-based tariff, originally from the US and available in Homer's library is set for the base-case. A second advanced tariff, based in real data from the state of Maharashtra, India, defines an escalating price depending on active and reactive power demand, which are added up. Net-metering is assumed to allow surplus electricity to be exported back to the grid. In addition, for both renewable resources an ESS is optionally included to allow stable an uninterrupted supply of clean electricity, while also maximizing electricity self-consumption. An EV charging station with 10 x 150 kW chargers is considered. The population of EVs is made of 70% large EVs (150 kW maximum charging power) and 30% of small EVs (50 kW maximum charging power).

Homer Grid simulates various scenarios and provides an optimal design with the lowest Net Present Cost (NPC). For both wind and solar PV, the ESS was beneficial to the system's cost, despite the high CAPEX required. The optimum wind-powered system resulted in an LCOE of $ 0.101 per kWh with the standard tariff, and $ 0.036 per kWh with the advanced tariff. The annual CO_2 emissions calculated are 167.9 ton CO_2. The optimum solar-powered system resulted in an LCOE of $ 0.140 per kWh with the standard tariff, and $ 0.022 per kWh with the advanced tariff. The annual CO_2 emissions calculated are 167.3 ton CO_2. The authors highlight that the Indian electricity market is inexpensive, which explains the discrepancy between the two tariffs. They conclude comparing the proposed methodology using Homer Grid to other studies relying on MATLAB models and Linear Programming techniques. According to the authors, Homer Grid provides greater assistance to analyse different tariff structures while minimizing costs and CO_2 emissions. In addition, Homer Grid simulates a real EV charging and renewable generation environment, while the other techniques require various assumptions to simplify the system's behaviour – thus leading to non-practical results.

2.4.5 Synthetic load profiles based on different commercial fleet behaviour and charging strategy

(Simolin et al., 2021) study EV fleet behaviour in South Germany in terms of mobility and charging strategies to generate synthetic EV charging profiles. The study explores three different databases (Get eReady, iZEUS, and CROME) to investigate various aspects of EV usage and infrastructure. These databases provide valuable insights into different aspects of EV adoption, usage, and charging infrastructure, with varying data collection methods and focus. Fleet data such as vehicle location, SoC, charging location (home, work, public), time and energy, and number of parking and charging sessions is used to generate load profiles.

They study the impact of fast charging and load shifting based on different maximum charging powers (3.7 kW or 22 kW). Charging strategies constrained by vehicles available parking time are defined:

- Charging vehicles with the lowest possible power to meet the demand over their parking time.
- Charging starts immediately after vehicles park, with maximum power, until a minimum range of 20 km obtained. The remaining electricity is provided at the end of the parking period.
- All charging is performed at the end of the parking time, before the vehicle departures.

To generate synthetic charging profiles, two approaches are followed. In the direct method, charging data from the vehicle, or charging station is used to calculate power demand, considering the inherent power losses. The proposed indirect method, which the authors claim is simpler, requires only one charging dataset per vehicle and charging type, and only three charging parameters. Figure 8, below, compares synthetic load profiles, over a week, generated for a 100 EV-fleet with vehicles charging at least once a day with maximum power of 3.6 kW.

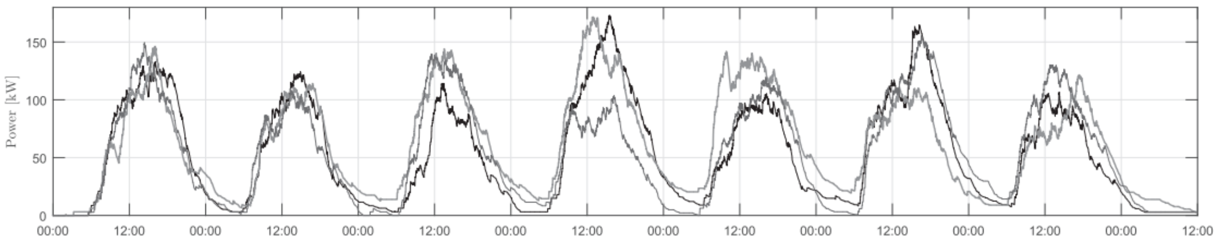


Figure 8: synthetic load profiles with different charging strategies (Simolin et al., 2021).

The authors identified that load curves are more influenced by the moment in which charging is initiated, than it is with varying maximum charging power. The last two strategies lead to almost no difference. Charging with minimum power leads to a smoother load profile. The obtained synthetic curves and results are compared with literature references for validation. Weekly behaviour is representative, and all comparable work show peak demand times. Nonetheless, peak heights and times of occurrence are not consistent throughout the literature. The authors highlight that EV load profiles are utterly related to user groups, location of charging and charging power, thus different use cases require detailed analysis.

2.4.6 Electric Vehicle charging with dynamic network tariffs at a parking lot

Dynamic electricity prices based on day-ahead market encourage users to consume electricity at times with lower prices, which does not mean system costs are lower. It can lead to new consumption peaks, creating challenges and higher costs to reinforce and operate transmission and distribution grids. (Verbist et al., 2023) propose a dynamic network tariff for a parking lot EV charging use case in the Netherlands. They propose and EV charging and discharging optimization strategy whose objective function includes minimizing Charge Point Operator (CPO) costs, maximizing vehicles SOC, and minimizing power losses, congestion, and voltage oscillations from a DSO perspective. The latter is translated into costs based on power flow modelling and dynamic network tariffs. The final dynamic tariff is composed by day-ahead market electricity costs, and network costs. The authors concluded that a stacked tariff considering dynamic electricity and network costs are beneficial for DSOs, and reduce CPO costs when compared to uncontrolled charging. As a result, DSOs, CPOs and end users benefit from lower costs and more profitable businesses. In addition, they see greater savings obtained when V2G is considered (40% lower costs than baseline, while V1G reaches only 20%). Yet, an extensive use of V2G increases power losses and lead to lines congestion. They suggest a constrained V2G optimization could to during peak moments could lead to maximum CPO profits.

2.4.7 Electric Vehicle smart charging and blockchain technology-based green energy certificates

(Ayo et al., 2023) suggest the use of Renewable Energy Certificates (RECs), a class of Environmental, Social and Governance (ESG) assets that are commonly traded in voluntary carbon markets, to certify EV green smart charging. Such certificates must be traceable, reliable, and secure, bringing about great technological challenge and high development and operational costs. Central authorities regulate this market to avoid errors, double-counting and green washing. (Ayo et al., 2023) propose an innovative approach to use blockchain technology and RECs to track the origin of green electricity for EV charging. The authors highlight the use of RECs to increase residential and industrial access to carbon markets, as well as transparency to enable flexibility markets with granular tracking. In addition, they reference RECs' use in the USA, where, among other players, EV charging station owners can purchase them in the voluntary carbon market.

In their methodology, (Ayo et al., 2023) develop a Proof-of-Concept project with a real-case micro-grid located in Singapore. The percentage of emission-free electricity being used in EV charging is tracked, matching generation and consumption in sub-hourly timestamps. The grid-connected micro-grid has an installed capacity of 50 kWp, an energy storage system of 33 kW / 91 kWh lithium-ion batteries + 1 kW / 10 kWh ZINC-AIR batteries, and diesel gensets able to supply 40 kW / 50 kVA. In the location, the base electricity load is ~5 kW and the EV charging station has a 10 kW maximum power capacity. In the trials, a maximum power of 3.7 kW was defined with no further smart charging strategies, and the vehicle used is a Nissan Leaf 2012 with 24 kWh battery.

Data from charging session, onsite generated and stored electricity, electricity grid purchases and real-time electricity mix data obtained via API are used. A modular approach to account for the increased complexity that comes with higher granularity is proposed. In the first step, EV charging energy use and time of charging is certified. Next, locally generated electricity is matched to the time of charging, but the electricity mix is not considered. Thus, at this stage it is impossible to track the origin of the purchased electricity. Finally, micro-grid data as well as the electricity mix is included to certify the percentage of green electricity originated within the charging session period.

Their work was able to effectively track the origin of green electricity used for EV charging. They express, nonetheless, that in a real network environment smart charging must be considered to account for existing constraints and maximize the match between RE and EVs. For example, by managing charging based on ToU tariffs, self-consumption maximization or even flexibility market signals, lower operational costs are achieved. Among others, warehouse depot fleet or warehouse managers with renewable generation onsite are possible clients for such technology (Ayo et al., 2023).

2.5 Research summary and gaps

The literature is vast when it comes to EV smart charging studies. In this chapter, an overview of EV smart charging technology and RE integrations with grids has been provided. In addition, ongoing trends on utility EV smart charging tariffs and services, and CO_2 emission trading mechanisms are reviewed.

Concerning EV smart charging tariffs, (Beaufils & Pineau, 2019) state that utility tariffs must be cost reflective, but it is crucial to provide price stability and predictability for consumers. While fixed ToU EV tariffs encourage off-peak EV charging, they can lead to a new peak demand time. Fixed energy prices increase the system overall peak in early evening hours. Combining demand charges and time-variant prices is an interesting alternative for utilities and EV owners. (Hildermeier et al., 2022) provide a comprehensive overview of EV smart charging tariffs and services in Europe. Dynamic ToU tariffs expose EV owners to day-ahead market electricity prices and are the most common type of tariff offered exclusively to smart charging, especially in the Nordic countries. In Germany, the development of such tariffs is ongoing. (Ensslen et al., 2016) validate the willingness to pay for EV smart charging services from businesses in Germany.

Smart EV charging with RE case studies are widely present in the scientific community. (Beaufils & Pineau, 2019) analyse residential EV charging and solar integration, but do not explore different tariff structures. The authors validate smaller charging power is beneficial to decrease the household peak demand. (Boonrach et al., 2021) go a step further and assess integrating not only PV panels but also batteries for residential EV charging. Homer Grid software is used to identify the optimum design for this use case and demonstrate the economic feasibility of local RE integration with EV charging. The authors only consider scenarios with no grid purchases, thus no analysis on different tariff structures is performed. (Pavan et al., 2019) study the integration of EV charging with an existing micro-grid system with solar PV and batteries. Fixed electricity prices from solar, battery and grid purchases are considered in the smart charging algorithm, and a large self-consumption rate is achieved. Nonetheless, since the micro-grid is already in place their work does not evaluate if the installed capacity is optimal for the existing EV demand. (Ghatak et al., 2021) also use Homer Grid to study wind, solar PV and storage integration for a public EV fast charging system. Two different tariff structures based on demand charges are also studied, and the authors highlight the benefit of Homer Grid for this purpose. However, no dynamic ToU tariffs are analysed. (Simolin et al., 2021) model synthetic EV fleet demand curves based on different smart charging strategies. Their simulation on smart charging strategies is limited, effectively, to a comparison between charging at maximum power versus at lowest charging power. Furthermore, no dynamic charging strategy is considered, and the authors do not study the impact on costs and CO_2 of their approach from a customer or utility perspective. (Verbist et al., 2023) propose a dynamic tariff and charging strategy based on grid operation constraints for a parking lot with EV chargers. The authors successfully model a tariff that benefit both DSOs, CPOs and customers, but highlight the existing implementation challenges and innovative aspect of their solution.

The potential and effective CO_2 emissions reduction in road transportation from smart charging strategies and carbon emission certificate systems is also covered. Transition to EVs effectively helps reduce overall CO_2 emissions via a CO_2 emission trading system (Heinrichs et al., 2014) (Haywood & Jakob, 2023), which validates the implementation of the recently announced EU ETS II system. Smart charging enhances the integration with renewables, especially solar PV, decreasing direct and indirect emissions in the electricity system (Xu et al., 2020). A blockchain-based technology to generate green energy certificates was proposed by (Ayo et al., 2023), helping companies track their emissions accurately by considering the electricity mix at the time of consumption. Their work merges a smart charging algorithm to maximize PV self-consumption in a PV and battery micro-grid with the green energy certificate methodology.

This literature review indicates several references within the realm of EV smart charging and road transportation decarbonization. Research shows integration with local RE resources is beneficial to reduce costs and CO_2 emissions, and smart charging enhances the integration with grids by providing flexibility on the demand side. To achieve that, innovative utility tariffs targeted to EV charging are being developed, and EV aggregators have an important role to intermediate and optimize EV charging according to grid signals.

Specific case studies require detailed modelling to account for mobility needs, local constraints, and electricity systems. EV charging demand can be modelled by accounting for driving behaviour, EV data and parking times. When available, EV charging infrastructure data directly showcases the demand for electricity in specific locations and use cases. While some researchers develop their own algorithms, Homer Grid stands out as a powerful modelling software to simulate various micro-grid designs and complex electricity tariff structures integrated with EV charging. The software identifies the systems with lowest Net Present Cost, which translates into a cost-effectiveness analysis from a decision-making perspective. Smart charging strategies are limited, however, and no dynamic electricity tariffs smart charging strategies are identified in the literature. Furthermore, Homer Grid easily quantifies the CO_2 reduction emission in comparison to a standard electricity mix carbon footprint. To achieve more granularity in CO_2 emissions certification, (Ayo et al., 2023) propose a blockchain-based approach that certifies green electricity usage on an hourly basis. No studies were found to use a similar approach and consider the electricity mix in such granular basis.

The performed literature review identified many studies proposing renewable electricity integration with smart charging, as well as different tariff structures. EV charging demand profiles are generated via different methodologies, and no work goes in-depth to assess how flexible the demand is to account for that in smart charging strategies. Moreover, no smart charging strategies to leverage on day-ahead-market indexed tariffs volatility are studied. HOMER Grid stands out as a powerful modelling tool, although some authors develop their own optimization algorithms for pre-defined renewable energy systems.

This thesis covers an existing literature gap, proposing a methodology to model and analyse smart charging strategies based on granular, dynamic electricity prices from the day-ahead-market, and local renewable electricity integrations. For a specific commercial EV fleet case study in Berlin, Germany, HOMER Grid is used to generate smart EV charging loads and energy balances considering solar PV panels and batteries integration. Such models are used to analyse the impact of adopting a Real-Time-Pricing (RTP) tariff indexed to the day-ahead market, identifying the optimum system configuration that leads to lowest costs. Furthermore, the carbon impact of such systems is assessed, quantifying direct and indirect emissions from electricity purchases from the grid, as well as self-generated solar PV electricity. The proposed methodology quantifies costs and CO_2 emissions for different systems, providing a framework for decision makers to opt on decentralized renewable energy assets (solar PV and batteries) investment and RTP smart charging strategies adoption. The work provides background to support the ongoing development of RTP tariffs in Europe for a commercial EV fleet use case, comparing different smart charging strategies and renewables integration.

Chapter 3

Case study description and simulations methodology

This chapter describes the EV charging case study, consisting of mobility company charging their 65 Electric Vehicles fleet in a private charging infrastructure at a parking lot. Real charging data is used to model current EV charging behaviour and understand the existing charging flexibility and optimization opportunities (Section 3.1). For different smart charging strategies, EV charging loads and energy balances are generated using HOMER Grid. Results from HOMER Grid's results are combined with Day-Ahead market prices and generate a model with varying solar PV and battery capacities (Section 3.2). Direct and indirect carbon emissions and the use of renewable electricity locally and from grids are calculated in all simulations to account for the carbon impact of smart charging strategies and renewable electricity integrations (Section 0).

3.1 Use Case description: commercial Electric Vehicle fleet

3.1.1 Electric Vehicle fleet, charging infrastructure data and demand

A company based in Berlin, Germany, owns a 65 EVs fleet and offers mobility services for their customers via a mobile application, both on-demand and via a scheduling feature. The vehicles are charged primarily at the company's charging infrastructure, located in a parking lot. Vehicles are driven all days of the week by different drivers, in two shifts (08:00 to 20:00 and 20:00 to 08:00), with slight variations based on client's demand.

The fleet is composed of 30 Hyundai Ioniq, and 35 Nissan Leaf vehicles. Table 3-1 presents the fleet vehicles' specifications, related to range and charging capacity.

Table 3-1 EV fleet vehicles battery and charging capacity.

Vehicles	Hyundai Ioniq	Nissan Leaf
# vehicles	30	35
Battery capacity (kWh)	54	39
Efficiency (Wh / km)	183	166
Charging capacity (kW_{AC})	6.6	6.6
Charging capacity (kW_{DC})	49	46

The company owns a parking lot where vehicles are charged. There are 46 slow charging ports, with 11 kW_{AC} capacity, and 12 fast charging ports, with up to 50 kW_{DC} capacity. The fast-charging infrastructure (50 kW_{DC}) is used when vehicles must quickly recharge their batteries before resuming their work schedule. On the other hand, slow chargers (11 kW_{AC}) are used for charging the vehicles between work shifts, when the vehicles stay longer in the parking lot.

Motivated to reduce its operational costs, the company shared their charging data from 2022 to analyse possible opportunities for smart charging. A data cleaning procedure was performed to validate charge sessions only if the transaction data is fully recorded, total energy consumption is >1 kWh and <100 kWh, and the "loading time" (time during which the vehicle is connected to the charging station) is greater than 0. From the original 29809 transactions dataset, 26186 valid charging sessions are considered for the analysis. Total annual demand for EV charging (ED_{EVs}) is 414,758 kWh / year.

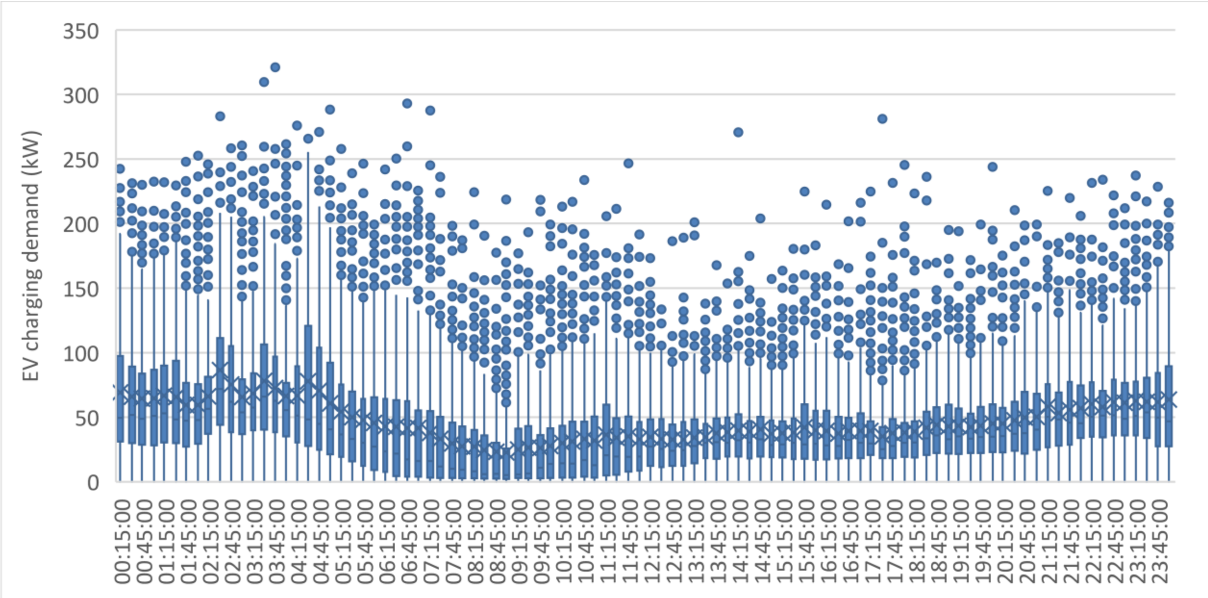


Figure 9 Daily average EV charging profile in 2022.

presents a box and whisker chart of the daily EV power demand throughout 2022. Figure 10 divides the load coming from slow AC chargers and from fast DC chargers. The crosses indicate the average values, boxes indicate the standard deviation interval, and the outliers are indicated clearly outside of the average range.

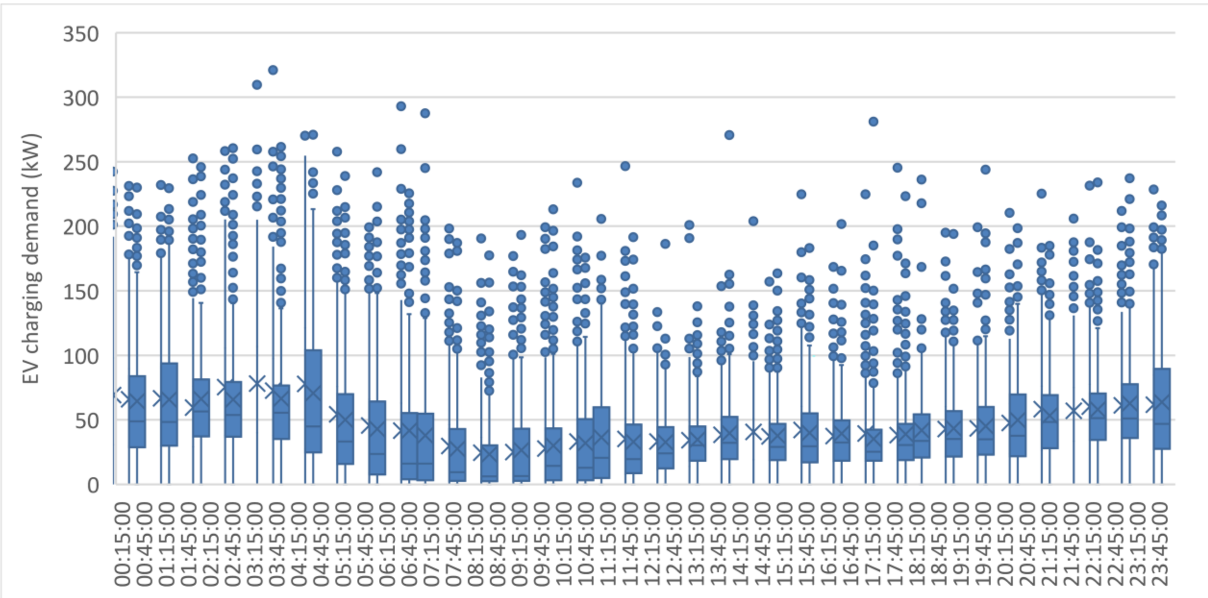


Figure 9 Daily average EV charging profile in 2022.

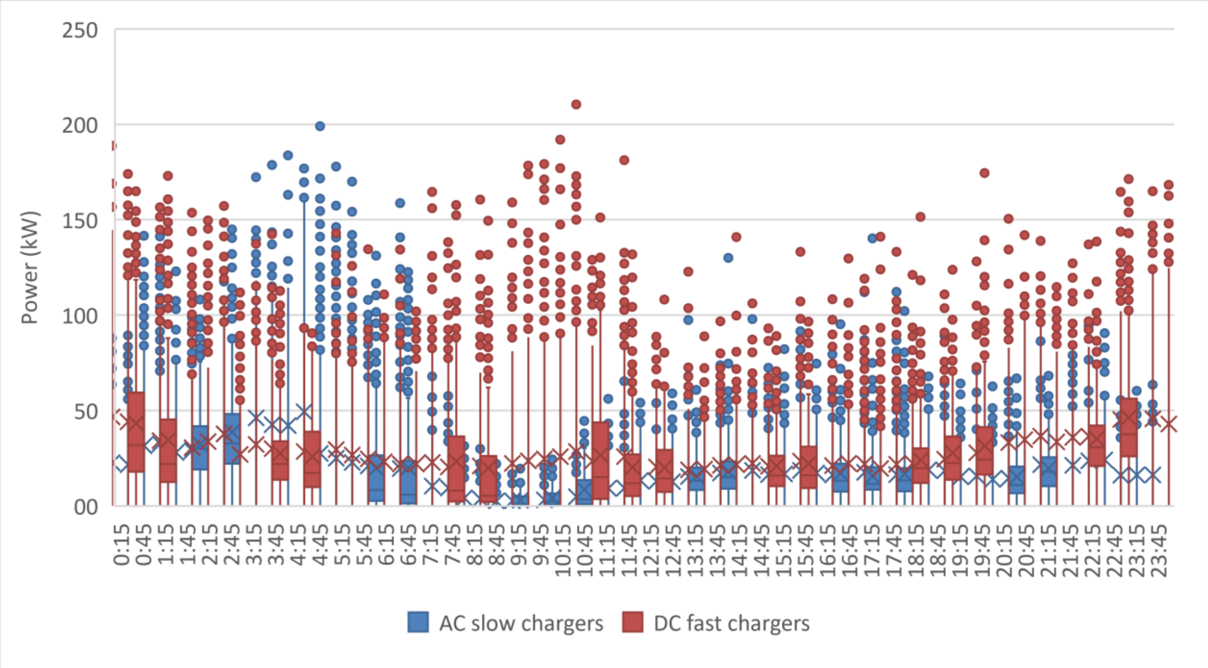


Figure 10 – Daily average EV slow and fast charging profile in 2022.

Further analysis on the data provided can help understand the different charging behaviour concerning the vehicles demand for immediate battery recharge. Table 3-2 presents the fleet energy demand and time vehicles remain connected to the 11 kW_{AC} and 50 kW_{DC} chargers on weekdays and weekends. In addition, the average time vehicles are connected per session indicate how much charging flexibility exists for each type of charger.

Table 3-2: Average slow and fast charging sessions data in 2022.

11 kW_{AC} (slow charging)	**Weekdays**	**Weekends**	**Week**
Sessions (# / day)	23.5	33.7	26.4
Energy demand (kWh / session)	15.7	12.9	14.9
Total energy demand (kWh / day)	369.3	434.9	387.9
Time connected to charger (h / session)	13.9	14.2	14.0
Time charging (h /session)	2.4	2.0	2.3
Idle time (h / session)	11.5	12.2	11.7
50 kW_{DC} (fast charging)	**Weekdays**	**Weekends**	**Week**
Sessions (# / day)	33.1	50.6	38.0
Energy demand (kWh / session)	12.9	14.1	13.2
Total energy demand (kWh / day)	427.1	711.0	507.6
Time connected to charger (h / session)	0.5	0.5	0.5
Time charging (h /session)	0.3	0.3	0.3

Idle time (h / session)	0.2	0.2	0.2

Vehicles are connected to fast DC chargers for shorter periods in comparison to the lower power AC chargers. On average, vehicles only stay plugged onto DC chargers for 30 minutes, while for AC chargers they remain connected for 14 hours to fulfil an average charging demand of 13.2 kWh and 14.9 kWh, respectively. In addition, the DC infrastructure is used more frequently and delivers more energy throughout the whole week. On weekdays, DC chargers deliver 427 kWh/day to the fleet, while AC chargers are used to charge 370 kWh/day. On weekends, a more pronounced behaviour is seen. Fast charging is responsible for 711 kWh/day of the demand, which is more than two times bigger than the 435 kWh/day from AC chargers.

As expected, the different set of chargers are being used according to the company operation's needs. The higher demand for fast charging occurs during times when drivers are facing a busier driving schedule. For example, during weekend nights more clients request the company's services to go out for entertainment. On the other hand, vehicles are connected to the slow chargers in between drivers shifts (08:00 to 20:00 and 20:00 to 08:00). They stay connected for longer times (14.9 hours per session), even though the demand for 14.9 kWh is supplied in 2.3 hours at 6.6 kW charging power. Thus, on average vehicles remain idle in the parking lot for 11.7 hours, or 84% of the time they are parked. For the fast-charging infrastructure, though, the average idle time per session is only 12 minutes per session. As a result, very little flexibility exists to manage and optimize EV charging for the fast charging demand. For slow charging, however, there is room for smart charging strategies based on slower charging speeds (i.e. varying charging power) or shifting the demand to times of lower electricity prices and higher renewables shares.

0 presents the average hourly demand for slow and fast charging on weekdays and weekends in details.

3.1.2 Electricity connection and costs

The electricity provision for the charging infrastructure is dedicated, i.e. independent from other loads. It has a maximum connection capacity of 400 kW. The company pays for electricity based on a flat electricity tariff, with no specific EV charging tariff. A power demand charge of € 8.5 per kW peak per month is paid to the local utility. In 2022, the electricity prices for commercial sites were € 0.33 per kWh, in the first semester, and € 0.53 per kWh, in the second semester (Statista, 2023).

3.2 EV smart charging approaches and modelling

The opportunity for EV smart charging and renewable electricity infrastructure integration exists, however some constraints must be respected.

The data presented in section 3.1.1 showed fast chargers must be considered "on-demand", i.e. with no flexibility that would allow an optimization based on dynamic tariffs nor peak shaving. On the other hand, vehicles are connected to slow chargers on average for 14h, and 83% of this time window is not used for charging. Thus, smart charging is considered only for the slow-charging infrastructure and the fast-charging infrastructure is considered a fixed load. Furthermore, the grid connection capacity of 400 kW is assumed the maximum, as the company is not willing to invest in grid connection reinforcement.

The parking lot where the charging infrastructure is set up has a rooftop with 1000 m^2 available for PV panels. Considering an average installed capacity ratio of 200 Wp / m^2, the available rooftop space translates into a maximum PV installation of 200 kWp. A stand-by area for batteries installation is also available. Thus, the opportunity to reduced costs and environmental impact of EV charging via solar PV and/or batteries integrations is present.

The company intends to adopt a Real-Time-Pricing EV tariff (RTP tariff), indexed to the day-ahead market in Germany (DA market prices). It follows the existing trend towards dynamic tariffs, presented in the literature review (chapter 2). The intrinsic spot market price volatility must be considered. Thus, charging times and power must be scheduled to match times of lower electricity prices, constrained by the vehicles' availability, and charging flexibility mentioned above. Furthermore, since a considerable part of the total electricity costs comes from power charges, reducing charging peaks is also relevant. Peak shaving can be achieved via reducing charging power, shifting demand times and/or renewables integrations. Five smart charging strategies are proposed, aiming to minimize costs based on peak shaving and/or electricity purchasing at lower costs through charging schedules.

HOMER (Hybrid Optimization of Multiple Electric Renewables) Grid 1.10.2 software is used to model the system, where the fast charging demand is fixed and the 5 proposed smart charging strategies are modelled for the flexible, slow charging load. In addition, solar PV and batteries cost parameters and a Fixed Price (FP) utility tariff are also input. The software simulates various systems with different solar PV and battery capacities, and indicates project economics, and operational performance information through an energy balance over the year (HOMER Software, 2023). These energy balances provide load profile data considering the proposed smart charging strategies, over the whole year, and solar PV and batteries operational performances.

Such smart charging load profiles and solar PV and batteries operational behaviour are used on a dynamic energy balance model in Microsoft Excel, with varying solar PV and batteries capacity. Electricity purchasing costs are calculated based on a Real-Time-Pricing (RTP) tariff, utilizing raw prices from the day-ahead (DA) market from Germany over the year. Grid power fees are calculated based on the peak demand over each month of the year. Carbon impact of such systems is calculated by combining the hourly composition of the electricity mix. Project economics such as Levelized Cost of Energy (LCOE), Net Present Costs, Capital Expenditures (CAPEX) and Operational Expenditures (OPEX) are calculated based on system's operations. Direct and indirect CO_2 emissions from the electricity mix during time of grid purchases, as well as from local solar PV and batteries, indicate the environmental benefit of different systems. Microsoft Excel's Solver using a GRG Non-linear solving method is used to identify the ideal architecture for any project indicator optimization, i.e. the composition of smart charging strategy, solar PV capacity and battery capacity that leads to the optimum result for the chosen parameter (e.g. LCOE, CO2 emissions, etc.). This model becomes a powerful system to understand the system behaviour under different assumptions and focus is given to identify the architecture leading to lowest LCOE in different scenarios.

The methodology used for modelling such systems is presented in the following sections in detail.

3.2.1 HOMER Grid modelling

HOMER Grid is a popular software used to simulate the operation of decentralized energy systems. It performs energy balance calculations over a year, and extrapolates that onto the project lifespan. To run a simulation in HOMER Grid, the following inputs are given: solar PV and batteries capital and operational costs, base load (when applicable), EV charging demand (modelled based on vehicles availability, energy demand and charging power capabilities), and utility tariff.

For each timestep, HOMER performs an energy balance to supply the defined load (base electricity, and EV charging) from locally generated electricity (via solar PV panels), storage systems (batteries), and grid purchases. In addition, utility tariffs include the possibility to sell electricity back to the grid via different schemes (net metering, net sales). HOMER performs such energy balance for all configurations (resources and capacities) that are requested, presenting project economics and operational indicators over the specified project lifetime.

The software also has an optimizer (HOMER Optimizer®) that uses a proprietary derivative-free algorithm to search for the system with the lowest Net Present Cost (NPC). NPC is the present value of the system considering purchasing, installation, and operation costs, discounted by the present value of revenues that are earned over the project lifetime. After running simulations with different systems configurations and capacities, HOMER Grid provides the cost-optimum design options in a table, as well as detailed data such as energy balances (including load data at 15 minutes intervals) and project economics (HOMER Software, 2023).

Nevertheless, HOMER's optimization results are not used directly. The outputs under interested for this project are the generated EV charging load profiles for different smart charging strategies and solar PV and batteries operational behaviour. These will serve as basis for a model that calculates actual project costs based on Germany's DA market prices, explained in Section 3.2.3. Figure 11 depicts the system diagram that was defined for this use case.

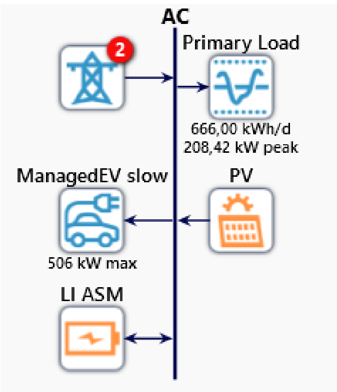


Figure 11 HOMER Grid System diagram (HOMER Software, 2023)

The following subsection details how these are modelled as well as the required inputs.

3.2.1.1 Project Economics

While HOMER Grid provides different project economics indicators, this work mostly focuses on Levelized Cost of Energy (LCOE), which comprise all capital and operational costs over the project lifetime, Capital Expenditures (CAPEX) and Operational Expenditures (OPEX) costs:

$$LCOE = \frac{C_{ann,tot}}{E_{served}} \tag{1}$$

$$C_{aan,tot} = CRF(i, R_{proj}) \times C_{NPC,tot} \tag{2}$$

$$CRF(i, R_{proj}) = \frac{i(1+i)^{R_{proj}}}{(1+i)^{R_{proj}} - 1} \tag{3}$$

Where:

$C_{ann,tot}$ = total annualized cost of the system (€/year)

E_{served} = total electrical load served (kWh/year)

$C_{NPC,tot}$ = total net present cost (€), considering CAPEX and OPEX cash flow over the project lifetime.

i = annual discount rate (%)

CRF = capital recovery factor

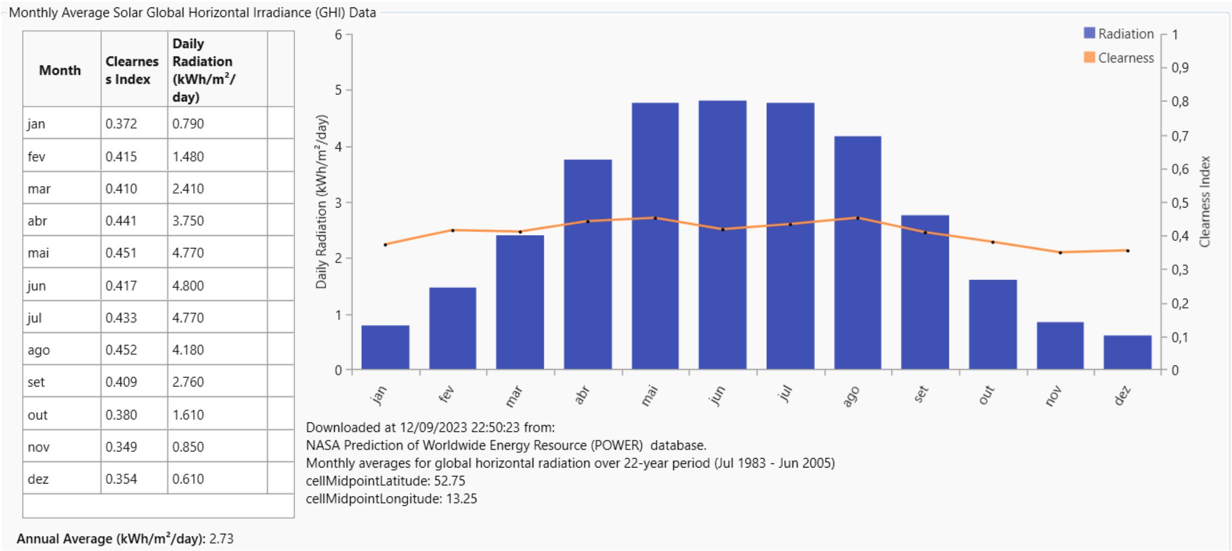
R_{proj} = project lifetime (years)

In all simulations, the nominal discount rate (i) is considered 8% and the project lifetime (R_{proj}) is 25 years. Although it is a high interest rate, this figure was agreed upon with the case study's company, based on their identified project risks and internal investment decision processes.

3.2.1.2 Solar PV electricity generation

HOMER Grid simulates different solar PV capacities and calculates electricity production, as well as installation and operational costs. The 200 kWp constraint from the rooftop available area is included, and commercial Solar PV costs from (U.S. Department of Energy, 2023b) are considered. CAPEX of € 1505 per kW includes panels and micro-inverter purchasing and installation, and O&M costs of € 16.99 per kW per year. Since micro-inverter costs are included in CAPEX figures, solar PV panels are designed in the AC bus.

Solar irradiance data is downloaded directly via the software from *NASA Prediction of Worldwide Energy Resource (POWER)* database. It considers the monthly averages for global horizontal radiation over a 22-year period, for a latitude in the north of Berlin, in Germany (52.75° N and 13.25° W). Figure 12 presents the GHI irradiation data assumed in all simulations to calculate the solar PV electricity generation on a yearly basis.



Month	Clearness Index	Daily Radiation (kWh/m²/day)
jan	0.372	0.790
fev	0.415	1.480
mar	0.410	2.410
abr	0.441	3.750
mai	0.451	4.770
jun	0.417	4.800
jul	0.433	4.770
ago	0.452	4.180
set	0.409	2.760
out	0.380	1.610
nov	0.349	0.850
dez	0.354	0.610

Figure 12 GHI Irradiation Data (HOMER Software, 2023).

3.2.1.3 *Lithium-Ion battery storage*

Lithium-ion batteries (LIB) are considered for the energy storage system. The standard 1 kWh LIB from Homer is added, with 0.80 kWh storage capacity (considering it must keep 20% State-oof-Charge minimum), and 1.1 kW charging and 2.64 kW discharging capacities per module.

Costs are obtained from the National Renewable Energy Laboratory (NREL) Annual Technology Baseline. CAPEX adds up to € 717 per kWh, including battery pack, battery operation system, DC-AC inverter, and installation. No O&M costs are considered (U.S. Department of Energy, 2023a). Since CAPEX also includes DC-AC inverter, batteries are also designed in the AC bus.

3.2.1.4 *Utility tariff in HOMER Grid*

Demand charges are fixed according to the existing contract (€ 8.5 per kW per month), and no dynamic demand charges are considered. Grid sales are considered € 0.082 per kWh according to (Wirth & Fraunhofer ISE, 2023).

As mentioned in 3.1.2, average Commerce and Industry electricity costs in Germany in 2022 were € 0.33 per kWh, in the first semester, and € 0.53 per kWh, in the second semester (Statista, 2023). These values are considered for the Flat Price (FP) tariff prices, which is the baseline tariff for this study.

Although HOMER Grid allows the user to input a data-series of electricity prices to compose a new tariff, it cleans the data with an unclear methodology. When volatile DA market prices are input, the volatility is smoothened out and the resulting tariff is not representative of the real energy market dynamics. For this reason, it was decided that the RTP tariff would not be evaluated through HOMER Grid, and actual project costs are analysed according to the model described in section 3.2.3.

3.2.1.5 Base Electricity Load

HOMER Grid allows synthetic load profiles to be modelled for industries, commercial and residential buildings, as well as load files with granularity as small as every 5 minutes. The software recommends importing load data for higher accuracy. For this case study, no building load is considered since the EV charging infrastructure is independently connected. Section 3.2.1.6, below, explains how flexible EV demand is modelled in different smart charging strategies and its interaction with the base load (non-flexible EV load).

3.2.1.6 EV smart charging in HOMER Grid

HOMER Grid offers two types of EV chargers: on-demand and deferrable EV chargers. On-demand chargers consider charging is not flexible, and the electricity demand is fixed according to the charging behaviour data. Deferrable chargers, on the other hand, consider charging is flexible and explore that to minimize project costs, allowing HOMER users to simulate smart charging strategies.

For this case study, as explained, the fast-charging infrastructure is considered not flexible, i.e. all electricity is provided on demand. Nonetheless, since the charging infrastructure data is provided with 15 minutes granularity, the slow charging demand data is directly considered the model's base load. The reason for that is to get higher accuracy in representing the actual demand, since HOMER converts charging demand data into electricity demand.

Deferrable chargers are used to model the case study's slow charging demand. 46 chargers with maximum charging power of 11 kW and an EV fleet population of 35 Nissan Leaf and 30 Hyundai Ioniq vehicles are considered. The frequency in which vehicles are connected to chargers on an hourly basis (visits per hour) over the year are input to indicate the charger occupation. The average EV energy demand per session ($E_{EV\ per\ session}$) of 15 kWh, presented in Section 3.1, is set. The mean time vehicles are connected to chargers ($t_{EV\ connected}$) and maximum charging power per EV ($P_{EV\ \max}$) are also inputs, and key for HOMER Grid to optimize charging. According to the software manual, HOMER will decrease the charging power ($P_{charging}$) in comparison to ($P_{EV\ \max}$), or delay a charging session to reduce the system overall peak demand per month. Charging sessions last for an amount of time ($t_{EV\ session}$) so that:

$$E_{EV\ per\ session} = t_{EV\ session} \times P_{charging}$$

(4)

Where $E_{EV\ per\ session}$ is given in kWh, $t_{EV\ session}$ in hours, and $P_{charging}$ in kW.

HOMER Grid does not have a feature to schedule EV charging sessions based on lower RTP tariff prices over time-windows during which vehicles are connected to chargers ($t_{EV\ connected}$). It defines the charging power and time to minimize the overall power peak over that time. To implement smart charging strategies based on scheduled charging sessions, the time vehicles are connected and charging powers must be set according to the scheduled conditions (time and charging power). The time vehicles remained connected to chargers ($t_{EV\ session}$) is set according to the charging schedule time-windows ($t_{EV\ scheduled}$). The maximum charging power ($P_{EV\ max}$) is set to match the scheduled charging power ($P_{scheduled}$).

$$P_{EV\ max} = P_{scheduled} = \frac{E_{EV\ per\ session}}{t_{EV\ scheduled}}$$

(5)

By doing so, flexibility is non-existent over the scheduled time-window since the expected demand can only be achieved if maximum charging power is used over the whole time-window.

3.2.2 EV smart charging strategies

Below, each modelling approach for smart charging strategies is presented in detail, indicating the figures assumed in each case. These are used as input into HOMER Grid models to generate new EV charging load profiles over the year.

3.2.2.1 Real-Time-Pricing (RTP) utility tariff

Even though HOMER Grid does not directly calculate real electricity costs based on DA market prices, as explained in session 3.2.1.4, these are used as reference to propose the smart charging strategies presented below. A RTP EV tariff, indexed to the Day-Ahead (DA) electricity market in Germany, is generated using raw data from BZN | DE-LU market (entso-e, 2023b). **Error! Reference source not found.**Over the year, on weekdays lower prices are usual near the middle of the day, when solar power production is higher and demand is not at its peak, and over the night, between 23h and 06h. On weekends, the low prices remain throughout all morning and mid-afternoon, until they start increasing at peak electricity demand times after 18h. The original data is shown in Annex B.

3.2.2.1.1 Strategy 1: Minimum charging power, no charging schedule

In this strategy, it is assumed that EVs need to fulfil their charging demand 2 hours before the end of the total 14 hours in which they are parked and connected to chargers, as explained in Section 3.1.1. Thus, scheduled charging time ($t_{EV\ connected\ S1}$) is equal to 12 hours, and the maximum charging power ($P_{EV\ \max S1}$) is:

$$P_{EV\ \max S1} = P_{charging\ S1} = \frac{E_{EV\ per\ session}}{t_{EV\ scheduled\ S1}} = \frac{15\ kWh}{12\ h} = 1.25\ kW \tag{6}$$

EV charging frequency (visits per hour) are kept the same as the slow charging baseline.

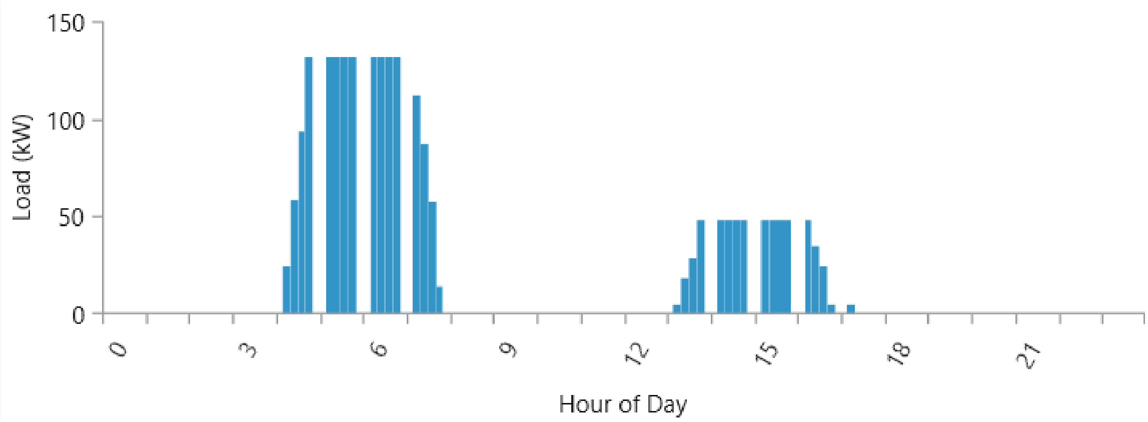


Figure 16 Daily average EV charging load profile for Strategy 2 (HOMER Software, 2023).

3.2.2.1.2 Strategy 2: Average charging power and scheduled charging

To deal with volatile dynamic electricity prices, EV charging must be scheduled and controlled to occur at moments with lower prices. This strategy considers an average charging power ($P_{charging\ S2}$) equal to 5 kW. To achieve the required 15 kWh of demand per session, the time of charging session ($t_{EV\ session\ S2}$) must be equal to:

$$t_{EV\ session\ S2} = \frac{E_{EV\ per\ session}}{P_{charging\ S2}} = \frac{15\ kWh}{5\ kW} = 3\ hours \tag{7}$$

A fixed monthly charging schedule based on average prices is created, considering the two operational shifts that the company follows (08:00 to 20:00 and 20:00 to 08:00). The 3 hours with lowest prices are identified over the year and are the basis to define the charging schedule in HOMER. For months where the lowest prices are not concurrently forming a 3-hours-window for charging, it is considered that charging will occur within the hours in which lowest prices are present. Over the year, charging occurs between 04:00 and 08:00 and between 13:00 and 15:00, with monthly variations.

The distribution of charging demand within the two operational shifts on weekdays and weekends, presented in Table 3-3, is considered to define the charging demand.

Table 3-3 Flexible charging demand distribution over weekdays and weekends

Period	Flexible charging demand (kWh)	Charging demand ratio (% of flexible demand)
08:00 - 20:00 weekdays	158.4	16%
20:00 - 08:00 weekdays	252.1	25%
08:00 - 20:00 weekends	153.4	15%
20:00 - 08:00 weekends	440.4	44%

3.2.2.1.3 Strategy 3: Lower charging power and scheduled charging

Similarly to strategy 2, this smart strategy creates a charging schedule but considers a lower charging power ($P_{charging\ S3}$) equal to 2.5 kW. To achieve the required 15 kWh of energy per session the time of charging session ($t_{EV\ scheduled\ S3}$ must be equal to:

$$t_{EV\ session\ S3} = \frac{E_{EV\ per\ session}}{P_{charging\ S3}} = \frac{15\ kWh}{2.5\ kW} = 6\ hours \tag{8}$$

The 6 hours with lowest prices are identified over the year and are the basis to define the charging schedule in HOMER. Time-windows of lower electricity prices considered in Strategy 3 are presented in Annex D. The same flexible charging demand distribution shown in Table 3-3 is considered. Over the year, charging occurs mostly between 09:00 until 19:00 and between 00:00 and 06:00, with monthly variations.

3.2.2.1.4 Strategy 4: Lower charging power and distributed scheduled charging

This strategy aims to exploit the varying electricity prices with higher flexibility, combining the higher charging power from strategy 2 and the longer charging window of strategy 3. An average charging power ($P_{charging\ S4}$) equal to 5 kW is considered, leading to a charging time ($t_{EV\ session\ S4}$) of 3 hours. However, the demand within the shift is dividing into two time-windows of 3 hours to generate two charging opportunities.

3.2.2.1.5 Strategy 5: Higher charging power and solar PV maximization

This strategy aims to exploit the opportunity for higher solar PV integration by scheduling charging closer to times of higher solar PV generation rates. An average charging power ($P_{charging\ S4}$) equal to 5 kW is considered, leading to a charging time ($t_{EV\ session\ S4}$) of 3 hours. Charging sessions are scheduled to occur between 04:00 and 08:00, and between 11:00 and 14:00.

3.2.3 Dynamic modelling with Real-Time-Pricing (RTP) tariff

HOMER Grid's results are used to generate a flexible model, capable of comparing all smart charging strategies and system architectures based on actual electricity grid data. For every time interval (j = 15 min), power exchanges within the system are calculated based on smart charging load profiles from HOMER Grid. Solar PV (P_{PV_j}) production data is generated using irradiance and conversion parameters presented in section 3.2.1.2. Using technical data presented in Section 3.2.1.3, batteries charge ($P_{bat\ C_j}$) and discharge ($P_{bat\ D_j}$) rates and battery charge (E_{bat}) are calculated based on surplus or insufficient solar PV generation. No energy arbitrage is considered using the battery, i.e. the storage system will not charge with electricity from the grid. Finally, grid purchases (GP_j) and grid exports (GE_j) are calculated, respectively, to cover the demand or to deal with surplus solar electricity, according to system's energy balance.

$$E_{EV_j} + GS_j + P_{bat\ C_j} = P_{PV_j} + P_{bat\ D_j} + GE_j \tag{9}$$

$$GE_j = P_{PV_j} - (E_{EV_j} + P_{bat\ C_j}) \ \in \ GS_j \ < \ 400\ kW \tag{10}$$

$$GP_j = P_{PV_j} - (E_{EV_j} + P_{bat\ D_j}) \tag{11}$$

$$\left(E_{bat\ j} < \ E_{bat\ max} \ \wedge \ P_{PV\ j} > E_{EV_j}\right) \ \rightarrow \ P_{bat\ Cj} = \min\left(P_{bat\ C\ max}\ ; \left(P_{PV_j} - E_{EV_j}\right);\ \left(E_{bat\ max} - E_{bat\ j}\right) \times 4\ \right) \tag{12}$$

$$\left(E_{bat\ j} > \ E_{bat\ min} \ \wedge \ P_{PV\ j} < E_{EV_j}\right) \ \rightarrow P_{bat\ Dj} = \min\left(P_{bat\ D\ max}\ ; \left(E_{EV_j} - P_{PV_j}\right);\ \left(E_{bat\ j} - E_{bat\ min}\right) \times 4\ \right) \tag{13}$$

$$E_{bat\ j+1} = E_{bat\ j} + \left(P_{bat\ C\ j} \times \eta_C - \frac{P_{bat\ D\ j}}{\eta_D}\right) \times 4 \tag{14}$$

All power rates presented above are converted into energy by multiplying for the time interval (j = 15 minutes) in hours. η_C and η_D represent, respectively, battery charging and discharging efficiency.

The Real-Time-Pricing (RTP) tariff prices (P_{RTP_j}), presented in section 3.2.2.1, represent Germany's day-ahead (DA) market prices and are matched to electricity purchased for every time interval, simulating real electricity purchase costs (C_{RTP}) if a DA-market indexed tariff is adopted. Revenues from grid sales (R_{sales}) are also calculated over the year considering the sales price (P_{sales}) of € 0.082 per kWh (section **Error! Reference source not found.**).

$$C_{RTP} = \sum_{j=1}^{35040} \mathrm{GP_j} \times P_{RTP_j} \tag{15}$$

$$R_{sales} = \sum_{j=1}^{35040} \mathrm{GE_j} \times P_{sales} \tag{16}$$

Carbon impact indicators are also calculated for every time interval, and the methodology is described in Section 0.

These energy balances are generated for every smart charging strategy EV load profile, and solar PV and storage capacities are kept as input variables. An optimization algorithm using Excel's Solver (GRG Non-linear solving method) allows an effective analysis of different optimization factors, such as Levelized Cost of Energy (LCOE), Net Present Cost (NPC), Capital Expenditures (CAPEX) and Operational Expenditures (OPEX), and carbon impact and renewable electricity ratio. Sensitivity analysis on project financial metrics (interest rate and project lifetime) and equipment costs can also be easily performed.

3.3 CO_2 emissions from electricity generation sources

Data on electricity mix's renewable electricity share and direct CO_2 emissions on an hourly basis, in 2022, was obtained from (Electricity Maps, 2023a). The company is an industry reference to provide granular data on electricity production and carbon footprint, both commercially and open source. This data was used to calculate direct and indirect emissions from electricity purchases from HOMER Grid's energy balances, allowing a total carbon intensity calculation for different simulated scenarios.

3.3.1 Renewables share and CO_2 direct emissions from the electricity mix

Electricity Maps is a company providing data on several countries' electricity mix carbon intensity. While real-time data can be commercially purchased and acquired via APIs, an open source dataset is available for past years behaviour. A complex methodology is followed to calculate, on an hourly basis, a countries' electricity mix direct and indirect CO_2 emissions and renewables share, and it is summarized below focusing on Germany (Electricity Maps, 2023b).

1. Collecting data from reliable sources, with hourly granularity or higher.

Data is gathered from government sources, such as energy ministries, government-affiliated sources, such as official statistical bureau, Transmission System Operators or Distribution System Operators, such as entso-e, and utility companies that generate or manage power directly.

In the case of Germany, real-time electricity data is sourced from the European Network of Transmission System Operators for Electricity (entso-e). Production capacity data per resource is gathered from Frauenhofer ISE (Hydropower, coal, natural gas and oil, wind and solar PV), IAEA & BASE (Nuclear), and from Bundesnetzagentur (Geothermal and Unknown sources). Electricity transmission through neighbouring countries is also considered based on data from entso-e.

2. Computing carbon intensity based on Emission Factors.

Electricity Maps provides hourly data on the electricity mix's direct CO_2 emissions (CO_2DE_{MIX}), related to the operational CO_2 emissions in generation plants, and indirect carbon equivalent emissions (CO_2IE_{MIX}) based on life-cycle analysis of generation plants. For every generating technology in a zone, Emission Factors (EFs) are calculated considering local power plants direct CO_2 emissions (Operational EF) and environmental impact from cradle-to-grate (Life-cycle EF), reaching an average value for each resource in that location.

Various databases are combined to generate a regional EFs database. In Germany, the Intergovernmental Panel on Climate Change (IPCC) 2014 Fifth Assessment (Schlömer et al., 2014) directly provides most EFs from a multitude of peer-reviewed studies, as well as other studies are gathered. Verified emissions from different power plants within EU-ETS regulation (European Commission, 2022) are matched to electricity generation data per power plant (entso-e, 2023a) for some resources. Table 3-4 presents the different generation sources EFs for Germany's electricity production mix.

Table 3-4 Germany electricity mix EFs for different resources (Electricity Maps, 2023b).

Generation resource	Operational EF (g_{CO_2} / kWh)	Life-cycle EF ($g_{CO_2\,Eq.}$ / kWh)
Gas	540.6	660.6
Oil	880.9	1124.9
Coal	1073.0	1152.4
Wind	0.0	12.6
Hydro	0.0	10.7
Solar	0.0	35.1
Biomass	0.0	439.1
Nuclear	0.0	5.1
Geothermal	0.0	38.0
Hydro discharge	297.2	297.2
Battery discharge	297.2	297.2
Unknown source*	575.0	700.0

When data to track generation origin is missing, electricity generated from unknown sources is considered non-renewable and produced from a mix of fossil fuels.

Electricity generation data per technology, is combined with EFs to calculate direct CO_2 emissions (CO_2DE_{MIX}) and life-cycle carbon equivalent emissions (CO_2IE_{MIX}) from the electricity mix. The exchange of electricity across borders between Germany and Belgium, Denmark, Sweden and Norway is considered, as well as local EFs and their zones' electricity mix at those times.

Data on the Renewable Ratio (RR_{MIX}) is also obtained, for each timestep, based on the following equation:

$$RR_{MIX} = \frac{E_{renewables} + S_{discharge}}{E_{consumption}}$$

(17)

Where $E_{renewables}$ represents the amount of electricity produced from geothermal, hydro, solar and wind resources, $S_{discharge}$ represents the amount of electricity discharged from hydro-pumped storage and battery storage systems, and $E_{consumption}$ represents all electricity consumed.

Following to the methodology presented above, the average carbon footprint of electricity consumed in Germany, in 2022, is presented in Table 3-5, below.

Table 3-5 Carbon intensity of electricity mix in Germany in 2022 (Electricity Maps, 2023b).

$CO_2DE_{\text{MIX 2022}}$ (g_{CO_2} / kWh)	$CO_2IE_{\text{MIX 2022}}$ ($g_{CO_2\ eq.}$ / kWh)	Renewable Ratio (RR_{MIX})
404.98	472.64	49%

While the figures above present an average value for 2022, Electricity Maps also provides hourly data for the whole year, which was used to quantify emissions in the simulated systems. When combined with day-ahead-market prices, a relationship between lower electricity prices and lower electricity mix carbon impact is seen. Figure 13**Error! Reference source not found.** presents that correlation for 2022 data, indicating that lower charging costs should lead to lower EV charging carbon intensity and higher usage of renewable electricity.

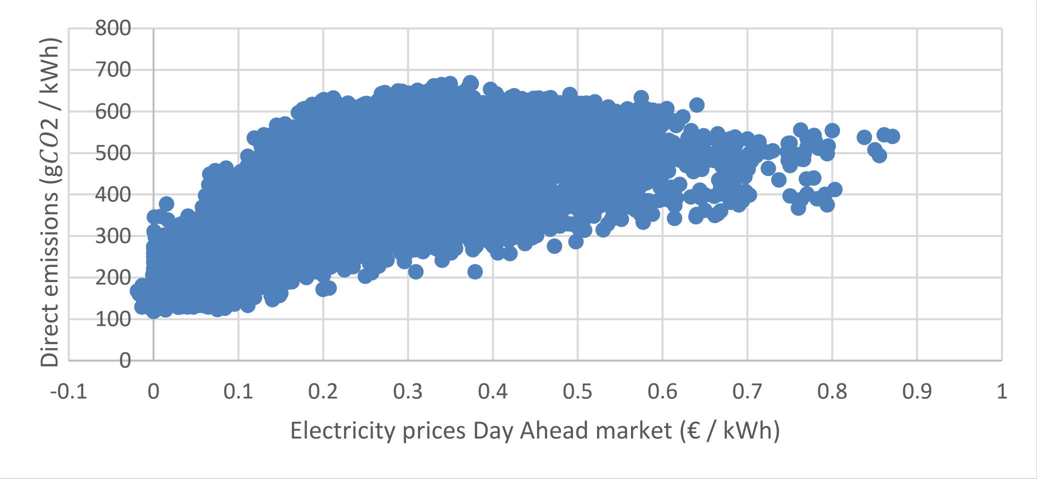


Figure 13 Direct CO_2 emissions in the electricity mix and day-ahead market prices in Germany, 2022.

3.3.2 Smart charging strategies carbon impact calculation

Hourly data on the electricity mix carbon intensity is combined with energy balances from HOMER Grid's simulations. For every time interval j, the electricity mix direct (CO_2DE_{MIX}) and indirect (CO_2IE_{MIX}) carbon impact, as well as the indirect CO_2 emissions from solar PV production (CO_2IE_{PV}) are calculated:

$$CO_2DE_{MIX_j} = GP_j \times CO_2DE_{\mathrm{MIX\,j}} \tag{18}$$

$$CO_2IE_{MIX_j} = GP_j \times CO_2IE_{\mathrm{MIX\,j}} \tag{19}$$

$$CO_2IE_{PV\ j} = E_{PV\ j} \times EF_{PV} \tag{20}$$

$$CO_2IE_{bat\ j} = E_{bat\ D\ j} \times EF_{bat} \tag{21}$$

Where the GP is grid purchases (kWh), E_{PV} is solar electricity production (kWh), $E_{bat\ D}$ is energy discharged from battery (kWh), GS is grid sales (kWh) and EF_{PV} and EF_{solar} are the lifecycle emission factor of solar PV and battery technologies in Germany.

Each system's carbon impact indicators (CO_2DE_{EV} and CO_2IE_{EV}) are obtained from adding up hourly emissions and dividing the sum by the electricity consumption (total electricity for EVs, or total electricity purchased from grid).

$$CO_2DE_{EV} = \frac{\sum_{j=1}^{35040} CO_2DE_{S_j}}{ED_{EVs}}$$

(22)

$$CO_2IE_{EV} = \frac{\sum_{j=1}^{35040} CO_2IE_{MIX_j} + \sum_{j=1}^{35040} CO_2IE_{PV_j}}{E_{EVs}}$$

(23)

Where E_{EVs} is the annual electricity demand for EV charging within the designed system.

The amount of renewable electricity consumed from the grid (RE_{MIX_j}) interval is also calculated. By adding these up over the year and dividing by total electricity purchased from the grid, the renewable ratio of electricity purchased for the system over the year (RR_{MIX}) is calculated.

$$RE_{MIX\ j} = GP_j \times RR_{MIX}$$

(24)

$$RR_{MIX} = \frac{\sum_{j=1}^{35040} RE_{MIX\ j}}{\sum_{j=1}^{35040} GP_j} = \frac{RE_{MIX}}{GP}$$

(25)

The renewable electricity ratio to fulfil EV charging demand (RR_{EV}) is also calculated, by considering all renewable electricity used in the system over the year (RE_{EV}) and the total EV demand. Electricity flowing into and out of the storage system is neglected, since all electricity stored is coming from the solar PV system and used for EV charging.

$$RE_{EV\ j} = RE_{MIX_j} + P_{PV_j} - GS_j$$

(26)

$$RR_{EV} = \sum_{j=1}^{35040} \frac{RE_{EV_j}}{(GP_j + E_{PV_j} - GS_{PV_j})} = \frac{RE_{EV}}{E_{EVs}}$$

(27)

Along with project economic indicators, the above presented environmental metrics can help understand the impact of smart charging strategies and renewables integrations both locally and in a systemic level.

Chapter 4

Results and analyses

This chapter presents the thesis results and analyses on smart charging strategies and renewables integrations for Real-Time-Pricing (RTP) tariffs. Section 4.1 establishes the project's baseline based on a Fixed Price (FP) tariff and the original EV load demand and profile. It indicates the benefits of adopting a RTP tariff with no smart charging strategies. In section 4.2, EV charging loads for different smart charging strategies modelled using HOMER Grid are presented, and an analysis is done on the impact of such strategies to minimize operational costs and increase the usage of renewable electricity from grids. In section 4.3, results from integrating solar PV and batteries locally are presented, identifying the Winning Architecture (WA) that leads to lowest Levelized Cost of Energy (LCOE) in different scenarios. Section 4.4 presents a sensitivity analysis on electricity prices, solar PV and battery capital costs and project interest rate, again indicating the WA for varying project parameters. In section 4.4.5 a discussion is made on the obtained results.

4.1 Real-Time Pricing (RTP) tariff adoption

The baseline simulation, as described, considers no smart charging strategy nor renewable electricity integration with the EV charging infrastructure, which annually demands 414 MWh. A total grid power charge of € 26,482 per year is calculated based on monthly peaks. When considering a Fixed Prices tariff (FP tariff), electricity costs add up to € 174,469 per year, leading to a € 200,951 annual electricity bill. When a Real-Time-Pricing tariff indexed to the Day Ahead market (RTP tariff) is adopted, costs are reduced significantly. While the demand charge remains the same, costs related to purchasing electricity reach € 92 588 per year. In total, € 119,071 are spent annually if a RTP tariff is adopted. Figure 14 presents grid purchasing demand matching the baseline EV charging load, and cumulative grid power costs, and electricity purchasing costs for the FP and RTP tariffs.

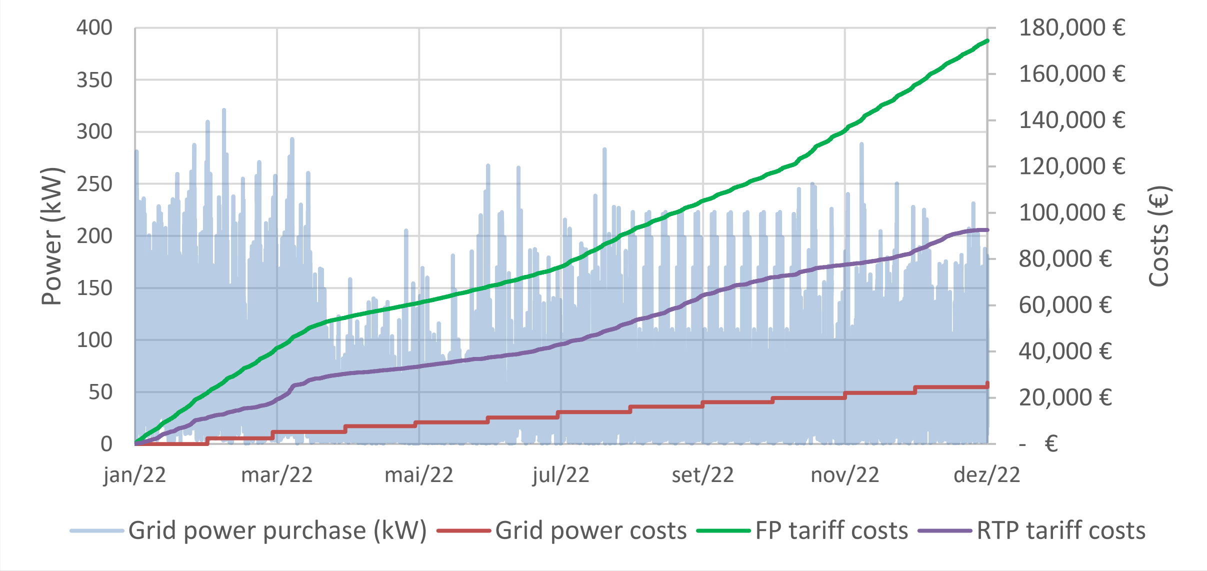


Figure 14 Baseline grid purchasing demand, and cumulative electricity bill costs over the year.

In both cases, with no RE integration, no investment is made (CAPEX is equal to zero), and no operational costs other than electricity expenses are present. Thus, annual operational costs (OPEX) are equal to the electricity bill. Table 4-1 present the baseline project economics.

Table 4-1 Baseline project economics, no RE integrations.

	Net Present Cost (€)	LCOE (€ / kWh)	CAPEX (€)	OPEX (€ / yr)
FP tariff	2,346,062 €	0.530 €	0	200,951 €
RTP tariff	1,390,123 €	0.314 €	0	119,070 €

Clearly, based on the use case baseline demand and electricity market prices, in Germany, in 2022, adopting a RTP tariff is advantageous from an economical perspective. Operational costs are reduced by more than € 80,000 per year, and LCOE is decreased from € 0.530 per kWh to € 0.314 per kWh driven by lower prices in the day-ahead market when compared to the commercial rate. Over the project lifetime, the effect on NPC is close to € 1,000,000.

The baseline carbon intensity and percentages of renewable electricity use are established. On average, electricity consumed from the grid has a direct emission rate of 416.2 gCO_2 per kWh, and an indirect impact of 484.4 gCO_2 eq. per kWh. The renewable ratio (RR) of electricity consumed by the system is 47.4%. Since all electricity demand is coming from the electricity grid, these represent the emissions and RR of electricity used to charge EVs.

From this point on, the above presented figures considering a RTP tariff are defined as the baseline to compare different smart charging strategies and renewable electricity integration scenarios.

4.2 EV Smart charging strategies

In this section, managed EV charging average load profiles are presented for the different smart charging strategies modelled in HOMER Grid. These indicate the slow charging flexible demand, which is added up to the fixed fast charging demand data to generate the total load profile for each scenario. A table comparing all strategies to the baseline scenario (with no smart charging) is presented from an economical and environmental perspective, supporting the explanation of how such strategies impact on electricity consumption from the electrical grid. Smart charging 3 and 4 lead to very similar load profiles, and for this reason their results are presented in the same subsection.

4.2.1 Smart charging Strategy 1

Smart charging Strategy 1 considers charging at the lowest power over the whole charging window, for every session. Strategy 1 effectively reduces the slow charging demand peak, as the average daily EV charging load profile indicates in Figure 15. As a result, the overall demand peaks decrease, leading to reduced grid power costs.

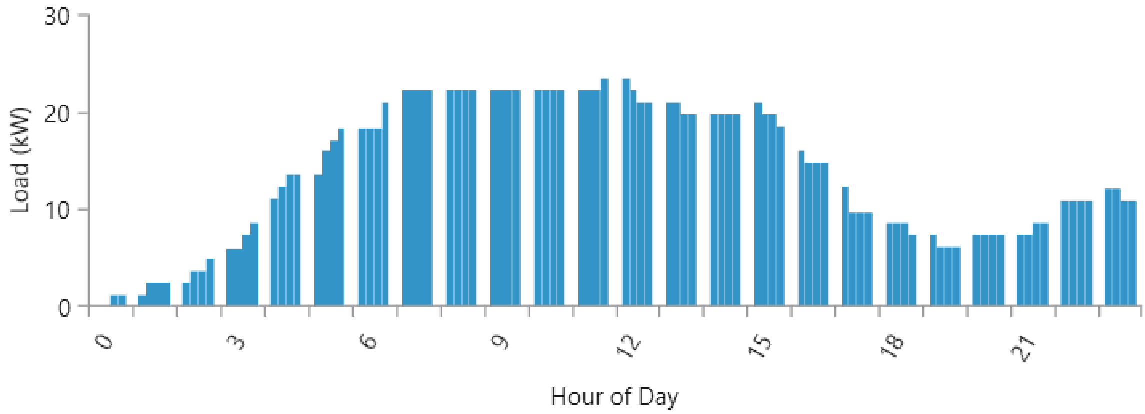


Figure 15 Average daily EV charging load profile for Strategy 1 (HOMER Software, 2023).

Annual grid power charges reach € 17,095 per year, nearly € 10,000 (35%) lower than the baseline. Electricity purchase costs increase by € 2,500 per year because of purchasing occurring at different times. Annually, € 6,951 are saved when adopting smart charging Strategy 1 when compared to the baseline. Overall, LCOE is reduced from € 0.314 per kWh to € 0.296 per kWh.

Concerning the impact on electricity grid's carbon impact, both direct and indirect emissions are lower than the baseline, and a higher ratio of renewable electricity is used. Table 4-2 presents the project economics and environmental indicators for Strategy 1, comparing them to the baseline. Smart charging Strategy 1 improves all project indicators, even though it increases electricity costs.

Table 4-2 Economical and environmental comparison between Strategy 1 and baseline.

	Strategy 1	**Baseline**	**Difference (%)**
NPC (€)	1,308,971 €	1,390,124 €	-5.8%
LCOE (€/kWh)	0.296 €	0.314 €	-5.8%
OPEX (€/yr)	112,120 €	119,071 €	-5.8%
Grid power costs (€/yr)	17,095 €	26,483 €	-35.4%
Electricity purchase costs (€/yr)	95,024 €	92,588 €	2.6%
Direct emissions (gCO2 / kWh)	411	416	-1.3%
Indirect emissions (gCO2 eq. / kWh)	479	484	-1.1%
Renewables Ratio EVs	48.1%	47.4%	1.4%
Renewables Ratio Mix	48.1%	47.4%	1.4%

4.2.2 Smart charging Strategy 2

Smart charging Strategy 2 schedules EV charging at times of lower electricity prices in the morning and early afternoon, within 3-hours-intervals. This leads to higher charging peaks, especially in the morning when demand is higher. These lead to higher grid power costs, which are compensated by electricity purchasing at lower prices. Figure 16 presents the daily average EV charging load profile over the year for Strategy 2.

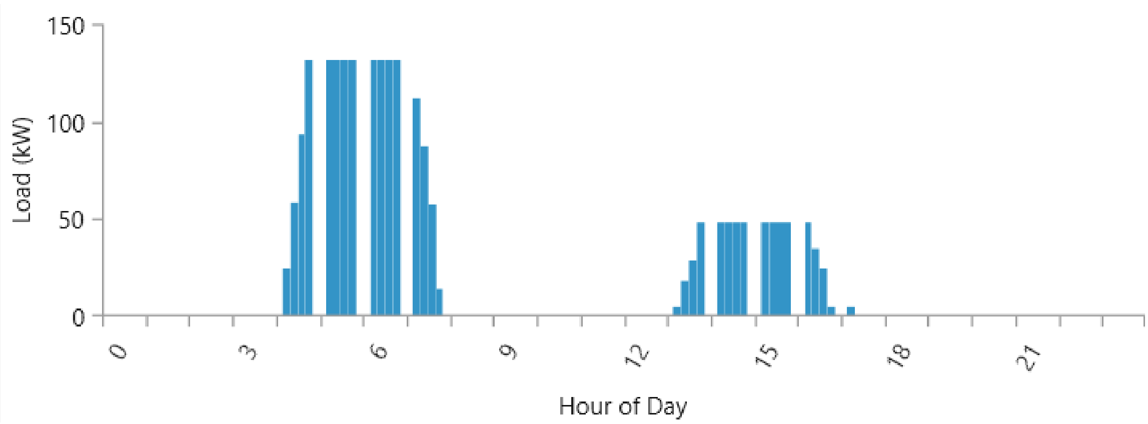


Figure 16 Daily average EV charging load profile for Strategy 2 (HOMER Software, 2023).

Annual grid power costs are € 19,353, which are lower than the baseline. According to expected, electricity purchase costs are also reduced, reaching € 88,589 per year from charging at times with average lower prices. Overall, LCOE is reduced from € 0.314 per kWh to € 0.285 per kWh.

Concerning the impact on electricity grid's carbon impact, both direct and indirect emissions are lower than the baseline, and a higher ratio of renewable electricity is used. Table 4-3 presents the project economics and environmental indicators for Strategy 2, comparing them to the baseline. Smart charging Strategy 2 improves all project indicators.

Table 4-3 Economical and environmental comparison between Strategy 2 and baseline.

	Strategy 2	**Baseline**	**Difference (%)**
NPC (€)	1,260,194 €	1,390,124 €	-9.3%
LCOE (€/kWh)	0.285 €	0.314 €	-9.3%
OPEX (€/yr)	107,942 €	119,071 €	-9.3%
Grid power costs (€/yr)	19,353 €	26,483 €	-26.9%
Electricity purchase costs (€/yr)	88,589 €	92,588 €	-4.3%
Direct emissions (gCO2 / kWh)	411	416	-1.2%
Indirect emissions (gCO2 eq. / kWh)	479	484	-1.1%
Renewables Ratio EVs	47.9%	47.4%	1.0%
Renewables Ratio Mix	47.9%	47.4%	1.0%

4.2.3 Smart charging Strategies 3 and 4

Smart charging Strategy 3 and 4 schedules EV charging at times of lower electricity prices in the morning and early afternoon, within 6-hours-intervals. Strategy 3 considers all vehicles will charge at 3 kW during the 6-hours schedule times. For Strategy 4, two EVs will charge for 3 hours at 6 kW, subsequently. Although both strategies consider different charging powers, the charging schedule is similar. Since the EV fleet is composed of various vehicles charging at the same time, the total EV charging load profile for both is similar. For strategy 3, one charging session occurs for 6 hours at 3 kW charging speed, while for Strategy 4 two 3-hour sessions occur within the 6 hours.

In both cases, the charging strategy leads to smoother charging peaks, and electricity purchases at lower prices. Figure 17 and Figure 18 present the daily average EV charging load profile over the year for Strategy 3 and Strategy 4, respectively.

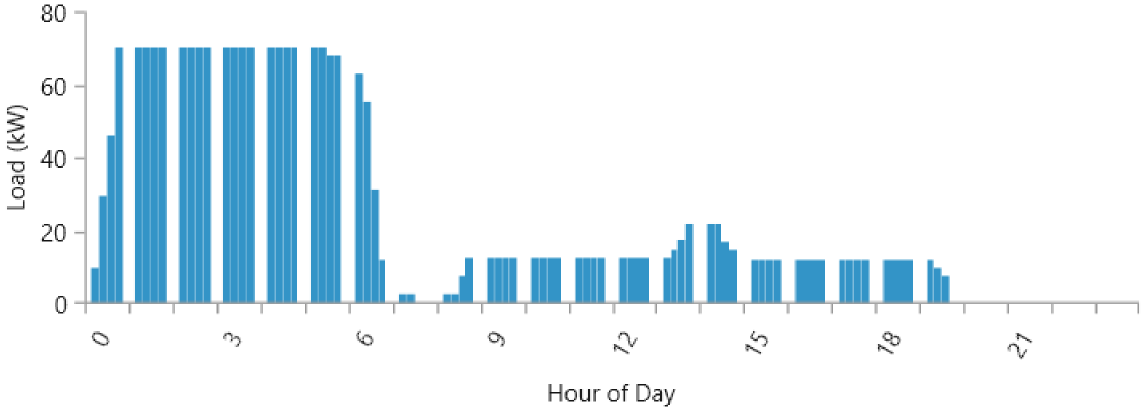


Figure 17 Daily average EV charging load profile for Strategy 3 (HOMER Software, 2023).

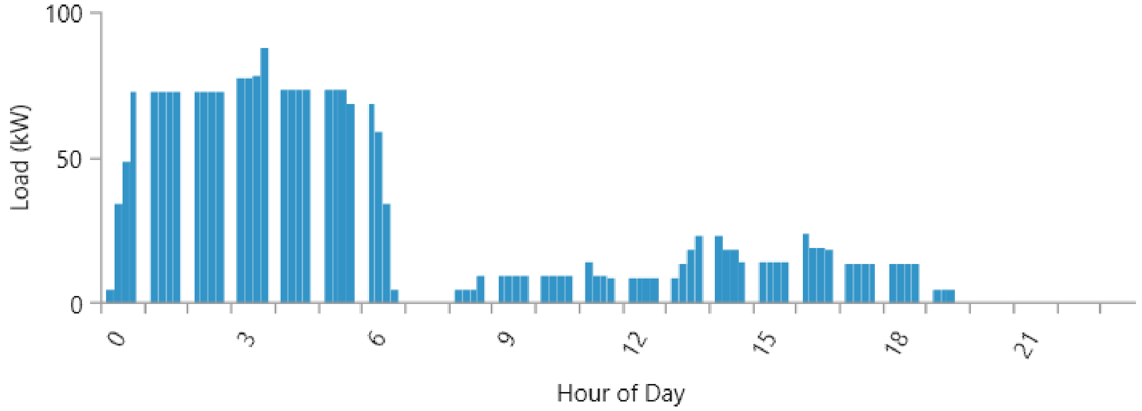


Figure 18 Daily average EV charging load profile for Strategy 4 (HOMER Software, 2023).

As a result of similar EV charging load profiles, project results are roughly the same. Annual grid power costs are close to € 17,500. According to expected, electricity purchase costs are also reduced, reaching € 89,850 per year from charging at times with average lower prices. Overall, LCOE is reduced from € 0.314 per kWh to € 0.283 per kWh.

Concerning the impact on electricity grid's carbon impact, both direct and indirect emissions are lower than the baseline, and a higher ratio of renewable electricity is used. Table 4-4presents the project economics and environmental indicators for Strategy 3 and 4. The column on the right indicates the difference between the average of Strategy 3 and Strategy 4 indicators, and the baseline's. All project indicators are improved.

Table 4-4 Economical and environmental comparison between Strategy 3 and 4 and baseline.

	Strategy 3	Strategy 4	Baseline	Avg. difference (%)
NPC (€)	1,252 752 €	1,255,179 €	1,390,124 €	-9.8%
LCOE (€/kWh)	0.283 €	0.283 €	0.314 €	-9.8%
OPEX (€/yr)	107,304 €	107,512 €	119,071 €	-9.8%
Grid power costs (€/yr)	17,458 €	17,633 €	26,483 €	-33.7%
Electricity purchase costs (€/yr)	89,846 €	89,879 €	92,588 €	-2.9%
Direct emissions (gCO2 / kWh)	410	410	416	-1.4%
Indirect emissions (gCO2 eq. / kWh)	478	478	484	-1.3%
Renewables Ratio EVs	48.1%	48.1%	47.4%	1.3%
Renewables Ratio Mix	48.1%	48.1%	47.4%	1.3%

4.2.4 Smart charging Strategy 5

Smart charging Strategy 5 schedules EV charging within 3-hours-intervals, aiming to maximize solar PV usage. Thus, for the shift occurring between 08:00 – 20:00, charging occurs between 11:00 – 14:00, at times of higher solar PV electricity penetration (in grids and locally). The morning demand is kept at times of lower prices, according to Strategy 2's schedule. Figure 19 presents the average EV charging load profile over the year for Strategy 5.

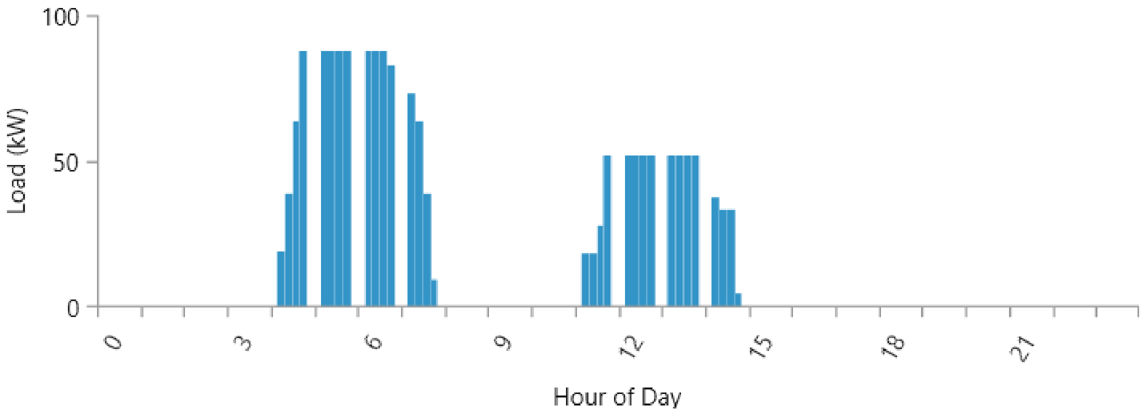


Figure 19 Average EV charging load profile for Strategy 5.

Grid power costs reach € 18,826 per year, which are also lower than the baseline. Because the charging schedule is defined based on solar PV penetration, it does not necessarily mean lower prices in the day-ahead market. As a result, the annual costs of electricity are similar to the baseline, at € 92,385 per year. Overall, LCOE is reduced from € 0.314 per kWh to € 0.293 per kWh.

Concerning the impact on electricity grid's carbon impact, both direct and indirect emissions are lower than the baseline and that any of the other smart charging strategies. Table 4-5 presents the project economics and environmental indicators for Strategy 5, comparing them to the baseline. Smart charging Strategy 2 improves all project indicators.

Table 4-5 Economical and environmental comparison between Strategy 5 and baseline.

	Strategy 5	Baseline	Difference (%)
NPC (€)	1,298,363 €	1,390,124 €	-6.6%
LCOE (€/kWh)	0.293 €	0.314 €	-6.6%
OPEX (€/yr)	111,211 €	119,071 €	-6.6%
Grid power costs (€/yr)	18,826 €	26,483 €	-28.9%
Electricity purchase costs (€/yr)	92,385 €	92,588 €	-0.2%
Direct emissions (gCO2 / kWh)	404	416	-3.0%
Indirect emissions (gCO2 eq. / kWh)	471	484	-2.7%
Renewables Ratio EVs	49.0%	47.4%	3.3%
Renewables Ratio Mix	49.0%	47.4%	3.3%

4.2.5 Discussion

All smart charging strategies reduce the overall peak consumption, every month, by shifting the slow EV charging demand according to the proposed smart charging strategies. Figure 20 presents the monthly peak demand (at 15 minutes intervals) resulting from each smart charging strategy.

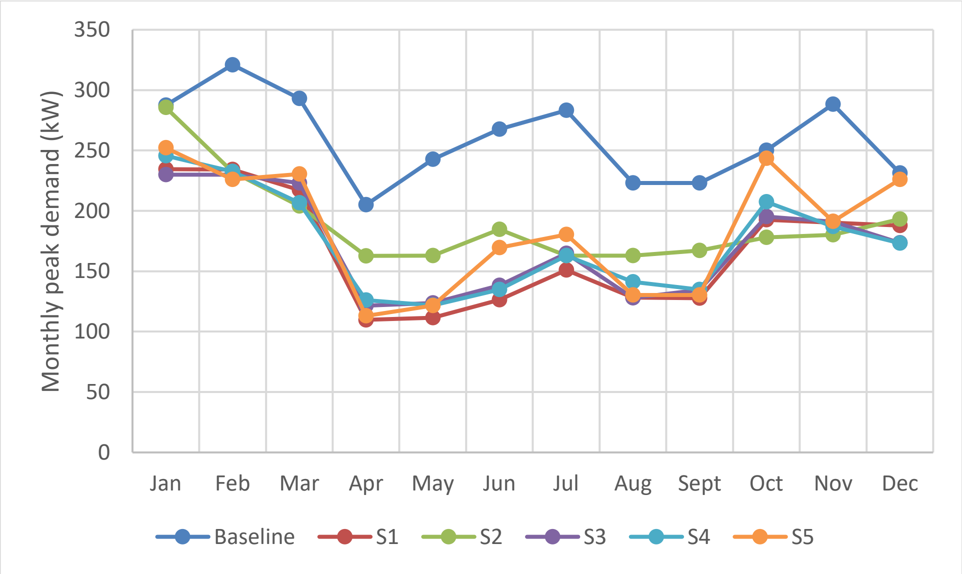


Figure 20 Monthly peak demand for baseline load and all smart charging strategies.

Except for Strategy 2, all smart charging strategies reduce the costs of purchasing electricity based on day-ahead market prices. Table 4-6, below, presents an overview of economic indicators for the smart charging strategies presented above. Average demand charges and electricity purchase costs per kWh consumed over the year are presented, obtained by dividing the total annual costs by the amount of electricity purchased for every smart charging strategy.

Table 4-6 Smart charging strategies economic indicators, no RE integration.

	NPC (€)	LCOE (€ / kWh)	OPEX (€ / yr)	Power costs (€ / kWh)	Electricity costs (€ / kWh)
Baseline	1 390 124 €	0.314 €	119 071 €	0.064 €	0.223 €
Strategy 1	1 308 971 €	0.296 €	112 120 €	0.041 €	0.229 €
Strategy 2	1 260 194 €	0.285 €	107 942 €	0.047 €	0.214 €
Strategy 3	1 252 752 €	0.283 €	107 304 €	0.042 €	0.217 €
Strategy 4	1 255 179 €	0.283 €	107 512 €	0.043 €	0.217 €
Strategy 5	1 298 363 €	0.293 €	111 211 €	0.045 €	0.223 €

In a scenario with no local Renewable Electricity integration, smart charging Strategies 3 and 4 lead to lowest project costs (NPC, LCOE and OPEX) driven by combined savings from demand charges and electricity purchasing. Although Strategy 1 significantly reduces demand charges, the impact on electricity purchase costs outweighs this benefit. Similarly, in smart charging Strategy 2 electricity purchase costs are the lowest, but demand charges are not reduced enough to result in overall lower costs. Strategy 5 saves both in demand charges and electricity purchase costs, but overall costs are higher than S2, S3 and S4. Nonetheless, all smart charging strategies lead to lower costs than the baseline.

The carbon impact of such smart charging strategies is shown in Table 4-7.

Table 4-7 Smart charging strategies environmental indicators, no RE integration.

	Direct emissions (gCO2/kWh)	Indirect emissions (gCO2 eq/kWh)	Renewables Ratio EVs	Renewables Ratio Mix
Baseline	416	484	47.4%	47.4%
Strategy 1	411	479	48.1%	48.1%
Strategy 2	411	479	47.9%	47.9%
Strategy 3	410	478	48.1%	48.1%
Strategy 4	410	478	48.1%	48.1%
Strategy 5	404	471	49.0%	49.0%

Again, all smart charging strategies lead to lower direct and indirect carbon emissions, and higher renewable electricity ratios to charge EVs. While the impact of Strategies 1, 2, 3, and 4 are very similar, Strategy 5 delivers on reducing emissions further by using higher shares of renewables. An absolute increase of 1.6% of renewables is achieved in comparison to the baseline (from 47.4% to 49.0%) by charging at times of higher renewable shares in the electricity mix. Driven by charging with extra 6,565 kWh of green electricity from the electricity grid, over the year Strategy 5 reduces 5.1 ton CO_2 in direct emissions and 5.3 ton $CO_2\ eq$. In indirect emissions when compared to the baseline.

4.3 Solar PV and batteries integrations

This section explores the impact of integrating solar PV and batteries to the smart charging strategies presented in Section 4.2. The results from optimizing the system design for lowest Levelized Cost of Energy (LCOE) are presented. The winning architecture is identified with solar PV panels only, and no batteries. A discussion is made on the impact of integrating solar PV panels only, and a combination of solar PV with batteries, based on simulations results, systems' operations, and economic and environmental indicators.

4.3.1 Solar PV integration

The integration of solar PV panels reduces the need for purchasing electricity from the grid. As a result, operational costs are reduced and higher renewables shares are achieved for EV charging, leading to reduced direct CO2 emissions. Nonetheless, the cost of purchasing and installing a large PV system is not always compensated by its benefits. Figure 21 shows the relationship between solar PV capacity and LCOE for all smart charging strategies.

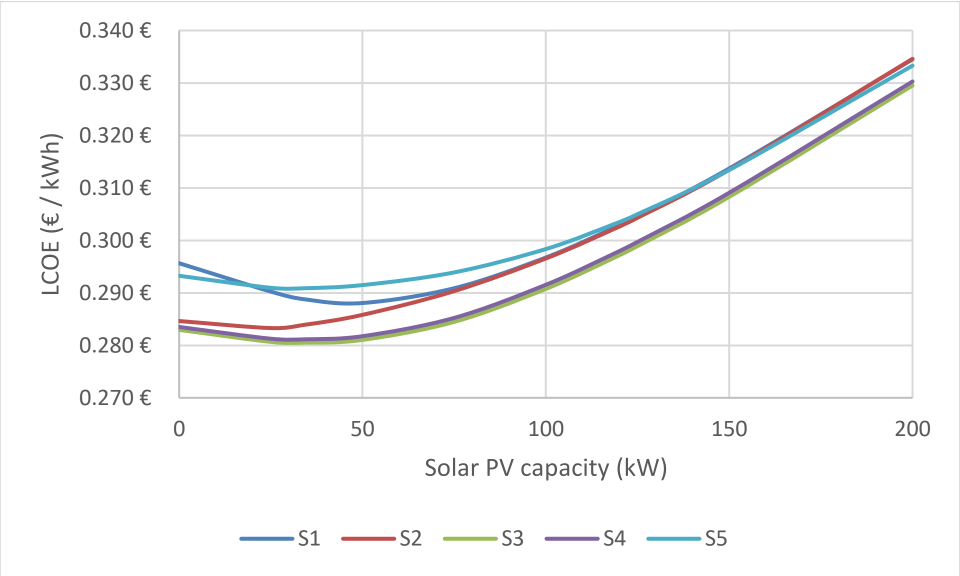


Figure 21 Impact of solar PV capacity on LCOE, for all smart charging Strategies (S).

All curves indicate a similar trend towards reaching minimum LCOE around 25 kW and 50 kW. For systems which larger capacities, LCOE increases rapidly. Smart charging Strategies 3 and 4 again outperform the other strategies, leading to the lowest LCOE for every PV size. This is explained by their EV charging load profile presented in Section 4.2.3, in which a large charging window of 6 hours occurs near mid-day every day. Thus, matching solar PV production for a large time-window. Smart charging Strategy 5 also schedules EV charging session around mid-day. However, a 3-hour window is defined, and as a result a larger PV system needs to be in place to supply the larger demand peaks. Furthermore, the shorter charging window leads to higher demand charges, as described before, increasing the system operational costs.

Figure 22 indicates the relationship between solar PV system, LCOE, and CAPEX and OPEX for smart charging Strategy 3. Minimum LCOE is achieved with 34.4 kWp solar PV capacity. For systems larger than that, the increase in CAPEX is not compensated by the reduced OPEX over the project lifetime.

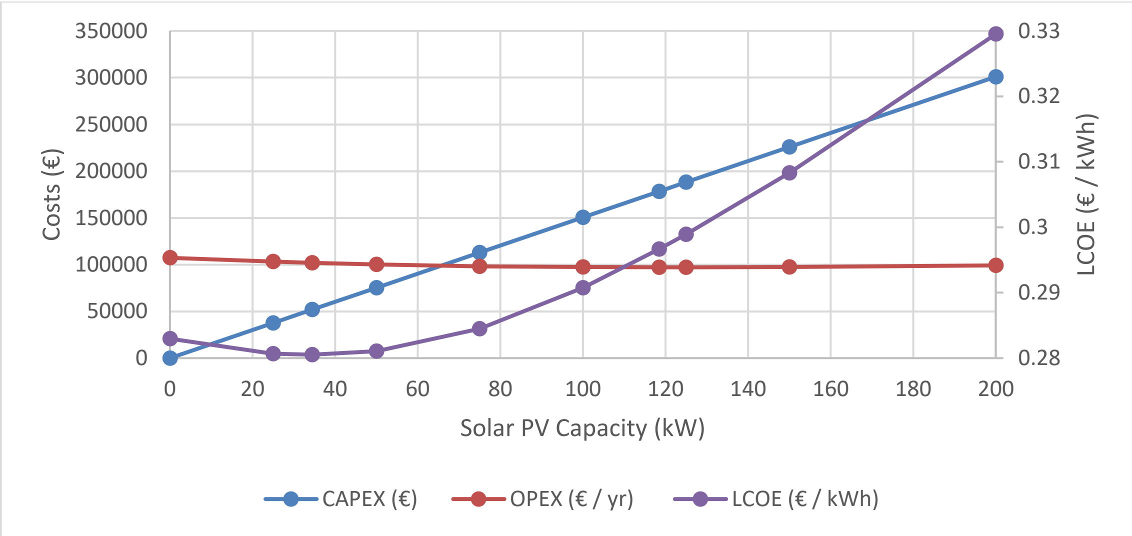


Figure 22 Impact of solar PV capacity in LCOE, CAPEX and OPEX for smart charging strategy 3.

As expected, larger solar PV systems increase the percentage of renewable electricity used for EV charging. With 200 kWp of PV capacity, 82% of electricity used to charge EVs comes from renewable sources. Most of it comes directly from the PV system, though, and the renewable ratio of electricity coming from the electricity grid decreases with larger PV systems. This is explained by the decreased demand for grid purchases at times of higher solar PV electricity generation in the mix (around noon). Nevertheless, both direct and indirect CO2 emissions per kWh of electricity consumption decrease with larger PV systems. Figure 23 presents, for smart charging Strategy 3, the relationship between solar PV capacity, renewable electricity ratios and CO2 emissions per kWh consumed for EV charging.

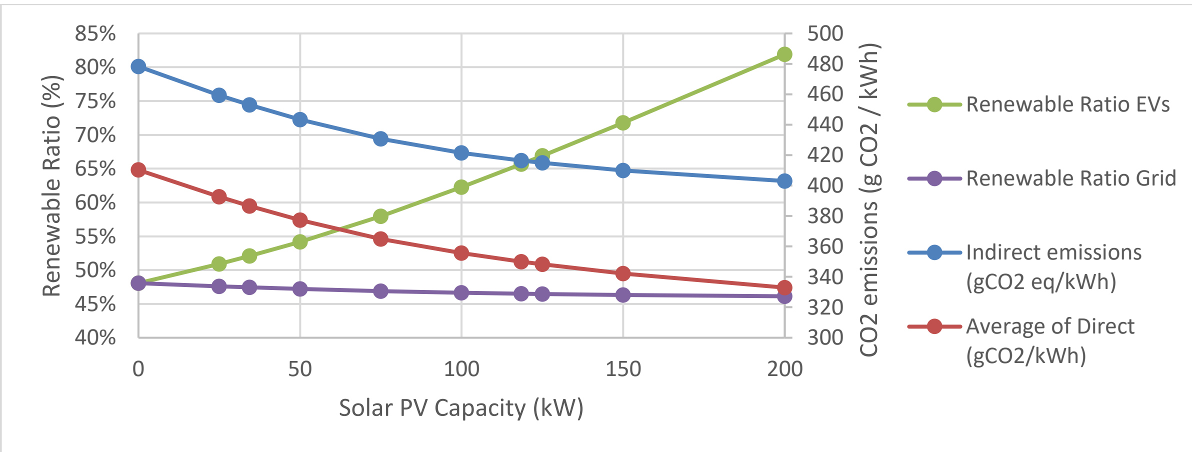


Figure 23 Impact of solar PV capacity on renewable electricity usage and CO_2 emissions using Strategy 3.

Following the methodology detailed in Section 3.2.3, the system design is optimized for lowest Levelized Cost of Energy (LCOE). The system architecture leading to the lowest LCOE also lead to the lowest Net Present Cost (NPC). As presented above, smart charging Strategy 3 again leads to the lowest costs, and a 34.4 kWp solar PV system is integrated. Annually, 32.6 MWh of electricity are produced from the solar system, reducing the demand for grid purchases to 386.3 MWh per year. Grid sales from solar PV surplus reach 4.2 MWh per year. Only 7% of the EV charging demand is supplied by the solar PV system, but 87% of the locally generated electricity is consumed.

Seasonal effects of solar PV production directly impact the system operation. The graphs below present monthly average power exchange profiles for PV production, total and slow charging EV loads, grid purchases and grid sales along with electricity prices from the day-ahead market. Figure 24 presents average figures for June, and Figure 25 presents average figures for December. Solar PV peak of 14.5 kW is achieved in June, and 8.1 kW in December, thus indicating the importance of simulating such system over the whole year.

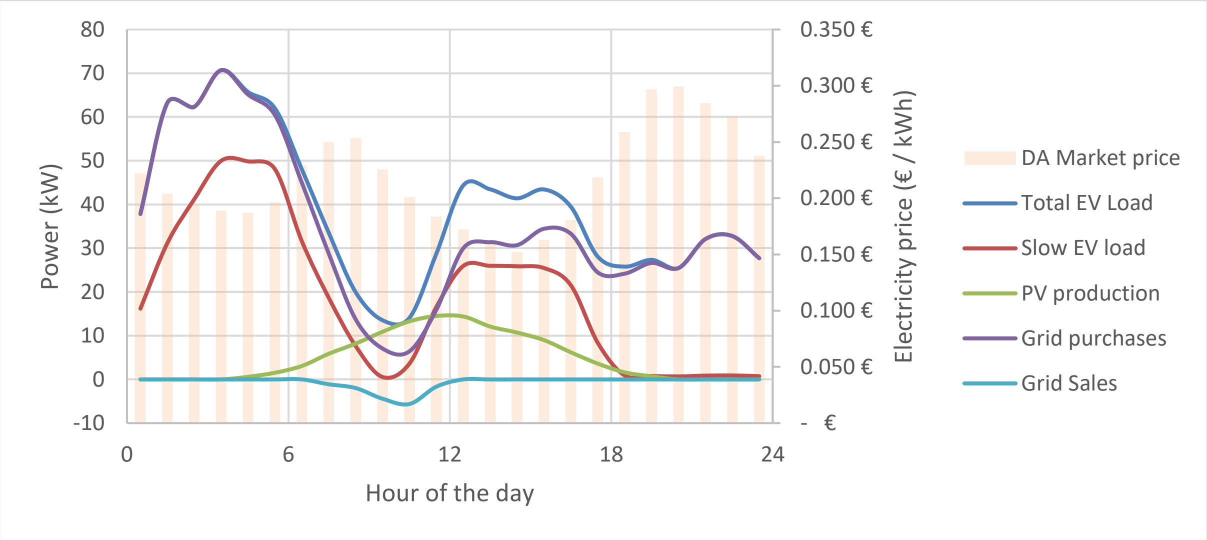


Figure 24 Winning architecture daily average loads and DA market prices in Jun-22.

Most electricity produced is used to charge EVs, however before noon surplus PV is sold back to the grid since there is not enough EV demand. Grid purchases are reduced in times of higher prices from shifted demand. In June, electricity is more expensive in late morning hours and between 19:00-23:00, with prices of € 0.25 - € 0.30 per kWh. Electricity over the night and in the early afternoon cost around € 0.20 and € 0.15 per kWh, respectively.

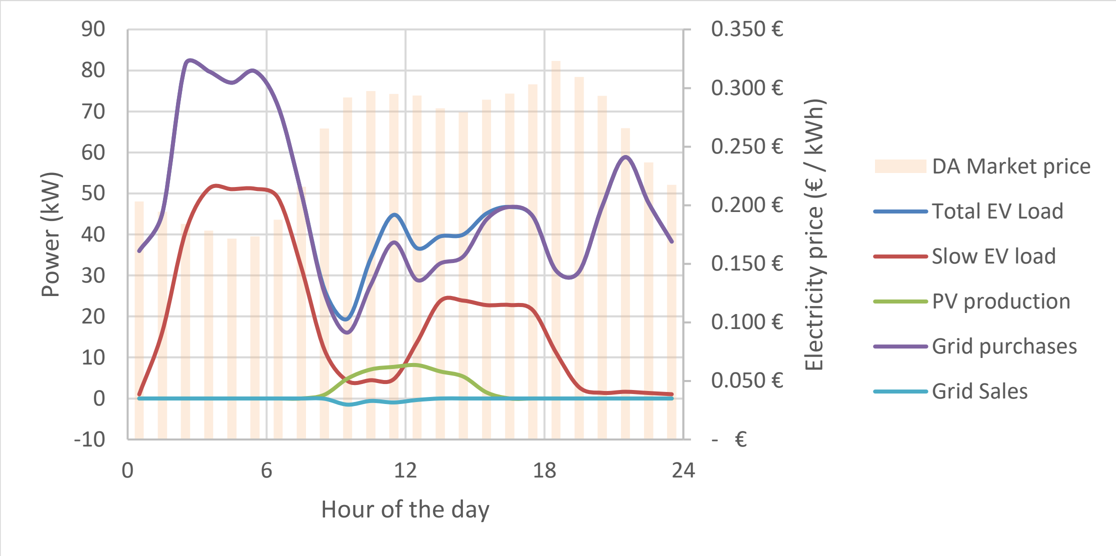


Figure 25 Winning architecture daily average loads and DA market prices in Dec-22.

During December, electricity prices remain high even in the early afternoon, consistently above € 0.300 per kWh between 10:00 and 20:00. Solar PV production is smaller than during the summer, with mild impact in reducing grid purchases. The shifted EV demand for times of lower electricity prices reduces costs overall. The largest demand occurs between 2:00 and 6:00, when electricity is at its lowest prices between € 0.175 and € 0.200 per kWh.

The system's LCOE is reduced to € 0.281 per kWh. Annual grid demand charges cost € 17,485. Electricity purchase costs are significantly reduced, reaching € 83,560 per year, at an average cost of € 0.216 per kWh purchased (not considering grid fees, electricity only). The system's annual operational costs reach € 101,950, and a CAPEX of € 51,772 is required to install the PV system.

Table 4-8 presents the project economics and environmental indicators for such system, comparing them to the baseline (no solar PV, no smart EV charging strategy, presented in section **Error! Reference source not found.**). It indicates the lower operational costs leading to 10.7% reduction in LCOE and NPC, as well as environmental benefits of implementing such systems. Direct and indirect CO2 emissions for every kWh consumed for EV charging are reduced, and the ratio of RE used to charge EVs increases from 47.4% to 52.1%. The ratio of renewable electricity from the grid is similar to the baseline.

Table 4-8 Economical and environmental comparison between winning architecture and baseline.

	Winning Architecture (WA)	Baseline	Difference (%)
NPC (€)	1,242,027 €	1,390,124 €	-10.7%
LCOE (€/kWh)	0.281 €	0.314 €	-10.7%
CAPEX (€)	51,773 €	0	-
OPEX (€/yr)	101,951 €	119,071 €	-14.4%

Demand charges costs (€/yr)	17,458 €	26,483 €	-34.1%
Electricity purchase costs (€/yr)	83,560 €	92,588 €	-9.8%
Direct emissions (gCO2 / kWh)	387	416	-7.1%
Indirect emissions (gCO2 eq. / kWh)	453	484	-6.4%
Renewables Ratio EVs	52.1%	47.4%	9.9%
Renewables Ratio Mix	47.5%	47.4%	0.1%

4.3.2 Solar PV and batteries integration

The integration of batteries along with solar PV support electricity self-consumption, minimizing grid purchases and grid sales. While this leads to lower operational costs, capital requirements to install such storage systems are significant, reducing the overall cost reduction potential. Results from batteries integration with 34.4 kWp from the winning architecture (WA, presented in Section 4.3.1) are presented.

The use of different smart charging integrated with solar PV and batteries is presented in **Error! Reference source not found.**, indicating the impact of different battery sizes on the projects' LCOE.

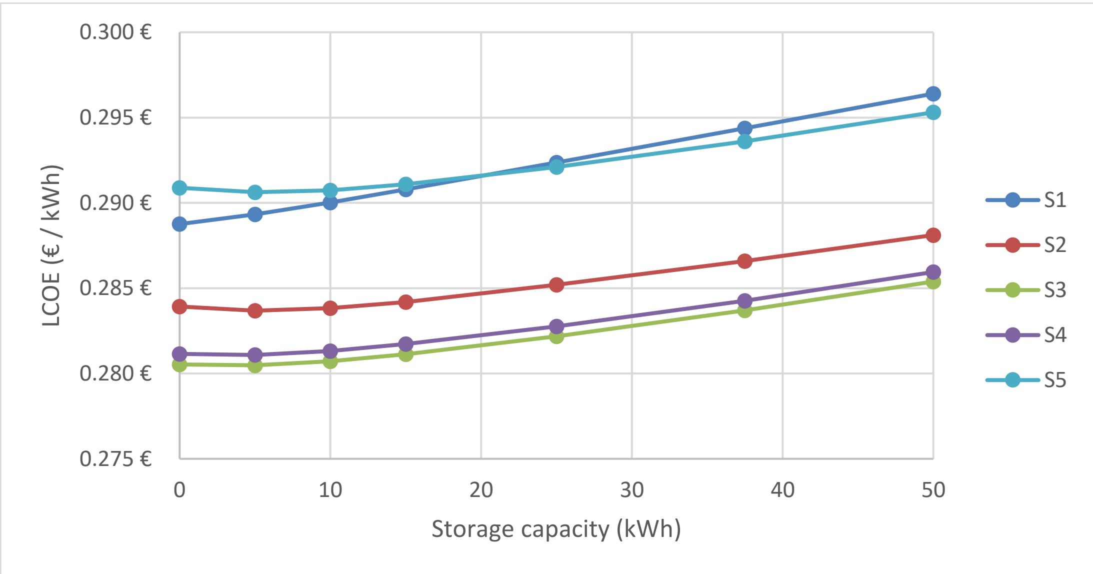


Figure 26 Impact of storage capacity on LCOE for a 34.4 kWp system (WA).

Once again, Strategies 3 and 4 outperform the other smart charging strategies. By shifting the evening demand to times of lower prices, grid purchases avoid peak electricity prices and solar PV and storage maximize locally generated electricity usage. Lower LCOE is found in smaller systems, up to 10 kWh. As storage capacity is increased, higher solar PV self-consumption rates are obtained, but higher capital expenses offset the savings from electricity purchase over the project lifetime.

For the same 34 kWp and smart charging Strategy 3, Table 4-9 shows the impact of different storage systems on grid sales and purchases, and on project economics. LCOE remains at per kWh for systems with 0, 5, 10 and 15 kWp capacity.

Table 4-9 Grid sales, purchases, and project costs for 34.4 kWp PV system and varying storage sizes.

Storage Capacity (kWh)	Energy discharged (kWh/yr)	Grid Sales (kWh/yr)	Grid purchases (kWh / yr)	CAPEX (€)	OPEX (€ / yr)	LCOE (€ / kWh)
0	0	4,239	386,335	51,772 €	101,951 €	0.281 €
5	989	3,254	385,346	55,357 €	101,627 €	0.281 €
10	1,667	2,580	384,668	58,942 €	101,412 €	0.281 €
15	2,148	2,104	384,188	62,527 €	101,260 €	0.281 €
25	2,843	1,416	383,492	69,697 €	101,043 €	0.282 €
37.5	3,467	802	382,868	78,660 €	100,850 €	0.284 €
50	3,874	405	382,461	87,622 €	100,724 €	0.285 €

For this system, 47,474 kWh of solar PV electricity are produced every year, and little financial benefit comes from investing in batteries. LCOE figures remain unchanged for storage systems between 0 and 15 kWh of storage, at € 0.281 per kWh. 50 kWh of batteries reduces the amount of electricity sold from 4,239 to 405 kWh per year, or almost by ten times. However, CAPEX increases by € 36,000, reaching € 78,600, which is not compensated in the long run since operational costs are reduced by only € 1,200 per year, leading to a LCOE of € 0.285 per kWh.

For this system, integrating storage maximizes solar PV electricity self-consumption and reduces direct and indirect CO2 emissions only very slightly. When comparing a system with no storage to one with 50 kWh capacity, direct and indirect emissions are decreased from 385.4 to 382.7 gCO_2 per kWh, and from 451.7 to 451.0 $gCO_{2\,eq}$ per kWh, respectively. Similarly, the renewable electricity ratio of electricity used for EV charging increases from 51.2% to 51.6% from better use of solar PV generated electricity, and the electricity grid renewable ratio decreases slightly from 47.6% to 47.5%. **Error! Reference source not found.** indicate these trends for different battery sizes and 34.4 kWp of storage.

Comparatively, the impact of increasing storage sizes on electricity self-consumption is larger for larger PV systems. While for a 34.4 kWp the system approaches 100% of self-consumption with 50 kWh of storage, for PV systems larger than 100 kWp the trend shows self-consumption rates increasing almost linerarly with storage capacity, as indicated in Figure 27. As a result, for a 150 kWp PV system, minimum LCOE is obtained with 61.2 kWh of storage, increasing the solar PV self-consumption rate from 56% (with no storage) to 64%. This difference results in storing and using 11.4 MWh of solar PV electricity for EV charging, instead of selling it back to the grid at lower prices. While for this case study results indicate higher economical advantage for smaller PV systems with no storage, this behaviour must be considered.

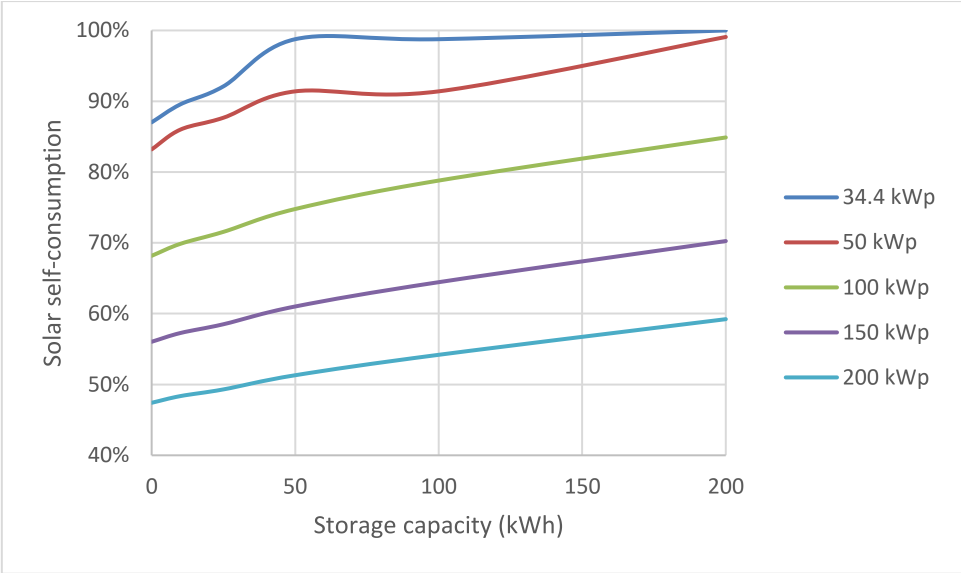


Figure 27 Solar PV and storage capacities influence on solar PV self-consumption.

4.3.3 Discussion

An alternative system with 34.4 kWp solar PV capacity and 10 kWh of storage leads to similar NPC and LCOE to the Winning Architecture presented in section **Error! Reference source not found.**. Annually, 32.6 MWh of electricity are produced from the solar system. 1.7 MWh of electricity is stored in the batteries, reducing grid sales to 2.6 MWh and grid purchases to 384.7 MWh per year. The adoption of batteries increases solar PV self-consumption to 92%, covering an extra 0.3% of the total EV demand.

In contrast, a larger PV system with 150 kWp solar capacity and 61.2 kWh of storage leads to higher LCOE and NPC even with lower operational costs. Annually, 142.4 MWh of solar electricity are generated, 13.9 MWh of which being stored in the batteries and resulting in selling 48.6 MWh (34% of production) back to the grid, and purchasing 320.9 MWh from the grid. OPEX reduces significantly to reach € 93,000 per year, but LCOE and the project's NPC increase to € 0.306 per kWh and € 1,356,475, respectively, given the required CAPEX of almost € 270,000.

While the larger system is not economically beneficial, it leads to lower carbon emissions and higher renewable electricity usage for EV charging. In comparison to the baseline scenario, direct CO2 emissions are reduced by 21%, from 416 to 329 gCO_2 per kWh consumed. Indirect emissions are reduced by 16%, from 484 to 404 $gCO_{2\,eq.}$ per kWh, given the life-cycle carbon impact of batteries is considered in the calculation and decreases the benefit of maximizing solar PV usage. The smaller PV and battery system environmental results are similar to the winning architecture.

The simulation results indicate that integrating batteries supports higher solar PV self-consumption rates, reducing the carbon impact of EV charging. However, the high capital costs for installing batteries does not compensate the operational costs reduction, resulting in no benefits from batteries integration from an economic perspective. The use of batteries for energy arbitrage purposes, charging with cheaper electricity and discharging at times of higher prices to charge EVs could lead to different results, however such algorithms were not considered in this work.

Table 4-10 presents all project indicators for the described systems, allowing a thorough comparison between economic and environmental indicators.

Table 4-10 Economical and environmental comparison between winning architecture and baseline.

	Large PV and battery	**Small PV and battery**	**Solar only (WA)**	**Baseline**
Solar PV capacity (kWp)	150.0	34.4	34.4	0
Storage capacity (kWh)	61	10	0	0
NPC (€)	1,356,475 €	1,242,901 €	1,242,027 €	1,390,124 €
LCOE (€/kWh)	0.306 €	0.281 €	0.281 €	0.314 €
CAPEX (€)	269,630 €	58,942 €	51,773 €	0
OPEX (€/yr)	93,093 €	101,412 €	101,951 €	119,071 €
Demand charges costs (€/yr)	17,458 €	17,458 €	17,458 €	26,483 €
Electricity purchase costs (€/yr)	69,097 €	83,157 €	83,560 €	92,588 €
Direct emissions (gCO2 / kWh)	329	385	387	416
Indirect emissions (gCO2 eq / kWh)	404	453	453	484
Renewables Ratio EVs	58.3%	51.2%	52.1%	47.4%
Renewables Ratio Mix	46.1%	47.4%	47.5%	47.4%

4.4 Sensitivity Analysis

The presented results indicate that, for this case study and considering the costs parameters from Chapter 3. Varying electricity prices, solar PV and batteries costs, and also project financial parameters can lead to different system architectures with lowest LCOE. In this section, system architectures generating lowest LCOE are presented, based varying these parameters by -20%, -10%, +10% and +20% in comparison to original figures.

4.4.1 Electricity prices

Electricity prices (P_E) from the day-ahead market are proportionally multiplied by -20%, -10%, +10% and +20% for every time interval in the dataset, keeping the original data set variability. Table 4-11 presents the winning architecture for each scenario. Lower electricity prices decrease the benefits of integrating solar PV and batteries, and significantly reduce systems' LCOE. For electricity prices 20% cheaper than the day-ahead market prices in 2022, lowest LCOE € 0.235 per kWh is obtained with a 9.2 kWp solar system, reducing the project Net Present Cost by 16% from € 1,242,000 to € 1,041,360. On the other hand, if day-ahead market prices are 20% higher than in 2022, 51.0 kWp of solar PV capacity and no batteries leads to the lowest LCOE of € 0.323 per kWh.

Table 4-11 Sensitivity analysis on battery costs, winning architectures (WA) results.

	$P_{E-20\%}$ WA	$P_{E-10\%}$ WA	Baseline WA	$P_{E+10\%}$ WA	$P_{E+20\%}$ WA
Solar PV Capacity (kWp)	9.2	19.7	34.4	47.7	51.1
Storage Capacity (kWh)	0.0	0.2	0.0	6.0	0.0
NPC (€)	1,041,360 €	1,143,064 €	1,242,027 €	1,337,456 €	1,433,806 €
LCOE (€/kWh)	0.235 €	0.258 €	0.281 €	0.302 €	0.324 €
CAPEX (€)	13,859 €	29,820 €	51,772 €	75,990 €	76,831 €
OPEX (€/yr)	88,010 €	95,355 €	10,1951 €	10,8051 €	116,231 €
Grid power costs (€/yr)	17,458 €	17,458 €	17,458 €	17,458 €	17,458 €
Electricity costs (€/yr)	70,363 €	77,425 €	83,560 €	89,296 €	97,227 €
Direct emissions (gCO2 / kWh)	403	396	387	378	377
Indirect emissions (gCO2 eq. / kWh)	471	463	453	444	443
Renewables Ratio EVs	48.9%	49.9%	51.0%	52.2%	52.3%
Renewables Ratio Mix	47.9%	47.7%	47.4%	47.2%	47.2%

4.4.2 Solar PV costs

Solar PV purchase and installation costs (P_{PV}) are replaced from the original € 1,505 to € 1,204 (-20%), € 1,354 (-10%), 1,655 (+10%) and 1,806 (+20%) per kW.

Lower solar PV costs make it more interesting to install larger PV systems integrated with storage. With 20% cheaper PV systems, an LCOE of € 0.277 per kWh is achieved with 52.1 kWp solar PV and 5.9 kWh storage capacities.

On the other hand, higher PV costs decrease the incentive to install such systems. With 20% more expensive PV systems, an LCOE of € 0.282 is obtained with 14.2 kWp solar PV capacity and no batteries.

Table 4-12 presents the winning architecture for each scenario.

Table 4-12 Sensitivity analysis on solar PV costs, winning architectures (WA) results.

	$P_{PV-20\%}$ WA	$P_{PV-10\%}$ WA	Baseline WA	$P_{PV+10\%}$ WA	$P_{PV+20\%}$ WA
Solar PV Capacity (kWp)	52.1	45.9	34.4	23.4	14.2
Storage Capacity (kWh)	5.9	4.7	0	0.0	0
NPC (€)	1,228,070 €	1,235,457 €	1,242,027 €	1,246,906 €	1,249,175 €
LCOE (€/kWh)	0.277 €	0.279 €	0.281 €	0.282 €	0.282 €
CAPEX (€)	66,940 €	65,467 €	51,773 €	38,800 €	25,763 €
OPEX (€/yr)	99,456 €	100,215 €	101,951 €	103,480 €	104,791 €
Grid power costs (€/yr)	17,458 €	17,458 €	17,458 €	17,458 €	17,458 €
Electricity purchase costs (€/yr)	80,530 €	81,507 €	83,560 €	85,438 €	87,012 €
Direct emissions (gCO2 / kWh)	375	379	387	394	400
Indirect emissions (gCO2 eq. / kWh)	441	446	453	460	467
Renewables Ratio EVs	52.5%	52.0%	52.1%	50.2%	49.4%
Renewables Ratio Mix	47.1%	47.2%	47.5%	47.6%	47.8%

4.4.3 Battery costs

Battery costs (P_{bat}) are replaced from the original € 717 to € 574 (-20%), € 645 (-10%), € 789 (+10%) and € 860 (+20%) per kWh. Table 4-13 presents the winning architecture for each scenario.

Lower battery costs directly impact on the optimum storage capacity. Slightly larger solar PV systems are coupled with storage to generate the lowest LCOE. The system architecture with 20% lower battery costs indicates an LCOE of € 0.280, with 38.5 kWp solar and 6.4 kWh storage capacities.

On the other hand, higher battery costs do not impact the winning architecture, since lowest LCOE is already obtained with a system with no storage. Thus, indicating that installing batteries only becomes profitable at lower capital costs per kWh, or at higher electricity prices as shown in subsection 4.4.1.

Table 4-13 Sensitivity analysis on battery costs, winning architectures (WA) results.

	$P_{bat-20\%}$ WA	$P_{\mathrm{bat}-10\%}$ WA	Baseline WA	$P_{\mathrm{bat}+10\%}$ WA	$P_{\mathrm{bat}+20\%}$ WA
Solar PV Capacity (kWp)	38.5	37.4	34.4	34.4	34.4
Storage Capacity (kWh)	6.4	4.9	0.0	0.0	0.0
NPC (€)	1,240,974 €	1,241,383 €	1,242,027 €	1,242,027 €	1,242,027 €
LCOE (€/kWh)	0.280 €	0.280 €	0.281 €	0.281 €	0.281 €
CAPEX (€)	61,560 €	59,474 €	51,772 €	51,772 €	51,772 €
OPEX (€/yr)	101,022 €	101,236	101,951 €	101,951 €	101,951 €
Grid power costs (€/yr)	17,458 €	17,458 €	17,458 €	17,458 €	17,458 €
Electricity purchase costs (€/yr)	82,597 €	82,827 €	83,560 €	83,560 €	83,560 €
Direct emissions (gCO2 / kWh)	383	384	387	387	387
Indirect emissions (gCO2 eq. / kWh)	450	451	453	453	453
Renewables Ratio EVs	51.5%	51.4%	51.0%	51.0%	51.0%
Renewables Ratio Mix	47.3%	47.4%	47.4%	47.4%	47.4%

4.4.4 Interest rate (i)

Project interest rate (i) are replaced from the original 8.0% to 6.4% (-20%), 7.2% (-10%), 8.8% (+10%) and 9.6% (+20%). Table 4-13 presents the winning architecture for each scenario.

Similarly to the impact of reducing capital costs, lower interest rate de-risk the investment and investing in large solar PV and battery systems become more economically interesting. The operational savings obtained in the long run become more significant than the impact of CAPEX in the cash flow. With 6.4% interest rate, the winning architecture is identified with 47.7 kWp solar and 6.5 kWh storage capacities, achieving an LCOE of € 0.275 per kWh.

On the other hand, higher project interest rates decrease the incentive to invest in solar PV and batteries. This is explained because the operational costs savings in the long run have lower benefit because of higher discount rates, but CAPEX is spent in the first year of the project and is not discounted in the cash flow. With 9.6% interest rate, the winning architecture is identified with 21.0 kWp solar PV capacity and no batteries, achieving an LCOE of € 0.285 per kWh.

Table 4-14 Sensitivity analysis on interest rate, winning architectures (WA) results.

	$i_{-20\%}$ WA	$i_{-10\%}$ WA	Baseline WA	$i_{+10\%}$ WA	$i_{+20\%}$ WA
Solar PV Capacity (kWp)	47.7	42.9	34.4	27.7	21.0
Storage Capacity (kWh)	6.5	5.3	0.0	0.0	0
NPC (€)	1,406,237 €	1,319,587 €	1,242,027 €	1,171,787 €	1,107,183 €
LCOE (€/kWh)	0.275 €	0.278 €	0.281 €	0.283 €	0.285 €
CAPEX (€)	76,411 €	68,349	51,772 €	41,615 €	31,563 €
OPEX (€/yr)	99,900 €	100,528	101,951 €	102,893 €	103,788 €
Grid power costs (€/yr)	17,458 €	17,458 €	17,458 €	17,458 €	17,458 €
Electricity costs (€/yr)	81,154 €	81,936 €	83,560 €	84,722 €	85,820 €
Direct emissions (gCO2 / kWh)	378	381	387	391	395
Indirect emissions (gCO2 eq. / kWh)	444	447	453	458	462
Renewables Ratio EVs	52.2%	51.8%	51.0%	50.51%	50.0%
Renewables Ratio Mix	47.2%	47.3%	47.4%	47.57%	47.7%

4.4.5 Discussion

The presented sensitivity analysis indicates that the largest influence on project economics is driven by electricity prices. That is aligned to the results presented in section 4.1, where the adoption of a RTP tariff based on 2022 day-ahead market prices in Germany reduces LCOE from € 0.530 to € 0.314 per kWh. In addition, both solar generation and storage systems power flows are significantly lower than grid exchanges (purchases). As a result, varying electricity prices over the year lead to significant impact in electricity costs if charging is not properly managed, as indicated by the achieved savings with different smart charging strategies. The impact of price volatility is not investigated here, yet it is expected that the existing challenges to integrate growing renewables in a market ongoing electrification of transportation and other industries maintain market dynamics volatile.

Considering average day-ahead market prices were used to generate the smart charging schedules presented in this work, a dynamic charging scheduling algorithms could combine peak shaving and lower prices-signals to schedule charging optimally. This, however, requires mobility patterns prediction, i.e. understanding the times vehicles are going to be connected to chargers and their energy demand for the next period of operation. Although this falls out of the scope of this work, the identified results indicate that such strategy could enhance savings even further.

The impact of solar PV and batteries hardware and installation costs is also relevant. Since figures used in this work are obtained from the National Renewable Energy Laboratory (NREL) (U.S. Department of Energy, 2023a, 2023b) and not from real market suppliers, the benefits of local renewables integrations can be influenced by real market prices. In the same platform, NREL's work indicates market trends towards decreasing CAPEX for solar PV and batteries in the coming years, as it has been happening over the last decades. Based on current prices, however, investing in solar PV technology is a beneficial decision from an economical and environmental perspective. In addition, solar PV usage maximization can be achieved based on weather and solar generation forecasts integrated with the above-mentioned dynamic charging strategy. The use of stationary storage system is beneficial to maximize solar PV self-consumption, and it can also support energy arbitrage algorithms to maximize electricity purchases at lower costs. Furthermore, the development of bi-directional charging technology can replace the need for stationary storage systems, by leveraging on the idle EV's batteries to also perform energy arbitrage.

Different companies adopt different investment strategies using their defined project economic parameters. The optimal system architecture depends on such figures, and decision makers must assess project cash flows to make an informed decision.

Finally, current inflation rates are rising worldwide, which poses uncertainty on certain materials and commodities – like electricity, raw material for solar PV panels and lithium-ion batteries manufacturing - over the next years. The topic of inflation has not been evaluated in this work, but higher overall prices could lead to different results. The sensitivity analysis presented in section 4.4 analysed individually the impact of varying electricity, solar PV panels and batteries costs. It indicates that the developed tool is powerful to analyse different scenarios, which could combine different prices for all of these variables.

Chapter 5

Conclusions

This chapter presents this work’s conclusions. Main results from the literature review (Chapter 2), use case and methodology (Chapter 3) and results (Chapter 4) are reviewed.

The current thesis intended to analyse cost reduction and carbon emissions reduction potential from different smart charging strategies and renewable electricity self-consumption. Simulations were performed based on a case study of a commercial EV fleet of 65 vehicles charging at their depot. The work explored the following research questions:

- What are the economic and environmental benefits from adopting smart charging strategies, aiming to shave charging peaks and shift demand according to charging schedules?
- What are the economic and environmental benefits from integrating solar PV and batteries with EV smart charging?
- What is the ideal system architecture to minimize project costs over its lifetime?

It explored the impact of different smart charging approaches using a Real-Time-Pricing utility tariff, and renewable electricity local integration. Based on the methodology proposed in this work, various simulations were performed, and economical and environmental indicators were generated. A powerful model to evaluate different scenarios and support investment decision making was developed. This chapter presents the main conclusions obtained throughout the work, providing final remarks about the results presented in each chapter. Future research opportunities are suggested to enhance the knowledge on this thesis topic, impacting EV and energy markets stakeholders, businesses owning EVs and the scientific community.

Chapter 2 presented a comprehensive literature review, targeted to identify similar work under the realm of electric vehicles smart charging and renewable electricity integrations. (Barman et al., 2023), (Sadeghian et al., 2022), (Beaufils & Pineau, 2019) provided an overview of smart charging technology, grids integrations with renewable electricity and EVs. After that, the research focused on EV tariffs trends, and road transportation environmental impact reduction and presented several case studies.

(Barman et al., 2023) highlighted the need for smart charging technology reactive to market signals, enhancing synergies between EVs and electricity grids. The authors describe the existing approaches divided by network charging, shift charging, charging with excess renewables and, on-site renewables integrations and managed charging. These reduce the impact of increased electricity demand from EV adoption, and support grids integrations with renewable electricity. (Hildermeier et al., 2022) reviewed the availability of smart charging tariffs and services in European markets. The authors identified dynamic Time-of-Use tariffs, following spot market prices, as the leading trend in Northern Europe.

(Beaufils & Pineau, 2019), (Boonrach et al., 2021), (Pavan et al., 2019), (Ghatak et al., 2021), (Simolin et al., 2021) and (Verbist et al., 2023) explored local integrations with solar PV, wind and storage systems, smart charging approaches and different utility tariffs structures. The majority focused on project economics, aiming to identify economically feasible solutions for the case studies. HOMER Grid was identified as a common software to perform EV charging and renewable electricity integration simulations, but no study is found to assess dynamic tariffs.

(Haywood & Jakob, 2023), (Heinrichs et al., 2014), and (Xu et al., 2020) studied the environmental impact of electric mobility and the role of carbon emissions accounting and carbon credits mechanisms. The increased adoption of EVs results in higher emissions in electricity systems from fossil fuels-based power plants, especially natural gas. In addition, the adoption of an EU-ETS system to cover transportation is expected to have little impact on fossil fuels production for vehicles because of its price inelasticity. To achieve overall emission reduction, carbon credits tend to be purchased from electricity market players, where decarbonization will occur at lower costs. A pilot project proposed by (Ayo et al., 2023) used granular green electricity certificates to account for green electricity used to charge an EV with local solar electricity and grid purchases.

The literature review identified a gap, where no study evaluated different smart charging strategies based on RTP tariffs and renewable electricity integrations, measuring both economic and environmental benefits. Thus, the aim of this thesis was to investigate these potential benefits.

Chapter 3 presented the case study along with the modelling and simulation methodology. The case study consisted of a German ride-sharing company owning 65 EV fleet and charging at their own parking lot. Data from 2022 was used to measure a total EV demand of 414.8 MWh per year. The company adopted a fixed electricity tariff at € 0.33 per kWh in the first semester of 2022, and € 0.53 per kWh in the second semester of the year. In addition, the utility tariff included a grid power rate of € 8.5 per kW per month, based on the highest demand peak for each month.

The charging infrastructure consisted of 46 slow charging ports (maximum 11 kW) and 12 fast charging ports (maximum 50 kW). Fast chargers were used on demand throughout the day and provided 57% of total demand. Slow chargers were used between operational shifts (08:00 to 20:00 and 20:00 to 08:00), when vehicles parked for 14 hours. Since no smart charging strategy was adopted, vehicles started charging once they were plugged onto chargers. Yet, charging sessions lasted only 2.3 hours and vehicles stood idle in the parking lot for 11.7 hours every shift. This result identified and opportunity to implement smart charging strategies in the flexible slow EV charging demand. he parking lot had an available rooftop area to install up to 200 kWp solar PV capacity, and area and infrastructure to install up to 200 kWh of batteries capacity. A grid connection capacity of 400 kW was in place.

Five smart charging strategies were proposed. Strategy 1 focused on peak shaving and based on starting charging sessions according to the baseline profile, but charging occurred at minimum power rate to distribute the load. Strategy 2, 3 and 4 scheduled charging sessions to match times of lower day-ahead market prices. While Strategy 2 considered a 3-hour charging window, Strategy 3 and 4 extended that to 6 hours. Strategy 5 also generated charging schedules, but matched charging to times of lower carbon intensity using data related to the electricity grid in Germany.

Baseline EV charging load profiles, grid power charges, electricity prices and solar PV and lithium-ion batteries costs were input into HOMER Grid software. Solar PV and battery capital and operational costs were obtained from the National Renewable Energy Laboratory (U.S. Department of Energy, 2023a, 2023b). Solar PV CAPEX was set at € 1,505 per kWp, and operation and maintenance (O&M) were € 16.99 per kWp per year. Batteries CAPEX was set at € 717 per kWh, and O&M were neglected. Smart charging strategies were modelled using HOMER Grid, generating new load profiles and energy balance data. These were combined with day-ahead market prices in a new model proposed by the author, that used solar PV and battery capacities as input. Outputs consisted of project costs and financial parameters, such as Levelized Cost of Energy (LCOE), CAPEX and OPEX, and environmental indicators such as direct and indirect CO2 emissions, and renewable electricity usage for EV charging. Based on energy balances for every 15 minutes of the year, this dynamic model was a powerful tool to evaluate different configurations, with or without solar PV and batteries integrations. The system architecture leading to the lowest LCOE could be identified under different scenarios using Microsoft Excel's Solver with a GRG Non-linear solving method.

Chapter 4 presented simulation results, along with discussions on the impact of smart charging strategies and renewable electricity integrations on systems operations, project financials and EV charging carbon impact. First, the impact of adopting a RTP tariff on the baseline EV charging load. Next, EV loads and project economics were presented for 5 smart charging strategies, along with a discussion on their behaviour. The benefits of integrating solar PV was presented, identifying the system architecture leading to lowest LCOE overall. Results from integrating solar PV and batteries were also presented through two different system architectures, showcasing that the integration of batteries was not economically advantageous. Finally, results from a sensitivity analysis on electricity prices, solar PV and battery CAPEX and project interest rates were presented.

Section 4.1 presented the impact of adopting a Real-Time-Pricing (RTP) tariff to cover the baseline demand over the year. It showed significant EV charging costs savings. In comparison to fixed electricity prices, LCOE decreased from € 0.530 to € 0.314 per kWh, leading to € 80,000 lower operational costs per year. These results clearly indicate the price difference between retail and spot markets, since retail distributors are involved in spot market dynamics, and need to ensure their profitability via electricity revenues. With dynamic tariffs, smart charging strategies plays an important role to minimize operational costs.

Section 4.2 presented the results of the five proposed EV smart charging strategies, providing valuable insights into the trade-offs and advantages of each approach. Unless expressed otherwise, the cost reductions achieved presented below are compared to the baseline scenario using RTP tariffs and no smart charging.

For strategy 1, power charges were reduced by € 9,400 per year and electricity costs increased by € 2,400 per year, reducing LCOE to € 0.296 per kWh. Direct and indirect CO2 emissions were reduced by 5 gCO_2 per kWh and 5 $gCO_{2\,eq}$ per kWh, avoiding the emission of 2.1 ton of CO_2 and $CO_{2\,eq.}$ per year for this case study. The renewable electricity share for EV charging increased to 48.1%. Strategy 1 focused on peak shaving and demonstrated its potential to reduce grid charges and decrease operational costs overall, even though it did not exploit dynamic price opportunities from the day ahead market.

For strategy 2, grid power charges were reduced by € 7,130 per year and electricity costs decreased by € 4,000 per year, reducing LCOE to € 0.285 per kWh. Direct and indirect CO2 emissions were reduced by 5 gCO_2 per kWh and 5 $gCO_{2\,eq}$ per kWh, avoiding the emission of 2.1 ton of CO_2 and $CO_{2\,eq.}$ per year for this case study. The renewable electricity share for EV charging increased to 47.9%. Strategy 2 focused on charging EVs in 3-hour windows at lower day-ahead market prices and indicated the opportunity to reduce grid purchase costs. Since EV demand was concentrated in smaller time-windows, higher charging peaks were obtained in comparison to Strategy 1, reducing the benefits of peak shaving.

For strategy 3 and 4, results were quite similar and were presented together. Grid power costs were reduced by € 9,025 per year and electricity costs decreased by € 2,750 per year, reducing LCOE to € 0.283 per kWh. Direct and indirect CO2 emissions were reduced by 6 gCO_2 per kWh and 6 $gCO_{2\,eq}$ per kWh, avoiding the emission of 2.5 ton of CO_2 and $CO_{2\,eq.}$ per year for this case study. The renewable electricity share for EV charging increased to 48.1%. The benefit of expanding the charging schedules to 6-hour intervals decreases peak demand and grid power charges. Since charging schedules occurs at times of lower day-ahead market prices, electricity costs are also reduced. Strategy 3 and 4 lead to the lowest LCOE within all strategies, combining concepts from Strategy 1 (peak shaving) and Strategy 2 (charging scheduling).

For strategy 5, grid power costs were reduced by € 7,650 per year, but electricity costs remained almost unchanged, resulting in an LCOE of € 0.293 per kWh. Direct and indirect CO2 emissions were reduced by 12 gCO_2 per kWh and 13 $gCO_{2\,eq}$ per kWh, avoiding the emission of 5.0 ton of CO_2 and 5.4 $CO_{2\,eq.}$ per year for this case study. The renewable electricity share for EV charging increased to 49.0%. Strategy 5 generated charging schedules based on times of lowest carbon impact from grid purchases. The environmental benefits were delivered, but since this strategy does not exploit lower electricity prices, operational costs are not reduced as much as they are with Strategies 3 and 4.

The obtained results from the modelled smart charging strategies, with no local renewable electricity integration, identified several potential benefits. Minimizing charging power (Strategy 1) lead to lower grid power charges. Charging primarily at times of lower electricity prices while avoiding peaks (Strategies 3 and 4) lead to the lowest LCOE and highest cost savings opportunity. Charging primarily at times of lower electricity grids emission factors (Strategy 5), on the other hand, successfully decreased direct and indirect CO2 emissions, but at higher operational costs. Although a relationship between lower day-ahead electricity prices and lower direct CO2 emissions exists, as indicated in Session 3.3.1, it does not seem to mean that minimizing costs leads to minimum carbon impact, and vice-versa. Nevertheless, implementing smart charging strategies requires no capital investments and can save costs, and increase renewable electricity usage.

Session 4.3.1 presented results from solar PV integrations. For every PV system capacity analysed, smart charging strategies 3 and 4 again outperformed the other ones in terms of reduced LCOE. The LCOE optimization algorithm indicated a winning architecture with 34.4 kWp of solar PV capacity using smart charging Strategy 3. 32.6 MWh of electricity was produced over the year, and 28.4 MWh of it was used to charge EVs, reaching 87% of solar PV self-consumption. Although CAPEX reached € 51,700, grid demand costs and electricity costs were each reduced by € 9,000 (total € 18,000) per year. As a result, LCOE was € 0.281 per kWh, the lowest among all simulations. Direct and indirect CO2 emissions were reduced by 29 gCO_2 per kWh and 31 $gCO_{2\,eq}$ per kWh, respectively, avoiding the emission of 12.0 ton of CO_2 and 12.9 $CO_{2\,eq.}$ per year for this case study. The renewable electricity share for EV charging increased to 52.1%. Over the 25 years of project lifetime, the winning architecture saved € 148,000 for the EV fleet in Net Present Cost.

A system combining smart charging Strategy 3 with 150 kWp and 61 kWh reduced grid purchasing demand by 93.8 MWh per year. OPEX was reduced by € 26,000 per year from reduced grid power costs

(€ 9,000) and electricity costs (€ 23,500). CAPEX requirements increased significantly to € 269,600, resulting in an LCOE of € 0.306 per kWh. Direct and indirect CO2 emissions were reduced by 87 gCO_2 per kWh and 80 $gCO_{2\,eq}$ per kWh, respectively, avoiding the emission of 36.1 ton of CO_2 and 33.2 $CO_{2\,eq.}$ per year for this case study. The renewable electricity share increased to 58.3%. Over the 25 years of project lifetime, the winning architecture saved only € 33,700 for the EV fleet in Net Present Cost.

These results seem to indicate that the combination of smart charging and solar PV production directly reduces operational costs and carbon emissions. Solar PV production helped minimizing EV charging demand peaks, and it directly decreased the need for purchasing electricity. When combined with smart charging Strategy 3 to keep grid purchases at times of lower prices, operational costs were reduced significantly. In addition, local solar PV production does not emit CO2 directly, and its indirect emission factor (35.1 $gCO_{2\,eq.}$ per kWh) is over 13 times smaller than the average German grid's mix (472.6 $gCO_{2\,eq.}$ per kWh). Although larger PV systems maximized cost savings and emissions reductions, as systems grew in capacity the capital requirements became too large, and CAPEX increases were not offset by operational cost reductions. Therefore, properly sizing the solar PV system based on actual EV demand and smart charging strategies seems to be crucial to maximize cost savings and identify the most financially interesting projects.

Session 4.3.2 presented results from integrating batteries with PV systems to maximize solar self-consumption. Once again, smart charging Strategies 3 and 4 lead to lowest LCOE than the others. Nonetheless, results seem to indicate that investing in batteries is not economically interesting.

A system architecture using smart charging Strategy 3 and a 10 kWh storage system coupled with the winning architecture's 34.4 kWp of solar PV capacity was presented. Solar PV self-consumption increased to 92.1%, and the system utilized 30.1 MWh per year of solar PV electricity to charge EVs. CAPEX increased to € 59,000. Grid power costs were the same as the system with no storage, implicating that the proposed storage system did not influence overall EV peak demand. In comparison to the PV-only system, electricity purchase costs were reduced by only € 400 per year, and the same LCOE of € 0.281 per kWh was achieved. By adding batteries to the system, direct CO2 emissions were reduced by 2 gCO_2 per kWh, but indirect emissions remained the same since batteries bring about a higher life-cycle impact, offsetting the benefits from lower grid purchase demand. The renewable electricity share for EV charging increased from 52.1% with solar PV only to 52.2% with solar PV and batteries.

A larger solar PV and storage system (150 kWp and 61 kWh) was also presented. Solar PV consumption increased to 93.7 MWh (65% of the total 142.4 MWh produced by the PV system), reducing grid electricity purchase costs to € 69,100 per year but not impacting on grid demand charges. The € 269,600 capital cost required to install such system increased the project's LCOE to € 0.306 per kWh. Such system maximized emissions reduction and renewable electricity usage. When compared to the baseline scenario, direct and indirect CO2 emissions were reduced by 36.1 gCO_2 per kWh and 33.2 $gCO_{2\,eq}$ per kWh, avoiding the emission of 136.4 ton of CO_2 and 167.6 $CO_{2\,eq.}$ per year for this case study. The renewable electricity share for EV charging increased to 58.3%.

Based on the presented results, solar PV and batteries indicate increased electricity self-consumption rates, decreasing operational costs and reducing carbon emissions. Nevertheless, the investment in batteries is not solely justified on project economics, because of high capital requirements in comparison to the benefits generated. Furthermore, the ongoing development of vehicle-to-grid and bi-directional charging technologies could soon enough make stationary storage even less necessary. This work did not consider using batteries for energy arbitrage purposes, which would most likely enhance savings opportunities from day-ahead market prices volatility. These results indicated the environmental benefits of integrating solar PV and storage systems come at a higher cost, driven by large battery capital requirements.

Section 4.4 presented a sensitivity analysis on electricity prices, solar PV and batteries CAPEX, and project interest rate. As expected, lower electricity prices decrease the benefits of solar PV and batteries integrations, and higher electricity prices make them more attractive. Similarly, lower hardware CAPEX directly encourages larger systems to be built, and vice-versa. Nonetheless, lower battery costs lead to optimum architecture of similar solar PV and larger storage capacities. Finally, lower project interest rate de-risk the investment and investing in large solar PV and battery systems become more economically interesting.

Final conclusions:

This thesis provided a comprehensive analysis to evaluate EV smart charging strategies and local renewable electricity integrations, measuring economic and environmental aspects. Results obtained successfully addressed the research questions.

Adopting smart charging strategies can save costs and decrease the environmental impact of EV charging, at no capital requirements. Charging strategies proposed in this work go hand-in-hand with the dynamic electricity tariff adoption trend presented by (Hildermeier et al., 2022). These tariffs encourage EV smart charging in sync with energy market dynamics, offering price incentives to charge EV with greener energy. These savings are enhanced with smart charging, which can decrease grid power fees and electricity purchasing costs.

The benefits of integrating solar PV and batteries to reduce emissions and operational costs is clear. However, higher capital expenses for larger systems are not always compensated by lower operational costs in the long run. Sizing the ideal solar PV and batteries system depends upon properly modelling EV smart charging demand profiles, so that solar PV self-consumption, grid purchases and grid sales can be accurately quantified.

For this case study, the lowest LCOE was obtained for a system with solar PV only, since adding batteries increased project costs. 34.4 kWp of solar PV capacity was integrated to a smart charging strategy based on 6-hour charging windows of lower electricity prices from the day ahead-market in Germany. This system reduced electricity demand at times of solar PV production, minimized EV charging peaks, purchased electricity at lower prices, and increased the use of renewable electricity to charge the EV fleet.

Future directions:

(Beaufils & Pineau, 2019) indicated that utility pricing must be cost reflective and provide price stability and predictability for customers. Given the proposed RTP tariffs is indexed to the day-ahead electricity market, it directly exposes EV owners to energy markets volatility and, to some extent, unpredictability. To incentivize the adoption of EVs and dynamic tariffs, smart charging strategies and cost savings opportunities must be thoroughly distributed to potential users. This thesis delivered a comprehensive analysis, indicating the advantages and disadvantages of smart charging strategies and renewable electricity integrations, as well as a methodology that can be applied for different case studies. A framework based on a similar methodology could be developed to identify the optimum system in various conditions. While this case study implicated a complex EV charging demand, with fast on-demand chargers and flexible slow chargers, other use cases may be more standard and applicable to a wider audience.

This thesis proposed and identified considerable savings from smart charging strategies based on fixed charging schedules. Yet, it is suggested that dynamic smart charging strategies should be evaluated to maximize market opportunities in real time and minimize projects risks (Verbist et al., 2023). Energy arbitrage, grid balancing services, vehicle-to-grid and vehicle-to-building value streams could make EV charging not only cheaper, but also greener by combining different smart charging strategies depending on market dynamics. Dynamic smart charging algorithms are more complex, requiring demand, pricing and self-consumption forecasting as well as they should react on real-time to market signals to maximize EVs synergies with grids and maximize project economics for EV owners. These value streams are a window of opportunity for commercial EV fleets, and studying these based on concrete use cases is a great extension of this work.

The impact of EV smart charging on grids renewable electricity integration has not been studied in-depth in the context of EU ETS and transportation decarbonization in Europe. More complex smart charging strategies, such as the ones presented in this thesis, could enhance the outcomes of researches using similar methodology to (Haywood & Jakob, 2023) and (Heinrichs et al., 2014).

While green electricity credits are still not commonly applied to smart charging in Europe, accounting for the environmental impact of EV charging is crucial to make the transition towards electric mobility green. Measuring carbon impact is the first step towards minimizing it, and companies may opt for reducing their emissions for their own reasons. Another identified research opportunity is to expand (Ayo et al., 2023)'s green electricity accounting methodology using blockchain technology, using this thesis' approach to simulate different smart charging strategies and renewable electricity integrations considering dynamic electricity tariffs.

References

Ayo, O., Zhang, H., Moreira, R., Bertin, D., & Zribi, N. (2023). Electric Vehicle Charging with Fractional Renewable Energy Certificates Using Blockchain Technology. *2023 IEEE Belgrade PowerTech*, 01–07. https://doi.org/10.1109/PowerTech55446.2023.10202972

Barman, P., Dutta, L., Bordoloi, S., Kalita, A., Buragohain, P., Bharali, S., & Azzopardi, B. (2023). Renewable energy integration with electric vehicle technology: A review of the existing smart charging approaches. *Renewable and Sustainable Energy Reviews*, *183*, 113518. https://doi.org/10.1016/j.rser.2023.113518

Beaufils, T., & Pineau, P.-O. (2019). Assessing the impact of residential load profile changes on electricity distribution utility revenues under alternative rate structures. *Utilities Policy*, *61*, 100959. https://doi.org/10.1016/j.jup.2019.100959

Boonrach, N., Janjamraj, N., & Bhumkittipich, K. (2021). Optimal Energy Storage System in Residential Micro-Grid for EV Charging Station Penetration. *2021 International Conference on Power, Energy and Innovations (ICPEI)*, 37–40. https://doi.org/10.1109/ICPEI52436.2021.9690687

Electricity Maps. (2023a). *Data Portal—Germany* [dataset]. https://www.electricitymaps.com/data-portal/germany

Electricity Maps. (2023b). *Electricity Maps Methodology*. https://www.electricitymaps.com/methodology

Ensslen, A., Gnann, T., Globisch, J., Plötz, P., Jochem, P., & Fichtner, W. (2016). Willingness to Pay for E-Mobility Services: A Case Study from Germany. *Proceedings of Karlsruhe Service Community Workshop*, 1–14.

entso-e. (2023a). *Actual Generation per Generation Unit—BZN | DE-LU* [dataset]. https://transparency.entsoe.eu/generation/r2/actualGenerationPerGenerationUnit

entso-e. (2023b). *Day-ahead Prices Germany—BZN | DE-LU* [dataset]. https://transparency.entsoe.eu/transmission-domain/r2/dayAheadPrices/show?name=&defaultValue=true&viewType=GRAPH&areaType=

BZN&atch=false&dateTime.dateTime=01.01.2022+00:00|CET|DAY&biddingZone.values=CTY|10Y1001A1001A83F!BZN|10Y1001A1001A82H&resolution.values=PT15M&resolution.values=PT30M&resolution.values=PT60M&dateTime.timezone=CET_CEST&dateTime.timezone_input=CET+(UTC+1)+/+CEST+(UTC+2)

European Commission. (2022). *EU Emission Trading System (EU ETS) Union Registry—Verified Emissions for 2021* [dataset]. https://climate.ec.europa.eu/eu-action/eu-emissions-trading-system-eu-ets/union-registry_en

European Parliament. (2022). *A European Green Deal* | *Revision of the EU emission trading system (ETS)*. https://www.europarl.europa.eu/legislative-train/carriage/revision-of-the-eu-emission-trading-system-(ets)/report?sid=6501

Ghatak, A., Alfred, R. B., & Singh, R. R. (2021). Optimization for Electric Vehicle Charging Station using Homer Grid. *2021 Innovations in Power and Advanced Computing Technologies (i-PACT)*, 1–7. https://doi.org/10.1109/i-PACT52855.2021.9696626

Haywood, L., & Jakob, M. (2023). The role of the emissions trading scheme 2 in the policy mix to decarbonize road transport in the European Union. *Transport Policy*, *139*, 99–108. https://doi.org/10.1016/j.tranpol.2023.06.003

Heinrichs, H., Jochem, P., & Fichtner, W. (2014). Including road transport in the EU ETS (European Emissions Trading System): A model-based analysis of the German electricity and transport sector. *Energy*, *69*, 708–720. https://doi.org/10.1016/j.energy.2014.03.061

Hildermeier, J., Burger, J., Jahn, A., & Rosenow, J. (2022). A Review of Tariffs and Services for Smart Charging of Electric Vehicles in Europe. *Energies*, *16*(1), 88. https://doi.org/10.3390/en16010088

HOMER Software. (2023). *HOMER Grid—Distributed Energy + EV Charging* (1.10.2). https://www.homerenergy.com/products/grid/index.html

International Energy Agency. (2023). *Global EV Outlook 2023: Catching up with Climate Ambitions*. OECD. https://doi.org/10.1787/cbe724e8-en

Pavan, A. M., Lughi, V., & Scorrano, M. (2019). Total Cost of Ownership of electric vehicles using energy from a renewable-based microgrid. *2019 IEEE Milan PowerTech*, 1–6.

https://doi.org/10.1109/PTC.2019.8810736

Sadeghian, O., Oshnoei, A., Mohammadi-ivatloo, B., Vahidinasab, V., & Anvari-Moghaddam, A. (2022). A comprehensive review on electric vehicles smart charging: Solutions, strategies, technologies, and challenges. *Journal of Energy Storage*, *54*, 105241. https://doi.org/10.1016/j.est.2022.105241

Schlömer, S., Hänsel, G., de Jager, D., & Neelis, M. (2014). *Technology-specific Cost and Performance Parameters*.

Simolin, T., Rauma, K., Viri, R., Mäkinen, J., Rautiainen, A., & Järventausta, P. (2021). Charging powers of the electric vehicle fleet: Evolution and implications at commercial charging sites. *Applied Energy*, *303*, 117651. https://doi.org/10.1016/j.apenergy.2021.117651

Statista. (2023). *Annual electricity prices (including electricity tax) for industrial businesses in Germany from 1998 to 2022* [dataset]. https://www.statista.com/statistics/1050448/industrial-electricity-prices-including-tax-germany/

U.S. Department of Energy. (2023a). *NREL Annual Technology Baseline—Commercial Battery Storage 2022* [dataset]. https://atb.nrel.gov/electricity/2022/commercial_battery_storage

U.S. Department of Energy. (2023b). *NREL Annual Technology Baseline—Commercial PV 2022* [dataset]. https://atb.nrel.gov/electricity/2022/commercial_pv

Verbist, F., Panda, N. K., Vergara, P. P., & Palensky, P. (2023). *Impact of Dynamic Tariffs for Smart EV Charging on LV Distribution Network Operation* (arXiv:2306.10775). arXiv. http://arxiv.org/abs/2306.10775

Wirth, H., & Fraunhofer ISE. (2023). *Recent Facts about Photovoltaics in Germany*.

Xu, L., Yilmaz, H. Ü., Wang, Z., Poganietz, W.-R., & Jochem, P. (2020). Greenhouse gas emissions of electric vehicles in Europe considering different charging strategies. *Transportation Research Part D: Transport and Environment*, *87*, 102534. https://doi.org/10.1016/j.trd.2020.102534

Annexes

Annexes … describe

Annex A. EV fleet charging behaviour

This annex presents detailed EV fleet charging data. Average demand data and charging sessions behaviour are presented for the slow and fast charging infrastructure, on weekdays and weekends.

Slow AC charging in weekdays and weekends (2022).

	Sessions started (# per period)	Energy demand (kWh / session)	Mean time connected (h/session)	Time charging per session (% of total)
Weekdays	**23.55**	**15.09**	**13.71**	**17%**
00:00:00	1.24	15.7	13.7	17%
01:00:00	1.73	17.3	14.2	18%
02:00:00	2.09	17.8	14.1	19%
03:00:00	1.67	17.6	12.9	21%
04:00:00	0.90	16.2	11.5	21%
05:00:00	0.04	12.5	12.9	15%
06:00:00	0.17	8.1	8.8	14%
07:00:00	0.10	13.7	10.1	21%
08:00:00	0.06	10.4	11.5	14%
09:00:00	0.14	14.4	6.0	36%
10:00:00	0.35	14.7	14.1	16%
11:00:00	0.66	13.1	17.1	12%
12:00:00	1.12	14.1	14.0	15%
13:00:00	1.31	15.0	10.7	21%
14:00:00	1.17	13.6	10.8	19%
15:00:00	1.17	13.0	12.5	16%
16:00:00	1.07	14.7	14.9	15%
17:00:00	1.16	13.4	12.4	16%
18:00:00	1.32	15.3	13.4	17%
19:00:00	0.97	13.9	13.9	15%
20:00:00	0.90	13.2	17.3	12%
21:00:00	1.56	13.8	17.4	12%
22:00:00	1.66	15.0	14.6	16%
23:00:00	0.99	15.4	14.0	17%
Weekends	**33.65**	**16.11**	**14.52**	**17%**
00:00:00	1.11	14.5	14.8	15%
01:00:00	1.27	15.7	13.3	18%
02:00:00	2.39	18.4	16.0	17%
03:00:00	4.13	17.9	13.8	20%
04:00:00	5.12	18.4	16.1	17%
05:00:00	3.63	18.0	14.7	19%
06:00:00	2.18	17.3	15.1	17%
07:00:00	0.29	16.3	15.4	16%
08:00:00	0.13	13.1	13.3	15%
09:00:00	0.11	15.6	15.1	16%

10:00:00	0.19	14.1	11.0	19%
11:00:00	0.55	14.0	9.6	22%
12:00:00	0.57	13.9	12.2	17%
13:00:00	0.85	14.3	8.9	24%
14:00:00	0.88	12.0	9.3	20%
15:00:00	1.08	12.6	10.9	18%
16:00:00	1.07	14.7	14.3	16%
17:00:00	0.79	15.1	12.5	18%
18:00:00	0.94	14.7	7.9	28%
19:00:00	1.08	13.5	14.0	15%
20:00:00	1.31	12.4	17.8	11%
21:00:00	1.40	12.6	17.5	11%
22:00:00	1.68	14.6	21.0	11%
23:00:00	0.91	15.1	11.7	20%

Fast DC charging in weekdays and weekends (2022).

	Sessions started (# per period)	Energy demand (kWh / session)	Mean time connected (h/session)	Time charging per session (% of total)
Weekdays	**33.05**	**12.92**	**0.49**	**55%**
00:00:00	1.97	15.3	0.5	66%
01:00:00	1.11	14.6	0.5	57%
02:00:00	1.68	15.0	0.6	50%
03:00:00	1.05	15.2	0.6	49%
04:00:00	0.59	15.5	0.7	48%
05:00:00	0.19	9.4	0.3	61%
06:00:00	0.34	7.8	0.3	48%
07:00:00	0.20	8.1	0.3	60%
08:00:00	0.41	8.4	0.3	52%
09:00:00	1.00	12.7	0.5	58%
10:00:00	1.67	13.3	0.5	60%
11:00:00	1.81	12.7	0.5	55%
12:00:00	1.54	13.2	0.5	55%
13:00:00	1.39	12.9	0.5	52%
14:00:00	1.27	12.5	0.5	52%
15:00:00	1.40	12.9	0.5	53%
16:00:00	1.21	11.7	0.5	51%
17:00:00	1.16	11.8	0.5	54%
18:00:00	1.57	11.7	0.5	53%
19:00:00	1.71	11.7	0.5	54%
20:00:00	2.27	12.2	0.5	56%
21:00:00	2.51	12.5	0.5	56%
22:00:00	2.41	12.5	0.5	56%
23:00:00	2.57	13.6	0.5	61%

Weekends	50.59	14.06	0.51	58%
00:00:00	3.89	13.8	0.5	59%
01:00:00	3.88	15.4	0.5	67%
02:00:00	3.72	16.0	0.6	60%
03:00:00	3.29	17.2	0.6	60%
04:00:00	2.57	16.8	0.6	56%
05:00:00	1.63	16.0	0.6	55%
06:00:00	1.85	14.9	0.6	56%
07:00:00	0.66	13.6	0.4	66%
08:00:00	0.72	10.8	0.5	44%
09:00:00	0.94	13.6	0.5	59%
10:00:00	1.73	14.1	0.5	62%
11:00:00	1.52	14.4	0.5	62%
12:00:00	1.25	13.1	0.5	55%
13:00:00	1.53	12.0	0.5	49%
14:00:00	1.40	12.8	0.5	54%
15:00:00	1.57	13.0	0.5	58%
16:00:00	1.92	13.0	0.5	53%
17:00:00	1.60	13.2	0.5	54%
18:00:00	1.68	13.0	0.5	60%
19:00:00	1.94	11.6	0.5	49%
20:00:00	2.35	13.1	0.5	57%
21:00:00	2.68	12.4	0.5	56%
22:00:00	3.09	12.4	0.5	56%
23:00:00	3.17	13.5	0.5	60%

Annex B. Day-ahead market prices in Germany, 2022.

The table below presents average day-ahead market prices in € per kWh, over the year in Germany, in 2022, for every day of the week. The colourful gradient background helps identify the times at which prices were lower, on average.

Hour of the day	Sunday	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday
00 – 01	0.19 €	0.20 €	0.23 €	0.24 €	0.23 €	0.22 €	0.22 €
01 – 02	0.18 €	0.18 €	0.22 €	0.22 €	0.22 €	0.21 €	0.20 €
02 – 03	0.17 €	0.17 €	0.21 €	0.22 €	0.21 €	0.20 €	0.19 €
03 – 04	0.16 €	0.17 €	0.21 €	0.21 €	0.20 €	0.20 €	0.18 €
04 – 05	0.16 €	0.17 €	0.21 €	0.21 €	0.21 €	0.20 €	0.18 €
05 – 06	0.16 €	0.19 €	0.23 €	0.23 €	0.22 €	0.22 €	0.18 €
06 – 07	0.16 €	0.24 €	0.28 €	0.27 €	0.26 €	0.27 €	0.19 €
07 – 08	0.16 €	0.28 €	0.32 €	0.31 €	0.30 €	0.30 €	0.20 €
08 – 09	0.16 €	0.30 €	0.33 €	0.33 €	0.31 €	0.31 €	0.21 €
09 – 10	0.15 €	0.28 €	0.31 €	0.30 €	0.28 €	0.29 €	0.20 €
10 – 11	0.14 €	0.25 €	0.27 €	0.27 €	0.26 €	0.26 €	0.19 €
11 – 12	0.13 €	0.23 €	0.26 €	0.25 €	0.24 €	0.24 €	0.17 €
12 – 13	0.12 €	0.22 €	0.24 €	0.24 €	0.23 €	0.23 €	0.16 €
13 – 14	0.10 €	0.21 €	0.23 €	0.23 €	0.22 €	0.21 €	0.14 €
14 – 15	0.09 €	0.21 €	0.23 €	0.22 €	0.22 €	0.21 €	0.13 €
15 – 16	0.11 €	0.22 €	0.25 €	0.24 €	0.23 €	0.22 €	0.15 €
16 – 17	0.14 €	0.24 €	0.26 €	0.26 €	0.25 €	0.23 €	0.17 €
17 – 18	0.19 €	0.28 €	0.30 €	0.29 €	0.28 €	0.26 €	0.21 €
18 – 19	0.24 €	0.32 €	0.34 €	0.33 €	0.31 €	0.29 €	0.25 €
19 – 20	0.27 €	0.34 €	0.36 €	0.36 €	0.33 €	0.31 €	0.26 €
20 – 21	0.26 €	0.32 €	0.34 €	0.33 €	0.31 €	0.29 €	0.25 €
21 – 22	0.25 €	0.29 €	0.31 €	0.30 €	0.29 €	0.27 €	0.24 €
22 – 23	0.24 €	0.27 €	0.28 €	0.27 €	0.27 €	0.26 €	0.23 €
23 – 00	0.22 €	0.24 €	0.25 €	0.24 €	0.23 €	0.23 €	0.21 €

Annex C. Day-ahead market prices considered in Strategy 2 charging schedule.

Day-ahead market lowest prices on weekdays considered in Strategy 2.

	jan/22	fev/22	mar/22	abr/22	mai/22	jun/22	jul/22	ago/22	set/22	out/22	nov/22	dez/22
08:00 - 09:00												0,30 €
09:00 - 10:00												
10:00 - 11:00												
11:00 - 12:00												
12:00 - 13:00	0,19 €	0,12 €	0,22 €							0,13 €	0,19 €	
13:00 - 14:00	0,19 €	0,12 €	0,22 €	0,15 €	0,15 €	0,19 €	0,27 €	0,42 €	0,29 €	0,13 €	0,19 €	0,31 €
14:00 - 15:00	0,19 €	0,12 €	0,22 €	0,15 €	0,14 €	0,18 €	0,25 €	0,41 €	0,29 €	0,13 €	0,20 €	0,30 €
15:00 - 16:00				0,15 €	0,14 €	0,19 €	0,26 €	0,43 €	0,31 €			
16:00 - 17:00												
17:00 - 18:00												
18:00 - 19:00												
19:00 - 20:00												
20:00 - 21:00												
21:00 - 22:00												
22:00 - 23:00												
23:00 - 00:00			0,24 €									
00:00 - 01:00												
01:00 - 02:00		0,10 €		0,15 €								
02:00 - 03:00	0,13 €	0,10 €	0,24 €	0,15 €	0,17 €	0,20 €	0,30 €	0,43 €	0,29 €	0,12 €		
03:00 - 04:00	0,12 €	0,10 €	0,24 €	0,15 €	0,17 €	0,20 €	0,30 €	0,42 €	0,28 €	0,11 €	0,10 €	0,18 €
04:00 - 05:00	0,13 €				0,17 €	0,20 €	0,30 €	0,42 €	0,29 €	0,12 €	0,10 €	0,17 €
05:00 - 06:00											0,10 €	0,17 €
06:00 - 07:00												
07:00 - 08:00												

Day-ahead market lowest prices on weekends considered in Strategy 2.

	jan	fev	mar	abr	mai	jun	jul	ago	set	out	nov	dez
08:00 - 09:00	0,12 €										0,15 €	0,19 €
09:00 - 10:00												0,21 €
10:00 - 11:00												
11:00 - 12:00												
12:00 - 13:00		0,09 €	0,12 €							0,09 €		
13:00 - 14:00	0,13 €	0,08 €	0,09 €	0,06 €	0,08 €	0,08 €	0,11 €	0,19 €	0,17 €	0,08 €	0,16 €	
14:00 - 15:00	0,13 €	0,08 €	0,09 €	0,05 €	0,07 €	0,07 €	0,09 €	0,18 €	0,16 €	0,07 €	0,15 €	0,22 €
15:00 - 16:00				0,05 €	0,08 €	0,09 €	0,10 €	0,22 €	0,18 €			
16:00 - 17:00												
17:00 - 18:00												
18:00 - 19:00												
19:00 - 20:00												
20:00 - 21:00												
21:00 - 22:00												
22:00 - 23:00												
23:00 - 00:00		0,10 €										
00:00 - 01:00												
01:00 - 02:00												
02:00 - 03:00			0,19 €	0,13 €					0,23 €			
03:00 - 04:00		0,10 €	0,19 €	0,13 €	0,14 €			0,38 €	0,23 €	0,10 €		
04:00 - 05:00	0,10 €	0,10 €		0,13 €	0,15 €	0,16 €	0,24 €	0,37 €	0,22 €	0,10 €	0,13 €	0,17 €
05:00 - 06:00	0,10 €				0,15 €	0,16 €	0,24 €	0,37 €		0,10 €	0,13 €	0,17 €
06:00 - 07:00	0,09 €					0,16 €					0,13 €	0,17 €
07:00 - 08:00			0,19 €				0,24 €					

Annex D. Day-ahead market prices considered in Strategy 3 charging schedule.

Table 0-1 Day-ahead market lowest prices on weekdays considered for Strategy 3.

	jan	fev	mar	abr	mai	jun	jul	ago	set	out	nov	dez
08:00 - 09:00											0,21 €	0,30 €
09:00 - 10:00												
10:00 - 11:00	0,21 €	0,14 €	0,25 €								0,21 €	
11:00 - 12:00	0,21 €	0,13 €	0,24 €	0,17 €	0,17 €	0,21 €	0,32 €	0,46 €	0,35 €	0,15 €	0,20 €	
12:00 - 13:00	0,19 €	0,12 €	0,22 €	0,16 €	0,16 €	0,20 €	0,29 €	0,43 €	0,31 €	0,13 €	0,19 €	0,32 €
13:00 - 14:00	0,19 €	0,12 €	0,22 €	0,15 €	0,15 €	0,19 €	0,27 €	0,42 €	0,29 €	0,13 €	0,19 €	0,31 €
14:00 - 15:00	0,19 €	0,12 €	0,22 €	0,15 €	0,14 €	0,18 €	0,25 €	0,41 €	0,29 €	0,13 €	0,20 €	0,30 €
15:00 - 16:00	0,21 €	0,13 €	0,24 €	0,15 €	0,14 €	0,19 €	0,26 €	0,43 €	0,31 €	0,14 €		0,31 €
16:00 - 17:00				0,16 €	0,16 €	0,20 €	0,28 €	0,46 €	0,35 €	0,16 €		0,32 €
17:00 - 18:00												
18:00 - 19:00												
19:00 - 20:00												
20:00 - 21:00												
21:00 - 22:00												
22:00 - 23:00												
23:00 - 00:00			0,24 €						0,32 €			
00:00 - 01:00	0,14 €	0,10 €	0,25 €	0,16 €	0,19 €	0,22 €	0,35 €	0,46 €	0,32 €	0,13 €		
01:00 - 02:00	0,13 €	0,10 €	0,24 €	0,15 €	0,17 €	0,21 €	0,32 €	0,43 €	0,30 €	0,12 €	0,12 €	0,19 €
02:00 - 03:00	0,13 €	0,10 €	0,24 €	0,15 €	0,17 €	0,20 €	0,30 €	0,43 €	0,29 €	0,12 €	0,11 €	0,18 €
03:00 - 04:00	0,12 €	0,10 €	0,24 €	0,15 €	0,17 €	0,20 €	0,30 €	0,42 €	0,28 €	0,11 €	0,10 €	0,18 €
04:00 - 05:00	0,13 €	0,10 €	0,24 €	0,15 €	0,17 €	0,20 €	0,30 €	0,42 €	0,29 €	0,12 €	0,10 €	0,17 €
05:00 - 06:00	0,14 €	0,11 €		0,17 €	0,18 €	0,21 €	0,32 €	0,45 €		0,13 €	0,10 €	0,17 €
06:00 - 07:00											0,12 €	0,19 €
07:00 - 08:00												

Table 0-2 Day-ahead market lowest prices on weekends considered for Strategy 3.

	jan	fev	mar	abr	mai	jun	jul	ago	set	out	nov	dez
08:00 - 09:00	0,12 €										0,15 €	0,19 €
09:00 - 10:00	0,14 €										0,16 €	0,21 €
10:00 - 11:00	0,14 €	0,10 €	0,14 €			0,12 €						0,23 €
11:00 - 12:00		0,10 €	0,13 €	0,09 €	0,11 €	0,12 €	0,15 €	0,29 €	0,22 €	0,10 €	0,16 €	
12:00 - 13:00		0,09 €	0,12 €	0,08 €	0,10 €	0,10 €	0,13 €	0,23 €	0,20 €	0,09 €	0,16 €	
13:00 - 14:00	0,13 €	0,08 €	0,09 €	0,06 €	0,08 €	0,08 €	0,11 €	0,19 €	0,17 €	0,08 €	0,16 €	0,23 €
14:00 - 15:00	0,13 €	0,08 €	0,09 €	0,05 €	0,07 €	0,07 €	0,09 €	0,18 €	0,16 €	0,07 €	0,15 €	0,22 €
15:00 - 16:00	0,13 €	0,09 €	0,12 €	0,05 €	0,08 €	0,09 €	0,10 €	0,22 €	0,18 €	0,09 €		0,23 €
16:00 - 17:00				0,07 €	0,10 €		0,13 €	0,27 €	0,23 €	0,10 €		
17:00 - 18:00												
18:00 - 19:00												
19:00 - 20:00												
20:00 - 21:00												
21:00 - 22:00												
22:00 - 23:00												
23:00 - 00:00												
00:00 - 01:00	0,11 €											
01:00 - 02:00				0,13 €					0,23 €	0,11 €		
02:00 - 03:00		0,10 €	0,19 €	0,13 €	0,15 €	0,18 €	0,26 €	0,41 €	0,23 €	0,11 €	0,14 €	0,18 €
03:00 - 04:00	0,11 €	0,10 €	0,19 €	0,13 €	0,14 €	0,17 €	0,25 €	0,38 €	0,23 €	0,10 €	0,14 €	0,18 €
04:00 - 05:00	0,10 €	0,10 €	0,20 €	0,13 €	0,15 €	0,16 €	0,24 €	0,37 €	0,22 €	0,10 €	0,13 €	0,17 €
05:00 - 06:00	0,10 €	0,11 €	0,20 €	0,13 €	0,15 €	0,16 €	0,24 €	0,37 €	0,23 €	0,10 €	0,13 €	0,17 €
06:00 - 07:00	0,09 €	0,11 €	0,20 €	0,13 €	0,15 €	0,16 €	0,24 €	0,38 €	0,24 €	0,10 €	0,13 €	0,17 €
07:00 - 08:00	0,11 €		0,19 €		0,15 €	0,16 €	0,24 €	0,40 €			0,14 €	0,18 €