Smart Charging, Smarter Grids

Unlocking the Potential of Electric Vehicles in Mitigating Grid Congestion

Nico Brinkel

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Unlocking the Potential of Electric Vehicles in Mitigating Grid Congestion

Slim laden, Slimmere Netten

Het benutten van het potentieel van elektrische voertuigen om netcongestie tegen te gaan
(met een samenvatting in het Nederlands)

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Summary

Could the charging of electric vehicles (EVs) be a remedy to grid congestion, rather than a cause? The rapid adoption of EVs, heat pumps and photovoltaic systems has significantly increased the power flows through the electricity grid. This can induce grid congestion, especially since much of the additional grid load is concentrated at specific moments. However, smart EV charging, where charging demand is shifted to times of low grid usage, has been widely recognized as a potential remedy for this issue. Nonetheless, there remains a lack of understanding regarding the most effective ways to leverage the flexibility of EV charging to address grid congestion, particularly from a system-wide perspective. In this context, this dissertation explores different mechanisms that grid operators can use to stimulate smart charging, while also exploring two key barriers hindering the effective implementation of such smart charging systems.

The first three chapters of this thesis investigate the system impact of various mechanisms that grid operators can use to mitigate grid congestion through smart charging, including capacity-limitation systems and alternative grid tariff structures. **Chapter 2** examines a system based on a capacity-limitation product, where EVs optimize charging costs and/or emissions through smart charging while ensuring the total grid load stays within transformer capacity. It compares the costs and emissions induced by a transformer upgrade with the extra savings achieved through smart charging with a higher transformer capacity. The results show that, in nearly all scenarios, the costs and emissions of a transformer upgrade largely exceed the savings, indicating that upgrading the transformer is not optimal from a system value perspective.

Chapter 3 explores how moving away from traditional grid tariff structures can help to mitigate grid congestion. It examines how EV charging patterns adapt to various alternative grid tariff structures and evaluates these tariffs based on principles used by regulatory agencies. The findings reveal that most alternative tariff structures reduce the need for grid investments and lower overall system costs, as they have only a marginal impact on charging costs. Additionally, the study shows that alternative grid tariff structures result in a fairer distribution of grid costs between households and EV charging stations.

The work in **Chapter 4** studies a specific case in which a company EV fleet,

specifically a shared EV fleet operated by a car-sharing company, is used for mitigating grid congestion through a capacity-limitation system. Private EVs do not need to adjust their charging schedules in this system. The findings show that a relatively small number of shared EVs are sufficient to resolve all grid congestion problems in the studied grid. Furthermore, the impact of implementing this system on the charging costs for the shared EVs is relatively low.

Chapters 5 and 6 address two key barriers that hinder the effective implementation of smart charging systems for mitigating grid congestion. **Chapter 5** presents a framework designed to reduce uncertainties associated with applying smart charging in practice. These uncertainties include the total number of charging sessions, their charging demand, and EV arrival and departure times, which often lead to conservative smart charging strategies to ensure user charging needs are met. The framework uses aggregation to translate the charging characteristics of an EV fleet into three representative parameters for each 15-minute timestep. The results indicate that high forecasting accuracy (R^2 scores up to 0.98) can be achieved for all parameters. **Chapter 6** examines technical barriers that hinder the effective implementation of smart charging systems. It reports findings from large-scale smart charging tests, revealing that a considerable share of the EV models currently on the market are unable to handle charging pauses during smart charging. Instead, these models require a constant minimum charging current of 6 amperes, even during periods of high grid load. Model simulations in this chapter show that this technical limitation reduces the effectiveness of different smart charging applications, such as mitigating grid congestion and reducing charging costs, by half. The chapter also proposes several concrete solutions to address this issue.

In conclusion, this thesis has demonstrated that the studied mechanisms to promote smart charging for mitigating grid congestion effectively reduce the need for grid reinforcements and lower overall system costs. As a result, EV smart charging should be regarded as a crucial solution to address grid congestion issues. Hence, grid operators and policymakers must focus on implementing mechanisms that support the widespread adoption of smart charging. In addition, this thesis has shown that different barriers still hinder the effective implementation of smart charging, but it has also presented concrete solutions to overcome these problems.

Samenvatting

Zou het opladen van elektrische voertuigen (EV's) een oplossing kunnen zijn voor netcongestie, in plaats van een oorzaak ervan? De snelle adoptie van EV's, warmtepompen en zonnepanelen heeft de hoeveelheid stroom die door het elektriciteitsnet moet worden vervoerd aanzienlijk verhoogd. Dit kan leiden tot netcongestie, vooral omdat veel van de extra netbelasting geconcentreerd is op specifieke momenten. Slim opladen van EV's, waarbij de laadvraag wordt verschoven naar momenten van lage netbelasting, wordt echter alom erkend als een mogelijke oplossing voor dit probleem. Toch blijft er een gebrek aan inzicht over de meest effectieve manieren om de flexibiliteit van het opladen van EV's te benutten om netcongestie aan te pakken, vooral vanuit een systeembreed perspectief. In dit kader onderzoekt dit proefschrift verschillende mechanismen die netbeheerders kunnen inzetten om slim laden te stimuleren. Daarnaast worden twee belangrijke barrières belicht die een effectieve implementatie van dergelijke slimme laadsystemen belemmeren.

De eerste drie hoofdstukken van dit proefschrift onderzoeken de systeemimpact van verschillende mechanismen die netbeheerders kunnen gebruiken om netcongestie te verminderen door middel van slim laden, waaronder capaciteitsbeperkende systemen en alternatieve netwerktariefstructuren. **Hoofdstuk 2** bekijkt een systeem gebaseerd op een capaciteitsbeperkend product, waarbij EV's hun kosten en/of emissies optimaliseren door slim te laden, terwijl zij er ook voor zorgen dat de totale netbelasting binnen de capaciteit van de transformator blijft. Het vergelijkt de kosten en emissies die gepaard gaan met een transformatorverzwaring met de extra besparingen die met slim laden bereikt kunnen worden bij een hogere transformatorcapaciteit. De resultaten tonen aan dat in vrijwel alle scenario's de kosten en emissies van een transformatorverzwaring de besparingen ruimschoots overtreffen, wat erop wijst dat een transformatorverzwaring vanuit systeemwaarde-perspectief niet optimaal is.

Hoofdstuk 3 onderzoekt hoe het afstappen van traditionele netwerktariefstructuren kan helpen om netcongestie te verminderen. Het analyseert hoe laadpatronen van EV's zich aanpassen aan verschillende alternatieve netwerktariefstructuren en evalueert deze tariefstructuren op basis van principes die door regelgevende instanties worden gehanteerd. De bevindingen tonen aan dat de meeste alternatieve tariefstructuren de noodzaak van netinvesteringen verminderen en de totale systeemkosten verlagen, aangezien ze slechts een marginale impact hebben op de laadtarieven.

Bovendien toont de studie aan dat alternatieve netwerktariefstructuren resulteren in een eerlijkere verdeling van netwerkkosten tussen huishoudens en EV-laadstations.

Het onderzoek in **Hoofdstuk 4** bestudeert een specifieke casus waarin een EV-vloot van een bedrijf, in dit geval een vloot elektrische deelauto's van een deelautobedrijf, gebruikt wordt om netcongestie te verminderen via een capaciteitsbeperkingssysteem. In dit systeem hoeven particuliere EV's hun laadprofielen niet aan te passen. De resultaten tonen aan dat een relatief klein aantal elektrische deelauto's nodig is om alle netcongestieproblemen in het bestudeerde elektriciteitsnet op te lossen. Bovendien blijkt dat de invoering van dit systeem slechts een beperkte impact heeft op de laadkosten voor de elektrische deelauto's.

Hoofdstuk 5 en **Hoofdstuk 6** behandelen twee belangrijke barrières die een effectieve implementatie van een slim-ladensysteem voor het tegengaan van netcongestie belemmeren. **Hoofdstuk 5** presenteert een raamwerk dat probeert om de onzekerheden te verminderen die men in de praktijk tegenkomt bij het toepassen van slim laden. Onzekerheid over het totale aantal laadsessies, hun laadvraag en de aankomst- en vertrektijden van EV's zorgen ervoor dat conservatieve slimme laadstrategieën worden toegepast in de praktijk, om er zeker van te zijn dat aan de laadbehoeften van gebruikers wordt voldaan. Het raamwerk maakt gebruik van aggregatie om de laadkarakteristieken van een EV-vloot om te zetten in drie representatieve parameters voor elke tijdstap. De resultaten tonen aan dat een hoge voorspellingsnauwkeurigheid (R^2-scores tot 0,98) kan worden behaald voor alle parameters. **Hoofdstuk 6** kijkt naar technische obstakels die de effectieve implementatie van slim-ladensystemen belemmeren. Het presenteert de resultaten van grootschalige slim laden testen, waaruit blijkt dat een aanzienlijk deel van de EV-modellen op de markt niet goed om kan gaan met laadpauzes tijdens slim laden. In plaats daarvan vereisen deze modellen een constante minimale laadstroom van 6 ampère, zelfs tijdens periodes van hoge netbelasting. Modelsimulaties in dit hoofdstuk laten zien dat deze technische beperking de effectiviteit van verschillende toepassingen van slim laden, zoals het verminderen van netcongestie en het verlagen van oplaadkosten, met de helft vermindert. Het hoofdstuk stelt daarnaast meerdere concrete oplossingen voor om dit probleem aan te pakken.

Samenvattend heeft dit proefschrift aangetoond dat de onderzochte mechanismen ter bevordering van slim laden voor het verminderen van netcongestie de behoefte aan netverzwaringen effectief verminderen en de totale systeemkosten verlagen. Daarom moet slim laden van EV's worden beschouwd als een cruciale oplossing voor netcongestieproblemen. Het is dan ook essentieel dat netbeheerders en beleidsmakers zich richten op de implementatie van mechanismen die de brede adoptie van slim laden bevorderen. Daarnaast heeft dit proefschrift laten zien dat verschillende barrières de effectieve implementatie van slim laden nog in de weg staan, maar heeft het ook concrete oplossingen voor deze problemen voorgesteld.

Nomenclature

Acronyms

AC	Alternating Current
ACER	European Union Agency for the Cooperation of Energy Regulators
aFRR	automatic Frequency Restoration Reserve
BEV	Battery Electric Vehicle
BRP	Balance Responsible Party
CEER	Council of European Energy Regulators
CPO	Charge Point Operator
CPP	Critical Peak Pricing
DA	Day-Ahead
DC	Direct Current
DER	Distributed Energy Resource
DSO	Distribution System Operator
EV	Electric Vehicle
GCT	Gate Closure Time
GHG	Greenhouse Gas
HPC	High Performance Computing
HV	High Voltage
ICE	Internal Combustion Engine
IEA	International Energy Agency
LRMC	Long-Run Marginal Costs
LULUCF	Land Use, Land-Use Change and Forestry
LV	Low Voltage
LVD	Low Voltage Directive
MAE	Mean Absolute Error
MV	Medium Voltage
NRA	National Regulatory Authorities
OCPP	Open Charge Point Protocol
PHEV	Plug-in Hybrid Electric Vehicle
PV	Photovoltaic
RMSE	Root Mean Square Error

RTP	Real-Time Pricing
SoC	State-of-Charge
SRMC	Short-Run Marginal Costs
ToU	Time-of-Use
TSO	Transmission System Operator
V2G	Vehicle-to-Grid
VKT	Vehicle-Kilometer Travelled
WAPE	Weighted Absolute Percentage Error

Model variables

ϕ	Binary variable ensuring continuous charging
e_{cons}	Electricity consumption of a grid user
δ	Cycle depth of a charging/discharging cycle
c_{battdeg}	Total battery degradation costs
c_{el}	Total retail electricity costs
c_{grid}	Total grid expansion costs
$c_{\text{gt,fixed}}$	Total expenses on the fixed grid tariff component
c_{gt}	Total expenses on grid tariffs
$c_{\text{peak,exc}}$	Costs of exceeding the estimated optimal peak demand
c_{priority}	Priority cost to favour the earliest charging time among equal-tariff options, enhancing user comfort
c_{system}	Total system costs
e_{ch}	Net accumulated charging volume of a charging session
e_{exc}	Total energy exceedance above the subscribed capacity in a capacity-subscription grid tariff scheme
g_{battdeg}	Total battery degradation emissions
g_{el}	Total emissions from electricity consumption/feed-in
g_{grid}	Total emissions from grid expansions
g_{system}	Total system emissions
$p_{\text{ch,tot}}$	Net total EV charging power in a grid/of a charging station
p_{ch}	Charging power of EV charging session/virtual battery
p_{disch}	Discharging power of EV charging session/virtual battery
p_{flex}	Provided charging flexibility
$p_{\text{grid,peak}}$	Peak grid load
p_{grid}	Total net grid load
$p_{\text{peak,exc}}$	Exceedance of the estimated optimal peak demand at a specific moment in a capacity grid tariff scheme
p_{peak}	Peak demand of a grid user during a predefined period

Indices and Sets

$j \in \mathcal{J}$	Set of used fuel types for electricity generation
$k \in \mathcal{K}$	Set of emission bins when making a Pareto frontier

$m \in \mathrm{M}_{\mathrm{tot}}$	Set of considered months in the assessment timeframe
$n \in \mathscr{N}$	Set of charging sessions in the assessment timeframe
$p \in \mathscr{P}$	Set of charging sessions in the assessment timeframe by privately-owned EVs
$s \in \mathscr{S}$	Set of charging sessions in the assessment timeframe by shared EVs
$t \in \mathscr{T}$	Set of timesteps in the assessment timeframe
$v \in \mathscr{V}$	Set of virtual battery subsets

Model parameters

$\mathscr{D}_{\mathrm{charge}}$	Average annual charging demand at an EV charging station
$\mathrm{E}_{\mathrm{ch,max}}$	Maximum accumulated charging energy of a virtual battery
$\mathrm{E}_{\mathrm{ch,min}}$	Minimum accumulated charging energy of a virtual battery
$\mathrm{E}_{\mathrm{dem}}$	Charging demand of a charging session
$\mathrm{E}_{\mathrm{priv,org}}$	Charging demand of all private EVs in the assessment timeframe without the adoption of shared EVs
$\mathrm{E}_{\mathrm{priv}}$	Total charging demand of all private EVs
$\mathrm{E}_{\mathrm{shared}}$	Total charging demand of all shared EVs
$\mathrm{i}_{\mathrm{num}}$	Number of elapsed timesteps since the beginning of a charging session.
L	Lifetime of the grid
$\mathrm{l}_{\mathrm{cable}}$	Length of cable reinforcement
M	A sufficiently large positive constant used in the Big M method to favour the earliest charging time among equal-tariff options
m	Battery degradation exponent indicating cycle life sensitivity to depth of discharge
$\mathrm{M}_{\mathrm{corr}}$	Share of missing generation attributed to a specific fuel type
N_{CS}	Expected number of charging stations at a specific EV adoption rate
$\mathrm{N}_{\mathrm{eol,actual}}$	Actual number of cycles of a battery to end of life at a specific cycle depth
$\mathrm{N}_{\mathrm{eol,full}}$	Full equivalent cycles of a battery to end of life at a specific cycle depth
$\mathrm{N}_{\mathrm{eol,ref}}$	Reference number of full equivalent cycles of a battery at 100% cycle depth
N_{hh}	Number of households
$\mathrm{P}_{\mathrm{available}}$	Available capacity for a specific grid tariff value
$\mathrm{P}_{\mathrm{ch,coa}}$	Charging power in a *charging-on-arrival* scenario
$\mathrm{P}_{\mathrm{ch,latest}}$	Charging power in a *latest charging* scenario
$\mathrm{P}_{\mathrm{ch,max}}$	Maximum charging power of a charging session/virtual battery
$\mathrm{P}_{\mathrm{ch,min}}$	Minimum required charging power of a charging session
$\mathrm{P}_{\mathrm{ch,ref}}$	Charging power in the reference charging schedule
$\mathrm{P}_{\mathrm{disch,max}}$	Maximum discharging power of a charging session/virtual battery
P_{gc}	Size of a user's grid connection

$P_{gen,CBS}$	Generation from CBS
$P_{gen,missing}$	Missing generation data from ENTSO-E Transparency Platform
$P_{gen,TP}$	Generation from ENTSOE-E Transparency Platform
P_{gen}	Total generation using a specific fuel type
$P_{load,Ps}$	Load from ENTSOE-E Powerstats
$P_{net\ export}$	Net electricity export from the Netherlands
$P_{non\text{-}EV}$	Non-EV load in a grid
$P_{peak,opt}$	Estimated optimal peak demand
P_{PV}	Total PV generation
P_{sub}	Subscribed capacity level in a capacity-subscription grid tariff scheme
$P_{tr,max}$	Transformer capacity
r	Discount rate
t_{arr}	Arrival time of charging session at the charging station
t_{dep}	Departure time of charging session at the charging station
α_{EV}	EV adoption rate
α_{shared}	Adoption rate of shared EVs
Δt	Timestep duration
ϵ	Maximum emissions for a considered bin
η_{ch}	Charging efficiency
η_{disch}	Discharging efficiency
$\eta_{driving}$	Driving efficiency
γ_{retail}	Parameter indicating whether retail electricity costs are considered
γ_{vkt}	Reduction in vehicle-kilometers travelled with shared EV adoption
$\mu_{mileage}$	Average annual mileage of a car
Φ	Battery degradation function
π_{batt}	Battery investment costs
π_{cable}	Costs for cable reinforcement
π_{el}	Electricity retail tariff
π_{exc}	Tariff for exceeding the subscribed capacity in a capacity-subscription grid tariff scheme
$\pi_{peak,exc}$	Tariff for exceeding the estimated optimal peak demand in a capacity-based grid tariff scheme
π_{peak}	Tariff value of a capacity-based grid tariff scheme
π_{sub}	Subscription fee per kW subscribed in a capacity-subscription grid tariff scheme
π_{trans}	Costs of an transformer upgrade
π_{vol}	Tariff value of a volumetric ToU grid tariff scheme
ρ_{car}	Car possession rate of households
θ_{cable}	Emissions from cable reinforcements
θ_{el}	Emission factor of electricity
θ_{trans}	Emissions from a transformer upgrade

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Chapter 1

Introduction

1.1 Context

Humankind owes its existence to Planet Earth, which has provided the resources and conditions necessary for life's evolution. Paradoxically, human actions now endanger the habitability of the very planet that facilitated our development. Between 2011 and 2020, the global surface temperature was 1.1 °C higher than between 1850 and 1900 [1]. Human activities have indisputably caused this temperature increase through the emission of greenhouse gases (GHGs) [1], in particular carbon dioxide (CO_2) and methane (CH_4). Since 1750, atmospheric concentrations of these GHGs have increased by 47% and 156%, respectively [1]. Given our current status as net GHG emitters, the temperature will further increase in the coming years. The different emission scenarios presented by the Intergovernmental Panel on Climate Change (IPCC) project a temperature increase between 1.4 °C and 4.4 °C by the end of the century [1].

Current levels of global warming have already contributed to significant sea level rise and increased the frequency of extreme weather events, resulting in deadly floods, storms and droughts [1], [2]. Climate risks and their adverse impacts will increase with each incremental rise in global temperatures. In the near term, these impacts include flooding of coastal and low-lying regions, decreased food production, biodiversity loss and increased morbidity and mortality due to heat stress or food-borne, water-borne and vector-borne diseases. With further warming, more climate risks become irreversible and might trigger large-scale crises, including pandemics, large-scale migration and territorial disputes [1], [2].

To mitigate the impact of climate change, 195 governments around the world have pledged to keep the global temperature rise below 2 °C compared to pre-industrial levels and to pursue efforts to limit the temperature rise below 1.5 °C [3]. These targets can be translated into carbon budgets [4], [5], which delineate the maximum allowable cumulative GHG emissions to meet the climate targets.

To meet the 1.5 °C target, global GHG emissions should be reduced rapidly and immediately, aiming for net-zero global carbon emissions by 2050 and net-zero global GHG emissions between 2060 and 2080 [1], [6]–[9]. Consequently, substantial GHG emission reductions across all sectors are essential to realising these ambitious goals [1], [9], [10].

The transport sector is one of the main contributors to climate change. The sector heavily depends on oil products, such as petrol and diesel, to power vehicles and facilitate the movement of goods and people across the globe. The combustion of these fossil fuels releases large volumes of CO_2. Consequently, the transport sector is a major contributor to global GHG emissions, accounting for approximately 22% of the total in 2022 [11]. This contribution is even more significant in the EU, where the transport sector accounts for 37.4% of the CO_2 emissions and for 30.5% of the GHG emissions [12].

Figure 1.1 illustrates that road transport is the primary source of these emis-

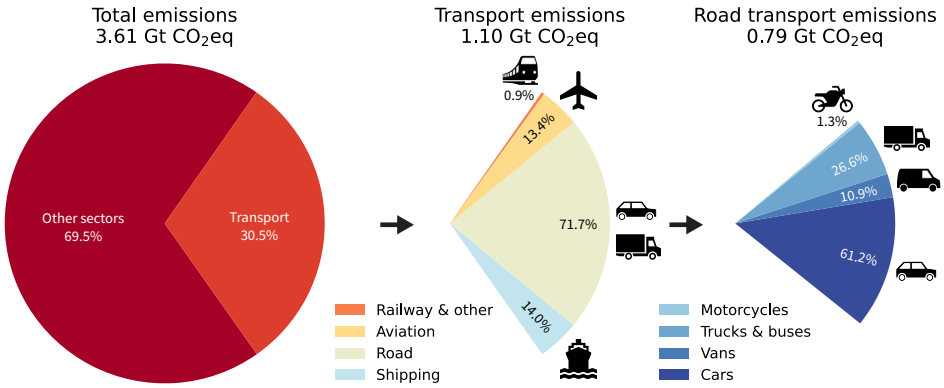


Figure 1.1: The contribution of transport emissions in the total direct GHG emissions for the EU-27 countries in 2019, along with a detailed breakdown of total transport emissions. Total emissions include international bunkers but exclude Land Use, Land-Use Change and Forestry (LULUCF) emissions and other memo items as defined in the common reporting format of UNFCCC. This figure is a remake of Figure 2 of [17] using data from [12].

sions. To reach net-zero emissions by 2050, a quick reduction in global transport emissions is required before 2030 [13], [14]. Different studies on decarbonizing the transport sector suggest that road transport should make the most significant relative contribution to emission reduction, especially in the short term [13], [15], [16].

1.2 Electric vehicles as a clean transport technology

One of the most widely considered options to decarbonize road transportation is to electrify vehicles, including cars, trucks and buses. An electric vehicle (EV) relies, at least partly, on an electric engine for propulsion. There are different types of EVs on the market, each with its own characteristics:

1. **Battery EVs:** These vehicles are fully electric and are powered by an onboard battery. The battery is recharged by connecting the vehicle to an EV charging station.

2. **(Plug-in) hybrid EVs:** These vehicles use both an electric engine and an Internal Combustion Engine (ICE). Generally, these vehicles operate all-electric for a specific range before the ICE takes over. Plug-in hybrid EVs use an onboard battery system to power the electric engine, which is recharged by connecting the EV to a charging station. As this vehicle type also contains a combustion engine, the capacity requirements for the battery are lower. Non-plug-in hybrids, which recharge through regenerative braking and excess engine power, are not considered as EVs in this context due to their very low battery capacity.

3. **Fuel cell EVs:** Instead of using a battery to power the electric engine, this EV type uses a fuel cell to convert hydrogen into electricity to power the engine. Hence, fuel cell EVs do not use an internal battery system for driving.

The main climate benefits of EVs compared to ICE vehicles come from the use phase of the vehicles. The combustion of petrol or diesel with conventional ICE vehicles results in high tailpipe emissions when driving these vehicles. In contrast, BEVs produce zero tailpipe emissions throughout their entire driving phase, and PHEVs produce zero tailpipe emissions during their electric-only driving phase, while FCEVs only emit water. The upstream emissions from electricity generation for charging EV batteries are generally much lower than the combined tailpipe and upstream emissions of ICE vehicles. This is due to the higher well-to-wheel efficiency of EVs [18], [19] and the typically lower emission factor of electricity compared to petrol or diesel. This effect is becoming more significant with the increased integration of renewable energy technologies, such as photovoltaic (PV) systems. On the other hand, the production process of EVs is more emission-intensive, mainly due to the high energy intensity of producing the onboard battery or fuel cell system.

Different studies aimed to quantify the lifecycle GHG emissions of EVs and their ICE vehicle counterparts. There is ongoing discussion about the best approach to perform this analysis [20]–[22] and the outcome depends on assumptions on, among others, the considered battery technology and the assumed advancements in their production process, the considered drive cycles, the lifetime mileage of the vehicles, the end-of-life treatment of the vehicles, the considered vehicle models and the considered electricity generation mix. In general, most studies indicate that EVs have lower lifecycle GHG emissions than ICE vehicles when considering the current electricity mix (12-61% lifecycle GHG emission reduction) [20], [23]–[28]. When considering further integration of renewable energy into the electricity mix, the reduction in lifecycle emissions for EVs is even greater, ranging from 55-93% [20], [23]–[27]. Some studies [24]–[26], [28], [29] suggest that EVs can have higher lifecycle emissions than ICE vehicles if the electricity mix has a high average emission factor, although they neglect that it is unlikely that the emission factor of electricity generation will remain high during the lifetime of the EV due to the increased adoption of renewables throughout the EV's lifetime. For more elaborate discussions on this topic, readers are referred to review papers such as [21], [30] and [31].

1.3 The rise of electric vehicles

EVs are not a novel technology. In fact, one could claim that the EV was invented before the gasoline car [32]. In 1881, the French carriage builder Charles Jeantaud and the chemist Camille Alphonse Faure equipped a *Tilbury carriage* with an electric motor and a tubular plate battery, which is an early version of the lead-acid battery. This system was further developed and by the end of the 19th century, EVs had a

substantial market share in different countries [32]. For instance, 38% of the cars produced in the United States in 1900 were EVs, compared to a market share of 22% for gasoline cars [33]. Factors such as the limited operating range and top speed of EVs, the increasing emphasis on vehicle speed performance, and the lack of a reliable electricity infrastructure contributed to the market dominance of ICE vehicles from 1910 onward [32], [33].

It took almost a century before EVs regained the interest of car manufacturers. In the early 1990s, the California Air Resources Board introduced the Zero Emission Vehicle mandate [34] to reduce air pollution and meet environmental goals. This mandate required a specific share of the sales of the main car manufacturers in the United States to be zero-emission vehicles. Several car manufacturers developed and introduced EV models to the market in response. However, after the Zero Emission Vehicle mandate was relaxed, partly influenced by a strong lobby from car manufacturers [35], the EVs were actively retracted from the market.[1]

However, from the early 2010s onward, car manufacturers began reintroducing EVs to the market, marking a significant breakthrough for the technology. This is mainly due to different factors. Firstly, advancements in battery technology played a pivotal role. The introduction of the lithium-ion battery improved the driving range of EVs [37], making them adequate to satisfy the transportation needs of most car owners. Secondly, falling costs for this technology have made EVs increasingly cost-competitive with ICE vehicles [38], [39]. Thirdly, governments have used various policy instruments to stimulate the adoption of EVs to meet the aforementioned climate targets. At the EU level, a maximum average emission value in CO_2/km has been determined for all car manufacturers, which applies to their newly-sold vehicles within the EU for each year [40]. National policies further supported this initiative, including tax benefits for EV ownership, subsidies for EV purchases, promotion of the rollout of EV charging infrastructure, and restrictions on the sale of ICE vehicles [11], [41], [42]. In the Netherlands, the government has actively promoted the adoption of electric vehicles through a threefold approach: first, by implementing reduced ownership and purchase taxes for EVs [43]; second, by providing subsidies to incentivize the purchase of electric vehicles [43]; and third, by mandating that all new passenger vehicles sold must be zero-emission by 2030 [44].

These developments have resulted in growing adoption rates of EVs. Figure 1.2 reports the share of battery and plug-in hybrid EVs in the total passenger car sales for the EU-27 and different European countries over the past years. In most countries, EVs now constitute 25% or more of total new car sales, indicating their increasingly substantial role in the current automotive landscape. In various Nordic countries, EVs already dominate the car market and make up the majority of car sales, while in other countries, including Spain and Italy, EV sales have yet to take off. Both battery

[1]The author highly recommends those interested in learning more about this to watch the documentary 'Who Killed the Electric Car' (2006) [36], directed by Chris Paine and distributed by Sony Pictures Classics.

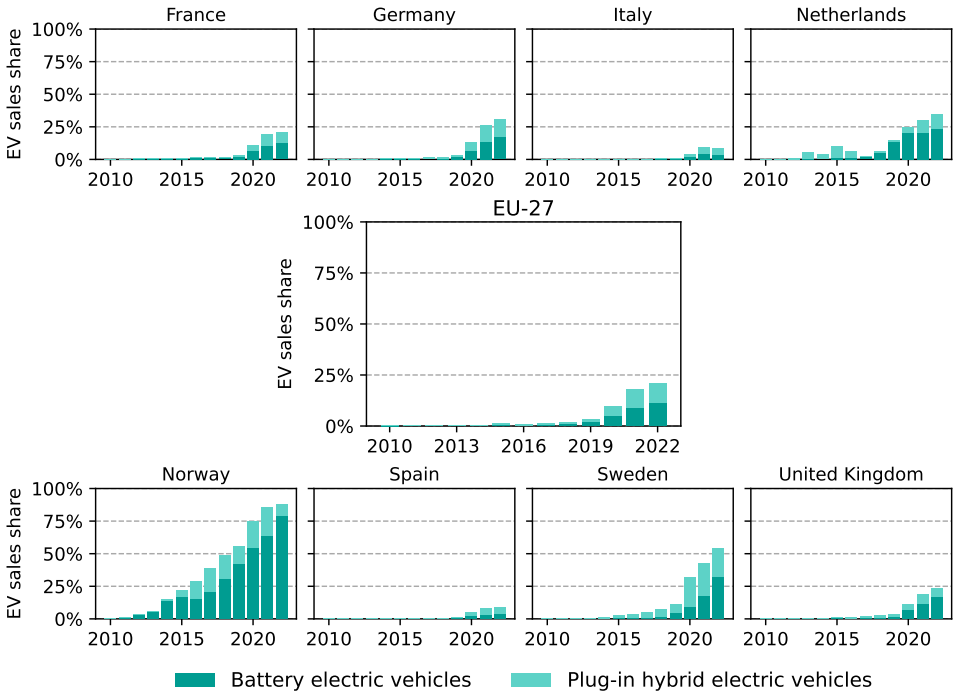


Figure 1.2: Share of EVs in the total passenger car sales between 2010 and 2022 in different European countries and the EU-27. Data from IEA [45].

and plug-in hybrid EVs contribute to current EV sales, while the role of fuel-cell EVs is almost negligible. Currently, there are no signs that the limited role of fuel-cell EVs will change in the coming years [46]–[48], mostly due to the limited availability of hydrogen. Therefore, in the context of this thesis, references to EVs specifically pertain to battery or plug-in hybrid EVs.

The expectation is that the pattern of growing EV adoption will persist in the upcoming years, leading to the near-complete electrification of the automotive fleet in the coming decades [47], [48]. The International Energy Agency (IEA) expects that the global EV fleet will grow by a factor of 8 between 2022 and 2030 [48]. For the Netherlands, ElaadNL, a leading innovation and research center on EVs and EV charging, projects that the passenger car fleet will become nearly fully electric between 2040 and 2050 (see Figure 1.3), depending on the considered EV adoption scenario [47].

1.4 Electric vehicles and the electricity grid

The ongoing transition towards an electric-based vehicle fleet does not only disrupt the automotive sector but also has far-reaching consequences across the entire energy

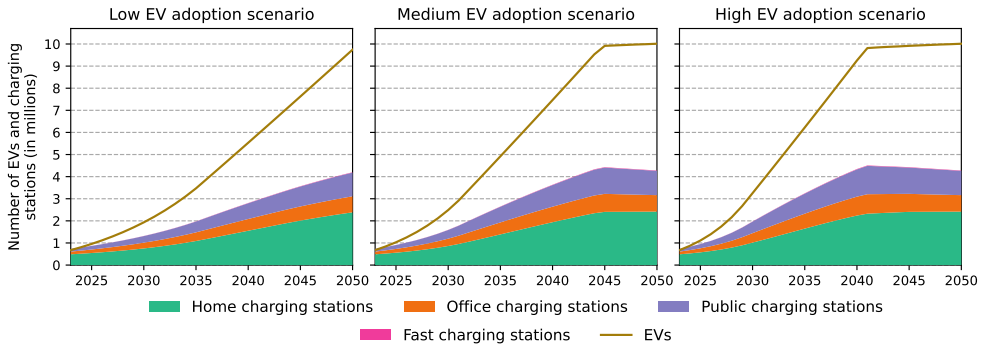


Figure 1.3: Three future adoption scenarios for the adoption of EVs and EV charging stations for the Netherlands, based on the scenarios outlined in the ElaadNL Outlook [47].

system. One major implication is that the energy requirements to fulfill road transportation needs will increasingly be provided by the electricity grid and a network of EV charging stations, rather than by a network of petrol stations. Thus, investments in EV charging infrastructure are required to enable this transition. ElaadNL has forecasted the number of electric vehicles in the Netherlands from 2023 to 2050, along with the necessary increase in the number of EV charging stations [47]. According to these projections (see Figure 1.3), the large majority of charging stations will be home, office or public charging stations. These charging stations are usually connected to the Low Voltage (LV) grid and can usually charge EVs with a power capacity of up to 22 kW. In contrast, the number of fast-charging stations, which are usually connected to the Medium Voltage (MV) grid with a considerably higher charging power (usually >100 kW), will be relatively small compared to the number of home, office and public stations.

With growing EV adoption rates, EV charging can pose a potential threat to grid stability across all grid levels. This threat arises primarily from the fact that most electricity grids were designed and installed decades ago, without considering the future demands of EV charging and other electrification processes, such as the deployment of heat pumps. Consequently, EV charging induces the risk that the power flows through the grid exceed its capacity [49], [50]. The most critical issue arising from this is thermal overloading of grid assets, such as electricity cables and transformer stations. This phenomenon, commonly known as grid congestion, can shorten the lifetime of these assets and induce blackouts. This risk affects both the LV grid and higher grid levels (i.e., MV and High Voltage (HV) grids) [51], as extra electricity will need to be transmitted through those MV and HV grids to enable EV charging at LV grids.

The grid congestion problems are amplified by the typical charging patterns of EVs. The arrival times of EVs at a charging station are generally concentrated at specific periods, such as the beginning of a workday at office charging stations and

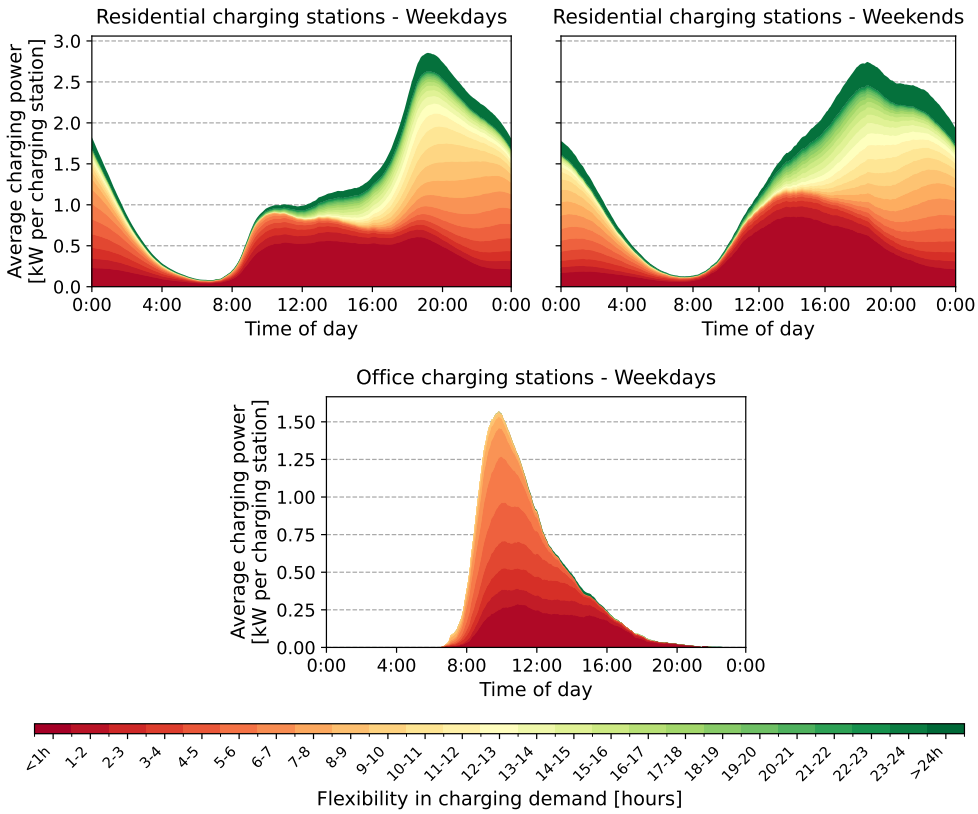


Figure 1.4: Average daily charging patterns per charging station and average charging flexibility for 2022 for residential and office charging stations. Based on 384 residential public stations in Utrecht, the Netherlands, and 39 office stations at the car park of a banking company in Utrecht province, the Netherlands. All charging stations contain two charging points. Charging flexibility is expressed as the difference between the required time to meet the EV's charging demand and the EV's connection time to the charging station in each session. Adjusted from [52] & [53].

early evening at residential charging stations [52], [54]. The default charging mode is *uncoordinated* or *uncontrolled* charging, in which EVs charge at maximum charging power upon arrival at the charging station until their charging demand is met. With this charging mode, concentrated arrival moments to the charging station will result in concentrated charging moments [52], [54]. This is illustrated by Figure 1.4, which portrays the average daily charging patterns at residential and office charging stations. It shows a distinct charging peak for residential stations in the early evening hours, while the charging demand for office stations peaks in the late morning.

These peak charging moments of residential and office charging stations coincide with the moments of highest demand of other grid connections at their respective locations [55]. Also, the charging power of an EV is significantly higher than the typical peak-time power consumption of a household. As a result, EV charging can

already cause grid congestion problems at relatively low EV adoption rates. Different studies that aimed to quantify the role of EV charging on grid congestion levels showed that, when isolating the effect of EV charging, grid congestion will occur at a 20-80% EV adoption rate [56]–[59]. This maximum EV adoption rate before grid congestion occurs depends on contextual factors, such as location and grid type under consideration. In the Netherlands, the impact of EV charging on grid congestion levels is particularly pronounced, as grid capacity problems are already a pressing problem. To avoid blackouts arising from congestion, there are currently serious constraints on the available transport capacity at HV and MV grid levels throughout the whole country for both the injection and withdrawal of electricity [60]. As a result, grid operators are limiting the number of new grid connections [61], which could delay large-scale projects such as renewable energy initiatives and new housing constructions. A report by ElaadNL [51] projects that around 35% of the HV/MV transformers and 20% of the MV/LV transformers in the Netherlands will face capcaity problems by 2030, which is up to 50% attributed to EV charging. In addition, the projection shows that 15% more MV/LV transformer stations will need to be installed before 2030. Next to congestion problems, the absence of resilient grid infrastructure to facilitate EV charging can also cause power quality problems in the grid, including undervoltage and voltage fluctuations [62]–[64]. These power quality problems can cause damage to electrical appliances and can cause light flicker.

Grid operators traditionally address congestion and power quality problems by reinforcing the grid. This may involve replacing existing electricity cables and transformer substations with higher capacity alternatives or installing new transformer substations to split one grid into multiple grids. However, large-scale grid reinforcements to accommodate the grid integration of EVs are not viable in the short term for several reasons. Firstly, these reinforcements come with high costs. For example, in the Netherlands, a new transformer station costs around €15,000, and replacing LV grid cables costs approximately €120,000 per km [65]. Given the extensive size of the Dutch electricity grid — about 225,000 km of LV cables, 111,000 km of MV cables and 11,000 km of HV cables [66] — a full-scale grid reinforcement would require investments of several billion euros. Additionally, there are various practical barriers to reinforcing the grid. For instance, the implementation of short-term grid reinforcements is constrained by a severe shortage of workers with the technical expertise needed to execute these projects [67], [68]. Moreover, there is a lack of available space in urban areas to install new transformer stations [69] and the administrative procedures for such processes (e.g., obtaining permits and coordinating with multiple stakeholders) can be lengthy.

1.5 Electric vehicle smart charging

Grid congestion problems can also be mitigated by stimulating more efficient usage of the electricity grid. By spreading the load in an electricity grid over time, peak loads can be avoided, reducing the risk that the power flows will exceed the grid's capacity. EV charging can play a pivotal role in this approach, as the charging of EVs is highly flexible. As illustrated in Figure 1.4, most EV charging sessions involve connection times that considerably exceed the time needed to meet the EV's charging demand [52], [54]. This means there is room to step away from *uncoordinated* or *uncontrolled* charging. Instead, EV charging demand can be shifted from moments with high grid load to off-peak moments during the EV's connection period to the charging station. This intelligent management of EV charging sessions, known as *smart charging*, can help to spread the charging load and reduce grid congestion, thereby reducing the need for grid investments.

Next to using EV smart charging to mitigate grid congestion problems, it can also serve a wide range of other functions. Firstly, one of the main applications of smart charging is to reduce charging costs (e.g., [70]–[72]), particularly when considering pricing schemes that consider Time-of-Use (ToU) tariffs. Through the application of smart charging, charging can be shifted from moments with high ToU tariffs to moments with low ToU tariffs, ultimately reducing EV charging costs. Secondly, EV smart charging can enhance the stability of the electricity system by providing balancing services to Transmission System Operators (TSOs) [73]–[75]. Balancing reserves are deployed to maintain the balance between electricity supply and demand in the electricity grid to avoid frequency deviations which could threaten system stability. In case of system imbalance, EVs can adjust their charging schedules to help restore grid balance, taking over this role from conventional, fossil-based power plants. Similarly, EV smart charging can contribute to resource adequacy in the electricity system by lowering EV charging demand during peak residual load times, thus reducing the need for generation from fossil-based power plants [76]. Additionally, smart charging can reduce the environmental impact of EV charging by scheduling it during moments with the lowest emission factor for electricity [77], [78]. In line with this, EV smart charging can facilitate the integration of renewable energy technologies into the electricity system by charging at moments with excess renewable power generation [79], [80], preventing the curtailment of renewable energy due to transmission constraints or insufficient demand.

Bidirectional charging, also known as Vehicle-to-Grid (V2G), is an advanced form of smart charging that allows EVs to inject stored energy from their batteries back into the grid [82]. V2G can significantly enhance the benefits of the smart charging applications discussed above. For example, in the context of smart charging to reduce charging costs, EVs now have the additional option to discharge their battery at moments with high ToU tariffs. In this way, the EV owner receives financial compensation for the electricity injected into the grid, and overall charging costs are

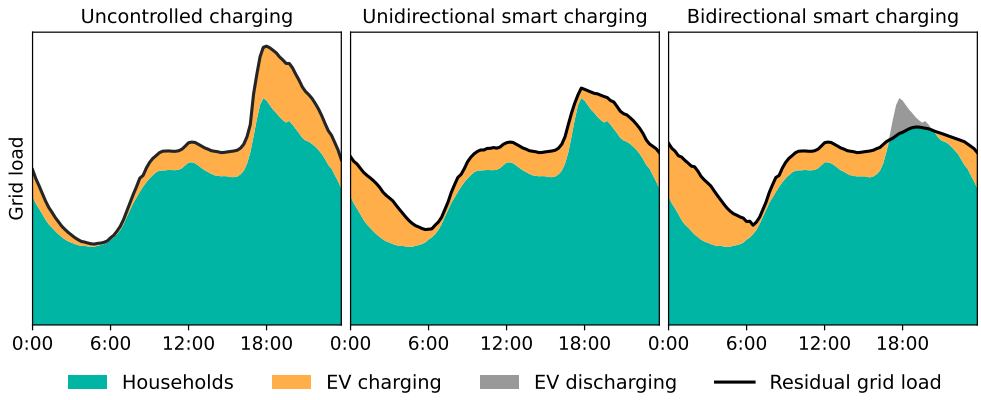


Figure 1.5: Illustrative example of how unidirectional and bidirectional smart charging can contribute to more efficient grid usage. The figure is inspired by [81].

further reduced [83]. Similarly, V2G can more effectively mitigate grid congestion than unidirectional smart charging. While unidirectional smart charging can pause charging during peak demand periods to mitigate the grid impact of EV charging, V2G technology can go further by also mitigating grid congestion issues from other grid assets. It does this by injecting electricity back into the grid during peak times, thereby reducing the overall peak grid load, as illustrated by Figure 1.5. Different studies indicate that V2G significantly enhances the effectiveness of smart charging in mitigating grid congestion problems. For instance, the authors in [84] demonstrate that V2G achieves a 40% greater reduction in peak demand compared to unidirectional smart charging. Similarly, the authors in [85] report that the peak load reduction potential of V2G is approximately twice as high compared to unidirectional smart charging, and the authors in [86] demonstrate a 3-4 times higher peak shaving potential with V2G.

1.6 Mechanisms for activating smart charging

As demonstrated in the previous sections, the potential of EV smart charging to mitigate grid congestion is substantial. Nevertheless, without appropriate incentives, EV users and charging station operators are unlikely to modify their charging schedules to support grid operators in alleviating congestion. The flexibility of EV charging could even be used for other forms of smart charging that can have an adverse impact on grid congestion levels [87]. Different mechanisms have been identified to unlock the flexibility of EV charging to mitigate grid congestion problems.

In the first considered mechanism, grid operators provide direct financial incentives to EV owners and charging station operators, hoping that this stimulates them to adjust their charging profiles to minimize the grid impact of EV charging. This can

be accomplished through the implementation of alternative grid tariff structures that are based on consumption patterns. Grid operators receive compensation for their transmission services through the grid tariffs paid by grid users. For small users in the Netherlands, these grid tariffs are traditionally dependent on the size of the grid connection and are independent of their actual consumption and generation patterns. Alternative grid tariff structures can be based on actual consumption and generation patterns of grid users and can provide grid users with a financial incentive to change their grid usage. These alternative grid tariff structures could, for instance, offer financial incentives to grid users to shift demand to off-peak periods or to reduce their peak demand, thereby contributing to mitigating grid congestion problems. Various grid tariff structures have been proposed in the literature, and several countries, including Belgium and Spain, have implemented different versions of these structures [88]–[90].

The second mechanism focuses on directly managing the power levels of grid users. In this approach, each grid user must keep its electricity consumption/injection below a predefined maximum limit, which is set by the grid operator for each timestep based on the anticipated grid load at that moment [91]. These limits are usually communicated day-ahead. In return, these grid users receive financial compensation. For EV charging, this means that operators of charging stations must keep the charging power below this limit but have the freedom to use the available charging capacity for any charging objective. This mechanism was recently introduced in the Dutch grid code as a *capaciteitsbeperkend contract* (capacity-limitation contract) for large grid connections [92], but is currently also rolled out on a large scale for EV charging at public charging stations in the Netherlands. In the Dutch public-private sector agreement *Slim laden voor iedereen* (Smart charging for everyone) [93], it was agreed that this mechanism, here titled as *Netbewust laden* (grid-aware charging), will be rolled-out on a national scale. Complying with this system is currently a requirement in the tenders for new public charging stations in different large cities [94]. A study by ElaadNL [51] predicts that rolling out this system will reduce the number of congested transformer stations by 10-15% by 2030 and 15-20% by 2035.

The third mechanism allows EVs to follow any charging schedule without predefined limits on the charging power during peak periods or direct financial incentives that stimulate smart charging. After the expected consumption/generation schedules of all grid users are communicated, the grid operator assesses whether there is a risk of grid congestion. In case of expected congestion, the grid operator requests one or multiple grid users to alter their consumption/generation patterns in order to resolve the potential congestion problem, offering financial compensation in return [95]–[97]. This mechanism has also been defined in the Dutch grid code as the *redispatch product* [92]. Grid operators are increasingly encouraged to procure flexibility from local flexibility markets when applying this mechanism. In such a flexibility market, owners of flexible grid assets (e.g., EV charging stations, heat pumps, stationary batteries) can make a flexibility offer (i.e., the maximum power

they are willing to reduce or increase) and specify the price they are willing to accept for providing flexibility. Grid operators then select offers based on the forecasted grid load and offered prices, aiming to mitigate congestion problems. This flexibility can be procured using short-term trading or through long-term contracts. Such flexibility markets have recently been implemented in the United Kingdom, France, Germany and the Netherlands [91].

These three main mechanisms will most likely be applied jointly by grid operators. In the Dutch action program for mitigating LV grid congestion [98], a roadmap is defined which states that grid operators must first apply preventive mechanisms for grid congestion, such as the introduction of alternative grid tariff structures and the rollout of capacity-limitation systems. For the remaining congestion problems, reactive mechanisms, such as the third mechanism introduced above, should be applied.

Numerous other mechanisms have been proposed next to the three main mechanisms identified before. For instance, multiple studies (e.g., [99]–[101]) propose systems which have a central controller, such as a Distribution System Operator (DSO), which directly controls the charging schedules for all charging sessions in a grid to meet the objective of minimizing grid congestion problems. However, it is questionable whether such systems are possible from a legal perspective, and whether such mechanisms will be socially accepted. Another mechanism which can stimulate the use of smart charging is the concept of cable pooling. This concept exists in multiple forms, but one of the forms is that multiple users share one grid connection. This stimulates the rollout of smart charging in order to ensure that the peak load remains below the size of the grid connection.

1.7 Current landscape of EV smart charging and barriers for future implementation

Multiple real-world smart charging pilots (e.g., [102]–[105]) have shaped the smart charging landscape and addressed key implementation hurdles. The concept is now beyond its infancy and is increasingly implemented on a larger scale. Smart charging is expected to become the norm in the coming years. The Netherlands aims for at least 60% of charging sessions to be smartly controlled by 2025 [93], which is stimulated by the fact that several Dutch municipalities now require the use of smart charging in the tenders for new public charging stations [94].

The concept of V2G is still in its infancy. The first V2G systems were brought to the market by Nissan in 2012, after the Fukushima disaster [106], [107]. These systems could provide V2G services, but only through a direct-current (DC) charger. Presently, there is no widespread adoption of V2G charging systems at alternating-current (AC) charging stations, which comprise most of the charging stations that are currently in use. This is mainly due to the absence of EV models on the market that

can handle AC V2G[2] and the absence of a widely adopted communication standard between the EV and charging station that enables V2G charging at AC charging stations. Currently, initiatives are in progress to encourage the adoption of the ISO 15118-20 communication standard [109], which enables bidirectional EV charging, among charging stations and EV models.

To ensure effective further implementation of smart charging for mitigating grid congestion, it is essential to address various barriers that might hinder this process. A first potential barrier could be the perception of EV users towards smart charging. A negative user perception could cause EV users to be more hesitant in adopting the concept. Multiple studies have explored the perspectives of EV owners on smart charging [110]–[113] and indicated that EV users generally have a positive perception towards smart charging. The main concerns identified by users were the loss of privacy [110], [111], [113], the loss of control and flexibility [110], [111], [113] and the potential insufficient range in case of unexpected departure from the charging station [110]–[113]. Other studies specifically looked into user perceptions of V2G [114]–[118]. They concluded that the risk of increased battery degradation and the additional risk of an insufficient driving range were perceived as the biggest barriers to the adoption of V2G. Addressing these concerns is essential for the successful implementation of smart charging projects.

The second barrier to a successful implementation of EV smart charging is linked to the discussion above. To avoid consumer dissatisfaction, EV smart charging must ensure users' charging demand is met by their departure time from the charging station. However, in practice, one usually faces uncertainties about the charging demand and departure time of a charging session, as the battery State-of-Charge (SoC) is not communicated between the EV and the charging station under the current standard protocol [119] and departure times depend on individual user decisions. As a consequence, the applied EV smart charging schedules will be more conservative to avoid user dissatisfaction, reducing the effectiveness of smart charging. Various methods have been proposed to address this uncertainty. Some studies suggest requesting input from EV users [120], [121], but users often inaccurately estimate their charging demand and departure time [122] and might not be eager to provide this information consistently. Other approaches involve forecasting necessary parameters for scheduling EV charging sessions (e.g., [123]–[126]) or developing strategies to account for these uncertainties during scheduling [127]–[129].

Thirdly, there are different technical barriers to the large-scale rollout of smart charging. Key elements for effective, large-scale implementation of smart charging are (i) hardware, such as the EVs and the EV charging stations; (ii) software, such as back office systems of charging stations and EVs, and (iii) standards, to ensure compatibility among system components [130]. Various barriers arise within each

[2]The Renault 5 e-tech, launched at the end of 2024, is the first production EV model capable of performing AC V2G [108].

of these aspects. The main hardware barrier linked to smart charging involves the technical capabilities of EVs and EV charging stations to perform smart charging and V2G. As discussed before, there are hardly any EV models on the market capable of performing V2G functions, and as Chapter 6 will highlight, different EV models do not respond adequately to smart charging signals. Cybersecurity can be seen as one of the main software barriers. The software enabling the required communication for smart charging should be resilient against cyberattacks to prevent the loss of privacy-sensitive information and the manipulation of charging signals [131]. The latter could cause grid congestion and power quality problems, potentially inducing blackouts [132]. Lastly, the most commonly used versions of the communication standards between EVs and charging stations [133], as well as between the charging stations and the back office [134], do not support V2G functions or allow for the communication of the battery's SoC and capacity, limiting the effectiveness of smart charging.

Lastly, there are different systemic barriers that currently hinder the adoption of smart charging and V2G. For instance, electricity stored in EVs and subsequently returned to the grid via V2G is subject to double taxation [135], thereby reducing the economic attractiveness of implementing V2G. In addition, the minimum bid size for participation in markets for providing grid services is relatively high, increasing the barrier to offering grid services through EV smart charging [136], [137]. There is currently also no framework in place for applying V2G at public charging stations, as it requires explicit user consent before a charging point operator can withdraw electricity from the EV battery to inject it into the grid. In addition, the current system lacks frameworks that provide business models that stimulate the use of smart charging for mitigating grid congestion [135], such as an alternative grid tariff structure.

1.8 Literature gaps & research questions

The previous sections on the different smart charging mechanisms and barriers underscore that this is a widely-studied topic. Despite the extensive attention dedicated to this topic, different aspects in this field are still under-explored.

Firstly, there is little insight into the value of smart charging for mitigating grid congestion from a system-level perspective. Many studies show how smart charging systems that benefit this purpose can reduce grid congestion levels or grid investment costs (e.g., [138]–[140]). However, these studies usually neglect that deploying these smart charging schemes can lead to opportunity costs for EV users. Due to the rollout of these smart charging systems, EV users may find themselves constrained from using smart charging for other applications that offer them more direct benefits, such as smart charging to reduce charging costs. Alternative options for mitigating grid congestion, such as grid reinforcements, might be more attractive from a system

level, as the extra benefits that can be obtained from alternative smart charging applications might outweigh the extra grid investment costs. The current scientific literature provides little insight into this trade-off.

Secondly, the optimal design of a realistic future smart charging system is an understudied topic in the current body of scientific literature. The literature review above showed that numerous smart charging systems have been proposed, but most of these systems cannot be realistically implemented in practice. For instance, the different studies that assume that EVs fully adjust their charging schedules to mitigate grid congestion problems neglect that it is unrealistic that EV users will accept these charging schedules, as alternative charging schemes (e.g., cost-optimized charging) provide more direct benefits to the user. Similarly, the different grid tariff structures for EV charging that were proposed in the literature neglect that regulators weigh a multitude of principles when selecting a tariff structure [141], which makes it uncertain whether these proposed tariff structures will be accepted in practice. Also, most studies that look into the potential value of V2G overlook the necessity of explicit user consent for nearly all V2G applications, as the energy that is discharged from the EV battery belongs to the EV owner. Consequently, the current scientific literature lacks realistic smart charging and V2G systems that address these factors, thereby lacking insight into the real potential value of smart charging and V2G.

Thirdly, not all barriers to the roll-out of smart charging that were identified in the previous section have been adequately addressed in the current literature. This is reflected in different ways. For instance, technical charging problems associated with EV smart charging receive limited attention in the current body of scientific literature. The smart charging models in the scientific literature generally presume that EVs perfectly respond to charging signals, without looking into the prevalence of technical smart charging problems, their impact on the effectiveness of smart charging and the potential measures to eliminate these problems. Similarly, the literature review in Chapter 5 will outline that there is currently an absence of frameworks that consider all uncertainties that are associated with EV smart charging. Consequently, there is a significant shortfall in strategies to address uncertainties and to roll out EV smart charging systems efficiently.

This thesis aims to address the different literature gaps by providing a more nuanced understanding of the potential of smart charging in mitigating grid congestion problems, and by laying the foundation for further optimizing smart charging systems. This will be done by answering the following research question:

What is the value of EV smart charging in mitigating grid congestion problems, and how can this value be effectively realized?

This main research question will be answered through two sub-questions. The first sub-question studies the system value of the different mechanisms that grid operators

Table 1.1: Overview of the different chapters of this thesis.

Chapter	Paper title	Co-authors	Publication status	Addresses sub-question
2	Should we reinforce the grid? Cost and emission optimization of electric vehicle charging under different transformer limits	W. Schram, T. AlSkaif, I. Lampropoulos & W. van Sark	Published in Applied Energy (2020)	1
3	Can grid tariffs be fair and efficient? A comprehensive evaluation of tariff designs for smart electric vehicle integration	F. van Montfoort	Submitted	1
4	Grid congestion mitigation in the era of shared electric vehicles	T. AlSkaif & W. van Sark	Published in Journal of Energy Storage (2022)	1
5	A novel forecasting approach to schedule aggregated electric vehicle charging	L. Visser, T. AlSkaif & W. van Sark	Published in Energy and AI (2023)	2
6	Enhancing smart charging in electric vehicles by addressing paused and delayed charging problems	T. van Wijk, A. Buijze, N. Panda, J. Meersmans, P. Markotić, B. van der Ree, H. Fidder, B. de Brey, S. Tindemans, T. AlSkaif & W. van Sark	Published in Nature Communications (2024)	2

can deploy to stimulate the use of smart charging for mitigating grid congestion, while the second sub-question addresses barriers to the roll-out of smart charging:

1. **What is the system value of different mechanisms that grid operators can use for mitigating grid congestion using EV smart charging?**

2. **What strategies can address barriers to the effective deployment of EV smart charging for mitigating grid congestion?**

Throughout this thesis, diverse analytical approaches will be used to address these questions. While the developed models can be broadly applied, the analyses will predominantly focus on LV grids and public charging stations, with a specific emphasis on the context of the Netherlands.

1.9 Thesis outline

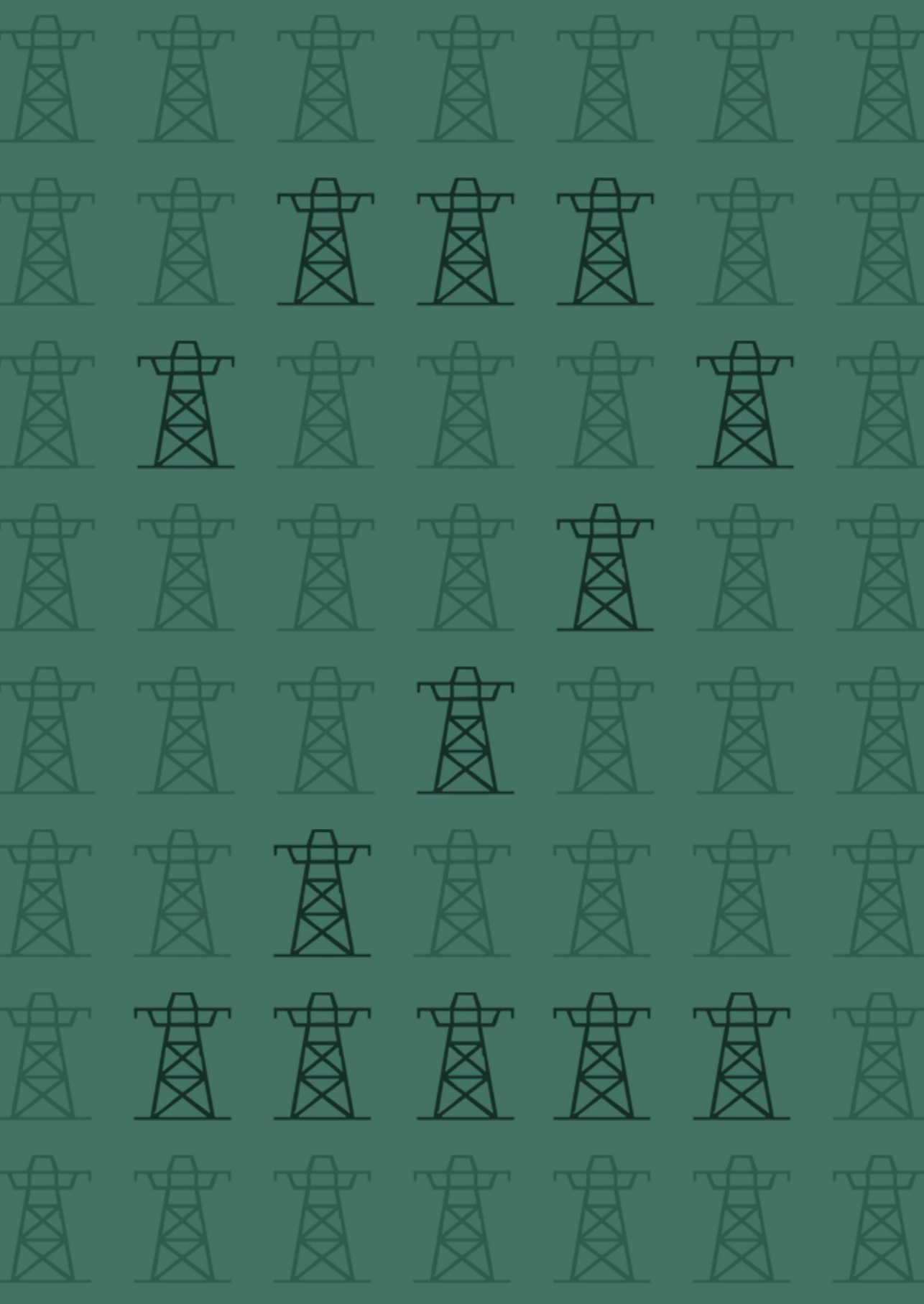
This thesis comprises seven chapters, five core chapters, which are outlined in Table 1.1, along with the introduction and conclusion. The table delineates the contributing co-authors for each chapter, the publication status, and the specific sub-questions addressed.

The first part of this thesis, consisting of **Chapters 2, 3 & 4**, addresses the first sub-question. These chapters study three different mechanisms that grid operators can deploy for mitigating grid congestion using EV smart charging. Chapter 2 offers a thorough analysis of the benefits of EV smart charging using a capacity-limitation system (as outlined in Section 1.6). This chapter assesses EV charging costs and emissions in scenarios both with and without grid reinforcements. It compares the

advantages of grid reinforcements in terms of reduced charging costs and emissions against the costs and emissions incurred from implementing those reinforcements, providing an evaluation of their overall impact on system costs and emissions. Subsequently, **Chapter 3** presents a comparative analysis of different grid tariff structures, examining the EV charging patterns under various tariff structures and evaluating the performance of these structures based on regulatory principles. This chapter thereby provides guidance to regulators and grid operators in selecting the future grid tariff scheme. **Chapter 4** studies a specific case in which a company fleet, specifically a fleet of shared EVs operated by a car-sharing company, is used for mitigating grid congestion through a capacity-limitation system. Compared to systems involving privately-owned EVs, this approach offers advantages such as greater acceptance of bidirectional charging by car-sharing companies and simplified communication, Additionally, the risk of unmet charging demand is reduced, thanks to the insights provided by reservation systems, which help better manage charging schedules and availability.

Chapter 5 and **Chapter 6** address key barriers to deploying smart charging for mitigating grid congestion, and thereby answer the second sub-question of this dissertation. The challenge of the different uncertainties that are associated with smart charging is addressed in **Chapter 5**. This chapter presents a forecasting framework that considers all required aspects for scheduling EV charging. This framework allows aggregators to reduce the uncertainties that they face when deploying smart charging, enhancing its effectiveness. On the other hand, **Chapter 6** focuses on resolving technical charging issues associated with smart charging. It provides insight into the occurrence of these issues and models the impact of paused and delayed charging problems on the effectiveness of smart charging. In addition, this chapter presents different solutions for eliminating these problems.

Finally, **Chapter 7** synthesizes the findings of this thesis, answering the research questions and providing final conclusions. Building on these insights, it offers actionable policy recommendations and outlines directions for future research, contributing to the effective deployment of EV smart charging systems and the mitigation of grid congestion.



Chapter 2

Should we reinforce the grid?

This chapter is based on the following publication, with minor edits for coherence within the thesis and in response to committee feedback:

N. Brinkel, W. Schram, T. AlSkaif, I. Lampropoulos, & W. van Sark (2020).

Should we reinforce the grid? Cost and emission optimization of electric vehicle charging under different transformer limits.

Applied Energy, 276, 115285.

Summary

With high electric vehicle (EV) adoption, optimization of the charging process of EVs is becoming increasingly important. Although the CO_2 emission impact of EVs is heavily dependent on the generation mix at the moment of charging, emission-minimization of EV charging receives limited attention. Generally, studies neglect the fact that cost and emission savings potential for EV charging can be constrained by the capacity limits of the low-voltage (LV) grid. Grid reinforcements provide EVs more freedom in minimizing charging costs and/or emissions, but also result in additional costs and emissions due to reinforcement of the grid. The first aim of this study is to present the trade-off between cost and emission-minimization of EV charging. Second, to compare the costs and emissions of grid reinforcements with the potential cost and emission benefits of EV charging with grid reinforcements. This study proposes a method for multi-objective optimization of EV charging costs and/or emissions at low computational costs by aggregating individual EV batteries characteristics in a single EV charging model, considering vehicle-to-grid (V2G), EV battery degradation and the transformer capacity. The proposed method is applied to a case study grid in Utrecht, the Netherlands, using highly-detailed EV charging session data as input. The results of the analysis indicate that even when considering the current transformer capacity, cost savings up to 32.4% compared to uncontrolled EV charging are possible when using V2G. Emission-minimization can reduce emissions by 23.6% while simultaneously reducing EV charging costs by 13.2%. This study also shows that in most cases, the extra cost or emission benefits of EV charging under a higher transformer capacity limit do not outweigh the cost and emissions for upgrading that transformer.

Highlights

- A system perspective on cost and emission tradeoff of electric vehicle (EV) charging.
- A multi-objective optimization method of EV smart charging and vehicle-to-grid (V2G).
- Costs and CO_2 emissions of EV smart charging and V2G can be reduced simultaneously.
- Smart charging can mitigate grid congestion problems in case of high EV penetration.
- Cost and emissions of grid reinforcement outweigh benefits of increased flexibility.

2.1 Introduction

With the substantial increase in electric vehicle (EV) charging sessions in low-voltage (LV) grids, optimization of the EV charging process receives growing attention. Currently, most EVs charge in an uncontrolled manner; the EV starts charging directly after connecting to the charging station, until its charging requirement is met. This charging strategy is generally regarded as undesirable, as a large share of the EVs start charging in the evening hours [54], [142]. This causes the EV demand peak to coincide with the evening electricity demand peak of households, inducing grid congestion and power quality problems [143], [144]. In addition, uncontrolled charging is not always efficient from a financial and/or CO_2 emission perspective.

For the majority of charging sessions, the EV connection time to the charging station largely exceeds the required time to meet its charging demand [54], [145]. This provides the opportunity to optimize the EV charging process by shifting EV charging over time. This process is frequently referred to as smart charging, coordinated charging or controlled charging. Smart charging algorithms have been proposed for a wide range of objectives. The majority of the proposed charging algorithms perform economic optimizations of EV charging [146], [147]: these algorithms aim to minimize the charging costs of EV owner or aggregators in case of unidirectional charging, or to maximize their economic benefits using vehicle-to-grid (V2G) technology. Other proposed EV smart charging algorithms aim to minimize CO_2 emissions [148], maximize self-consumption of photovoltaic (PV) solar energy [149] or mitigate congestion and power quality problems in LV grids [150], [151]. These research activities were followed by actual implementation and testing of smart charging algorithms in real-life environments [152], [153].

Numerous business case analyses have demonstrated the economic attractiveness of smart charging in different electricity markets, with potential financial benefits ranging from 106 €/year to 1008 €/year per EV [154], [155]. Despite previous research having illustrated that the specific hourly electricity generation mix is an important moderator of the CO_2 emission impact of EVs [156], emission-minimization through smart charging and V2G has only been addressed in a limited number of studies. Some of these studies operationalize this by minimizing the electricity imported from the grid [157], [158]. The limitation of this approach is that it fails to recognize that the emission factor of the electricity generation mix also shows large fluctuations over time, depending on the actual dispatch of e.g. renewables, coal- and gas-fired power plants [159]. Others translate emissions to costs and subsequently minimize on these adapted cost functions [160], [161]. This eliminates the possibility to do a pure emission-based optimization, and it therefore underestimates the mitigation potential of smart charging and V2G. The limitations of these previous studies can be addressed by constructing emission profiles which can be used as input in the emission optimization process [162], [163]. To the best of our knowledge, only Zakariazadeh et al. [164] and Hoehne et al. [148] have applied this approach to

smart charging or V2G. However, both studies only consider a short timescale and neglect day-to-day variations in emissions. Battery degradation is also not considered in both studies, while this can have important implications for the Pareto frontier in battery multi-objective optimization [163]. Furthermore, Hoehne et al. [148] do not determine the trade-off between charging costs and emissions and only consider plug-in hybrid EVs, while Zakariazadeh et al. [164] consider unrealistic synthetic price and emission profiles which overestimate the variability in emissions and prices by a factor of 10 [159], [165].

A second gap identified in scientific literature is the limited attention of the potential adverse impact of smart charging and V2G on grid congestion. Increasing grid congestion induced by EV charging can occur when a large set of EVs charge simultaneously at moments with low electricity costs or emissions. Distribution System Operators (DSOs) are required to accommodate the needs of all system users and requests for new connections in the LV-grid [166], which could result in increasing need for grid reinforcements in order to accommodate smart charging and V2G. On the one hand, grid reinforcements cause that EVs are less constrained by the grid capacity in minimizing costs and emissions. On the other hand, grid reinforcements result in extra emissions and socialized costs from manufacturing and installing grid assets. This demonstrates the need to determine whether the economic and environmental benefits of smart charging with a higher grid capacity limit outweigh the costs and emissions of grid reinforcements.

Building on the identified gaps in the literature, this work offers several contributions to the scientific community. It presents a novel framework for evaluating the system value of grid reinforcements by comparing the cost and emission benefits of smart EV under a higher grid capacity limit with the costs and emissions of grid reinforcements. The framework uses an efficient method to model aggregated charging patterns for large EV fleets, while accounting for EV battery degradation, V2G capabilities and transformer constraints. It also explores the trade-off between cost and emission minimization in EV charging, offering the first realistic assessment of this dynamic. The framework is validated through a real-world case study, considering varying EV and PV adoption rates, emission profiles, and pricing schemes.

This chapter is outlined as follows: Section 2.2 presents the system architecture, discusses a method to model the aggregated charging pattern of a large set of EVs at low computational time and provides the multi-objective optimization problem formulation. Section 2.3 provides a literature review on battery degradation experiments, determining the empirical relationship between cycle depth and battery degradation. Section 2.4 introduces the investigated case study and provides an overview of the data inputs. Section 2.5 presents the multi-objective optimization results, including a sensitivity analysis on the effect of different critical parameters such as EV adoption rate, PV adoption rate and V2G on the outcomes. Lastly, the discussion is presented in Section 2.6 and conclusions and suggestions for future research are presented in Section 2.7.

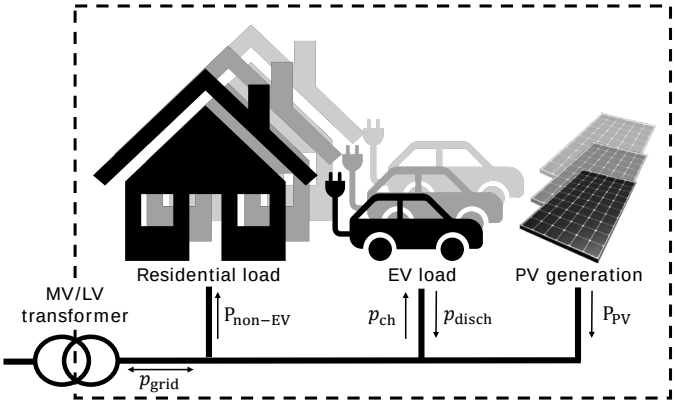


Figure 2.1: The proposed system architecture.

2.2 Methods

2.2.1 System architecture

Figure 2.1 shows the system architecture of this study. The system boundaries contain a single LV grid, which connects a number of households, PV systems and EV charging stations. In the assessment timeframe, a set of EV charging sessions is conducted at the EV charging stations in the investigated LV grid. An aggregator can control the charging and discharging of the EVs to optimize economic and/or environmental objectives. The grid operator communicates the available grid capacity at each timestep to the aggregator, which ensures that the power flows through the Medium Voltage (MV)/LV transformer remain within the transformer limits and the charging needs of the EVs are met.[3] EV demand is assumed to be the only shiftable load and furthermore EVs are able to feed electricity into the grid (i.e., V2G). This study assumes perfect foresight in residential load, PV generation, Time-of-Use (ToU) tariffs, emission profiles and EV availability.

2.2.2 System costs and system emissions

A transformer upgrade and/or cable reinforcements provide EV fleet operators with more freedom in minimizing EV charging costs and/or emissions without being constrained by the grid capacity. However, to evaluate whether transformer or grid reinforcements are desirable from a system perspective, costs and emissions from the production and installation of a transformer and electricity cables should also be

[3]The system examined in this chapter is an example of a capacity-limitation system, as defined in the Dutch grid code in 2022 [92] Under this system, the grid operator can impose restrictions on grid usage for grid users at specific times. In exchange, grid users receive financial compensation.

taken into account. Costs and emissions associated with battery degradation should also be considered to account for the potential extra battery degradation with V2G compared to unidirectional charging. System costs and emissions are defined in equations 2.1a and 2.1b as follows:

$$c_{\text{system}} = c_{\text{el}} + c_{\text{battdeg}} + c_{\text{grid}}, \tag{2.1a}$$

$$g_{\text{system}} = g_{\text{el}} + g_{\text{battdeg}} + g_{\text{grid}}, \tag{2.1b}$$

where c_{system} and g_{system} are respectively the annual system costs and emissions, c_{el} and g_{el} are the total annual retail electricity costs and emissions for the whole LV grid, c_{battdeg} and g_{battdeg} are the total annual costs and emissions resulting from EV battery degradation and c_{grid} and g_{grid} are the annualized costs and emissions from grid reinforcements.

Grid reinforcement costs (c_{grid}) and emissions (g_{grid}) are annualized by using equations 2.2a and 2.2b:

$$c_{\text{grid}} = \frac{(\pi_{\text{trans}} + l_{\text{cable}}\pi_{\text{cable}})\,r}{\left(1-(1+r)^{-L}\right)} \tag{2.2a}$$

$$g_{\text{grid}} = \frac{\epsilon_{\text{trans}} + l_{\text{cable}}\epsilon_{\text{cable}}}{L}, \tag{2.2b}$$

where π_{trans} and ϵ_{trans} represent the total costs and emissions of producing and replacing a transformer (partly dependent on transformer capacity), π_{cable} and ϵ_{cable} represent respectively the costs and emissions for reinforcing one kilometer of cable, l_{cable} represents the total cable length that is reinforced and L represents the assumed lifetime of the grid (usually 35-50 years), assuming that the transformer and the cables have the same lifetime. Grid reinforcement costs are discounted to consider the time value for money; r represents the discount factor, reflecting how much less future costs are valued compared to present costs.

2.2.3 Modelling aggregated EV charging patterns

Nearly all EV optimization models optimize the charging behaviour of individual EV sessions, since each charging session has its unique plug-in time, plug-out time, charging requirement and maximum charging rate (e.g., [167], [168]). With high EV penetration, optimization of individual EV sessions could result in a significant computational burden, as each individual EV session adds a set of variables to the optimization problem. This computational burden can hinder policymakers and DSOs to perform techno-economic scenario studies for a long time horizon and for a large number of case-specific grids, considering a large number of parameters.

A study by Tang et al. [169] has proposed a method to model the aggregated charging behaviour of a large pool of EVs in a LV grid at one timestep as a single variable, inducing a considerable reduction in the computational time. The method

Table 2.1: Overview of parameters for optimizing the aggregated charging demand of EV charging session subset v, adapted based on Tang et al. [169]

$E_{ch,max,t,v}$	The maximum accumulated charging energy at timestep t of EV set v is equal to the required charging energy of all EVs of session set s that connected to the grid between $t = 0$ and t.
$E_{ch,min,t,v}$	The minimum accumulated charging energy assures that the charging requirement of individual charging sessions is met before unplugging. $E_{ch,min,t,v}$ is equal to accumulated charging volume of all EVs in session set v that connected to the grid between $t = 0$ and t in the 'latest charging scenario'. The 'latest charging' scenario assumes that the charging schedule of an EV is delayed to the latest and that an EV charges at maximum charging power in the required number of timesteps to meet its charging demand before unplugging.
$P_{ch,max,t,v}$	The maximum charging power of EV set v at timestep t is equal to the maximum charging power of all EVs of EV session set v connected to the grid at timestep t.
$P_{disch,max,t,v}$	The maximum discharging power of EV set v at timestep t is equal to the maximum discharging power of all EVs of EV session set v connected to the grid at timestep t, excluding EVs that are charging in the latest charging scenario at timestep t. This avoids the model to discharge at maximum power one timestep before an EV unplugs, resulting in unmet charging demand.

converts the required charging volume, maximum charging power, plug-in time and plug-out time of individual EV charging sessions into an aggregated maximum charging power ($P_{ch,max,t}$), minimum accumulated charging energy ($E_{ch,min,t}$) and maximum accumulated charging energy ($E_{ch,max,t}$) per timestep for a set of charging sessions, as described in Table 2.1. This method allows the charging behaviour of this set of charging sessions to be modelled as a single community battery with a variable (i.e., time-dependent) battery capacity.

This study proposes two modifications to the methods of Tang et al. [169]. First, this study proposes to model accumulated EV charging behaviour as multiple community batteries with a variable battery capacity instead of as a single community battery, since Tang et al.'s methods can underestimate the costs or emissions of EV smart charging. This is since the maximum charging power $P_{ch,max,t}$ is aggregated for multiple EV charging sessions, which allows the model to meet the charging requirement of individual charging sessions by charging with a higher charging power than physically possible for an individual charging session. This study proposes to divide the set of EV charging sessions into V subsets, indexed by $v \in \mathcal{V}\{1, 2, ..., V\}$, in a chronological order based on the plug-in time. Subsequently, $P_{ch,max,t,v}$, $P_{disch,max,t,v}$, $E_{ch,max,t,v}$ and $E_{ch,min,t,v}$ are determined for every timestep and for every subset. The number of subsets V can be varied to determine a balance between computational

time and accuracy of the model. Second, this study proposes to extend the method of Tang et al. to V2G-systems by introducing a maximum discharging rate ($P_{disch,max,t,v}$) for the aggregated EV charging model. Table 2.1 discusses the proposed methods for determining $P_{disch,max,t,v}$.

2.2.4 Multi-objective optimization model formulation

Objective functions and ϵ-constraint

A common approach to address a problem with multiple objectives is to determine the Pareto frontier using the ϵ-constraint method [170]. Each optimization is first solved separately, calculating the two endpoints of the Pareto frontier. The cost and emission objective functions are formulated in equations 2.3a and 2.3b:

$$\min \sum_{t=0}^{T} \left(c_{el,t} + c_{battdeg,t} \right), \tag{2.3a}$$

$$\min \sum_{t=0}^{T} \left(g_{el,t} + g_{battdeg,t} \right), \tag{2.3b}$$

where c_{el} represents the electricity retail costs, t represents a timestep in the set of considered timesteps $\mathcal{T}\{0, 1, \ldots, T\}$, $c_{battdeg}$ the battery degradation costs, g_{el} represents the CO_2 emissions related to electricity consumption and $g_{battdeg}$ the CO_2 emissions related to battery degradation. c_{el} and g_{el} can be determined according to equations 2.4a and 2.4b:

$$c_{el,t} = \pi_{el,t} p_{grid,t} \Delta t \quad \forall t \in \mathcal{T}, \tag{2.4a}$$

$$g_{el,t} = \theta_{el,t} p_{grid,t} \Delta t \quad \forall t \in \mathcal{T}, \tag{2.4b}$$

where Δt is the considered timestep duration in hours, the ToU-tariff at timestep t is represented by $\pi_{el,t}$, the emission factor related to electricity consumption is represented by $\theta_{el,t}$ and the total amount of electricity withdrawn from (+) or injected to (-) the MV-grid is represented by $p_{grid,t}$.

Additional discharging and charging of an EV impacts the lifetime of the EV battery caused by cyclic ageing [171], [172]. Therefore, it is important to include battery degradation into the objective function, to ensure batteries are only discharged and charged if the benefits exceed the costs associated to battery degradation. If δ represents the cycle depth (i.e., change in state-of-charge in a charging/discharging cycle) of an EV battery system, then the battery degradation costs $c_{battdeg}$ and degradation emissions $g_{battdeg}$ at timestep t can be calculated using equations 2.5a and 2.5b:

$$c_{battdeg,t} = \pi_{batt} \sum_{v=1}^{V} \Phi\left(\delta_{v,t}\right) \quad \forall t \in \mathcal{T}, \tag{2.5a}$$

$$g_{\text{battdeg},t} = \theta_{\text{batt}} \sum_{v=1}^{V} \Phi\left(\delta_{v,t}\right) \quad \forall t \in \mathscr{T}, \tag{2.5b}$$

where π_{batt} are the battery investment costs and θ_{batt} are the emissions from producing a battery. The dimensionless battery degradation function $\Phi\left(\delta_{s,t}\right)$ is discussed in Section 2.3.

The minimum and maximum of the range in emissions are the outcome of equation 2.3b, and the emissions associated to the optimal solution found in equation 2.3a, respectively. Subsequently, the range in emissions is divided into K equally spaced bins ϵ_k, where $k \in \mathscr{K}\{1, 2, ..., K\}$. The ϵ-constraint can now be formulated by treating the emission function 2.3b as a constraint for each bin ϵ_k, as in equation 2.6, while optimizing for the cost-minimization objective:

$$\sum_{t=0}^{T} \left(g_{\text{el},t} + g_{\text{battdeg},t}\right) \leq \epsilon_k. \tag{2.6}$$

This approach allows to obtain the least-cost solution for a certain intended reduction in emissions. Only the cost-minimization runs of the multi-objective optimization are subject to this constraint. The objective functions 2.3a and 2.3b are subject to various other constraints, as discussed in the following sections.

Power balance constraint

The power balance constraint is formulated in equation 2.7:

$$p_{\text{grid},t} = \text{P}_{\text{non-EV},t} - \text{P}_{\text{PV},t} + \frac{1}{\eta_{\text{ch}}} \sum_{v=1}^{V} p_{\text{ch},v,t} - \eta_{\text{disch}} \sum_{v=1}^{V} p_{\text{disch},v,t} \quad \forall t \in \mathscr{T}, \tag{2.7}$$

where $\text{P}_{\text{non-EV},t}$ and $\text{P}_{\text{PV},t}$ represent the residential/non-EV load and PV generation in the investigated LV grid at timestep t. These are assumed to be non-controllable. $\text{P}_{\text{ch},v,t}$ and $\text{P}_{\text{disch},v,t}$ represent, respectively, the charging and discharging power at the EV battery of EV group v at timestep t and η_{ch} and η_{disch} represent the EV charging and discharging efficiencies.

Charging power constraints

The aggregated charging and discharging power of each subset of EVs are constrained by a maximum charging and discharging power, which are determined using the methods presented in Section 2.2.3:

$$0 \leq p_{\text{ch},v,t} \leq \text{P}_{\text{ch,max},v,t} \quad \forall t \in \mathscr{T},\ \forall v \in \mathscr{V}, \tag{2.8}$$

$$0 \leq p_{\text{disch},v,t} \leq \text{P}_{\text{disch,max},v,t} \quad \forall t \in \mathscr{T},\ \forall v \in \mathscr{V}. \tag{2.9}$$

Accumulated charging energy constraints

To model the charging behaviour of a group of EVs as a single community battery, the accumulated charging energy is constrained by a minimum and maximum accumulated charging energy, as discussed in Section 2.2.3:

$$\mathrm{E}_{\mathrm{ch,min},v,t} \leq e_{\mathrm{ch},v,t} \leq \mathrm{E}_{\mathrm{ch,max},v,t} \quad \forall t \in \mathscr{T},\ \forall v \in \mathscr{V}, \tag{2.10}$$

where $e_{\mathrm{ch},v,t}$ is a variable that represents the accumulated charging energy of EV group v at timestep t. $e_{\mathrm{ch},v,t}$ is defined as follows:

$$e_{\mathrm{ch},v,t} = \sum_{\tau=0}^{t} (p_{\mathrm{ch},v,\tau} - p_{\mathrm{disch},v,\tau})\Delta\mathrm{t} \quad \forall t \in \mathscr{T}, \tag{2.11}$$

where τ is a timestep between the beginning of the assessment timeframe and t.

Transformer capacity constraint

To avoid transformer overloading, $p_{\mathrm{grid},t}$ is constrained by the transformer capacity ($\mathrm{P}_{\mathrm{tr,max}}$) at every timestep t, as formulated in equation 2.12:

$$-\mathrm{P}_{\mathrm{tr,max}} \leq p_{\mathrm{grid},t} \leq \mathrm{P}_{\mathrm{tr,max}} \quad \forall t \in \mathscr{T}. \tag{2.12}$$

Since residential load and PV generation are assumed to be non-controllable in this study, only EV charging behaviour is altered to meet this constraint.

2.3 Battery degradation

Wöhler curves, or Stress – Number of cycles curves (S-N curves), are often used to predict material fracture under cycle loading [177]. This relation can also be applied to cyclic battery degradation [178]. Doing this, the relation between the number of full equivalent cycles until end of life $\mathrm{N}_{\mathrm{eol,full}}$ (i.e., the number of 100% equivalent cycles the battery can perform at a given cycle depth) and cycle depth δ takes the following general form:

$$\mathrm{N}_{\mathrm{eol,full}} = \mathrm{N}_{\mathrm{eol,ref}}\delta^{\mathrm{m}}. \tag{2.13}$$

By default, parameter $\mathrm{N}_{\mathrm{eol,ref}}$ reflects the number of cycles the battery can withstand under cycle depth of 100% (i.e., $\delta = 1$), whereas battery degradation parameter m is a degradation exponent that determines how sensitive the cycle life is to changes in depth of discharge. To obtain the number of actual cycles $\mathrm{N}_{\mathrm{eol,actual}}$ at a specific cycle depth until end of life, one needs to correct for the actual cycle depth:

$$N_{\mathrm{eol,actual}} = \frac{\mathrm{N}_{\mathrm{eol,ref}}\delta^{m}}{\delta} = \mathrm{N}_{\mathrm{eol,ref}}\delta^{\mathrm{m}-1}. \tag{2.14}$$

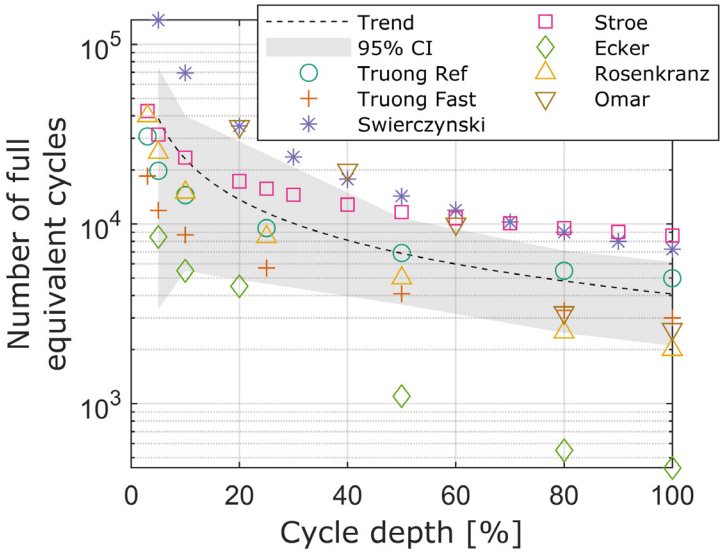


Figure 2.2: Cycle depth versus number of full equivalent cycles. Data from [171]–[176]. Trendline is an exponential fit of the averages of the studies; the 95% CI is the confidence interval of the mean for every cycle depth.

The degradation per cycle of the battery is the inverse of $N_{eol,actual}$. Considering half cycles instead of full cycles, this can be translated to the dimensionless degradation function $\Phi\left(\delta_{v,t}\right)$:

$$\Phi(\delta_{v,t}) = \frac{0.5}{N_{eol,ref}\delta^{m-1}} = \frac{0.5}{N_{eol,actual}}. \tag{2.15}$$

Note, as this function is non-linear, equations 2.5a, 2.5b and 2.6 are treated as piecewise linear functions in the optimization model by using four segments.

A literature review was performed to determine appropriate values for the parameters $N_{eol,ref}$ and m for lithium-ion EV batteries. Figure 2.2 shows the results of seven different studies; all studies comply to the general form presented in equation 2.13, with the R^2 for each individual study ranging from 0.92 to 1.00. For every cycle depth that was studied by more than four studies, the average value of $N_{eol,full}$ was taken. A trendline with the form of equation 2.13 was fitted using the MATLAB curve fitting toolbox; values of $N_{eol,ref}$ and m were determined at 4084 (±367; 95% confidence) and -0.7514 (±0.0324), respectively, with an adjusted R^2 of 0.997. These values are used as battery degradation parameters in this study.

Table 2.2: Details of the considered EV adoption scenarios

EV adoption	No. of EVs charging per year		No. of charging sessions per year	EV charging volume per year
	Local	Other		
25%	34	916	7339	132 MWh
50%	68	1832	14464	257 MWh
75%	102	2749	20778	372 MWh
100%	136	3665	28355	506 MWh

2.4 Data inputs

2.4.1 Case study specifications

This research considers an LV grid in a residential area in the Lombok district in Utrecht (the Netherlands) as a case study grid. This part of the distribution grid is used as a living lab in the Smart Solar Charging research project [152] to determine the impact of EV charging and PV generation on LV grids. For this research project, EV charging session data is logged from 26 EV charging stations and the PV generation from three PV systems is logged on a 5-minute basis.

The investigated grid has a radial outline and is connected to the MV grid through a 400 kVA transformer. The total cable length equals 3.3 km, divided over 19 feeder lines. Most cables in the grid are made out of copper, with cross-sectional areas ranging from 25 to 95 mm^2, as described in [63]. The total electricity demand in this grid equaled 1251 MWh in 2017.

The transformer capacity in this grid can be upgraded to 630 kVA. This study will compare the system costs and system emissions with and without transformer upgrades.

2.4.2 EV charging sessions

The analyses in this study are performed for different EV adoption rates, as depicted in Table 2.2. Future sets of EV charging sessions are generated to reflect high EV adoption rates, using the methods described in [52]. This method uses a stochastic Monte Carlo simulation to model charging sessions for a predefined number of EVs, accounting for the interdependencies between plug-in time, connection duration, and charging demand using historical charging session data. Two years of logged EV charging data from the investigated grid is used for generating future EV charging sessions. The different EV adoption rates in Table 2.2 represent the share of EVs in total number of cars possessed by households connected to the investigated grid, considering the current car possession rate of 0.4 car/household in the Lombok district [179]. Table 2.2 makes a distinction between local EVs and other EVs (e.g., visiting EVs), using the classification method in [52]. It is assumed that all electric

Table 2.3: Overview of parameter values used in this study for determining annualized grid reinforcement costs and emissions.

Parameter	Considered parameter value
π_{trans} (630 kVA)	€15,000 [65]
π_{cable}	120,000 €/km [65]
θ_{trans} (630 kVA)	136.3 t CO_2eq* [180]
θ_{cable}	12.5 t CO_2eq/km† [181]
r	3% [65]
L	40 years [65]
l_{cable}	3.3 km

* Jorge et al. [180] determined the life-cycle emissions for a 315 kVA transformer. This has been scaled to a 630 kVA transformer by using a scale factor of 0.8 [182]. Emissions from transformer losses were not considered, assuming that a transformer upgrade of 400 to 630 kVA does not result in additional transformer losses.

† This study assumes that underground copper cables are replaced with aluminum cables. The emissions from the production and installation of an aluminum cable are combined with the end-of-life emission benefits of copper cables.

Table 2.4: Overview of annualized grid reinforcement costs and emissions with different shares of cable reinforcements. All cable reinforcement scenarios considered transformer reinforcements.

% of cables reinforced	Annualized costs	Annualized emissions
0%	649 €/year	3.41 t CO_2eq/year
25%	4955 €/year	3.67 t CO_2eq/year
50%	9262 €/year	3.93 t CO_2eq/year
75%	13568 €/year	4.19 t CO_2eq/year
100%	17225 €/year	4.44 t CO_2eq/year

vehicles in the future are battery electric vehicles (BEVs) and that the ratio between local EVs and other EVs is the same as in the logged EV data.

2.4.3 Grid reinforcement costs and emissions

Table 2.3 shows general values for the costs and emissions of grid reinforcements used in economic and environmental assessments about grid reinforcements. In this study, we consider both scenarios with only transformer upgrades and scenarios in which 25%, 50%, 75% and 100% of the cables in the grid are reinforced. Table 2.4 presents the annualized reinforcement costs and emissions for each considered scenario, which are based on equation 2.2a and 2.2b.

Table 2.5: Overview of data inputs in this study.

Parameter	Description
PV generation profiles	Normalized 15-minute data (kW/kWp) from three logged PV systems in the Lombok district in Utrecht, the Netherlands.
Residential load profiles	Standardized household load profiles for 2018 from NEDU [183] and the total annual electricity consumption of all grid connections in the investigated grid in 2017 (as 2018 data was not available).
Price data	Day-ahead market prices in the Netherlands in 2018 in most runs. Automatic Frequency Restoration Reserve (aFRR) imbalance prices in the Netherlands in 2018 in the sensitivity analysis
Emission profiles	Average emission profiles are determined using the method in [159] and 15-minute generation data in 2018 from the Netherlands from [165]. Marginal emission profiles are determined using the methods in [156] and Dutch day-ahead market prices in 2018. Specific assumptions can be found in Appendix 2.A.
η_{ch}, η_{disch}	$\sqrt{0.87}$ [184]
Δt	15-minutes
Battery degradation parameters	Parameters presented in Section 2.3.
Battery investment costs	130 €/kWh [185]
Battery production emissions	104 kg CO_2eq/kWh [186]

2.4.4 Emission profiles and other data inputs

Table 2.5 provides an overview of the data inputs used in this study. The emission profiles form an important input for this study. Two different profiles are composed for the Netherlands in 2018: an average emission profile and a marginal emission profile. These are constructed according to the methods presented in [159] and [156]; more details can be found in Appendix 2.A. Average emission profiles are constructed by taking the weighted average emission factors of all electricity generating technologies in a certain timeframe (15 minutes in this study). This makes them especially suitable for CO_2 accounting purposes. Marginal emission profiles take the emission factor of one specific power plant, namely the one that is the price-setting unit in a certain time frame (typically one hour). An increase or decrease of demand leads to altered electricity generation of this power plant, which makes these profiles very suitable to determine the emission impact of charging optimization [187].

The assessment time horizon equals one year. To limit the computational burden of the simulation, the EV charging optimization is split into individual months to reduce

the computational complexity and memory requirements, which are subsequently combined to obtain the annual total electricity and battery costs. The simulation of each month also considers the EV charging sessions starting in the five days before the start of the month to assure that a representative number of EVs is charging at the beginning of the month. In addition, five days after the last day of the month are considered in each monthly optimization to allow EVs to finish their charging session. Battery degradation was only considered in simulations with V2G functions, as V2G can increase battery degradation compared to unidirectional EV charging. The number of EV subsets V equalled 50 for 25% EV adoption, 150 for 50% EV adoption, 200 for 75% EV adoption and 250 for 100% EV adoption, based on Section 2.5.3. Simulation was performed in Python [188] with the Gurobi [189] solver, using a laptop equipped with an Intel i7-5600U processor and a 16GB RAM.

2.5 Results

2.5.1 Multi-objective optimization results

The Pareto frontier showing the trade-off between cost-minimization and emission-minimization for EV charging is presented in Figure 2.3. This figure shows the trade-off for both marginal and average emissions and identifies the impact of a transformer upgrade from 400 kVA to 630 kVA on system costs and emissions.

Unidirectional charging

Figure 2.3 indicates that cost-minimization of unidirectional EV charging with a 400 kVA transformer results in a reduction of charging costs of 22.7% compared to uncontrolled charging. Emission-minimization of EV charging with a 400 kVA transformer can reduce charging emissions by 8.0% when considering average emission profiles and by 23.6% when considering marginal emission profiles. Even with 100% emission-minimization of EV charging, costs are reduced by 7.8% compared to uncontrolled charging when considering average emission profiles and by 13.2% when using marginal emission profiles.

Marginal emission profiles show a larger spread in emissions compared to average emission profiles (standard deviations in 2018 of 0.190 kg CO_2eq/kWh and 0.045 kg CO_2eq/kWh respectively, see also Figures 2.A and 2.B in Appendix 2.A), as a change in marginal power plant (e.g., from a coal- to a gas-fired power plant) has a direct substantial impact on the marginal emission factor. The impact of a different marginal power plant on the average emission factor is limited, since a large share of the total emissions are determined by relatively constant baseload generation.

Figure 2.3 indicates that the increase in costs when shifting from cost-minimization to emission-minimization is higher when using average emissions profiles than when using marginal emission profiles. An explanation can be found in the input data: the

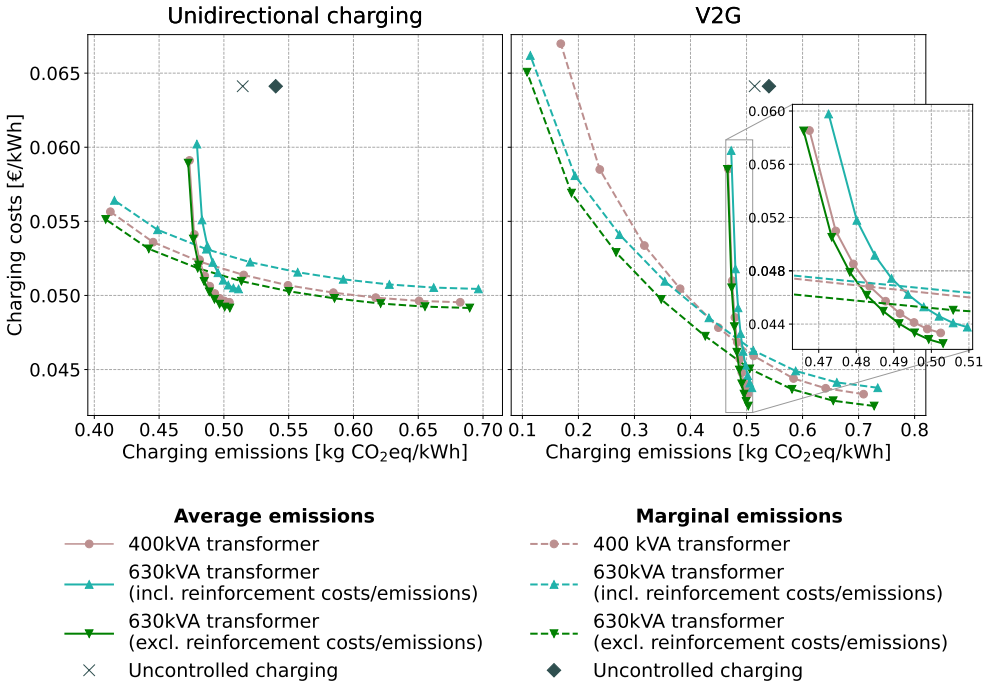


Figure 2.3: Pareto frontier for multi-objective optimization of costs and CO_2-emissions of EV charging, considering average and marginal emission profiles and considering unidirectional charging (left) and V2G (right). Pareto frontiers are presented for an EV adoption rate of 100% and an installed PV capacity of 400 kWp. Battery degradation costs and emissions are considered for all Pareto frontiers. For V2G, the costs and emissions are presented per net charged kWh (i.e., charging volume minus discharging volume).

lowest values of marginal emission factors coincide with lower prices than the lowest values of average emission factors. The lowest marginal emission factors are found in hours in which the most efficient gas-fired power plant is marginal; this implies a relatively low residual electricity demand, and thus relatively low prices.

Overall, the CO_2-abatement costs[4] when shifting from cost-based optimization to emission-based optimization range from 2.8 to 22.6 €/tCO_2eq with increasing levels of emission abatement when considering marginal emission profiles with a 400 kVA transformer. The CO_2-abatement costs range from 21.8 to 310.6 €/tCO_2eq when considering average emission profiles.

[4] CO_2-abatement costs are calculated by dividing the increase in system costs when shifting from cost-minimization towards a partly emission-based charging optimization by the decrease in system emissions when making this shift.

V2G

V2G functions allow for a larger reduction in charging costs and emissions, as EVs can inject electricity to the grid at moments with high costs or emissions. Figure 2.3 shows that the cost reduction potential of V2G compared to uncontrolled charging equals 32.4%, whereas the emission reduction potential equals 8.7% when using average emission profiles and 67.3% when using marginal emission profiles. This emission reduction with V2G is most profound for marginal emission profiles due to its high volatility in emissions. This high volatility causes that the emission benefits of discharging exceed the extra battery degradation emissions, resulting in high discharging volumes when minimizing emissions with marginal emission profiles. This also explains why the increase in EV charging costs with V2G is higher with marginal emission profiles when shifting from cost-based optimization to emission-based optimization. EV discharging volumes are higher when optimizing emissions using marginal emission profiles. This causes EVs to inject electricity to the grid at moments with high emissions, corresponding to low electricity prices, thus increasing the net charging costs of EV charging. The CO_2-abatement costs when shifting from cost-based optimization to emission-based optimization range from 5.9 to 43.8 €/tCO_2eq for marginal emissions and from 82.7 to 434.8 €/tCO_2eq for average emissions when considering V2G functions with a 400 kVA transformer.

Impact of transformer upgrade

Comparing the Pareto frontiers corresponding to 400 kVA and 630 kVA transformers in Figure 2.3 provides insight on the effect of a transformer upgrade on system costs and emissions. The results indicate that EV charging costs and emissions are lower with a 630 kVA transformer from the perspective of the aggregator (i.e., when neglecting transformer upgrading costs and emissions), since this Pareto frontier is located below the 400 kVA Pareto frontier in all scenarios. A transformer upgrade causes that EVs are less constrained in their charging behaviour by the transformer capacity, providing more freedom to EVs in minimizing their charging costs or emissions. However, Figure 2.3 shows that with unidirectional charging, a transformer upgrade is never beneficial from a system perspective in terms of both costs and emissions when also considering the costs and emissions for producing and installing a transformer.

A transformer upgrade has a more pronounced impact on system costs and emissions with V2G, since EVs are not only less frequently constrained by the transformer capacity during charging, but also less constrained during discharging. This allows EVs to inject more electricity to the grid at moments with beneficial prices and/or emissions. With V2G, the Pareto frontiers corresponding to the transformer capacities of 400 and 630 kVA (including transformer upgrading costs and emissions) intersect at EV charging emissions of 0.45 kg CO_2eq/kWh. This indicates that grid reinforcements are attractive from a system perspective in the investigated case study when

constraining the EV charging emissions to 0.45 kg CO_2eq/kWh or lower when EVs optimize their charging schedule using V2G.

2.5.2 Sensitivity analysis on system impact of grid reinforcements

To provide better insights under what circumstances grid reinforcements are beneficial from a system perspective, this section elaborates on how the system impact of grid reinforcements changes with different values for critical parameters, including the EV adoption rate, installed PV capacity, selected pricing scheme and level of grid reinforcement. These sensitivity analyses focus on the impact on system costs, since most DSOs still base decisions for grid reinforcements on financial grounds.

Impact of EV adoption rate and installed PV capacity

Figure 2.4 presents a breakdown of the change in system costs with a transformer upgrade from 400 kVA to 630 kVA for different EV adoption rates and different installed PV capacities for both unidirectional charging and V2G. Figure 2.4 indicates that in all cases with both unidirectional EV charging and V2G, the annualized investments outweigh the reduction in EV charging costs due to a transformer upgrade, resulting in an increase in system costs. An increase in total system costs implies that from a system perspective, under the assumptions in this study, it is not economically attractive to reinforce the grid to mitigate congestion problems induced by EVs.

A transformer upgrade leads to a larger decrease in EV charging costs with higher EV adoption rates. As a high EV load can cause transformer overloading, the number of times that EVs are constrained by the transformer capacity in charging at moments with low prices increases with the number of EVs connected to the grid. Subsequently, a transformer upgrade leads to a larger reduction in EV charging costs with higher EV adoption rates.

The decrease in EV charging costs with a transformer upgrade is lower with a higher installed PV capacity in the grid. PV generation causes that less power withdrawal from the MV grid is required to fulfil the electricity demand of EVs. As a consequence, EVs can meet a larger share of their charging demand at moments with low electricity prices without causing transformer overloading, thus a transformer upgrade has a less pronounced effect on the EV charging costs.

Impact of selected pricing scheme

With increasing integration of renewables into the electricity system, electricity prices could become more volatile. In addition, it is unlikely that all EVs will be subject to the same price-incentives as inputs in the optimization of their charging process, since EVs are optimized in the context of different (sub-)markets via the aggregator. To determine how these developments could affect the impact of grid reinforcements on system costs, additional simulations were performed in which different shares of

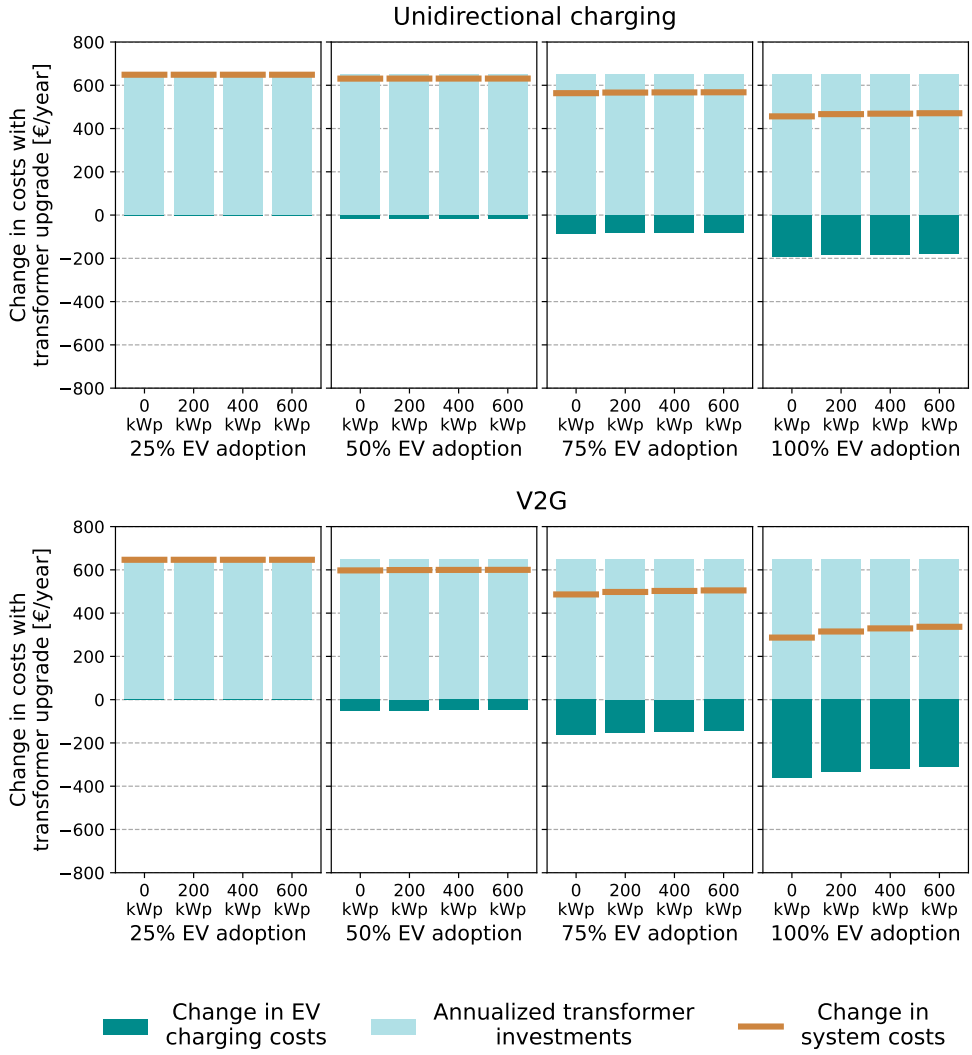


Figure 2.4: Annualized transformer investments, change in EV charging costs and change in system costs with a transformer upgrade of 400 kVA to 630 kVA in the investigated grid for different EV adoption rates and installed PV capacities with unidirectional charging (top) and bidirectional charging (bottom). No cable reinforcements are considered in this figure.

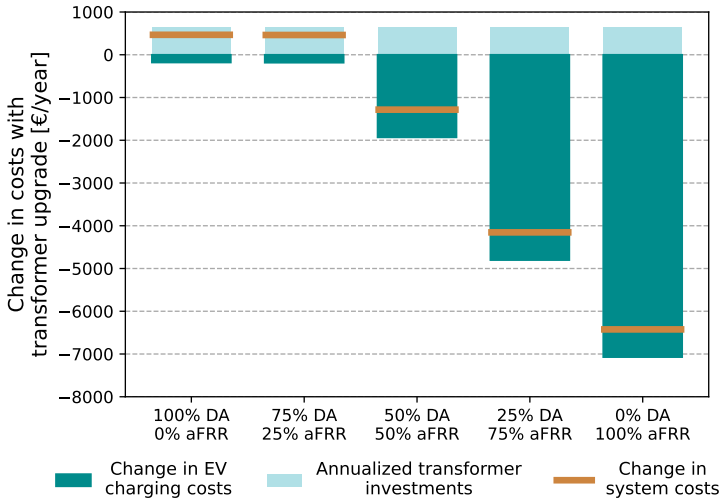


Figure 2.5: Annualized transformer investments, change in electricity costs and change in electricity costs with a transformer upgrade of 400 kVA to 630 kVA in the investigated grid for different shares of cars charging using aFRR and day-ahead (DA) prices in optimizing their charging process. Results are presented for an EV adoption rate of 100% and an installed PV capacity of 200 kWp.

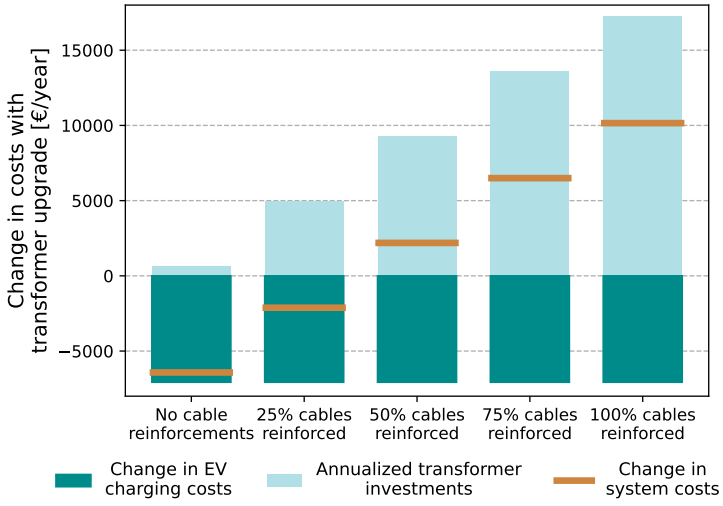


Figure 2.6: Annualized grid investments, change in electricity costs and change in electricity costs with a transformer upgrade of 400 kVA to 630 kVA in the investigated grid for different grid reinforcement scenarios. Results are presented for an EV adoption rate of 100% and an installed PV capacity of 200 kWp. All EVs in this scenario used aFRR prices to optimize their charging demand.

the EV fleet used the more volatile Dutch automatic Frequency Restoration Reserves (aFRR) prices in optimizing their charging schedule.

Figure 2.5 indicates that the decrease in EV charging costs with grid reinforcements outweighs the grid reinforcement investments when a large number of EVs bases its charging schedule on aFRR prices, using the scenario of 100% EV adoption with a 200 kWp installed PV capacity in the considered LV grid. This highlights the major impact of the volatility of the selected pricing scheme on the outcome of the analysis. The effect is less pronounced with a low share of EVs using aFRR prices to optimize their charging behaviour compared to a situation where all EVs use day-ahead market prices in their optimization process, as the most beneficial prices for EV charging do not occur at the same moments for both pricing schemes. Consequentially, EV demand peaks are better distributed over time, resulting in fewer moments in which the charging demand is constrained by the transformer capacity.

Impact of level of grid reinforcement

Figure 2.6 presents the change in system costs with different levels of cable reinforcement for a situation where 100% of the EVs are optimized based on the aFRR prices. This is the situation with the largest decrease in EV charging costs with grid reinforcements. The annualized grid investments rise sharply when grid reinforcements are required next to a transformer upgrade, since cable reinforcements require costly excavations. Even with high price volatility, grid reinforcements are not beneficial from a system perspective if a large share of the cables in the grid need to be reinforced.

2.5.3 Accuracy of EV community battery modelling method

Figure 2.7 compares the computational time and objective outcome of conventional methods for optimizing EV charging behaviour (i.e., creating variables for every individual charging sessions) with the computational time and objective outcome when using the methods proposed in Section 2.2.3. The results indicate that when the aggregated EV charging demand is optimized using one subset of EV charging sessions, as proposed by Tang et al. [169], the annual EV charging emissions are underestimated by 7.0% with a 100% EV adoption rate when considering marginal emission profiles. The underestimation in objective outcome equals 1.8% when optimizing using average emission profiles, 6.6% when optimizing using day-ahead prices and 12.5% when optimizing using aFRR prices. Increasing the number of subsets rapidly reduces this charging cost or emission estimation error, until this error is completely eliminated. The computational running time increases with a larger number of subsets, allowing users of the proposed method to make a trade-off between computational time and estimation error in results. Figure 2.7 indicates that aggregated EV charging demand can be optimized using a cost estimation error

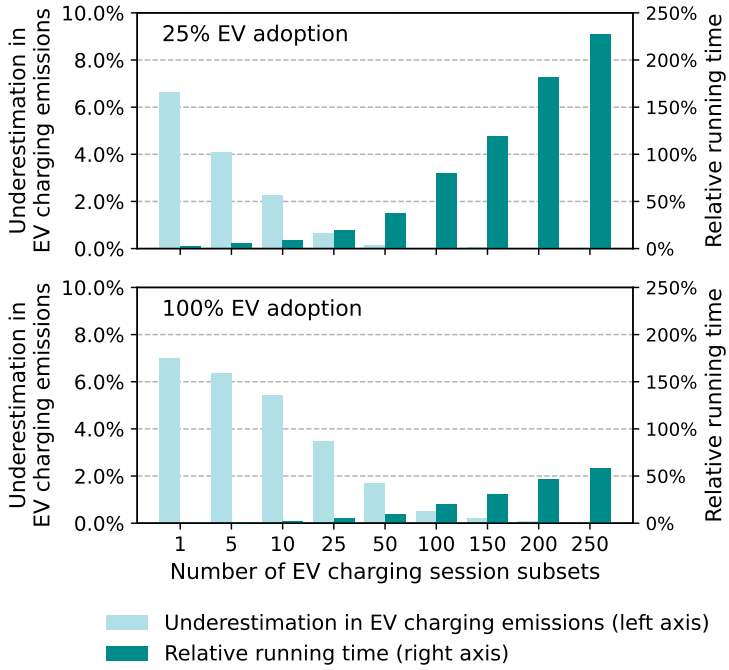


Figure 2.7: Underestimation in model outcome and relative computational running time of the aggregated EV charging model proposed in Section 2.2.3 using different numbers of EV charging session subsets. The model outcome and computational time of a conventional EV charging model formulation is taken as the reference. Installed PV capacity equals 200 kWp. EVs used marginal emission profiles to optimize their charging demand.

of 1% at a relative computational time of below 20% compared to conventional EV charging optimization methods. With lower EV adoption, a lower number of subsets is required to eliminate the inaccuracy in optimizing EV charging costs.

2.6 Discussion

This study presented Pareto frontiers to get insight in the trade-off between cost-based optimization and emission-based optimization of EV charging in an LV-grid under different transformer capacity limits. A model was developed to be able to optimize EV charging for a large group of EVs at lower computational cost compared to conventional EV optimization models, without losing accuracy in results. The results show that grid reinforcements to mitigate grid congestion caused by EV charging are in most situations not beneficial from both a cost and emission perspective; the additional costs and emissions in case of reinforcement outweigh the potential additional EV charging optimization benefits that can be obtained as a result of the higher transformer capacity. These results are robust for various future scenarios regarding

the penetration of PV and EVs, but not with much more volatile electricity prices. A second major finding was that even with the current transformer limitations, the costs and emissions related to EV charging can be decreased substantially. For example, emission-based charging optimization can reduce charging marginal emissions by 23.6% compared to uncontrolled EV charging, while also reducing the costs by 13.2%. With V2G, marginal emission savings of up to 67.3% are possible, while charging costs can be reduced by 32.4%.

These findings have important practical implications. For example, a transition from internal combustion engine vehicles to EVs can have a larger impact on emissions than often assumed - also in the short term. This could help countries in attaining their climate goals. Many studies consider the average generation mix to estimate the impact of this transition, whereas this study shows that EVs are adept to be charged with electricity that is less CO_2 intensive than the average of a country's generation mix.

Further, it was shown that a high penetration of EVs is possible under the current transformer limit for the investigated grid, and moreover, the current transformer limit provides ample possibilities for smart charging and V2G. In order for such a system to function, it is important that DSOs proactively invest in setting up systems such as the capacity-limitation system studied in this work.

Currently DSOs are legally obliged to accommodate the needs of all system users [166], which could mean that charging fleet operators should be financially compensated when they are constrained by the grid capacity. It should be reconsidered whether this system can be maintained in the future in grids with high EV adoption. An important recommendation is to think of a new framework which allows for a socially fair distribution of costs and benefits.

Two main categories of uncertainty should be considered when interpreting the results: uncertainty in input data and uncertainty in forecasting accuracy. One of the main sources of uncertainty in the input data are the used emission profiles. To determine the marginal emission profile, this study assumed marginal emissions are equal to the emissions of the plant with marginal costs closest to day-ahead market price. As discussed in [159], it is not always possible to determine the actual marginal power plant. More accurate marginal emission profiles can only be constructed if each balance responsible party (BRP) publishes the CO_2 intensity of their scheduled generation based on the unit commitment of their power plants. Given the large emission reduction potential of EV charging when optimizing EV charging using marginal emission factors, this study recommends countries or regions to publish live marginal emission factors to facilitate adoption of emission-based smart charging. These emission factors should be published in such a way that market-sensitive information of electricity generating companies is not revealed.

In addition, there is uncertainty regarding the future robustness of the price input data. The trade-off between cost-minimization and emission-minimization EV charging is heavily dependent on the CO_2-price. With higher CO_2-prices, gas-fired

power plants can become cheaper than coal-fired power plants, resulting in a merit order with alternating coal- and gas-fired power plants. A further increasing CO_2-price could make the trade-off between costs and emissions less severe, as electricity can be shifted to times with low emissions for lower or low additional costs. A last important notion in this context is the penetration of renewables. Higher penetration of renewables leads to a higher variation in emission profiles [156] and potentially leads to higher price volatility, which would increase the width of the Pareto frontiers.

This study assumed a perfect forecasting accuracy in PV generation, residential load, electricity prices, electricity generation emission factors and EV availability when scheduling the charging behaviour of EVs. Although multiple studies have developed forecasting methods which could be applied to LV grids, forecasting errors could be relatively large, especially since this study looks at a relatively small aggregation level (a single LV grid). Due to these forecast errors, grid congestion problems cannot be fully eliminated, causing that real-time correction of the charging schedule of EVs is required to mitigate risks on grid congestion problems. In addition, due to these imperfect forecasts, EVs might be charged more conservatively in practice to avoid grid congestion or unmet EV charging demand requirements. Thus, the actual potential of EVs to minimize costs or emissions may be lower than the theoretical potential identified in this study.

Although this study has concluded that grid reinforcements are not attractive in terms of cost and emissions from a system perspective when the focus is on congestion problems caused by deep penetration of EV charging in LV grids, our sensitivity analysis also suggested that this could be different with more volatile prices. Furthermore, it should be noted that the decision whether to reinforce the grid is based on multiple factors. Grid reinforcements are not only a solution to grid congestion problems, but could also be necessary to mitigate power quality problems [190]. Next to the large-scale integration of EVs, these problems could also be caused by i.a. greater penetration of variable renewable energy sources in the LV grid or electrification of space heating and cooking in buildings.

2.7 Conclusion and future research

This research addressed the question whether grid reinforcements are attractive from a cost or emission perspective in the context of a deep penetration of EVs. It was shown that the costs and emissions of grid reinforcements outweigh the benefits in costs and emissions in EV charging optimization resulting from increased grid capacity. However, substantial reductions in EV charging costs and emissions can be achieved under the current transformer capacity.

Future research could study to what extent it is possible to avoid grid congestion problems when using forecasts of the expected grid load when scheduling EV charging with a transformer capacity constraint. This research should compare the grid

congestion levels with different forecasting methods that are used with EV charging scheduling and should also evaluate different methods to mitigate grid congestion induced by forecast errors. Also, future research could look further into the economic and environmental attractiveness of grid reinforcements by using more-realistic EV charging schedules, which consider different electricity markets and uncertainty in EV departure times. Furthermore, future research could address when LV grid reinforcements are required from a technical perspective when considering congestion and power quality problems caused by greater penetration of variable renewable electricity generation in the LV grid, as well as the electrification of end-uses in buildings.

Appendix

2.A Assumptions emission profiles

The 15-minute average emission profiles and marginal emission profiles can be found in Figures 2.A and 2.B. The same methods were used as in [159] and [156], respectively. However, some assumptions and modifications were made to adapt the profiles to the year 2018.

2.A.1 15-minute average emission profiles

Because of missing data in [165], some data modifications had to be performed. When generation data of a specific technology for one hour was missing, data was filled using the forward fill method, i.e., data of the previous hour was used. When data of more than one hour was missing, the data of the previous day was used.

ENTSO-E Transparency Platform [165] provides generation values for biomass generation and solar generation. However, these values are low compared to official Dutch statistics [191]. Therefore, data was scaled to be in line with these statistics.

Subsequently, the remaining missing power generation in time step t was determined using the following equation:

$$\mathrm{P}_{\mathrm{gen,missing},t} = \mathrm{P}_{\mathrm{load,Ps},t} + \mathrm{P}_{\mathrm{net\ export},t} - \sum_{j}^{J} \mathrm{P}_{\mathrm{gen,TP},j,t} \tag{2.16}$$

i.e., the sum of the net export and the total Dutch electricity load taken per timestep from ENTSO-E Powerstats [192] was subtracted by the total known generation power of all power plants used fuel type j, with J being the set of fuel types for electricity generation provided by ENTSO-E Transparency Platform. For gas-fired and coal-fired electricity generation, ENTSO-E Transparency Platform provides for 2018 a part of the data and no data, respectively. For these technologies, it was determined which

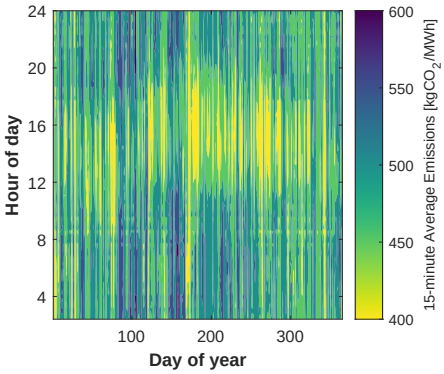


Figure 2.A: 15-minute average emission profile for the Netherlands in 2018.

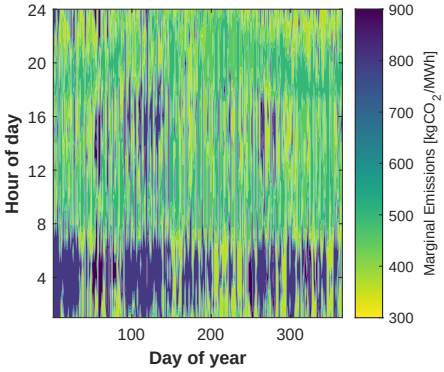


Figure 2.B: Marginal emission profile for the Netherlands in 2018.

fraction M_{corr} of the $P_{\text{gen,missing},t}$ could be attributed the generation of fuel type j:

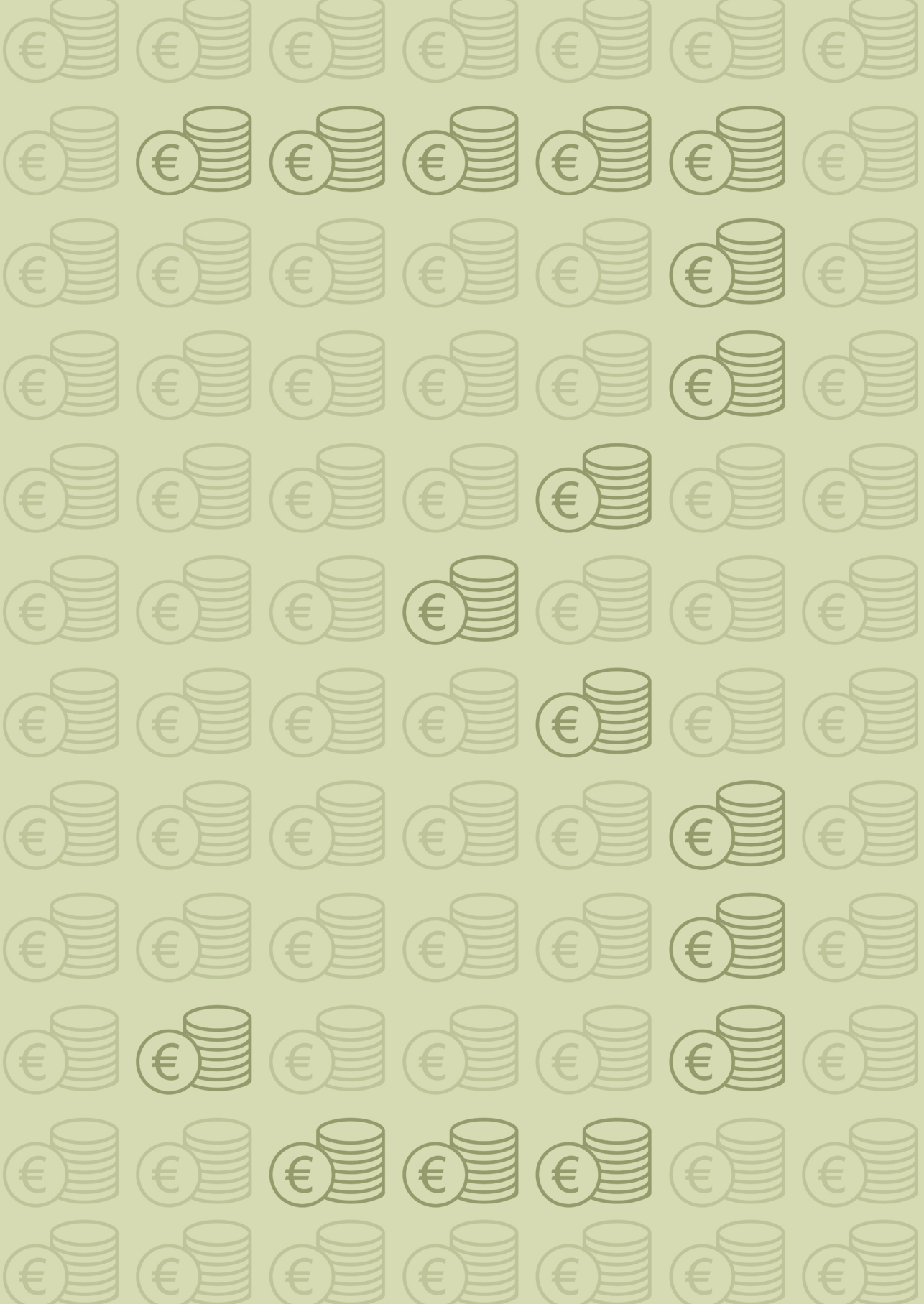
$$\mathrm{M}_{\text{corr},j} = \frac{\sum_t^T (\mathrm{P}_{\text{gen,TP},j,t}) - \mathrm{P}_{\text{gen,CBS},j}}{\sum_t^T \mathrm{P}_{\text{gen,missing},t}} \tag{2.17}$$

Now, the $\mathrm{P}_{\text{gen},j,t}$ of coal- and gas-fired power plants could be determined using:

$$\mathrm{P}_{\text{gen},j,t} = \mathrm{P}_{\text{gen, TP},j,t} + \mathrm{M}_{\text{corr},j}\mathrm{P}_{\text{gen,missing},t} \tag{2.18}$$

2.A.2 Marginal emission profiles

Three modifications were carried out compared to [156]. First, data for the fuel prices was taken from [193]. Second, the least efficient gas-fired power plant was assumed to be the Merwede-11 plant. Hence, the Velsen-24 plant, which is fired by blast-furnace gas, was excluded from the analysis. Third, a factor representing the upstream emissions was included, taken from [194].



Chapter 3

Can grid tariffs be fair and efficient?

This chapter is based on the following submission, with minor edits for coherence within the thesis and in response to committee feedback:

N. Brinkel & F. van Montfoort (2025).

Can grid tariffs be fair and efficient? A comprehensive evaluation of tariff designs for smart electric vehicle integration

Submitted.

Summary

The growing electricity demand from the rapid adoption of electric vehicles (EVs) poses challenges for electricity grids, which are already nearing capacity limits in many countries. EV smart charging can help alleviate these problems by optimizing charging times and speeds to reduce peak loads. However, current grid tariffs lack financial incentives to support this approach. To encourage efficient, grid-friendly EV integration, innovative tariff structures are being developed. Regulators must balance key principles such as efficiency, fairness, and simplicity when overseeing tariff design. Despite increasing interest in new tariff structures, comprehensive insight into their impact remains limited. This study introduces a framework to assess grid tariff structures based on their alignment with regulatory objectives, with a focus on how they influence smart charging behaviour in cost-optimizing EV users. The framework is used to evaluate six widely-discussed grid tariff structures. Using a real-world urban case study involving public EV charging stations in the Netherlands, the analysis examines how retail electricity pricing schemes (dynamic vs. fixed) and varying EV adoption rates affect the alignment of these tariff structures with key regulatory principles. The results suggest that alternative tariff structures can lower grid and overall system costs compared to traditional flat tariffs. Additionally, these alternative structures influence the distribution of grid costs, improving fairness by better aligning each user's tariff contribution with their impact on grid costs. However, no single tariff structure performs best across all aspects of grid tariff design, making the final tariff design choice a trade-off between these aspects.

Highlights

- We evaluate grid tariff designs on regulatory principles, focusing on EV charging.
- A novel modelling framework is presented for comprehensive assessment of different tariff designs.
- Six tariff designs are assessed using indicators linked to regulatory principles.
- Grid tariff reforms enhance alignment with cost-causation principle.
- Capacity-based tariff structures lead to highest system efficiency.

3.1 Introduction

3.1.1 Problem definition

The ongoing transition to a more sustainable energy system places increasing pressure on electricity distribution grids, which must accommodate higher and more volatile peaks in both demand and supply [56], [195]. A key driver of these peaks is Electric Vehicle (EV) charging, which contributes substantially to coincident demand and is expected to necessitate significant grid capacity expansions [54], [196]. In several regions, insufficient distribution capacity has already led to congestion and delays in connecting new users [60], [197]. Without effective mitigation strategies, local distribution grids risk becoming critical bottlenecks in the broader energy transition [198], [199].

Smart charging has emerged as a promising approach to alleviate these pressures. Unlike uncontrolled charging, where EVs begin charging immediately upon arrival, smart charging optimizes both the timing and power of electricity flows. This flexibility supports a range of objectives, including lowering charging costs [198], [199], reducing emissions [77], [200], and mitigating local grid congestion [201], [202]. Unlocking its potential to address capacity constraints requires targeted incentives aligned with this end.

Against this background, the design of grid tariffs is receiving increased attention. Grid tariffs, which are set by National Regulatory Authorities (NRAs) and paid by end-users to Distribution System Operators (DSOs), aim to recover the costs of the distribution grid while adhering to principles of cost recovery, efficiency, equity, and fairness [141], [203]–[205]. They play a central role in promoting efficient grid use, which is an increasing regulatory concern as grids face tighter constraints and more flexible demand. This is especially relevant for EV integration, where poorly designed tariff signals can drive costly reinforcements. Yet most tariffs remain flat, offering no incentive to ease grid pressure [88]. Beyond efficiency, tariffs also shape how costs are distributed across households and other grid users. As more users adopt Distributed Energy Resources (DERs) such as EVs, solar photovoltaic (PV) panels, and heat pumps, consumption profiles and grid impacts are becoming more diverse. This raises concerns about fair allocation of grid costs [206].

3.1.2 Literature overview

There is a growing literature on the design of distribution grid tariffs, driven by the rapid uptake of DERs. These technologies have transformed household electricity consumption and turned users into active market participants, raising fundamental questions about how grid costs should be fairly and efficiently allocated.

A first body of literature explores how different tariff designs affect the distribution of costs across different types of households. Several studies focus on exogenous

household profiles and examine how certain characteristics, such as income or DER ownership, shape distributional outcomes under various tariff structures [207]–[209]. Others study the effect of increased DER adoption on distributional outcomes. Under volumetric net-metering schemes, solar PV adoption reduces net grid consumption, prompting higher tariff levels and shifting residual grid costs onto non-solar households [210]. Küfeoğlu and Pollitt [211] find similar effects, though they find that increased EV adoption may partially mitigate this by raising net demand and easing upward pressure on tariffs.

A related strand of literature examines strategic household investment in DERs to reduce grid-tariff charges, modelled as a non-cooperative game. A key insight from this literature is that grid tariffs can incentivize households to adopt DERs primarily to avoid charges, shifting costs onto other households. This can lead to outcomes that undermine both fairness and efficiency. For example, Schittekatte et al. [212] show that peak-demand tariffs may encourage overinvestment in solar PV and batteries, resulting in inefficient outcomes and cross-subsidies between households. Hoarau and Perez [213] extend this approach by incorporating exogenous EV adoption, reaching similar conclusions. Most of these studies treat grid costs as fixed (i.e., sunk), though some have incorporated grid expansion costs to capture how tariff design affects grid costs [214].

A second related theme in the literature evaluates household demand response to various dynamic pricing schemes. The focus is on how households adjust their consumption in response to price signals, rather than on how costs are distributed. These include time-varying volumetric tariffs such as Critical Peak Pricing (CPP) [215]–[217], Real-Time Pricing (RTP) [217], [218], and segmented Time-of-Use (ToU) tariffs [219], [220]. Others emphasize peak-coincident capacity tariffs [206], [221] or capacity-subscription models combining volumetric and capacity charges [222], [223].

These approaches have been evaluated in various simulation studies. Steen et al. [224] modelled demand response from both EVs and household appliances under dynamic tariffs, while Fridgen et al. [225] compared twelve tariff designs in a microgrid with mixed technologies. Holweger et al. [226] and Young et al. [227] showed how dynamic tariffs could incentivize PV and battery integration to reduce peaks. Kirkerud et al. [228] explored tariff impacts on electric boiler operations. More recently, Hofmann et al. [229] modelled household demand response under five tariff regimes.

EV charging has become a central topic in the debate on grid tariff design, as it introduces peak demand that can strain distribution grids. Two recent studies are particularly relevant to our work, as they evaluate tariff performance in the context of growing EV adoption. Turk et al. [230] assess tariff impacts on peak demand and charging costs while accounting for dynamic retail prices, but do not evaluate broader regulatory principles such as fairness. Hennig et al. [231] propose a regulatory evaluation framework to compare grid tariffs across principles such as efficiency and

fairness. They apply this framework to EV charging, but they rely on exogenous tariff levels and do not consider the recovery of grid costs.

3.1.3 Gap in literature and contributions

Despite a growing body of literature on grid tariff design, important gaps remain. These particularly include the system-wide effects of EV charging, the interaction between grid tariffs and dynamic retail pricing, and the lack of comprehensive evaluations across key regulatory principles. Most existing studies assess a narrow set of tariff designs or focus on limited regulatory objectives. In addition, grid costs are often assumed to be fixed and independent of grid use, and demand responses to tariff structures are not always considered. While some studies incorporate time-varying retail prices, few explicitly examine how these interact with grid tariffs to shape electricity use. This chapter addresses these gaps through the following contributions:

1. We present a comprehensive framework to assess grid tariff structures across regulatory principles (i.e., efficiency, cost recovery, fairness, and predictability) using performance indicators such as grid costs, charging costs, and distributional outcomes. The framework places particular focus on how EV charging behaviour responds to different tariff structures;

2. The framework is applied to a comprehensive set of six tariff structures, including fixed, flat volumetric, flat capacity, capacity-subscription, and two types of time-varying tariffs. We address both the recovery of sunk costs for existing grid capacity and the expansion costs associated with increasing EV adoption;

3. We endogenously model grid investment needs based on simulated EV charging behaviour, incorporating smart charging responses to both grid tariffs and dynamic retail prices. Tariff levels are determined to ensure cost recovery, consistent with regulatory practice;

4. We assess how grid tariffs interact with time-varying retail electricity prices to influence EV charging patterns and grid usage, capturing a key but underexplored aspect of user behaviour;

5. We apply our framework to a representative Dutch urban grid using real-world data from public charging stations. Unlike most studies that focus solely on households, we include both residential users and Charging Point Operators (CPOs) to evaluate cost allocation under different tariff designs.

This work is outlined as follows. Section 3.2 provides theoretical background on regulatory principles and considerations of grid tariff design. The considered modelling framework used to evaluate different tariff structures and their impacts is introduced in Section 3.3. Subsequently, the results of the analysis are detailed in Section 3.4,

providing insights into the performance of various tariff structures. Finally, Section 3.5 presents a critical discussion of the findings and summarizes the key conclusions of this study.

3.2 Regulatory aspects of distribution grid tariff design

In this section, we provide background on key aspects of grid tariff design. We begin by discussing the cost and revenue structure of grid operators, highlighting the various cost components and how they are recovered through grid tariffs. Next, we outline the principles guiding NRAs in evaluating and approving alternative grid tariff structures. Subsequently, we outline how grid tariffs are implemented in practice across different countries.

3.2.1 Cost and revenue structure of grid operators

Tariff regulation by NRAs is crucial in sectors characterized by natural monopolies, such as electricity distribution, where competition is limited and a single operator manages the infrastructure. In such cases, regulatory oversight ensures that users receive fair pricing while allowing the operator to recover costs and earn a reasonable return.

The first step in grid tariff regulation is to define the costs of the distribution grid and to establish the allowed remuneration for the DSOs. This involves identifying, categorizing, and determining which costs will be recovered through tariffs. NRAs typically use revenue regulation methods, such as cost-plus regulation, or incentive-based approaches, such as yardstick competition and statistical benchmarking [232]. Subsequently, these recoverable costs are translated into tariffs for grid users.

Distribution grid costs encompass maintenance of grid assets, operational expenses (including metering, energy losses, and congestion management), and capital costs associated with grid capacity investments [88]. These costs are typically categorized by voltage levels (high, medium, and low voltage) and by the different services provided by the DSO, such as connecting users to the grid, the transportation of electricity, and other operational services. In addition, costs are distributed among various user groups, including electricity producers (e.g., power plants) and consumers of different sizes. In general, grid costs can be classified into three main categories:

1. *Short-Run Marginal Costs (SRMC)*: SRMC represent the costs of delivering an additional unit of output given current grid capacity, and include energy losses and real-time congestion management;

2. *Long-Run Marginal Costs (LRMC)*: LRMC reflect the costs of future grid capacity expansions, which are primarily driven by increased peak demand;

3. *Sunk costs*: Sunk costs stem from past grid investments that do not change with changing grid usage levels but still require recovery through tariffs.

Once the costs of the distribution grid are segmented and the total costs to be recovered through tariffs are established, the next step is to design the tariff structure for grid users. This chapter focuses on the design of use-of-system tariffs, which influence both the allocation of costs among users and the incentives they receive. Use-of-system tariffs cover the transportation of electricity across the grid and typically consist of energy-based charges, capacity-based charges, and fixed charges. These tariffs account for the majority of grid costs, approximately 80%, with the remaining costs covered by connection and metering charges [141].

3.2.2 Principles of tariff design

NRAs typically rely on a set of guiding principles when designing tariff structures. Although different overviews of these principles vary slightly, they generally converge on core objectives such as cost-recovery, efficiency, and fairness [141], [204], [205]. There is a consensus that different principles may be conflicting, such that designing tariffs always involves an inherent trade-off. Drawing from these overviews, we identify the following key principles:

Cost-recovery

The primary objective of tariffs is to generate sufficient revenue to cover the grid costs of a DSO. While there are multiple tariff structures capable of achieving cost recovery, the principle of cost-recovery serves as a constraint in determining the tariff levels once the tariff structure has been established. The tariff levels are regulated by the NRA, which evaluates the expected outputs and allowed revenues of a DSO during annual tariff reviews.

Efficiency

The efficiency principle aims to minimize overall system costs in order to maximize total welfare. Achieving economic efficiency requires that tariffs reflect only the marginal costs of grid usage (i.e., costs that vary with consumption and can be avoided), so that grid users take these costs into account when making decisions about their grid use [141]. Since grid costs are primarily driven by peak demand, efficient pricing implies that tariffs should be aligned with users' contributions to peak load, a concept commonly referred to as *peak responsibility* or *cost-causation* [233]–[235]. This aspect of the efficiency principle is commonly described as the *cost-reflectivity principle*.[5]

[5]We note that some studies consider an alternative interpretation of cost-reflectivity, where it is checked whether the tariffs paid by a grid user are in line with the grid costs they impose [233].

A complicating aspect is that a large share of grid costs are sunk costs that do not vary with consumption levels, which means that the sole application of marginal-cost pricing generally fails to recover all grid costs [206]. However, deviating from marginal-cost pricing may distort user decisions, potentially leading to inefficiencies. For example, tariffs above marginal costs may discourage grid users who would have been willing to use the grid at the marginal cost to do so, creating a deadweight loss by not serving demand that could be met efficiently [209], [236]. This aspect of the efficiency principle is often referred to as the *non-distortion principle*. To avoid such distortions, studies suggest recovering sunk costs through fixed charges [209], [236].

Equity and fairness

Regulators and policymakers frequently emphasize equity and fairness in tariff design, although these principles can be interpreted in various ways [209], [237]. A common view is that low-income and vulnerable households should be protected from excessive electricity bills to ensure affordable access to essential energy services [207], [236]. Policymakers also stress that tariff reforms should avoid disproportionately increasing costs for certain customer groups while others see reductions. Another fairness-based perspective links cost causation to tariff design, arguing that users who drive grid investments should bear a greater share of cost recovery [211]. Finally, tariffs may be designed to prevent cross-subsidization, where some users inadvertently shift the responsibility for recovering sunk costs onto others, particularly through mechanisms like net-metering combined with volumetric charges [212], [214].

Non-discrimination

The principle of non-discrimination asserts that there should be no undue discrimination in how grid users are charged. Users with similar load and injection profiles should be treated equally, meaning they should be charged in a similar manner, regardless of their customer class or the technologies they use. This principle emphasizes that tariffs should be non-discriminatory and neutral regarding the specific activities or technologies employed to withdraw or inject electricity into the grid, focusing instead on location and consumption patterns [141].

Predictability

The principle of predictability ensures that grid users can accurately estimate their charges, enabling informed investment decisions. For regulators and DSOs, predictable tariff structures facilitate the alignment of tariff levels with expected outputs and allowed revenues.

However, this approach is more related to fairness, as aligning individual tariff payments with cost responsibility does not necessarily promote overall system efficiency [211].

Simplicity

The principle of simplicity emphasizes that grid tariffs should be straightforward and easy for users to understand. Clear and simple tariff structures enable users to make informed decisions about their energy consumption and respond effectively to price signals.

3.2.3 Distribution grid tariffs in practice

We observe that in practice, tariffs for the use of the distribution grid can comprise three main components:

- *Fixed charges (€/period):* Fixed charge paid regardless of usage, often linked to the physical capacity of a user's grid connection;
- *Energy-based charges (€/kWh):* Volumetric charges based on the electricity volume withdrawn from or injected into the grid during a billing period;
- *Capacity-based charges (€/kW/period):* Charges determined by the user's capacity usage. These can be calculated using either measured capacity, which reflects the user's highest peak during a set interval (e.g., daily or yearly), or contracted capacity, which is based on predefined criteria such as fuse size or a selected subscription level.

The design of grid tariffs specifies how grid costs are allocated across these components. Traditionally, simple grid tariff structures for small-scale users were considered in most countries [88]. For instance, DSOs in the Netherlands only charge a fixed grid tariff, which is dependent on the physical capacity of their grid connection and independent of actual consumption patterns. Similarly, other countries (e.g., Greece, Romania and Luxembourg) also charge a time-independent volumetric fee. However, these tariff structures fail to account for temporal variations in grid use and do not incentivize efficient use of grid capacity.

To address these limitations, new tariff designs have emerged in recent years and several countries have begun implementing or considering reforms [88]. Capacity-based tariffs are gaining popularity due to their focus on peak demand, which is the main driver of grid expansions. For instance, Belgium (Flanders region) introduced a capacity-based distribution tariff in 2023, where households are charged based on their maximum demand (kW) in 15-minute intervals [89]. While these tariffs encourage individual peak reductions, they may not align with system-wide peaks, potentially distorting efficiency goals [233], [234]. Time-varying tariffs introduce temporal differentiation to better reflect grid use patterns. For instance, ToU tariffs apply predefined price blocks for peak, off-peak, and shoulder periods, while more dynamic designs like CPP or RTP adjust charges to reflect real-time conditions. ACER recommends evaluating the need for such differentiation based on cost efficiency and

grid congestion, considering contexts such as constrained capacity and price-elasticity of grid users [88]. Around 75% of the countries consider time-differentiation in the volumetric charges [88], although the granularity of these time-differentiated tariffs is often limited (e.g., day/night tariffs). Other countries introduced more complex tariff approaches. Spain has introduced a tariff structure with two capacity limits (off-peak and peak) and a three-period ToU tariff for energy consumption [90]. In Norway, the NRA has proposed a capacity-subscription tariff where consumers are charged for exceeding their subscribed capacity [222]. Italy has implemented an opt-in tariff design specifically for EV charging. Under this scheme, charging capacity is capped at 3.3 kW during peak hours, while higher capacities are permitted during nighttime and on Sundays [88].

Given the different tariff components and options for time-differentiation, there are numerous approaches to designing tariffs that aim to better reflect the underlying cost drivers of grid usage. A critical objective is to assess these designs in light of the regulatory principles of tariff design, outlined in the previous section.

3.3 Methods

In this section, we present the modelling framework used to evaluate alternative grid tariff structures under varying EV adoption rates. The framework is designed to evaluate tariff structures in line with the key regulatory principles that influence NRAs in their tariff design decisions. It explores the impact of different tariff structures on distribution grid costs and user behaviour as EV adoption rates rise.

The modelling framework considers different actors and consists of different elements, each playing an important role in analyzing the considered grid tariff structures on the key regulatory principles. These components and their interactions are outlined in Figure 3.1 and will be discussed individually.

3.3.1 Actors and their decision-making problems

In our modelling framework, we define three main types of actors involved in the electricity distribution grid, each with distinct roles and decision-making problems:

- *Distribution System Operator (DSO)*: The DSO is a regulated entity responsible for the operation and expansion of the distribution grid. The costs of the DSO are recovered through grid tariffs which are paid by grid users, including private households and CPOs. The NRA determines the grid tariff structure and approves tariff levels to ensure that DSOs achieve cost recovery.

- *Charge Point Operators (CPOs)*: CPOs operate public charging stations and determine the charging schedules for EVs charging at these stations. These charging schedules are determined using a linear optimization model, with each

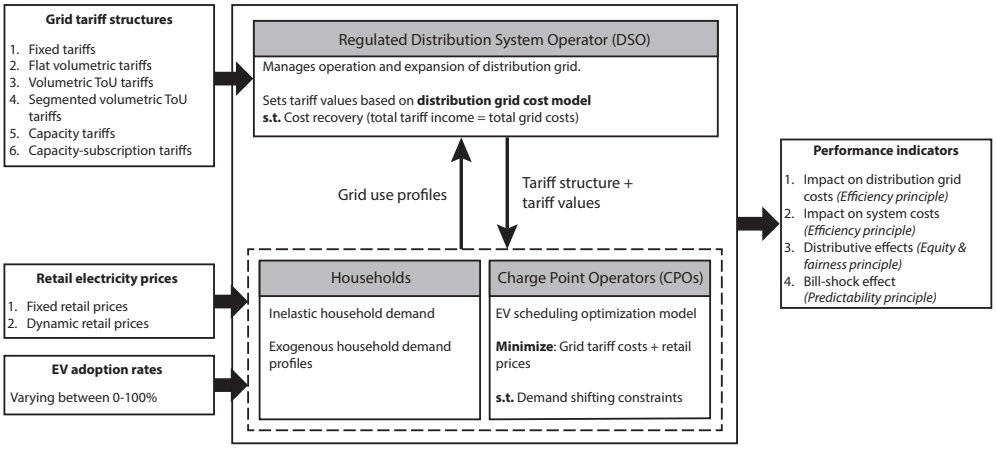


Figure 3.1: Overview of the considered modelling framework in this work.

session's charging power at each timestep as the main optimization variable. The objective of these models is to minimize the costs of meeting charging demand, including retail electricity costs and electricity grid tariffs. We assume that CPOs operate in a perfectly competitive environment and are price-takers. The CPO is subject to several constraints, for instance that EVs must be fully charged at the end of each session, considering exogenous EV arrival and departure times and their maximum charging power. CPOs are assumed to have complete information about these parameters and electricity prices during sessions but lack foresight regarding the number of future charging sessions and their details. They do not apply Vehicle-to-Grid (V2G) technology. The mathematical formulation underlying the charging scheduling models is detailed in Appendix 3.A.

- *Households*: Households are connected to the distribution grid, which they can use for both electricity withdrawal and injection. Each household follows an individual exogenous grid usage profile. This profile is determined by parameters such as household composition and ownership of rooftop PV systems. Households are assumed to be price-inelastic, meaning their electricity consumption profiles remain unaffected by retail electricity prices and grid tariffs. Furthermore, we assume that no home charging of EVs takes place.

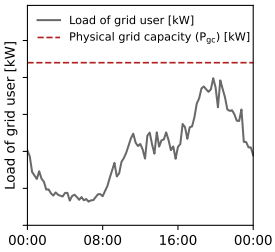
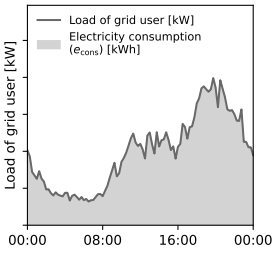
3.3.2 Tariff structures

This work analyzes six distinct grid tariff structures, encompassing the full range of tariff design approaches outlined in Section 3.2.3. The first two considered tariff structures (fixed tariffs and flat volumetric tariffs) act as baselines, as they are the traditional tariff structures in various European countries. The remaining four

tariff structures are designed to encourage demand response and are considered for implementation across various European countries. Table 3.1 presents the six considered tariff structures along with a visualization of each tariff structure, using a fictional one-day load profile of a grid user. The considered base assumptions for every considered tariff structure are outlined in Table 3.A in Appendix 3.G. Next to the six considered tariff structures, this work considers a scenario with a central controller which solely aims to minimize the overall demand peak, in order to get insight into the minimum required increase in distribution grid costs to accommodate all EV charging demand.

As shown in Table 3.1, each tariff structure includes a lump-sum fixed charge in addition to the usage-based component to ensure that they recover both sunk and expansion costs. Fixed charges are for recovering sunk costs, while the usage-based component covers expansion costs. This is further elaborated in Section 3.3.3.

Table 3.1: Overview of the considered grid tariff structures, including a visual explanation of the different considered grid tariff structures for a fictional load profile of one grid user.

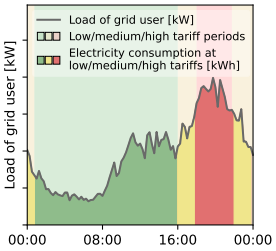
Tariff structure	Description of tariff structure	Visualization of tariff structure using one-day load profile example
1. Fixed tariffs	Uniform fixed tariff (€/year) based on the physical size of a user's grid connection (P_{gc}), independent of actual grid usage. This is the traditional tariff structure in different countries [88] and is therefore one of the baseline tariffs. A user's grid tariffs (c_{gt}) are determined as follows: $$c_{gt} = c_{gt,\,fixed,\,P_{gc}}$$ where $c_{fixed,\,P_{gc}}$ is the grid tariff value corresponding to grid connection size P_{gc}.	
2. Flat volumetric tariffs	A uniform €/kWh fee applies to total electricity consumption (e_{cons}), regardless of time of use. As it provides no incentives for demand response and it is a traditional tariff structure in many European countries [88], it serves as a baseline. The following equation determines a user's grid tariffs (c_{gt}): $$c_{gt} = c_{gt,fixed} + e_{cons}\pi_{vol}$$ where $c_{gt,fixed}$ is the fixed tariff component, e_{cons} is the total electricity consumption in kWh and π_{vol} is the grid tariff fee in €/kWh.	

3. Volumetric ToU tariffs

Time-differentation is considered in the €/kWh fee, incentivizing consumption shifts to periods with low grid stress. ACER recommends such time-varying tariffs [88], though research shows they can cause peak-shifting issues [238]. A user's grid tariffs (c_{gt}) are determined as follows:

$$c_{gt} = c_{gt,fixed} + \sum_{t}^{T} e_{cons,t}\pi_{vol,t},$$

where T is the set of timesteps indexed by t and $e_{cons,t}$ and $\pi_{vol,t}$ are the electricity consumption and grid tariff value at time t, respectively.

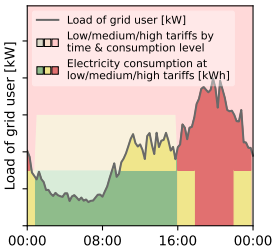


4. Segmented volumetric ToU tariffs

A variable capacity is available for different €/kWh fees at each timestep. If the consumption exceeds the available capacity for one fee, a higher fee applies for the extra consumption. This tariff structure encourages shifting consumption to off-peak periods while limiting peak-shifting problems [219], [239]. The following equation determines a user's grid tariffs (c_{gt}):

$$c_{gt} = c_{gt,fixed} + \sum_{t}^{T}\sum_{g}^{G} e_{cons,t,g}\pi_{vol,t,g},$$

where G is the set of considered tariff levels, indexed by g, $\pi_{vol,t,g}$ is the tariff level corresponding with g and $e_{cons,t,g}$ is the electricity consumption at this tariff level at timestep t.

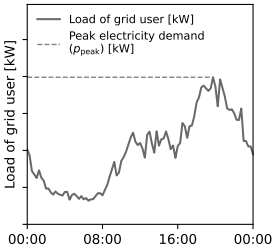


5. Capacity tariffs

Grid tariffs are based on peak consumption (kW) during a specific period, encouraging users to reduce peak demand. Capacity-based tariff structures, recently implemented in Flanders, Belgium [89], are considered among the most effective (e.g., [224], [225]). The following equation determines a user's grid tariffs (c_{gt}):

$$c_{gt} = c_{gt,fixed} + p_{peak}\pi_{peak},$$

where p_{peak} is the peak consumption in kW and π_{peak} is the peak fee in €/kW.

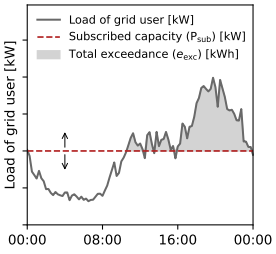


6. Capacity-subscription tariffs

Grid users subscribe to a capacity level (kW), paying a fixed fee based on it. If actual consumption exceeds the subscribed capacity, an exceedance fee is charged for the surplus. This tariff structure, recently implemented in Norway [222], encourages users to lower their subscribed capacity and stay within it. A user's grid tariffs (c_{gt}) are determined as follows:

$$c_{gt} = c_{gt,fixed} + \mathrm{P}_{sub}\pi_{sub} + e_{exc}\pi_{exc},$$

where P_{sub} is the subscribed capacity (kW), π_{sub} is the subscription fee (€/kW), E_{exc} is the total exceedance (kWh) and π_{exc} is the exceedance fee (€/kWh).



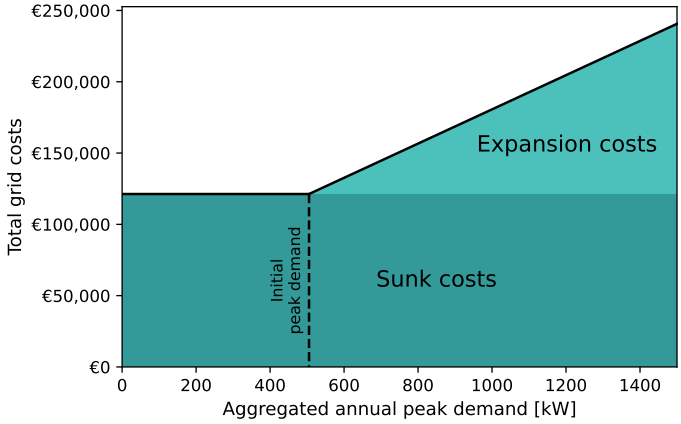


Figure 3.2: A visual representation of the applied distribution grid cost model for the considered case study of 650 households. The initial peak demand reflects the peak demand of grid users prior to the introduction of EV charging stations, with all initial costs considered sunk. If the total peak demand rises, the grid costs grow linearly due to grid expansions.

3

3.3.3 Setting grid tariff levels

In our modelling framework, tariff levels are determined to ensure full recovery of grid costs, including both sunk and expansion costs. For each EV adoption scenario, we simulate EV charging patterns across a range of tariff levels (see Table 3.A in Appendix 3.G) and identify the associated grid costs with a specific tariff level. We select the tariff level that most effectively achieves cost recovery (i.e., with the smallest difference between grid costs and total tariff income).

To achieve cost recovery, the total tariff income should equal the total grid costs. A simplified distribution grid cost model, illustrated in Figure 3.2 and similar to the model presented by Turk et al. [230], is used for determining grid costs. This distribution grid cost model makes a distinction between sunk costs and capacity-expansion costs (see Section 3.2.1). The sunk costs are assumed to equal the capacity costs of the electricity grid before introducing EVs. Furthermore, the model considers grid capacity expansions to be driven by increases in peak demand. In this model, it is assumed that grid-capacity expansions are indivisible and grow linearly with growing peak demand while maintaining the initial spare grid capacity. This linear assumption, instead of complexities such as lumpy capacity increments, reflects that a DSO typically manages numerous heterogeneous grids, each requiring expansion at varying rates of peak demand growth. The model excludes short-term operational costs of grid operation and social marginal costs, including opportunity costs related to capacity bottlenecks and connection queues for customers wanting to connect to the grid.

A fundamental assumption when setting tariff levels is that sunk costs are recovered through the uniform fixed tariff component that is considered for all tariff

structures. This approach is deemed optimal within our framework, as sunk costs are unrelated to grid usage and recovering them through fixed charges avoids distortions in user behaviour [209], [236]. Expansion costs, on the other hand, are recovered through usage-based charges of the different tariff structures that are linked to the electricity consumption patterns of households and CPOs. Tariff levels are calibrated to ensure that revenue from these charges equals the expansion costs. A key implication of this approach is that low expansion costs result in correspondingly low usage-based tariff levels, which may reduce the price signals and incentives provided by this tariff component.

3.3.4 Performance indicators

We define four performance indicators to assess how different grid tariff structures align with key regulatory principles set by NRAs. The principles of *non-discrimination* and *simplicity* are not covered in the performance indicators: the former is irrelevant as no discriminatory tariffs are studied, and the latter is difficult to quantify. Each indicator is evaluated under two retail electricity price scenarios: (i) a fixed retail price scenario, where CPOs respond only to grid tariffs, and (ii) a dynamic retail price scenario, where they react to both tariffs and hourly retail prices. This approach allows us to study the interaction between grid and retail pricing on EV charging behaviour and grid use. This section outlines the indicators and their links to regulatory principles.

Performance indicator 1: Impact on distribution grid costs (*Efficiency principle*)

Two performance indicators look into the *efficiency principle*, with the first indicator looking specifically into the aspect of this principle that is most relevant for grid operators: the overall grid costs. This indicator measures how effectively different tariff structures provide price incentives to mitigate the grid impact of increasing EV adoption, which is highly relevant for DSOs when managing their grids. The distribution grid costs of each tariff structure are determined using the distribution grid cost model from Section 3.3.3.

Performance indicator 2: Impact on system costs (*Efficiency principle*)

The second performance indicator looks into all aspects of the *efficiency principle* by quantifying the impact of a tariff structure on the overall system costs. Within this modelling framework, grid tariff structures not only affect distribution grid costs but can also influence retail electricity costs for EV charging when considering a dynamic retail price scenario, as it may create financial incentives to deviate from the charging schedule with the lowest retail electricity costs. This work defines the system costs of

a tariff structure (c_{system}) as follows:

$$c_{\text{system}} = c_{\text{grid}} + c_{\text{retail}}, \tag{3.1}$$

where c_{grid} are the total distribution grid costs and c_{retail} are the aggregated retail electricity costs for all grid users. In this analysis, the traditional grid tariff structures which provide no incentive for smart charging (i.e., fixed and flat volumetric tariffs), serve as a baseline.

Performance indicator 3: Distributional effects (*Equity and fairness principle*)

Thirdly, our modelling framework analyzes the distributive effects of grid tariff structures. The allocation of grid costs among users influences the perceived fairness of a tariff structure. This performance indicator looks into two aspects of cost distribution. It first studies how grid costs are distributed between user groups, specifically households and EV charging stations operated by CPOs. In addition, it analyzes whether the tariffs paid by individual grid users are in line with the grid costs they impose, reflecting *peak responsibility* or *cost-causation* [233]–[235]. The grid costs caused by a user are based on their contribution to the top 0.1% of 15-minute aggregated demand peaks in a year, and this contribution is multiplied by the total expansion costs. These estimated grid costs are then compared with the total amount the user paid through the usage-based component of the tariff, which is specifically designed to promote efficient use.

Performance indicator 4: Bill-shock effect (*Predictability principle*)

The last performance indicator provides insight into the *predictability principle* from a user perspective by quantifying the *bill-shock effect*. Bill-shock occurs if a grid user faces unexpectedly high grid costs, often due to a lack of awareness or understanding of complex tariffs [240]. Such a lack of understanding can lead households to deviate from optimal energy consumption patterns, potentially resulting in higher grid tariff costs. For CPOs, such deviations can result from technical communication issues that cause EVs to deviate from their optimal charging schedule [241]. The impact of these deviations on grid costs is assessed by analyzing how a doubling of the monthly consumption peak affects the grid tariff costs for each grid user.

3.3.5 Case study, data inputs and simulation outline

Introduction to case study

Our model to evaluate grid tariffs is applied to a case study of a distribution grid in an urban area in the Netherlands. This grid serves 650 households, each with unique injection and consumption profiles, which are assumed to be representative of the set of users in a DSO's service area. The model simulations consider EV adoption rates

ranging from 0% to 100%, assuming that all EV charging demand is met through public charging stations, as this is the predominant charging method in Dutch urban areas due to the limited availability of home charging [47].

Our case study models a distribution grid serving 650 households, which are representative of the set of users in a DSO's service area, each with unique injection and consumption profiles. The model simulations account for EV adoption rates ranging from 0% to 100%.

Data inputs

This work considers charging session data from 2022 from 380 residential public charging stations operated by the Dutch CPO *We Drive Solar* [242] as inputs for the EV charging scheduling optimization. These charging stations were active throughout the assessment timeframe, did not have fast-charging capabilities (a nominal capacity of either 17.5 kW or 24.1 kW per station) and were predominantly used by private EV owners. The charging session data provides information on the arrival and departure times, charging demand, car ID, charging pass ID, maximum charging power, and station ID for each session. Before using this data for optimization, several pre-processing steps are applied, as outlined in Appendix 3.B. Appendix 3.C presents insight into key characteristics of the considered set of charging sessions.

The individual electricity demand profiles of the 650 considered households were generated using the Artificial Load Profile Generator tool developed by [243]. This tool simulates realistic load patterns for households and has been calibrated with real consumption data. It can differentiate between various household configurations, including PV systems, heat pumps, home batteries, EVs, and combined heat and power systems. Detailed settings for household profile generation are provided in Appendix 3.B.

This work considers the 2022 day-ahead electricity market prices for the Netherlands, obtained from [244], as a proxy for the tariffs in a dynamic retail electricity tariff scheme. The distribution grid cost model assumes grid expansion costs of €3,000 per kW, equivalent to €120 per kW per year when considering a 2% discount rate over a 35-year lifespan.[6] This cost value is also considered when determining the sunk costs of the initial grid before introducing EVs, which are determined by multiplying the initial grid capacity by 120 €/kW. The initial grid capacity is assumed to be twice the peak demand of the considered households, implying a spare capacity equal to their peak demand. It is assumed that the spare grid capacity remains constant when the peak load increases.

[6]Reference [245] estimates that grid expansion costs in the Netherlands for 2017 ranged between 500-1386 €/kW for LV grids, between 200-494 €/kW for LV/MV transformer stations and between 350-1052 €/kW for MV grids. Due to inflation and the growing grid congestion problems, it is likely that these costs have increased in the past years.

Modelling details

All simulations are performed in Python version 3.11.5 [188], using Gurobi version 11.0.3 [189] as a solver for the optimization of EV charging schedules. The simulations use 15-minute timesteps, with an assessment timeframe of the year 2022. All computations were performed using the Eejit [246] high-performance computing cluster at the Faculty of Geosciences of Utrecht University.

Charging session optimization was conducted for each charging station in the EV charging session data. As explained in Appendix 3.A, the capacity and subscription tariffs require an estimated optimal capacity at the beginning of each month for the rolling optimization model, set as the average optimal capacity over the past three months. To determine the total EV charging load at a given EV adoption rate, the expected number of charging stations at this specific EV adoption rate was estimated based on parameters related to household car ownership, car usage statistics and driving efficiencies. This is detailed in Appendix 3.D. The total EV charging load at a given EV adoption rate is calculated by averaging the charging power of all stations at each timestep and scaling it by the expected number of charging stations at the given EV adoption rate.

3.4 Results

This section presents how different grid tariff structures perform on the performance indicators of the applied modelling framework for different EV adoption rates and for two retail electricity price scenarios: fixed and dynamic retail prices.

3.4.1 Impact on distribution grid costs

This section addresses the question of how different grid tariff structures influence distribution grid costs under varying levels of EV adoption and different retail electricity pricing schemes. Figure 3.3 reports the distribution grid costs for different grid tariff structures and EV adoption rates. The left panel presents results for fixed retail electricity prices, while the right panel covers the dynamic retail price scenarios. The fixed and flat volumetric grid tariffs serve as a baseline, as they offer no incentive for EVs to deviate from their default charging schedule (i.e., uncontrolled charging under fixed retail prices and charging solely optimized for retail electricity prices under the dynamic retail prices). For reference, the figure also includes the outcome under a centrally coordinated controller, which represents the theoretical minimum grid costs achievable through fully optimized charging across all EVs.

Our a priori expectation is that grid costs will increase with EV adoption due to additional load, but that tariff structures which provide incentives for load shifting will partly mitigate these costs. The results indicate that, in line with expectations, distribution grid costs increase with higher EV adoption due to greater demand

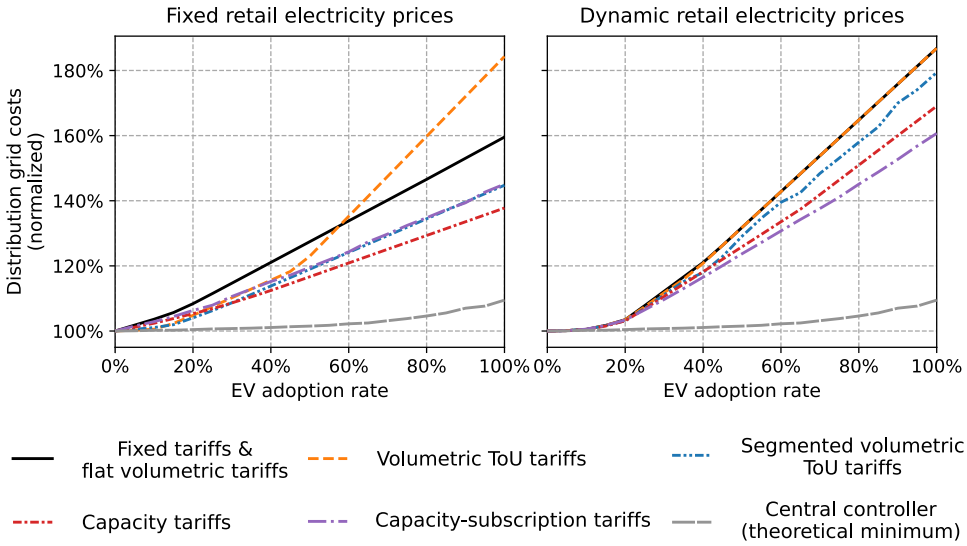


Figure 3.3: Distribution grid costs for the considered grid tariff structures for different EV adoption rates. Distribution grid costs are normalized to the costs with 0% EV adoption. The *'central controller'* scenario represents a situation where all charging stations focus exclusively on minimizing the overall demand peak (see Section 3.3.2), representing the minimum increase in grid costs to accommodate EV charging demand.

peaks from EV charging. However, the cost increase varies significantly across tariff structures. Under fixed retail electricity prices (left panel), where CPOs optimize charging solely based on grid tariffs, most alternative structures reduce grid costs compared to the fixed and flat volumetric tariffs baseline. We find that flat capacity tariffs result in the lowest grid costs, followed by capacity-subscription and segmented volumetric ToU tariffs. Notably, volumetric ToU tariffs lead to higher grid costs than the baseline in high EV adoption scenarios. The increase in grid costs is more pronounced under dynamic retail prices, as shown in the right panel of Figure 3.3. At 100% EV adoption, grid costs are more than 80% higher than the initial costs for fixed and flat volumetric grid tariffs, compared to a 60% increase under fixed retail prices. In line with previous observations, most alternative grid tariff structures reduce grid costs compared to the baseline of fixed and fixed volumetric grid tariffs, although their cost-saving effect is less substantial under dynamic retail prices.

Figure 3.3 also highlights the central controller's outcome, representing the minimum increase in grid costs needed to accommodate all EV charging demand. None of the alternative grid tariffs come close to this theoretical minimum, indicating that while EV charging could, in theory, be integrated into the grid at substantially lower grid costs, the considered grid tariff structures fail to achieve this.

To explain these observations, Figure 3.4 presents a two-day example of the overall grid load profiles for each grid tariff structure at different EV adoption rates. The

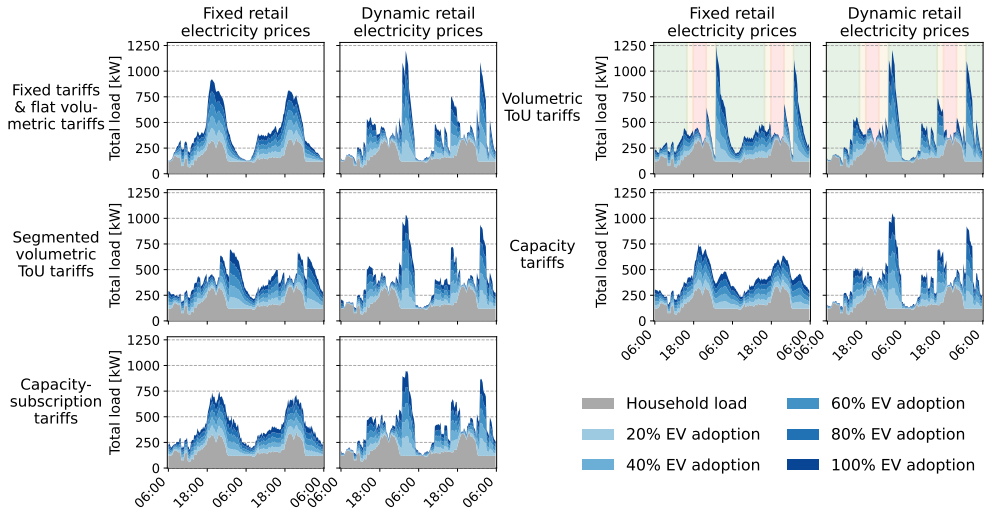


Figure 3.4: Total grid load profiles for each grid tariff structure for two illustrative days (7 April 6:00 - 9 April 6:00), considering different EV adoption rates. The coloured background for the Volumetric ToU tariff structure systems indicates that, respectively, high (red), medium (yellow), or low (green) tariff levels apply at a specific moment.

left panels show the charging patterns under fixed retail electricity prices, indicating that EV charging peaks align with household demand peaks for the fixed and flat volumetric grid tariff structures, which offer no incentive for smart charging. The volumetric ToU grid tariff structure encourages CPOs to shift most charging demand to the low-tariff period, creating a concentrated peak that exceeds the uncontrolled charging peaks and explaining the increase in grid costs under this tariff structure. A segmented volumetric tariff structure partially mitigates this by limiting the charging power available at the low tariff, while capacity-based tariff structures reduce peak demand by spreading charging over time, without fully delaying charging when the EV arrives.

Under dynamic retail electricity prices (right panels), CPOs concentrate charging demand during the lowest retail price hours between the EV's arrival and departure time, resulting in a volatile load profile with peaks that exceed those of uncontrolled charging. When an alternative grid tariff structure is introduced, the price signal from the dynamic retail prices often dominates, causing CPOs to prioritize charging during low retail price hours, limiting the impact of alternative tariff structures on EV charging patterns.

3.4.2 Impact on system costs

This section investigates whether alternative grid tariff structures, while reducing grid costs, might unintentionally increase other system costs. Specifically under dynamic

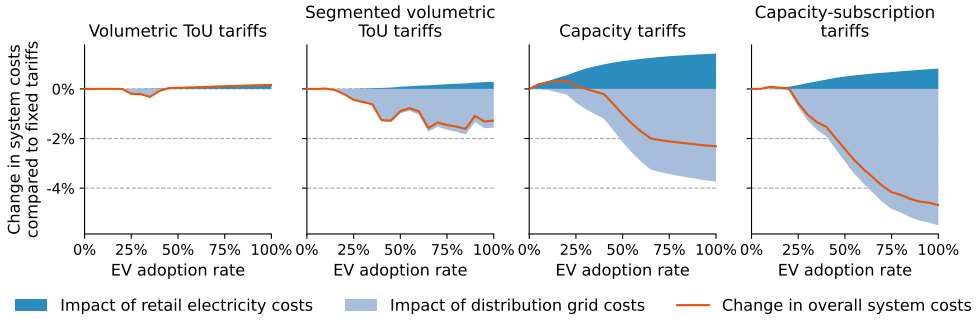


Figure 3.5: The impact of introducing different grid tariff structures on overall system costs compared to the baseline tariff structures (fixed and flat volumetric tariffs) for various EV adoption rates. This includes a detailed breakdown of the contributions from changes in retail electricity costs and changes in distribution grid costs. All results are for the scenarios with dynamic retail electricity tariffs.

retail prices, such grid tariffs can provide an incentive to deviate from the charging schedule with the lowest retail electricity costs, ultimately increasing these costs. To quantify this trade-off, it is crucial to evaluate the overall system impact before implementation, as reductions in grid costs could be offset by higher costs elsewhere. Figure 3.5 presents the impact of each tariff structure on overall system costs under dynamic retail prices[7], detailing the contributions from changes in retail electricity costs and changes in distribution grid costs. Results are compared to the baseline of fixed and flat volumetric grid tariffs, as these tariff structures do not provide an incentive to deviate from the charging schedule with the lowest retail electricity costs.

The figure shows that, for most grid tariff structures, the increase in retail electricity costs is relatively minor compared to the decrease in grid costs. The highest increase occurs with a capacity-based tariff structure, as the selected capacity level limits EV charging power at all times, including during low retail price periods. In contrast, ToU-based tariff structures have the lowest impact on retail electricity costs, as periods of low retail prices often coincide with low ToU grid tariffs. Given their limited impact on retail electricity costs, most of the considered tariff structures lead to an overall reduction in system costs, making their introduction beneficial from a system perspective. The exception is the volumetric ToU tariff structure, which increases total system costs due to its adverse effect on grid costs. With segmented volumetric ToU tariffs, system cost reductions do not follow a consistent downward trend with increasing EV adoption, as peak demand can rise more sharply under this tariff structure than under fixed tariffs between certain adoption levels. The largest system cost reductions are achieved with capacity-subscription tariffs, followed by segmented volumetric ToU tariffs.

[7]With fixed retail prices, only grid costs are affected by changes in charging schedules. These changes are shown in Figure 3.3.

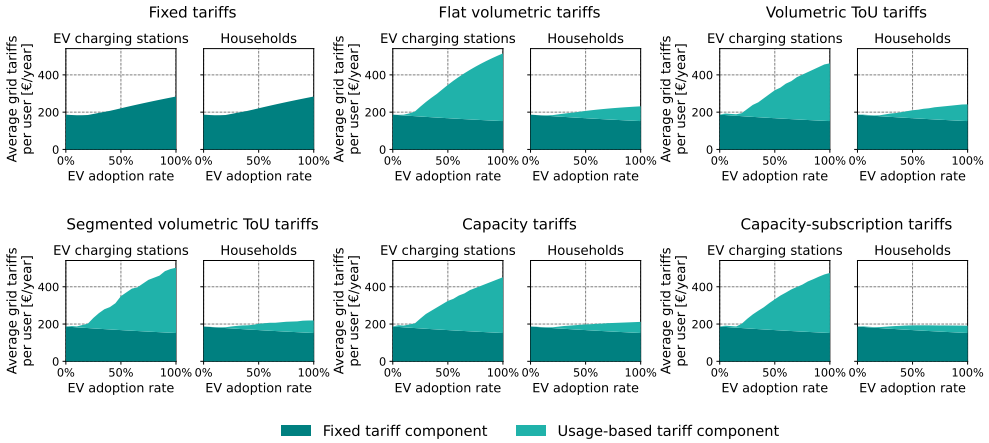


Figure 3.6: Average grid tariff costs in €/year for EV charging stations and households for different grid tariff structures under different EV adoption rates. Results are for a scenario with fixed retail electricity prices. A distinction is made between the fixed grid tariff component, covering sunk costs, and the usage-based grid tariff component, covering expansion costs.

3

3.4.3 Distributional effects

Distribution of grid costs among user groups

This subsection explores how different grid tariff structures influence the distribution of grid costs among user groups (i.e., households and EV charging stations) and whether they align with commonly used fairness principles such as cost-causation. First, to evaluate these distributional effects, Figure 3.6 shows the average grid tariff costs for households and EV charging stations under different EV adoption rates and tariff structures, considering a fixed retail electricity price scenario. The results for the dynamic retail price scenarios are presented in Figure 3.D in Appendix 3.F and show similar trends.

Figure 3.6 shows that for most tariff structures, the total grid tariff costs increase with increasing EV adoption for both households and EV charging stations, as these tariffs need to cover the higher grid costs with growing EV adoption. When breaking down the impact of the two tariff components, it is visible that the fixed grid costs decrease with higher EV adoption rates, since the sunk costs covered by this component are shared among more grid users. Conversely, the usage-based component increases to account for the growing expansion costs driven by higher EV demand. This component is significantly higher for charging stations, due to their greater annual or peak electricity consumption, which determines their contribution to the usage-based tariffs. For most alternative tariff structures, average household costs remain stable or rise only slightly, while costs for charging stations increase significantly. The growth in average grid tariff costs is lower for tariff structures that reduce distribution grid costs most effectively, such as capacity tariffs, since lower tariffs are needed to cover

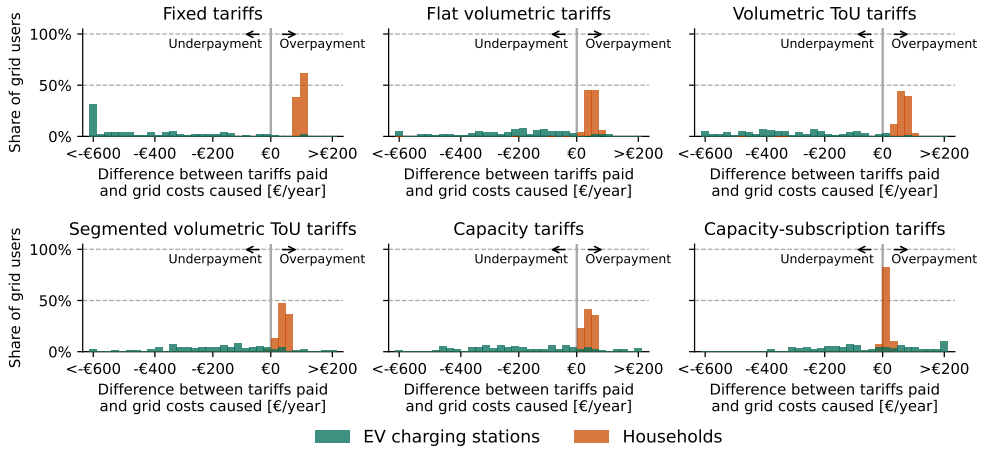


Figure 3.7: Histogram showing the distribution of grid users based on the difference between the usage-based grid tariffs they paid and the grid costs they caused. A distinction is made between households and EV charging stations. Positive values on the x-axis indicate users who paid more than the costs they imposed on the grid (i.e., they overpaid), while negative values indicate users who paid less than their cost contribution (i.e., they underpaid). Grid costs are assigned based on each user's contribution to the top 0.1% of system peak loads and associated grid expansion costs. The results are shown for a scenario with 100% EV adoption and dynamic retail electricity pricing.

total grid costs.

Alignment with peak responsibility concept

Second, we analyze the distributional effects of grid tariff structures by determining whether they induce alignment with the concepts of *peak responsibility* or *cost-causation*. These concepts require that grid users should pay tariffs based on the actual grid costs they impose, preventing cross-subsidization and promoting equitable cost distribution [233]. To assess this, Figure 3.7 compares the tariffs paid by grid users with the grid costs they caused. Similarly, Figure 3.E in Appendix 3.F shows a scatter plot comparing each grid user's contribution to overall grid peaks, which is the primary driver for grid costs, with their share of the total grid tariffs received by the grid operator.

Both figures show that fixed grid tariffs result in all households paying higher grid fees than the costs they actually impose, leading to overpayment under the cost-causation principle. Meanwhile, around 40% of EV charging stations would need to pay at least €600 more annually in grid tariffs to comply with this principle. This discrepancy arises because EV charging stations typically contribute more to the overall demand peak, yet they are charged the same grid fees as households with significantly lower peak contributions. Flat volumetric tariffs partly address this, since EV charging stations consume more electricity annually. However, this

Table 3.2: Effect of a doubling of the monthly consumption peak on the average grid tariffs paid by a grid user for different grid tariff structures. Results are presented for a 100% EV adoption rate.

	Fixed retail electricity prices	Dynamic retail electricity prices
Fixed grid tariffs	+0.0%	+0.0%
Flat volumetric grid tariffs	+0.0%	+0.0%
Volumetric ToU tariffs	+0.0%	+0.0%
Segmented volumetric ToU tariffs	+0.1%	+0.1%
Capacity tariffs	+31.4%	+44.3%
Capacity-subscription tariffs	+2.1%	+1.8%

effect weakens under other volumetric tariff structures, as EV charging stations can shift demand to low-tariff hours, while price-inelastic households primarily consume during high-tariff periods. Capacity-based tariffs reduce household overpayment due to their low peak use, but introduce a new misalignment among EV charging stations: both low- and high-consumption stations require similar capacity levels to be able to meet the demand of inflexible charging sessions, resulting in similar grid tariffs despite their difference in grid impact.

When comparing the alignment with the *peak responsibility* or *cost-causation* concept between between dynamic and fixed retail electricity price scenarios (see Figure 3.F in Àppendix 3.F for the fixed retail tariff results), it is visible that the gap between the tariffs paid and grid costs induced is larger in the dynamic retail electricity price scenarios. In these scenarios, the highest grid peaks occur at the hours with low retail electricity prices, when EV charging is concentrated and household demand is low. As a result, EV charging stations contribute more to peak demand, but their tariff payments do not fully reflect this impact.

3.4.4 Bill-shock effect

Table 3.2 quantifies the *bill-shock* effect, offering insight into the predictability of different grid tariff structures for users. It outlines how a doubling of the monthly consumption peak affects the grid tariffs paid by a grid user. Such a doubling may result from users' limited understanding of the tariff structure, lack of awareness of their electricity usage, or technical communication issues during the implementation of smart charging.

The table shows that this doubling has minimal effect for most tariff structures, with an average increase in a grid user's grid tariff costs of less than 3%. Capacity tariffs, however, are a clear exception: because they are directly tied to monthly peak demand, such a doubling leads to a substantial rise in the usage-based tariff component. This suggests that the risk of bill shock is largely limited to capacity-based tariff structures.

3.5 Discussion and conclusions

This section aims to outline the main findings of this work and to put them in a broader context by discussing their implications and limitations, as well as offering recommendations for future research.

3.5.1 Key findings and their implications

Our study highlights several key insights into the role of grid tariffs in facilitating EV integration into the electricity grid. These findings have important implications, both theoretically and practically. In this section, we will outline the key findings and discuss their implications.

First, this study demonstrated that growing EV adoption induces significant demand peaks under traditional grid-tariff structures, such as fixed lump-sum or time-constant volumetric tariffs. This, in turn, drives the need for substantial grid capacity expansions. This finding is in line with the current literature on this topic, which shows that EV integration necessitates major grid upgrades [56], [145]. It underscores the importance of developing mechanisms to mitigate these impacts, which we addressed by evaluating various alternative grid tariff structures.

Second, our analysis indicated that alternative grid tariff structures can reduce the need for grid expansions, although their effectiveness varies. In particular, the results indicated that capacity-based tariff structures were most effective in reducing peak demand, encouraging CPOs to lower charging speeds and reducing coincident peaks. This is in line with other discussions on future-proof tariff design [224], [225], [228]. Meanwhile, we showed that volumetric ToU tariffs shifted EV charging to off-peak hours, but created new grid peaks at higher EV adoption rates, ultimately leading to even higher expansion costs compared to the traditional tariff structures. This peak-shifting case is in line with traditional economic literature on peak-load pricing [238], [247], albeit in a new context. We show, in line with Turk et al. [230], that this is in particular a risk in a future with high EV adoption. This raises concerns about ToU tariffs for efficient grid use with high EV adoption rates.

Third, as part of this study, we examined how grid tariffs interact with dynamic retail electricity prices. Our results show that dynamic prices encourage simultaneous EV charging during low-price hours, increasing peak demand and the need for grid expansions. A new finding from this work is that they generally override the price signals from grid tariffs, reducing the effectiveness of grid tariffs in managing peak demand. This interaction plays a growing role in unbundled electricity markets, where EV users increasingly are turning to dynamic retail pricing models.

Fourth, another novel insight from our work is that the potential of alternative grid tariffs to reduce grid costs falls short of what can be achieved through more direct forms of flexibility management. We modelled to what extent grid-expansion costs can be reduced through coordinated charging managed by the DSO, sometimes

referred to as direct load control. This strategy ensures all EVs are fully charged by departure while minimizing grid impact. Compared to the performance of grid tariffs alone, the gains from coordinated charging are substantially larger, illustrating the additional potential of harnessing flexibility beyond tariff design.

Fifth, our work showed that alternative grid tariff structures can enhance the fairness of grid tariffs. We investigated the distributive effects of each grid tariff structure by looking at how they impact the grid tariffs paid by households and CPOs. Our findings show that fixed lump-sum tariffs disproportionately burden households, as rising grid costs stem largely from increased EV adoption, making equal distribution of grid costs among grid users unfair. In contrast, volumetric and capacity-based tariffs shift more costs to CPOs due to their high consumption and peak demand, a pattern also observed by Küfeoğlu & Politt [211] and Gunkel et al. [208]. However, it should be considered that this could impact the financial viability of public charging stations and slow their deployment.

Finally, this study highlights the inherent trade-off between regulatory principles for tariff design, a topic previously explored by Hennig et al. [231]. Our results show that capacity-based tariffs are most effective for grid efficiency, while volumetric tariffs offer better predictability and a fairer cost distribution.

3.5.2 Limitations

This study involves several modeling simplifications, which should be considered when interpreting the results. These assumptions were necessary to keep the analysis tractable while focusing on the key dynamics of grid tariffs under increased EV adoption.

A key assumption in this study is that CPOs have perfect foresight of departure times and charging demand, enabling highly optimized, price-responsive charging. However, in reality, CPOs are likely to act more conservatively to ensure EVs are sufficiently charged for unexpected departures, potentially overstating their responsiveness to tariffs. he grid cost model is also simplified: real-world grid expansions are often non-linear, lumpy, and influenced by geographic and regulatory constraints. Nevertheless, assuming linear growth was appropriate given the study's aim of extracting general insights.

Furthermore, household demand is treated as static, although in reality households may respond to tariffs, especially when equipped with flexible assets like heat pumps [248], [249]. Tariff structures may also influence household DER investments [212], [213], indirectly affecting grid use. Similarly, EV users are modeled as price-takers, yet under high adoption levels EVs could become price-setters in the electricity market, which would influence both wholesale market prices and the impact of tariffs on retail costs. Finally, the tariff structures in this study were simplified and could be made more dynamic, allowing for a more nuanced approach.

While these simplifications are necessary for a holistic analysis of alternative grid tariff structures, they do not the robustness of the main findings. The dynamics we observed under different tariff structures are likely to reflect real-world outcomes. For instance, even with more conservative smart charging or more detailed time-varying tariffs, the general trends would remain: part of the charging demand would still shift toward periods with the lowest tariffs, creating peaks similar to those observed in our results.

3.5.3 Future research

Future research should further look into identifying optimal grid tariff structures and we outline some directions in this section. First, to fully assess the impact of alternative tariff structures, future work should expand the modelling framework to include demand response from other flexible assets, such as private EV chargers, heat pumps and photovoltaics, and services like grid balancing enabled by smart charging. It could also explore how tariffs influence DER investments, as discussed by Schittekatte et al. [212] and Hoarau & Perez [213], to better understand potential distortionary effects. Additionally, incorporating other tools available to grid operators, such as capacity-limitation contracts, could help assess how these mechanisms interact with tariffs and affect regulatory outcomes.

In addition, we suggest that future research explores methods to enhance the effectiveness of grid tariffs in reducing grid expansions. A sensitivity analysis in Appendix 3.E indicated that higher tariff levels increase the effectiveness of tariff structures in reducing expansions, implying that NRAs might consider recovering a portion of sunk costs through the usage-based tariff component to raise tariff levels. However, Borenstein [236] and Brown et al. [209] warn that it may discourage users from consuming electricity at specific moments, potentially resulting in deadweight losses. It should be further studied to see to what extent this would occur in practice. Future research could also explore alternative approaches to tariff designs, such as differentiating between user types. Kolokathis et al. [250] proposed this approach, and it has been implemented in Italy, where tariffs vary between households and charging stations [88], allowing for more tailored pricing. However, it needs to be studied whether this approach conflicts with the non-discrimination principle. Finally, allowing users to choose among multiple tariff structures could improve predictability for inflexible users, enhance efficiency, and boost public acceptance. Further research should explore the feasibility, design, and fairness of such a system.

3.5.4 Policy recommendations

Our findings may have important implications for policy. Based on the analysis, we outline a number of recommendations for consideration.

First, policymakers should consider reforms of grid tariffs to better incentivize efficient EV charging. Our results show that EV charging can substantially increase peak demand, but also offers considerable flexibility. Capacity-based tariffs were found to be more effective than other designs in limiting grid impact. In contrast, ToU tariffs may inadvertently shift demand to the same low-price hours, reinforcing rather than relieving grid stress. This risk must be addressed in ToU tariff design, even though such approaches have been endorsed in recent policy reports (e.g., [88], [251]). Another reason for grid tariff reform is that it leads to a more equitable distribution of grid costs among users. In particular, volumetric-based tariff structures support a fairer allocation of grid costs by better aligning the grid tariffs paid by grid users' with their actual contribution to system costs.

Second, we note that tariffs alone, however, may not be sufficient. We recommend that DSOs and NRAs also explore mechanisms for directly accessing flexibility, such as non-firm connection agreements, flexibility markets, or direct load control. Our analysis shows that coordinated charging can achieve substantially lower grid costs than any of the tariff-based approaches we evaluated. These results suggest that contractual agreements between DSOs and CPOs could unlock significant benefits for both parties. However, the implementation of such mechanisms must be carefully evaluated in light of existing regulatory principles.

Finally, we recommend that tariff reforms take into account the trade-offs between competing regulatory objectives: efficiency, fairness, and predictability. Our findings confirm that no single tariff structure outperforms others across all criteria. Capacity-based tariffs promote efficient use of the grid, but volumetric tariffs perform better on predictability and equitable cost distribution. As previously highlighted by Hennig et al. [231], the relative importance of these principles is ultimately a political choice. We therefore do not endorse one specific design, but urge policymakers to weigh these trade-offs explicitly when designing or reforming grid tariffs. That said, tariff structures that risk raising total system costs, such as volumetric ToU tariffs under high EV adoption, should be avoided.

Appendix

3.A Mathematical formulation of EV charging models

This section introduces the optimization models employed for scheduling EV charging under various grid tariff structures. Since the models vary slightly depending on the specific grid tariff structure, a different model is introduced for each tariff structure.

3.A.1 Fixed, flat volumetric & volumetric ToU grid tariffs

The first optimization model is employed when a fixed, flat volumetric or volumetric ToU tariff structure is considered:

$$\min \quad c_{\text{gt}} + \gamma_{\text{retail}} c_{\text{el}} + c_{\text{priority}} \tag{3.2a}$$

s.t.

$$c_{\text{gt}} = \sum_{n}^{N} \sum_{t=\text{t}_{\text{arr},n}}^{\text{t}_{\text{dep},n}} p_{\text{ch},n,t}\, \Delta\text{t}\, \pi_{\text{vol},t} \tag{3.2b}$$

$$c_{\text{el}} = \sum_{n}^{N} \sum_{t=\text{t}_{\text{arr},n}}^{\text{t}_{\text{dep},n}} p_{\text{ch},n,t}\, \Delta\text{t}\, \pi_{\text{el},t} \tag{3.2c}$$

$$0 \leq p_{\text{ch},n,t} \leq \text{P}_{\text{ch,max},n} \quad \forall\, n \in \mathcal{N}, \forall\, t \in \left[\text{t}_{\text{arr},n}, \text{t}_{\text{dep},n}\right] \tag{3.2d}$$

$$\sum_{t=\text{t}_{\text{arr},n}}^{\text{t}_{\text{dep},n}} p_{\text{ch},n,t}\, \Delta\text{t} = \text{E}_{\text{dem},n} \quad \forall\, n \in \mathcal{N} \tag{3.2e}$$

$$c_{\text{priority}} = \frac{\sum_{n}^{N} \sum_{t=\text{t}_{\text{arr},n}}^{\text{t}_{\text{dep},n}} p_{\text{ch},n,t}\, \text{i}_{\text{num},n,t}}{\text{M}} \tag{3.2f}$$

The objective function of this model in eq. 3.2a is to minimize the sum of the total grid tariff costs (c_{gt}), the total retail electricity costs (c_{el}) and the total priority costs (c_{priority}) during the assessment timeframe. This timeframe is represented by the total set of timesteps $\mathcal{T}$, which is indexed by t, with T denoting the final timestep in $\mathcal{T}$. The parameter γ_{retail} equals 1 if dynamic retail electricity prices are considered in the optimization, and 0 if this is not the case. Equation 3.2b calculates the total grid tariff costs by summing the product of the charging power $p_{\text{ch},n,t}$ (in kW) for each charging session n at each timestep t, the duration of each timestep Δt (in hours) and the grid tariff level at the considered timestep $\pi_{\text{vol},t}$ (in €/kWh) across the set of charging sessions $\mathcal{N}$ within the assessment timeframe, with N denoting the last charging session in the set. $\text{t}_{\text{arr},n}$ and $\text{t}_{\text{dep},n}$ represent the arrival and departure times of charging session n, respectively. The total retail electricity costs are calculated in a similar way in eq. 3.2c, considering the retail price at each timestep $\pi_{\text{el},t}$ (in €/kWh). The charging power constraint in eq. 3.2d ensures that $p_{\text{ch},n,t}$ is within the allowable range, specifically between zero and the maximum allowable charging power $\text{P}_{\text{ch,max},n}$ for charging session n. The constraint in eq. 3.2e ensures that the charging demand of charging session n $\text{E}_{\text{dem},n}$ (in kWh) is met upon departure from the charging station. Lastly, the constraint in eq. 3.2f makes sure that if there are multiple possible charging times with the same tariff, priority is given to the earliest possible charging instance to optimize user comfort. It achieves this by summing the product of $p_{\text{ch},n,t}$ and $\text{i}_{\text{num},n,t}$, which indicates how many timesteps have elapsed since the start of the charging session n. This value is divided by the very large number

M to ensure that this priority cost term only impacts the objective function when multiple charging moments lead to the same cost.

3.A.2 Segmented volumetric ToU grid tariffs

The optimization model is slightly different when considering a grid tariff structure based on segmented volumetric ToU grid tariffs, as the grid tariff levels are no longer fixed for each timestep, but depend on the total consumed volume at the considered timestep:

$$\min \quad c_{\text{gt}} + \gamma_{\text{retail}} c_{\text{el}} + c_{\text{priority}} \tag{3.3a}$$

s.t.

$$c_{\text{gt}} = \sum_{t}^{T} \sum_{g}^{G} p_{\text{ch,tot},g,t}\, \Delta\text{t}\, \pi_{\text{vol},g,t} \tag{3.3b}$$

$$0 \leq p_{\text{ch,tot},g,t} \leq \text{P}_{\text{available},g,t} \quad \forall\, g \in \mathcal{G},\, \forall t \in \mathcal{T} \tag{3.3c}$$

$$\sum_{n}^{N} p_{\text{ch},n,t} = \sum_{g}^{G} p_{\text{ch,tot},g,t} \quad \forall\, t \in \mathcal{T} \tag{3.3d}$$

$$(3.2c) - (3.2f) \tag{3.3e}$$

This optimization model considers the same objective function, but the total grid tariff costs c_{gt} are determined differently. In this tariff structure, a set of grid tariff levels $\mathcal{G}$, indexed by g, is considered. Let G denote the total number of grid tariff levels in $\mathcal{G}$. For each level $g \in \mathcal{G}$ and each timestep t, a predefined available capacity $\text{P}_{\text{available},g,t}$ (in kW) is specified. The grid tariffs are applied sequentially: the lowest tariff level is considered first, and if the available capacity is exceeded, the next higher tariff applies to any additional consumption, and so on. The constraint in eq. 3.3b sums up the grid costs across all timesteps T and all grid tariff levels G, multiplying the total consumption at grid tariff level g $p_{\text{ch,tot},g,t}$ (in kW), the timestep duration Δt and the actual grid tariff level linked to g ($\pi_{\text{vol},g,t}$, in €/kWh) for each tariff and timestep combination. The allowable range for $p_{\text{ch,tot},g,t}$ is specified in constraint 3.3c for all grid tariff levels. Constraint 3.3d ensures that for every timestep that the summed charging power of all charging sessions n is equal to the sum of $p_{\text{ch,tot},g,t}$ across all considered grid tariff levels. Lastly, constraints 3.2c - 3.2f from the previous optimization model are considered again.

3.A.3 Capacity grid tariffs

The total grid tariff costs under this grid tariff structure depend on a grid user's monthly consumption peak. Modelling the EV charging schedules with this grid tariff structure involves a two-step approach. In the first step, the optimal consumption

peaks for every considered month are determined, assuming perfect information for all charging sessions occurring each month:

$$\min \quad c_{\text{gt}} + \gamma_{\text{retail}} c_{\text{el}} + c_{\text{priority}} \tag{3.4a}$$

s.t.

$$c_{\text{gt}} = \sum_{m}^{\text{M}_{\text{tot}}} p_{\text{peak},m}\, \pi_{\text{peak}} \tag{3.4b}$$

$$\sum_{n}^{N} p_{\text{ch},n,t} \leq p_{\text{peak},m} \quad \forall\, m \in M_{\text{tot}},\, \forall\, t \in T_m \tag{3.4c}$$

$$(3.2c) - (3.2f) \tag{3.4d}$$

The total grid tariff costs in eq. 3.4b are determined by summing the product of the consumption peak of each month m ($p_{\text{peak},m}$, in kW) and the capacity tariff level π_{peak} in €/kW/month. M_{tot} represents the set of considered months. The constraint in eq. 3.4d ensures that the total EV charging demand remains below $p_{\text{peak},m}$ for all timesteps in the considered month, which is represented by T_m.

In the second step, the EV charging schedules are determined again for the considered months, but using a rolling optimization approach. In this rolling optimization approach, the optimization is repeated for every individual timestep t' in the assessment period, considering all remaining timesteps of the assessment period. In this optimization, information about future charging sessions is not considered to prevent the model from anticipating at the beginning of the month that there will be a charging peak at the end of the month. In this way, more realistic charging schedules are obtained:

$$\min \quad \gamma_{\text{retail}} c_{\text{el}} + c_{\text{priority}} + c_{\text{peak,exc}} \tag{3.5a}$$

s.t.

$$\sum_{n}^{N_t} p_{\text{ch},n,t} \leq \text{P}_{\text{peak,opt,t}'} + p_{\text{peak,exc}} \quad \forall\, t \in \left[\text{t}', T\right] \tag{3.5b}$$

$$c_{\text{peak,exc}} = p_{\text{peak,exc}}\, \pi_{\text{peak,exc}} \tag{3.5c}$$

$$c_{\text{el}} = \sum_{n}^{N_t} \sum_{t=t'}^{\text{t}_{\text{dep},n}} p_{\text{ch},n,t}\, \Delta\text{t}\, \pi_{\text{el},t} \tag{3.5d}$$

$$0 \leq p_{\text{ch},n,t} \leq \text{P}_{\text{ch,max},n} \quad \forall\, n \in N_t,\, \forall\, t \in \left[\text{t}', \text{t}_{\text{dep},n}\right] \tag{3.5e}$$

$$\sum_{t=\text{t}'}^{\text{t}_{\text{dep},n}} p_{\text{ch},n,t}\, \Delta\text{t} = \text{E}_{\text{dem},n} - \sum_{\text{t}_{\text{arr},n}}^{t'} \text{P}_{\text{ch},n,t}\, \Delta\text{t} \quad \forall\, n \in N_t \tag{3.5f}$$

$$c_{\text{priority}} = \frac{\sum_{n}^{N_t} \sum_{t=\text{t}'}^{\text{t}_{\text{dep},n}} p_{\text{ch},n,t}\, \text{i}_{\text{num},n,t}}{\text{M}} \tag{3.5g}$$

A separate optimization is performed for every considered month and for every timestep t′ within the month. The optimization model only considers the timesteps between t′ and the end of the considered month. Instead of considering all charging sessions in the total assessment timeframe, it only considers the set N_t, which contains all active charging sessions at t′.

The model uses a different objective function in equation 3.5a compared to the previous optimization models, as c_{gt} is not considered in this function. This rolling optimization model considers an estimate of the optimal capacity of month m (based on the optimization output from the previous step, see modelling details in Section 3.3.5), and aims to keep the charging load below this capacity at all timesteps. As the model aimed to optimize the grid tariff costs in the previous step, total grid tariff costs are not optimized in this model. The term $c_{peak,exc}$ in the objective function represents the penalty costs in euros if the total charging load exceeds the predefined capacity. The constraint in equation 3.5b states that the total charging load should stay below the sum of the estimated optimal peak capacity $P_{peak,opt,t'}$ and the exceedance of this estimated optimum $p_{peak,exc}$ (both in kW). This estimated optimal capacity is, in principle, equal to the initial estimate of the optimal peak load, unless this capacity has been exceeded in previous timesteps, after which it equals the highest peak load until that moment. The constraint in equation 3.5c defines the exceedance costs as the product of $p_{peak,exc}$ and the exceedance fee $\pi_{peak,exc}$ in €/kW. This exceedance fee should be a very large number to ensure that the model aims to keep the peak charging power below the estimated optimum. The constraints in equations 3.5d - 3.5g are very similar to the constraints in equations 3.2c - 3.2f, but they focus only on the charging sessions in N_t, consider t′ as the starting timestep for the analysis, and account for the total charged volume up to t′ from previous iterations in the rolling optimization.

3.A.4 Capacity-subscription grid tariffs

The used model formulation for scheduling EVs with a capacity-subscription grid tariff structure is defined as follows:

$$\min \quad c_{gt} + \gamma_{retail} c_{el} + c_{priority} \tag{3.6a}$$

s.t.

$$c_{gt} = \sum_{m}^{M_{tot}} P_{sub,m}\, \pi_{sub} + \sum_{m}^{M_{tot}} e_{exc,m} \pi_{exc} \tag{3.6b}$$

$$e_{exc,m} = \sum_{t}^{T_m} p_{exc,t}\, \Delta t \quad \forall\, m \in M_{tot} \tag{3.6c}$$

$$p_{exc,t} \geq 0 \quad \forall\, m \in M_{tot}, \forall\, t \in T_m \tag{3.6d}$$

$$p_{\text{exc},t} \geq \sum_{n}^{N} \left(p_{\text{ch},n,t}\right) - \text{P}_{\text{sub},m} \quad \forall\, m \in M_{\text{tot}},\, \forall\, t \in T_m \tag{3.6e}$$

$$(3.2c) - (3.2f) \tag{3.6f}$$

Each grid user subscribes to a capacity level $\text{P}_{\text{sub},m}$ (in kW) before every month m in the considered set of months M_{tot} and is charged the subscription fee π_{sub} (in €/kW/month) for every kW subscribed. If the consumption during any timestep exceeds the subscribed capacity level, it is charged the exceedance fee π_{exc} (in €/kWh) for this exceedance. The total grid tariff costs are calculated according to constraint 3.6b, where $e_{\text{exc},m}$ represents the total exceedance in kWh during month m. This variable is defined in constraint 3.6c as the sum of the exceedance at individual timesteps ($p_{\text{exc},t}$, in kW), multiplied by the timestep duration. Constraints 3.6d & 3.6e outline that $p_{\text{exc},t}$ is equal to the difference between the total charging power at timestep t and the subscribed capacity level if this charging power exceeds this capacity level, and zero otherwise. Lastly, constraints 3.2c - 3.2f also apply to this optimization problem.

3.A.5 Peak load minimization

The analysis of the impact of different grid tariff structures in reducing grid costs in Section 3.4.1 also explores a scenario representing the theoretical optimal case, where the EV charging schedules are fully optimized to minimize peak grid load without considering costs (i.e., the *central controller* scenario). The following optimization algorithm was considered for these model simulations:

$$\min \quad p_{\text{grid,peak}} \tag{3.7a}$$

s.t.

$$p_{\text{grid},t} = \text{P}_{\text{non-EV},t} + \sum_{n}^{N} p_{\text{ch},n,t} \quad \forall\, t \in \mathcal{T} \tag{3.7b}$$

$$p_{\text{grid},t} \leq p_{\text{grid,peak}} \quad \forall\, t \in \mathcal{T} \tag{3.7c}$$

$$(3.2d)\ \&\ (3.2e) \tag{3.7d}$$

The objective of this model in eq. 3.7a is to minimize the peak grid load during the assessment timeframe ($p_{\text{grid,peak}}$, in kW). The total grid load at timestep t ($p_{\text{grid},t}$) is defined in eq. 3.7b as the sum of the aggregated non-EV (i.e., household) load ($\text{P}_{\text{non-EV},t}$, in kW) and the total EV charging load at this timestep. Constraint 3.7c ensures that the total grid load is below the peak grid load for all timesteps. Lastly, constraints 3.2d & 3.2e are considered in this model. This model is run 100 times for each considered EV adoption rate considering charging session data from a varying set of charging stations for each run. The average peak grid load value among all model runs is considered in the analysis.

3.B Data preparation steps

3.B.1 EV charging session data

Before performing the model simulations, different data preparation steps were performed for the used EV charging session data. First, charging sessions that were not feasible due to data errors (i.e., instances where the charging demand cannot be met within the connection timeframe when considering the maximum charging power), that had a charging demand below 1 kWh, that had a maximum charging power below 0 kW or above 23 kW or that had a connection time to the charging station of less than 15 minutes were excluded from the analysis. In some rare cases, different charging sessions shared exactly the same arrival time (to the nearest second) to the same charging station. If these charging sessions shared the same charging card ID, the first charging session in the data was kept. Otherwise, all charging sessions with the same arrival time and charging station ID were excluded from the data. In this data preparation process, 2.7% of the charging sessions were excluded from the analysis. The arrival and departure times were rounded to the previous 15-minute timestep for all charging sessions. Similarly, for charging sessions with a connection time to the charging station of more than 10 hours, a virtual departure time was set at 10 hours after arrival, since it is unrealistic that users will accept that the charging will be shifted for more than 10 hours. If a charging session became infeasible due to the updated arrival and departure times, the charging volume was set equal to the maximum possible charging volume in the adjusted connection time to the charging station.

3.B.2 Household profiles

Household profiles were simulated using the Artificial Load Profile Generator tool [243]. This tool distinguishes different household groups: Retired households (singles and couples), full-time working households (singles, couples and families) and part-time working households (couples and families). The distribution of these household groups is based on national statistics for the Netherlands regarding the retired population [252], household composition [253], and working status [254]. The load profile simulations did not account for heat pumps, home battery systems, EVs, or combined heat and power systems. Induction cooking was considered for 25% of the households and 25.2% of the households were equipped with a PV system, which is in line with the PV penetration rate for the Netherlands for 2022 [255]. All households with PV systems were randomly assigned 2 to 6 PV panels, considering a uniform distribution. This differs from the tool's original assumption that a household with PV systems should be energy-neutral. The tool was further enhanced by incorporating holidays into the load profiles. Monthly data on the percentage of the Dutch population that is on holiday [256] was used to estimate

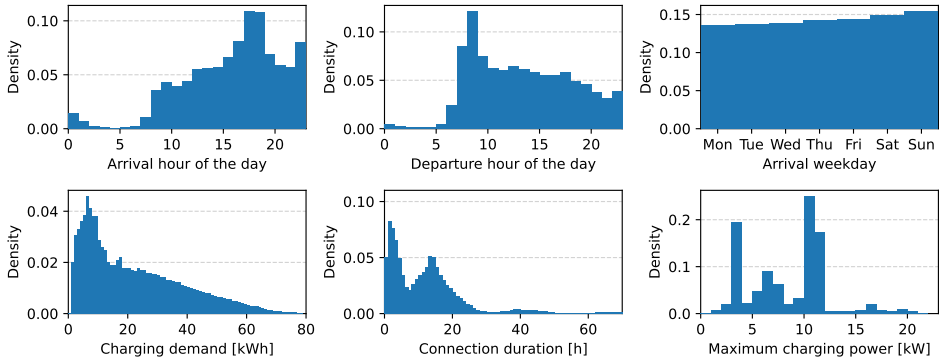


Figure 3.A: Histograms showing the distributions of key charging session characteristics for the considered set of charging sessions. These include the arrival and departure hours at the charging station, arrival weekdays, charging demands (i.e., charging volumes per session), connection durations (i.e., connection time to the charging station), and the maximum charging power during the session.

the likelihood of a household being on holiday, with durations randomly estimated between 7 to 21 days using a uniform distribution. During these periods, only the standby load of appliances was included in the household load. Lastly, since the annual electricity consumption of the generated profiles (excluding PV generation) was significantly lower than the average household consumption in the Netherlands, a scaling factor was applied to align the profiles with the 2022 average consumption of households in the Netherlands [257].

3.C Charging session characteristics

The model simulations considered 196,859 charging sessions from 380 residential public charging stations. Figure 3.A provides insight into the characteristics of the considered set of charging sessions.

3.D Estimation method for the expected number of charging stations

The expected number of charging stations N_{CS} at a specific EV adoption rate α_{EV} is based on the number of households N_{hh}, the car possession rate of households ρ_{car}, the average annual mileage of a car $\mu_{mileage}$, the driving efficiency $\eta_{driving}$, the average annual charging demand at an EV charging station $\mathscr{D}_{charge}$ and the charging efficiency η_{ch}:

$$N_{CS,\alpha_{EV}} = \frac{\alpha_{EV}\, N_{hh}\, \rho_{car}\, \mu_{mileage}\, \eta_{driving}}{\mathscr{D}_{charge}\, \eta_{charging}} \tag{3.8}$$

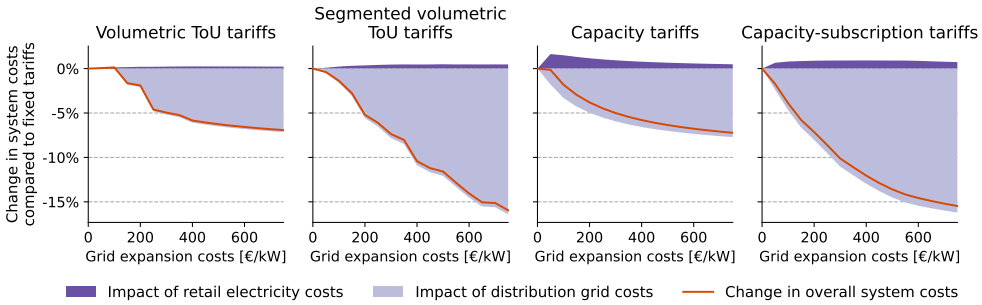


Figure 3.B: The impact of introducing different grid tariff structures on overall system costs compared to the baseline tariff structures (fixed and flat volumetric tariffs) for various grid expansion cost levels. This includes a detailed breakdown of the contributions from changes in retail electricity costs and changes in distribution grid costs. All results are for the scenarios with dynamic retail electricity tariffs for a 100% EV adoption.

This work considered the average car possession rate of 1.08 cars/household for the Netherlands [253], [258], an average annual mileage per car of 12,000 km [253], an average EV driving efficiency of 0.191 kWh/km [259], an average annual charging demand per charging station of 11,368 kWh (based on the used EV charging data) and a charging efficiency of $\sqrt{0.87}$ [163].

3.E Sensitivity analysis

This study assumed grid expansion costs of 120 €/kW, but these are highly dependent on local conditions and can vary considerably between locations. Since grid expansion costs impact the overall grid costs, they also affect the total tariffs that must be collected, influencing grid tariff levels. Higher grid expansion costs raise grid tariff levels, making their price signals more dominant, but this can also drive up retail electricity costs. To better understand the role of grid expansion costs, a sensitivity analysis was conducted to assess how variations in these costs affect the impact of each tariff structure on system costs, specifically for scenarios with dynamic retail prices.[8]

Figure 3.B reports the results of this sensitivity analysis, presenting the effectiveness of introducing different grid tariff structures in reducing system costs for various grid expansion cost values. It indicates that higher grid expansion cost values lead to greater system cost reductions for all tariff structures, as higher grid tariff levels are needed for cost recovery. This increases the price signal from grid tariffs, reducing the dominance of retail electricity prices in the EV scheduling process. On the other hand,

[8]Grid expansion cost values do not affect outcomes in fixed retail price scenarios, as the EV scheduling model only considers grid tariffs in cost optimization for these cases. These outcomes reflect dynamic retail price scenarios with very high grid tariff levels, where grid tariffs fully dominate retail prices, representing the maximum potential for reducing distribution grid costs using tariffs.

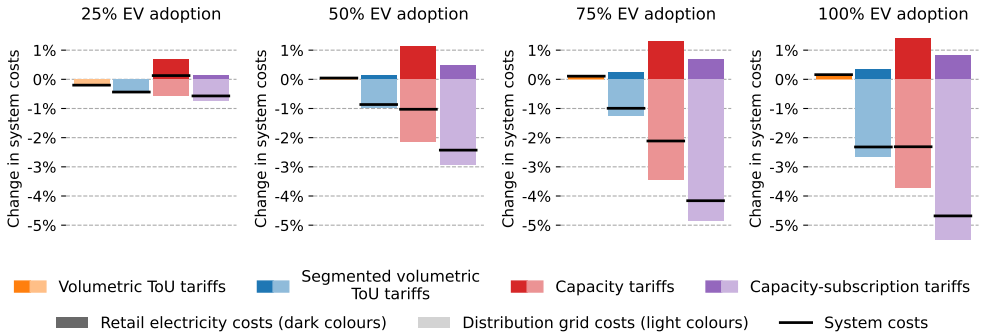


Figure 3.C: The impact of different grid tariff structures on overall system costs at various EV adoption rates, compared to the reference case of fixed grid tariffs. This includes a detailed breakdown of the contributions from changes in retail electricity costs (represented by dark colours) and changes in distribution grid costs (represented by light colours). All results are for the scenarios with dynamic retail electricity tariffs.

the figure illustrates that the expansion cost values have minimal impact on the retail electricity costs. Among the different tariff structures, capacity-subscription tariffs consistently yield the largest system cost reductions across all expansion cost levels, while segmented volumetric ToU tariffs become increasingly attractive as expansion costs rise. Both capacity-based and volumetric ToU tariffs tend to increase system costs when expansion costs are low but lead to system cost reductions when expansion costs are higher.

3.F Additional results

This section presents additional results that are shown in the main text. First, Figure 3.C presents the impact of each grid tariff structure on overall system costs for different EV adoption rates. Second, Figure 3.D shows the average grid tariff costs for households and EV charging stations under dynamic retail electricity price scenarios, whereas the main text focused on fixed retail price scenarios. While the overall trends remain similar, grid tariff costs are higher due to increased grid costs with dynamic retail prices. Third, Figure 3.E presents a scatter plot showing each grid user's contribution to overall grid peaks, which is the main driver for grid costs, versus their contribution to the total grid tariffs received by the grid operator. Lastly, Figure 3.F displays a histogram of the distribution of differences between actual tariff contributions and grid cost contributions for each grid user under fixed retail price scenarios, complementing the main text, which focused on dynamic retail price scenarios. The results indicate lower overpayment by households in the fixed retail price scenario.

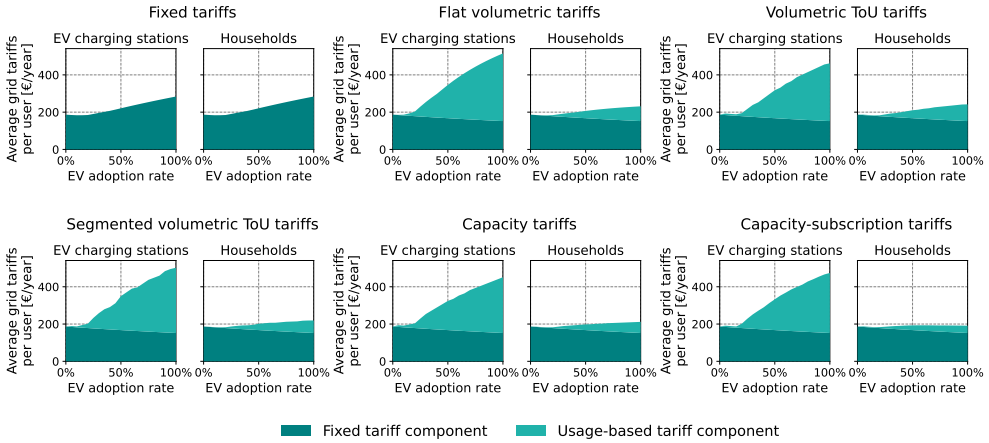


Figure 3.D: Average grid tariff costs in €/year for households and EV charging stations for different grid tariff structures under different EV adoption rates. Results are for a scenario with dynamic retail electricity prices. A distinction is made between the fixed grid tariff component, covering sunk costs, and the usage-based grid tariff component, covering expansion costs.

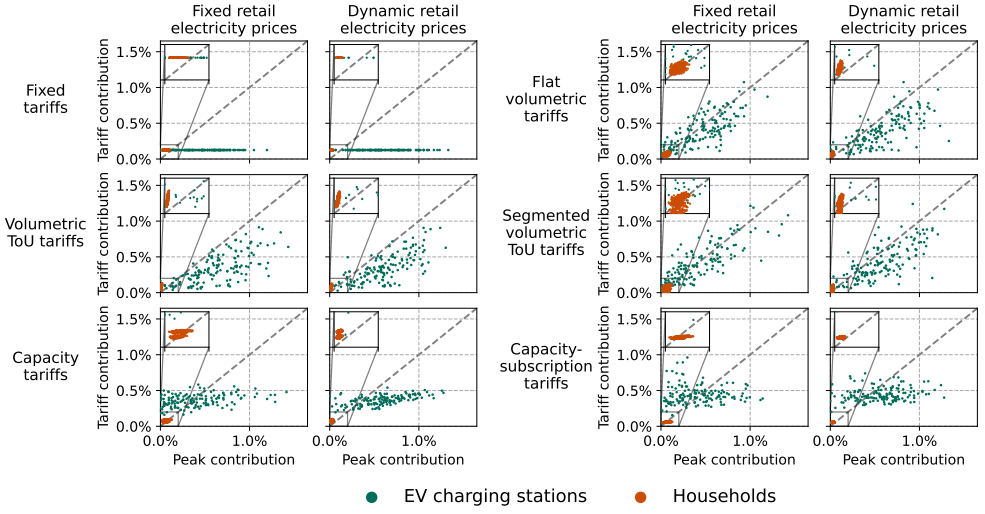


Figure 3.E: A scatter plot depicting each grid user's contribution to overall grid peaks versus their contribution to total grid tariffs (usage-based tariff component) for each considered grid tariff structure under a 100% EV adoption scenario.

3.G Base assumptions for considered grid tariff structures

Table 3.A presents an overview of the base assumptions considered for each tariff structure in this analysis.

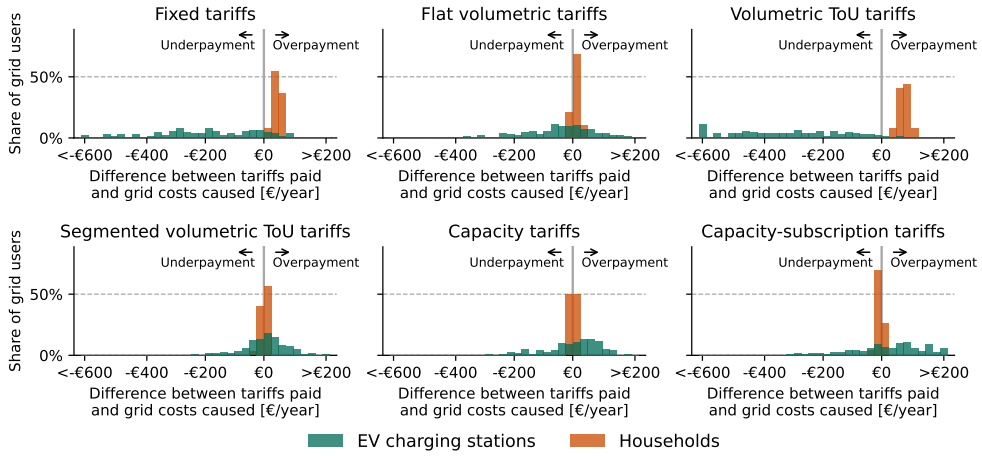
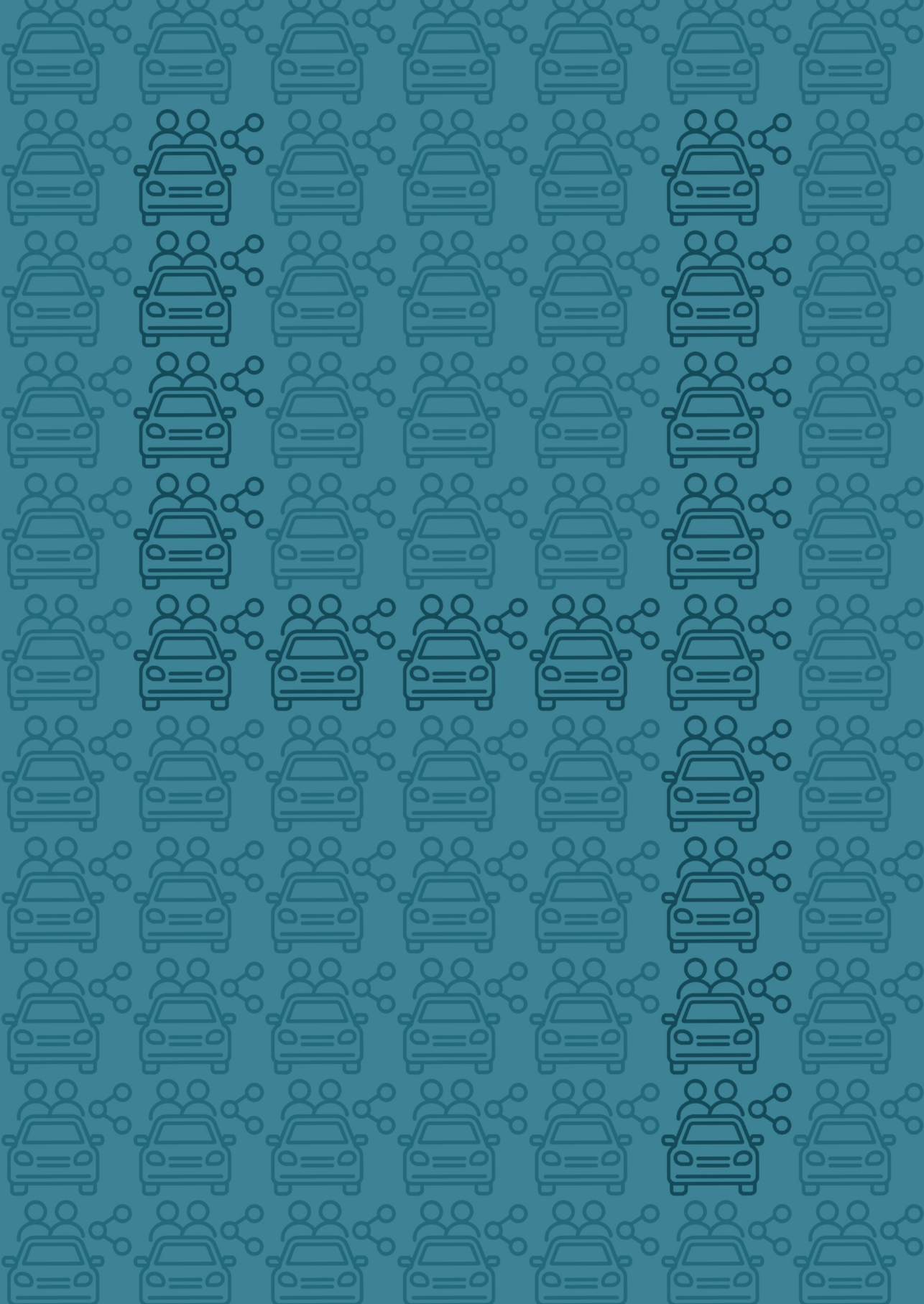


Figure 3.F: Histogram showing the distribution of grid users based on the difference between the usage-based grid tariffs they paid and the grid costs they caused. A distinction is made between households and EV charging stations. Positive values on the x-axis indicate users who paid more than the costs they imposed on the grid (i.e., they overpaid), while negative values indicate users who paid less than their cost contribution (i.e., they underpaid). Grid costs are assigned based on each user's contribution to the top 0.1% of system peak loads and associated grid expansion costs. The results are shown for a scenario with 100% EV adoption and fixed retail electricity pricing.

Table 3.A: Considered setup of the different considered grid tariff structures in this study.

Grid tariff structure	Tariff structure setup
1. Fixed tariffs	• Fixed tariff (€/year), which is the same for all grid users with the same grid connection size, independent of the actual consumption pattern.
2. Flat volumetric tariffs	• Flat volumetric tariffs (€/kWh), which are independent of the time of consumption, cover expansion costs. Sunk costs are covered through a uniform fixed tariff.
3. Volumetric ToU tariffs	• Volumetric tariffs (€/kWh), which depends on the moment of consumption, cover expansion costs. Sunk costs are covered through a uniform fixed tariff. • A three-tariff system is considered, with a ratio of 1:2:3 between the low, medium, and high grid tariff values. • The high grid tariff values are applied to the hours of the day with the highest household load (18:00-22:00). • The medium grid tariff values are applied between 16:00-18:00 and 22:00-00:00. • The low grid tariff values are applied for the remaining hours. • The same tariff schedule is applied for all days of the assessment period. • Model simulations were performed for tariff values between 0.0005 to 0.15 €/kWh for the lowest grid tariff, considering a stepsize of 0.0005 €/kWh. • No net metering is considered for households if their PV generation exceeds their electricity consumption at any given time.
4. Segmented volumetric ToU tariffs	• Volumetric tariffs (€/kWh), which depend on the moment of consumption, cover expansion costs. Sunk costs are covered through a uniform fixed tariff. • A three-tariff system is considered, with a ratio of 1:2:3 between the low, medium, and high grid tariff values. • During hours of the day with the highest household load (18:00-22:00), a grid connection pays the highest grid tariff value for all consumption. • Between 16:00-18:00 and 22:00-00:00 the grid connections pay the medium grid tariff for all consumption up to 4 kW. For all extra consumption, the high grid tariff is paid. • For all remaining hours, the grid connections pay the low grid tariff for all consumption up to 4 kW. For all extra consumption up to a total consumption of 8 kW, a grid connection pays the medium grid tariff. For all extra consumption, the high grid tariff is paid. • The same tariff schedule is applied for all days of the assessment period. • Model simulations were performed for tariff values between 0.0002 to 0.10 €/kWh for the lowest grid tariff, considering a stepsize of 0.0002 €/kWh. • No net metering is considered for households if their PV generation exceeds their electricity consumption at any given time.
5. Capacity tariffs	• Peak-based tariffs (€/kW-peak) cover expansion costs. Sunk costs are covered through a uniform fixed tariff. • The peaks are based on the average measured 15-minute consumption peak of a grid connection during each calendar month. • Model simulations were performed with tariff values ranging between 0.5 and 130.0 €/kW per year, considering a stepsize of 0.5 €/kW per year.
6. Capacity-subscription tariffs	• A combination of a capacity-based subscription tariff (€/kW-subscribed) and a volumetric exceedance fee (€/kWh-exceedance) cover expansion costs. Sunk costs are covered through a uniform fixed tariff. • Grid connections determine their subscribed capacity before each calendar month. The subscription fee is dependent on the subscribed capacity value. The subscribed capacity cannot be updated during the month. • An exceedance fee is applied for all consumption which exceeds the subscribed capacity. • The minimum subscribed capacity is 2 kW, which can be updated with stepsizes of 2 kW. • A fixed exceedance fee of 0.30 €/kWh is considered. • Model simulations were performed with subscription tariff values ranging from 0.2 €/kW and 75.0 €/kW, considering a stepsize of 0.2 €/kW.



Chapter 4

Mitigating grid congestion using shared electric vehicles

This chapter is based on the following publication, with minor edits for coherence within the thesis and in response to committee feedback:

N. Brinkel, T. AlSkaif, & W. van Sark (2022).

Grid congestion mitigation in the era of shared electric vehicles.

Journal of Energy Storage, 48, 103806.

Summary

Rapid integration of photovoltaic systems and electric vehicles in low-voltage grids increasingly causes grid congestion. To avoid costly grid reinforcements, distribution system operators are looking into applying electric vehicle smart charging algorithms to shift part of the load to off-peak hours. However, multiple barriers hamper the large-scale implementation of smart charging. These barriers can be alleviated when using electric vehicles in car sharing schemes for smart charging. Shared electric vehicles make up an increasing share of the car fleet and using these vehicles for smart charging exhibits different advantages over using private vehicles, including better predictable departure times and higher acceptance for smart charging. This study proposes a system for grid congestion mitigation using only shared electric vehicles and assesses this system's techno-economic potential. Results affirm that grid congestion problems can be fully mitigated in most grids using shared electric vehicles at relatively low car-sharing adoption rates. Also, the cost increase of using this system is negligible compared to a system with combined grid congestion mitigation of privately owned and shared EVs.

Highlights

- Barriers for mitigating grid congestion using EVs are lowered when using shared EVs.
- Novel system approach for mitigation of grid congestion using shared EVs only.
- Techno-economic assessment of this system using private & shared EV charging data.
- Congestion can be avoided using shared EVs only at relatively low shared EV adoption.
- Charging cost increase of the proposed system is negligible.

4.1 Introduction

High adoption of Electric Vehicles (EVs) puts stress on Low-Voltage (LV) grids, since EV charging can easily double the grid load and can cause high peak loads, induced by high simultaneity in EV charging moments [52], [54]. As the extra load of EV charging was not foreseen when designing the majority of LV grids, Distribution System Operators (DSOs) increasingly experience grid congestion and power quality problems.

The connection time of an EV to a charging station generally largely exceeds the required charging time [52], [260]. Hence, EV charging demand can be shifted to off-peak hours using smart charging, or EVs can inject electricity to the grid using vehicle-to-grid (V2G) technology without compromising on the battery energy level at departure [261], [262]. Mitigating grid congestion using EV smart charging is more cost-effective than reinforcing the grid [63], [263].

However, large-scale deployment of EVs as a flexibility resource by DSOs is hindered by multiple barriers. First, it requires secure and verifiable communication between grid operators and many decentralized actors (i.e., EV users, aggregators) [264], [265]. Implementation of such complex communication frameworks could lead to high costs. Second, a considerable share of the EV users may be hesitant to allow their EV battery to be used for smart charging or V2G [110], [266]. Third, grid operators need to be conservative in their EV smart charging algorithms, since the forecasting accuracy of the EV departure time is low [267] and EV users should not face an insufficient battery level for their intended trip at departure.

These barriers can be alleviated if DSOs contract EVs in car sharing schemes for the provision of flexibility for grid management. Car sharing is an alternative to car ownership and provides users short-term access to a fleet of shared cars managed by a third-party organization [268]. Car sharing is rapidly emerging worldwide, especially in urban residential areas; the number of car sharing members has grown by a factor of 40 between 2006 and 2018 [269] and further growth in the adoption of car sharing is expected [270]–[272]. Since the transport system is rapidly electrifying, most shared cars are likely to be electric in the future.

Using shared EVs instead of privately-owned EVs for grid management provides multiple advantages. Departure times of shared EVs are highly predictable, as they are booked through a reservation system. Consequentially, smart charging algorithms can be less conservative, increasing the potential for providing grid services. Moreover, the complexity of communication platforms is reduced as grid operators only need to communicate with a few car sharing companies when using EVs for grid management. Finally, fewer adjustments to the charging schedules of privately-owned EVs will be required to mitigate grid congestion, causing private EV owners not to unexpectedly face a low battery energy volume at departure.

Only few studies have looked into the future grid integration of shared EVs. In previous work, the authors have looked into the charging patterns of shared EVs [53].

Other authors studied the financial potential of shared EV participation in electricity markets [75], [273]. To our knowledge, no study assessed the potential of shared EVs to provide local grid services.

This study proposes a novel system approach for mitigating grid congestion in LV grids solely using shared EVs. This system can alleviate the barriers to smart charging for mitigating grid congestion and can thus avoid or delay grid reinforcements. It presents a model in which shared EVs cost-optimize their charging while respecting grid constraints, and privately-owned EVs can charge freely without considering grid constraints. The techno-economic potential of the proposed system is analyzed.

The novelty and relevance of this work can be highlighted as follows:

- To the best of our knowledge, this is the first work proposing the concept of using only shared EVs for the mitigation of grid congestion. As outlined above, this concept can alleviate several barriers of using EVs as a flexibility resource by DSOs, which can delay or avoid costly grid reinforcements;
- A system approach for the mitigation of grid congestion using only shared EVs is presented in this work, outlining the actions required by different actors and the needed communication framework between them;
- This work translates a system in which grid congestion is mitigated using only shared EVs into an optimization model for the charging of shared and privately-owned EVs;
- The viability of a system in which only shared EVs are used for the mitigation of grid congestion is extensively assessed from a techno-economic perspective;
- This study is one of the first studies using high-quality and real charging data of both shared and privately-owned EVs.

This chapter is outlined as follows. Section 4.2 describes the architecture of the proposed system and Section 4.3 provides the charging model formulation. Section 4.4 introduces the considered scenarios, the used input data and the outline of the model simulations. Subsequently, the results are presented in Section 4.5. The discussion in Section 4.6 and the conclusion in Section 4.7 are the last two sections of this work.

4.2 System architecture

This study proposes a system in which transformer congestion problems in LV grids are mitigated using shared EVs. This implies that privately-owned EVs can charge freely without considering grid constraints, and that no PV curtailment nor load shifting for residential appliances is required. The car-sharing company managing the charging schedules of the shared EVs is contracted by the DSO to ensure that no transformer congestion occurs (i.e., the power flows through the transformer

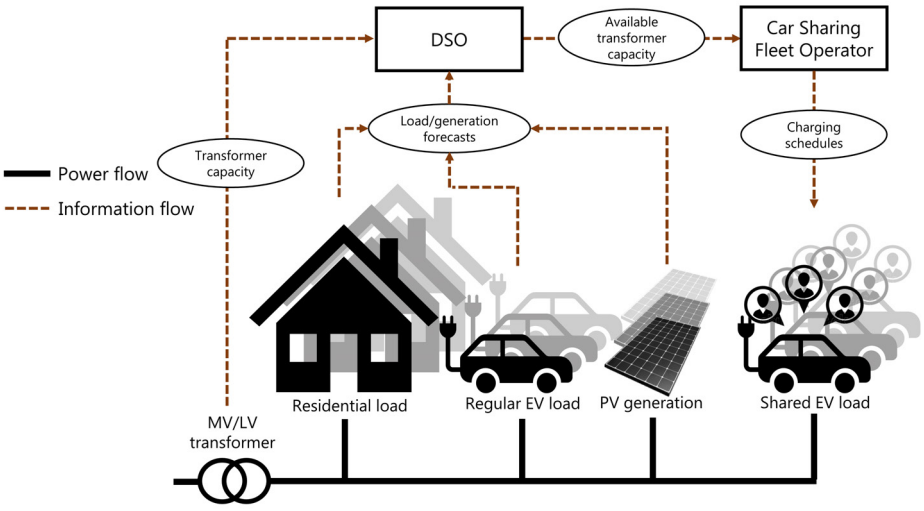


Figure 4.1: Visualization of the information flows and physical power flows in the proposed car sharing system architecture.

remain below the transformer capacity).[9] In order for such a system to function, a communication framework between different actors and different system components is required, which is visualized in Figure 4.1. This communication framework covers one LV grid and needs only two main actors; the DSO and the operators of car sharing platforms with shared EVs charging in the specific LV grid.

Grid congestion is mitigated using shared EVs using the following actions:

1. The DSO contracts one or multiple car sharing operators for the provision of flexibility using shared EVs;

2. The DSO forecasts the total residential load, PV generation and EV charging demand of privately-owned EVs for each timestep;

3. The DSO calculates the total forecasted transformer load excluding the load of shared EVs for each timestep and communicates this to the contracted car sharing operators;

4. The operators of the car sharing platforms use the reservation system of their car sharing platform to forecast the number of shared EVs connected to their

[9]The system studied for this car-sharing company closely resembles a capacity-limitation system, as introduced in the Dutch grid code in 2022 [92]. Under this system, the grid operator can impose restrictions on grid usage for users at specific times in exchange for financial compensation. A key difference in this case is that the grid operator can also enforce minimum charging/discharging requirements, if the total grid load, excluding shared EV charging, exceeds the grid capacity.

own charging stations for each timestep and their respective charging demand. The operator of these car sharing platforms perform an economic optimization of the charging schedules of their shared EV fleet, and assure that the total transformer load will not exceed the transformer capacity;

5. The operators of the car sharing platforms send the optimized charging schedules to the individual charging stations;

6. The car sharing platforms receive financial remuneration for the provision of flexibility to the DSO.

To be able to bring the transformer load below the transformer capacity when the communicated transformer load by the DSO already exceeds the transformer capacity for different timesteps, the shared EVs in the proposed system should be able to provide V2G services.

4.3 Model formulation

4.3.1 Optimization model of the proposed system

The economic optimization in step 4 of the proposed system in Section 4.2 can be translated to a mixed-integer optimization problem, in which shared EV operators minimize charging costs based on Time-of-Use (ToU) tariffs while also mitigating transformer congestion.

Objective function

This model aims to minimize charging costs for shared EVs for all charging sessions in one LV grid over the assessment timeframe, considering electricity costs and battery degradation costs:

$$\min \sum_{t=0}^{T} \left(c_{\mathrm{el},t} + c_{\mathrm{battdeg},t} \right), \tag{4.1}$$

where c_{el} represents the electricity (retail) cost function for shared EV charging for the studied LV grid, c_{battdeg} represents the battery degradation cost function for the studied LV grid, t represents a timestep in the set of considered timesteps $\mathcal{T}\,\{0, 1, \ldots, T\}$.

The electricity cost function for shared EV charging is defined as:

$$c_{\mathrm{el},t} = \pi_{\mathrm{el},t} \sum_{s=1}^{S} \left(\frac{1}{\eta_{\mathrm{ch}}} p_{\mathrm{ch},s,t} - \eta_{\mathrm{disch}} p_{\mathrm{disch},s,t} \right) \Delta \mathrm{t} \quad \forall t \in \mathcal{T}, \tag{4.2}$$

where $\pi_{\mathrm{el},t}$ represents the ToU-tariff for electricity at time t, p_{ch} and p_{disch} represent the charging and discharging power at the EV battery, respectively, η_{ch} and η_{disch} represent the charging and discharging efficiency, respectively, Δt is the duration

of one timestep and $\mathscr{S}$ is the set of charging sessions for shared EVs, indexed by $s = 0, 1, \ldots, S$.

Every charging/discharging cycle shortens the battery lifetime due to cycling ageing [171]. Battery degradation costs caused by cycling ageing are incorporated in the objective function to make sure that the battery only charges and discharges if the electricity cost benefits exceed the extra battery degradation costs. Battery degradation costs are a function of the battery investment costs π_{batt}, the piece-wise linear battery degradation function Φ and the depth of discharge of a charging or discharging cycle δ:

$$c_{\text{battdeg},t} = \sum_{s=1}^{S} \left(\pi_{\text{batt},s} \Phi \left(\delta_{s,t} \right) \right) \quad \forall t \in \mathscr{T}. \tag{4.3}$$

Section 2.3 provides detailed insight into the composition of this battery degradation function.

EV charging constraints

The charging and discharging power of shared EVs are bounded by the maximum charging or discharging capacity of the EV or the charging station ($\text{P}_{\text{ch,max},s}$ & $\text{P}_{\text{disch,max},s}$):

$$0 \leq p_{\text{ch},s,t} \leq \text{P}_{\text{ch,max},s} \quad \forall t \in [\text{t}_{\text{arr},s}, \text{t}_{\text{dep},s}], \ \forall s \in \mathscr{S}, \tag{4.4a}$$

$$0 \leq p_{\text{disch},s,t} \leq \text{P}_{\text{disch,max},s} \quad \forall t \in [\text{t}_{\text{arr},s}, \text{t}_{\text{dep},s}], \ \forall s \in \mathscr{S}, \tag{4.4b}$$

where $\text{t}_{\text{arr},s}$ and $\text{t}_{\text{dep},s}$ are the arrival and departure time of an EV, or start and end of a charging session s, respectively.

In addition, the optimization model ensures that all shared EVs have met their charging demand before departure:

$$e_{\text{ch},s,t_{\text{dep},s}} = \text{E}_{\text{dem},s} \quad \forall s \in \mathscr{S}, \tag{4.5}$$

where $e_{\text{ch},s,t_{\text{dep},s}}$ is the net accumulated charging volume at the EV battery for a charging session s at $\text{t}_{\text{dep},s}$, and $\text{E}_{\text{dem},s}$ is the required charging volume of charging session s at the EV battery. $e_{\text{ch},s,t}$ at time t depends on the accumulated charging volume at the previous timestep and on the charging and discharging power at time t:

$$e_{\text{ch},s,t} = \sum_{\tau \in [\text{t}_{\text{arr},s}, t]}^{t} \left(p_{\text{ch},s,\tau} - p_{\text{disch},s,\tau} \right) \Delta\text{t} \quad \forall t \in \mathscr{T}. \tag{4.6}$$

During all timesteps, the accumulated charging volume of a charging session cannot exceed the required charging energy to avoid overcharging of the EV battery. In most cases. the car fleet operators do not know the battery State-of-Charge (SoC) and

the battery could theoretically be empty at arrival. For this reason, the accumulated charging volume during a charging session must exceed the accumulated discharging volume at all timesteps. This is implemented in constraint 4.7 by setting the lower boundary of the accumulated charging energy at zero:

$$0 \leq e_{\text{ch},s,t} \leq \text{E}_{\text{dem},s} \quad \forall t \in \left[\text{t}_{\text{arr},s}, \text{t}_{\text{dep},s}\right], \ \forall s \in \mathscr{S}. \tag{4.7}$$

Grid constraints

The power balance constraint is formulated in equation (4.8):

$$\begin{aligned} p_{\text{grid},t} = \text{P}_{\text{non-EV},t} - \text{P}_{\text{PV},t} + \sum_{r=1}^{R}\left(\frac{1}{\eta_{\text{ch}}} p_{\text{ch},r,t} - \eta_{\text{disch}} p_{\text{disch},r,t}\right) \\ + \sum_{s=1}^{S}\left(\frac{1}{\eta_{\text{ch}}} p_{\text{ch},s,t} - \eta_{\text{disch}} p_{\text{disch},s,t}\right) \quad \forall t \in \mathscr{T}, \end{aligned} \tag{4.8}$$

where p_{grid} represents the transformer load, P_{res} represents the residential/non-EV load, P_{PV} represents the PV generation and $\mathscr{R}$ is the set of charging sessions for privately-owned EVs, indexed by $r = 0, 1, \ldots, R$.

To avoid transformer congestion, the transformer load constraint assures that the transformer load does not exceed the transformer capacity ($\text{P}_{\text{tr,max}}$) at all timesteps:

$$-\text{P}_{\text{tr,max}} \leq p_{\text{grid},t} \leq \text{P}_{\text{tr,max}} \quad \forall t \in \mathscr{T}. \tag{4.9}$$

4.3.2 Additional optimization models

Different other optimization models have been applied in this study to find the load-minimization potential of shared EVs, to simulate the charging patterns of privately-owned EVs in case of cost-optimization of those EVs and to determine EV charging costs in case of combined cost-optimization of shared and privately-owned EVs.

Peak load minimization of shared EVs

An additional peak load minimization optimization model has been applied in Section 4.5.1 to shared EVs to provide insight in the potential of shared EVs to reduce the transformer peak load in different scenarios. The objective of this optimization model is to minimize the transformer peak load during the assessment timeframe:

$$\min \ p_{\text{grid,peak}} \tag{4.10}$$

where $p_{\text{grid,peak}}$ represents the peak load in the assessment timeframe. This model was subject to the constraints in equations 4.4-4.8 and the constraint below:

$$p_{\text{grid},t} \leq p_{\text{grid,peak}} \quad \forall t \in \mathscr{T}. \tag{4.11}$$

Cost optimization of privately-owned EVs

This chapter considers different charging scenarios for privately-owned when studying the potential of shared EVs to mitigate transformer congestion. Next to uncontrolled charging of privately-owned EVs, this work considers scenarios in which they cost-optimize their charging demand, both with and without considering V2G functions (see Section 4.4.1). The optimization model applied to privately-owned EVs is very similar to the optimization model in Section 4.3.1, but is different in some aspects:

- Privately-owned EVs do not consider the transformer load in their charging optimization, thus the power balance and the transformer load constraints in equations 4.8 and 4.9 are not applied;
- The objective function in equation 4.1 and all EV charging constraints in equations 4.4–4.7 are applied to charging sessions of privately-owned EVs;
- The optimization models for privately-owned EVs that do not consider V2G, do not consider battery degradation costs in the objective function and do not consider discharging variables in equations 4.4, 4.6 and 4.8.

Combined cost-optimization and congestion mitigation of shared and privately-owned EVs

In Section 4.5.2, the economic viability of the proposed system is assessed by comparing the charging costs of the proposed system with a reference case in which both privately-owned EVs and shared EVs adapt their charging schedule to mitigate grid congestion. In contrast to the optimization model in Section 4.3.1, constraints 4.2, 4.3 and 4.4–4.7 are applied to charging sessions of both privately-owned and shared EVs.

4.4 Scenario Development, Data Inputs & Model Simulations

4.4.1 Scenario overview

The effectiveness of the proposed system is analyzed by applying the optimization model to a case study LV grid in a residential area for a wide range of scenarios. This study considers scenarios for: (i) different adoption rates of shared EVs, (ii) different reductions in vehicle-kilometer travelled (VKT) with adoption of shared EVs, (iii) different transformer capacities, (iv) different charging strategies of privately-owned EVs and (v) different electricity markets which are considered in the cost-optimization of EV charging.

Adoption scenarios of shared EVs

The adoption rate of shared EVs can differ significantly between different areas. The expected adoption of shared EVs is higher in urban areas due to the higher availability of alternative modes of transport [274]. To provide insight in the potential of shared EVs to mitigate grid congestion for different adoption rates of shared EVs, this study considers adoption rates between 5% and 95%.

VKT reduction scenarios

Shifting from private car ownership to car sharing generally reduces the number of trips by car by a person, as users in car sharing schemes have less direct access to a car. This lower car-usage is reflected in a reduction in VKT, which affects the number of shared EVs charging in a grid and thus affects the potential of shared EVs to mitigate grid congestion. Estimations on the reduction in VKT when adopting a shared EV show a wide range of values. Ref. [275] estimates a reduction in VKT of 15-20% for the Netherlands, However, a literature review of North American studies by [275] shows reductions in VKT between 3-80%. Ref. [276] compares reductions in VKT between different car sharing schemes and different European cities, and arrives at reductions in VKT ranging between 5-92%. This study considers reductions in VKT of 0%, 40% and 80%.

Transformer capacity scenarios

The transformer capacity affects the amount of transformer congestion and thus affects the effort required from shared EVs to mitigate transformer congestion problems. This analysis is conducted for transformer capacities of 250 kVA and 400 kVA, as these are typical transformer capacities for residential areas [277].

Charging scenarios for privately-owned EVs

Privately-owned EVs do not need to consider grid constraints when determining their charging patterns in the proposed system, but they can follow different charging strategies. This study considers scenarios for the following charging strategies of privately-owned EVs:

- *Uncontrolled charging*: EVs charge at maximum charging power after arrival until their charging demand is met;
- *Cost-optimized charging without V2G*: EVs minimize their charging costs by charging at moments with low ToU-tariffs. V2G functions are not considered here;

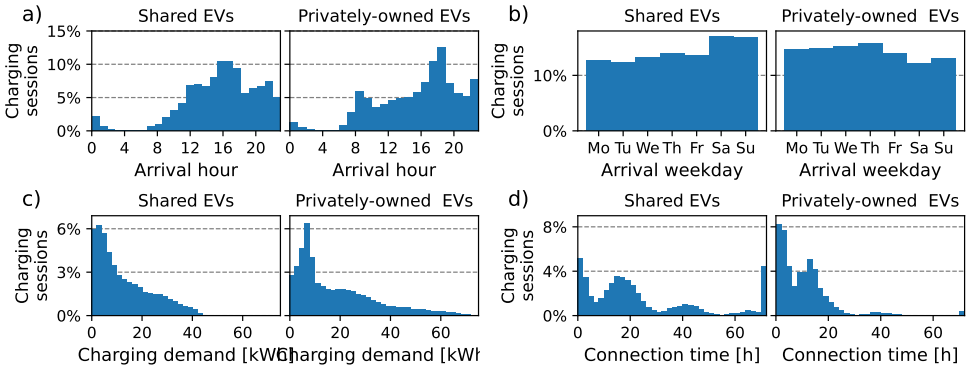


Figure 4.2: Histograms comparing key charging characteristics of shared and privately-owned EVs in the input data. Subplot a) shows the distribution of arrival hours for shared and privately-owned EVs. Subplot b) shows the distribution in arrival weekdays for shared and privately-owned EVs. Subplot c) shows the distribution in EV charging demand for charging sessions of shared and privately-owned EVs. Subplot d) shows the distribution in connection time for charging sessions of shared and privately-owned EVs. The data behind this figure considered 9,548 charging sessions of shared EVs and 32,801 charging sessions of privately-owned EVs.

- *Cost-optimized charging with V2G*: EVs minimize their charging costs based on the ToU-tariffs. V2G functions are available here, allowing EVs to inject electricity to the grid at moments with high ToU-tariffs.

Electricity market scenarios

However, EVs are also increasingly considered for other functions, such as the provision of grid services by participating in the automatic Frequency Restoration Reserves (aFRR) market [265], [278]. These markets have higher price volatility, offering greater potential for reducing charging costs via smart charging. The economic analysis in Section 4.5.2 is conducted using both day-ahead prices and aFRR prices as price inputs, assuming perfect foresight in market prices. The aFRR pricing scenario is an extreme case to obtain insight into the robustness of the economic analysis by representing the theoretical upper bound of potential cost savings achievable through smart charging. In practice, this scenario is unrealistic because aFRR prices are determined in real-time based on system imbalances and cannot be accurately predicted in advance. For scenarios where only a share of the EV fleet considers aFRR prices, the corresponding charging sessions are randomly selected.

4.4.2 Data inputs

EV charging data

This study used EV charging session data from between 8 January 2019 and 12 March 2020 from 277 charging stations with two charging sockets in residential areas

in the city of Utrecht, the Netherlands. The charging stations log the arrival time, departure time, charging volume and car-ID for each charging session. A subset of these charging stations also log the charging power over time on a 5 or 10 minute basis, which is used to determine the average charging power, maximum charging power and actual charging duration for each charging session.

Some of the charging stations are used by shared EVs from the car sharing company *We Drive Solar* [242]. Customers of the *We Drive Solar* car sharing company need a subscription and also pay per driven kilometer. In March 2020, the company's car fleet comprised three Tesla Model 3's with a 50 kWh battery capacity and 72 Renault ZOE's with a battery capacity ranging from 44-52 kWh. Privately-owned and shared EVs in the EV charging session data were distinguished based on their respective card IDs. The used data consists of 32,801 charging sessions of privately-owned EVs and 9,548 charging sessions of shared EVs.

The charging patterns of the considered charging sessions of privately-owned and shared EVs are substantially different, which is highlighted in Figure 4.2. This figure compares key charging characteristics of privately-owned and shared EVs. The figure indicates that the arrival moments of privately-owned and shared EVs are not similar. Figure 4.2a illustrates that the arrival hours of privately-owned EVs peak between 17:00-19:00, while this peak is less evident for shared EVs. Besides, a relatively high share of the shared EVs arrive after 20:00, in contrast to privately-owned EVs. In addition, shared EVs arrive more-frequently in weekends compared to privately-owned EVs, as shown in Figure 4.2b. Both observations could indicate that privately-owned and shared EVs are used for different purposes; privately-owned EVs are generally more used for commuting, while shared EVs are more used for leisure purposes.

From Figure 4.2c and Figure 4.2d can be deduced that the flexibility in charging is generally higher for shared EVs. On the one hand, Figure 4.2c shows that the charging demand of privately-owned EVs is generally higher compared to the charging demand of shared EVs. On the other hand, Figure 4.2d outlines that the connection time of shared EVs is on average higher compared to privately-owned EVs, indicating low utilization of shared EVs at some moments.

Simulation of EV charging sessions

A probabilistic model from [53] is used to simulate future EV charging sessions of privately-owned and shared EVs. This model requires historical EV charging data and the predicted total charging requirement of all charging sessions in one LV grid during the assessment timeframe as inputs for the simulation of charging sessions.

All scenarios assume a fully electrified car fleet. The total charging demand of privately-owned and shared EVs in the assessment timeframe (E_{priv} & E_{shared}) depend on the adoption rate of shared EVs (α_{shared}), the reduction in VKT when adopting

a shared EV (γ_{vkt}) and the total charging demand of privately-owned EVs without adoption of shared EVs ($E_{\text{priv,org}}$):

$$E_{\text{priv}} = E_{\text{priv,org}}(1-\alpha_{\text{shared}}) = \sum_{r=1}^{R} E_{\text{dem},r}, \tag{4.12a}$$

$$E_{\text{shared}} = E_{\text{priv,org}}\alpha_{\text{shared}}(1-\gamma_{\text{vkt}}) = \sum_{s=1}^{S} E_{\text{dem},s}. \tag{4.12b}$$

A value of 530 MWh was used for $E_{\text{priv,org}}$ for the selected case study grid, based on an average annual car mileage of 13,000 km [279], a car ownership ratio of 0.6 cars/household [179] and a fuel consumption of 0.2 kWh/km [280].

Grid data and electricity price data

An LV grid in the residential Lombok district in Utrecht, the Netherlands is used as a case study grid in this analysis. The grid serves 340 connection points, of which the majority are households, with an average annual electricity demand of 3420 kWh per grid connection. The capacity of the transformer of this grid has recently been reinforced from 250 kVA to 400 kVA. This study assumes a future installed PV capacity of 200 kWp. Normalized PV generation profiles from three large PV systems in the studied residential area were used as PV generation profiles in this analysis. Residential load profiles were generated using the standardized NEDU-profiles [183] and the total annual electricity demand of all connection points in this grid.

Day-ahead market prices and aFRR market prices in the Netherlands for 2019 [165] are used as price inputs in this study.

4.4.3 Model simulations

Model simulations for all considered scenarios are conducted in Python [188] using the Gurobi Modeling and Optimization package [189] using a high-performance computing cluster. The assessment timeframe of all analyses is one year using 15-minute timesteps, but to reduce the computational burden, this was split in three model simulations of four months. Charging sessions of five additional days before the assessment timeframe are also considered in the optimization model to assure that a representative number of EVs is connected to the grid at the beginning of the assessment timeframe. The model is run for five extra days after the end of the assessment timeframe to allow EVs that connected to the grid just before the end of the assessment timeframe to finish their charging session. This study used battery degradation parameters from [202] to model battery degradation, assuming a battery capacity of 50 kWh in case the battery capacity of the EV was unknown. A charging and discharging efficiency of $\sqrt{0.87}$ is used in this analysis [281]. Every scenario is

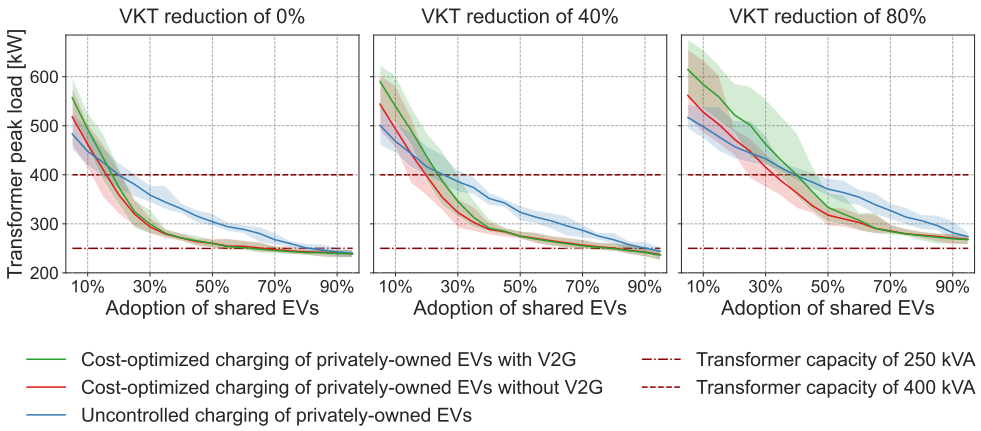


Figure 4.3: Annual transformer peak loads when applying a transformer peak load minimization algorithm to shared EVs for different considered scenarios. The values in the plots represent the average annual transformer peak load for the ten model runs. The shaded area represents the range in results (min/max) between the ten model runs.

run ten times using a newly-simulated set of EV charging sessions to obtain insight into the variability in results.

4

4.5 Results

4.5.1 Load minimization potential of shared EVs

Impact of shared EV adoption rate

Shared EVs are able to bring down transformer peak loads below the transformer capacity at relatively low adoption rates of shared EVs. This is presented in Figure 4.3, which reports transformer peak loads when a peak load minimization algorithm has been applied to shared EVs.

The capability of shared EVs to lower the transformer peak loads increases rapidly with higher adoption of shared EVs. This is induced by two mechanisms. First, higher adoption of shared EVs induces a shift away from private car ownership and thus causes a reduction in the charging demand of privately-owned EVs. As privately-owned EVs can charge without considering grid constraints in the proposed system, a reduction in their charging demand reduces the overall transformer load that shared EVs need to minimize. Second, more shared EVs are available at high adoption of shared EVs into inject electricity to the grid when the transformer load is high, resulting in an increased load-minimization potential.

Figure 4.3 shows that shared EVs can mitigate all transformer congestion problems in grids with a 400 kVA transformer at relatively low adoption of rates; in all considered scenarios, they can bring the peak transformer load below 400 kVA with

only a 20 to 30% adoption rate or higher. The potential of shared EVs to fully mitigate transformer congestion problems is lower in grids with a 250 kVA transformer. In such grids, shared EV adoption rates of 60 to 90% are required to bring the transformer peak load below its capacity, depending on the specific scenario.

Impact of the charging strategy of privately-owned EVs

The peak load-minimization potential of shared EVs is highly affected by the charging strategy of privately-owned EVs. Cost-optimization of privately-owned EVs with or without V2G causes large peaks in their charging demand at moments with favorable ToU-tariffs, and low charging demand at moments with less-favorable ToU-tariffs. At low adoption rates of shared EVs, only a limited number of shared EVs are connected to the grid at the moments with high charging demand of privately-owned EVs, limiting the potential to minimize transformer peak loads. The load-minimization potential of shared EVs in this scenario increases considerably with higher adoption of shared EVs; there are sufficient shared EVs connected to the grid at moments with high charging demand of privately-owned EVs to bring down the transformer load, while shared EVs can easily meet their own charging demand at the substantial share of time with very low charging demand of privately-owned EVs.

The charging demand of privately-owned EVs is less concentrated on specific moments when they charge in an uncontrolled manner. This increases the load-minimization potential of shared EVs with low adoption of shared EVs, due to the absence of high charging demand peaks. On the other hand, the constant load of privately-owned EVs causes that shared EVs constantly need to feed back electricity to the grid to minimize the peak transformer load while simultaneously meeting their own charging demand. This causes the peak load-minimization potential of the proposed system to be lower at high adoption of shared EVs when privately-owned EVs charge in an uncontrolled manner.

Impact of VKT reduction and variability in results

Higher VKT reductions reduce the potential to mitigate grid congestion problems using shared EVs only, since in this case less shared EVs are required to meet the passenger car traveling demand of shared EV users. As a consequence, less shared EVs are connected to the grid to reduce transformer peak loads.

All model runs are repeated ten times using different sets of simulated EV charging sessions. Figure 4.3 indicates that the spread in results among different model runs is relatively high, in particular with low adoption of shared EVs and with higher VKT reduction rates. The transformer peak load minimization potential of shared EVs depends on their availability at the moments with peak transformer loads. With relatively little shared EVs charging in the grid, the risk that a limited number of shared EVs is available to reduce transformer loads at one of those peak moments is

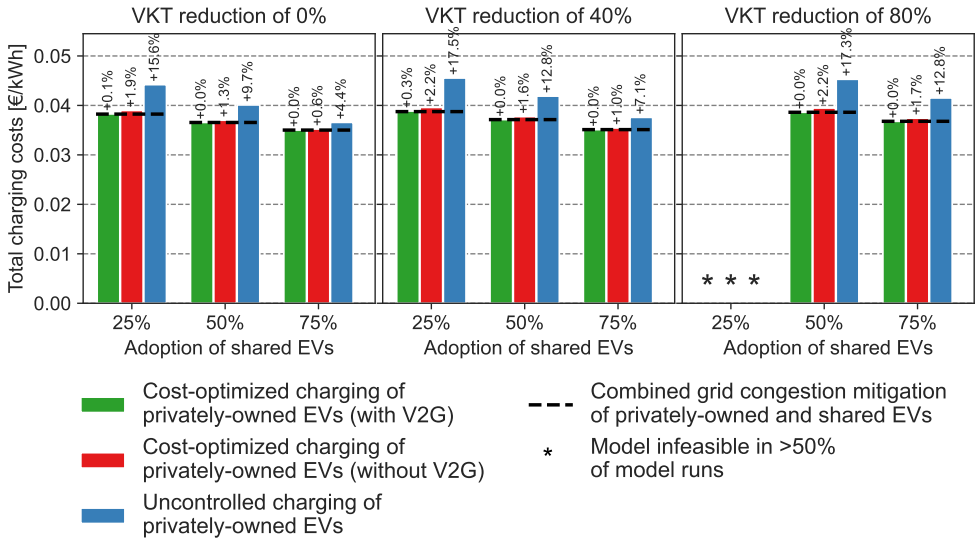


Figure 4.4: Combined average EV charging costs (electricity costs in the day ahead market and battery degradation costs) of privately-owned and shared EVs when using the proposed system in different scenarios. Results are presented for a grid with a 400 kVA transformer and in all scenarios, EVs only participate in the day-ahead electricity market. The dashed lines represent the average charging costs of a reference case with combined grid congestion mitigation of privately-owned and shared EVs. The cost-increase of using the proposed system compared to the reference case is reported as a percentage value.

high. This underlines that a minimum adoption rate of shared EVs is necessary before it can be considered as a reliable technology for the mitigation of grid congestion problems.

4.5.2 Economic viability of proposed system

The charging costs of the proposed system could be higher compared to a system in which private and shared EVs put in combined efforts to avoid grid congestion, since more flexibility options are available in the latter option. The economic attractiveness of the proposed system is determined by comparing the overall charging costs of the proposed system with the reference case in which both privately-owned and shared EVs consider transformer congestion in the optimization of their charging schedules. Figure 4.4 presents this comparison when EVs charge in the day-ahead market in a grid with a 400 kVA transformer capacity, considering different charging strategies of privately-owned EVs, different adoption rates of shared EVs and different VKT reductions when adopting a shared EV. The cost increase of when using the proposed system (colored bars) compared to the reference case (dashed lines) is indicated as a percentage value.

Impact of the charging strategy of privately-owned EVs

The cost difference is marginal when grid congestion is mitigated using shared EVs only and privately-owned EVs cost-optimize their charging demand using V2G (green bars in Figure 4.4). In all cases, the average cost increase compared to combined grid congestion mitigation is less than 0.3%, corresponding to less than 0.0001 euro/kWh. Using only shared EVs for the mitigation of grid congestion problems leads to slightly higher charging costs of shared EVs. However, a large part of this cost-increase is offset by the fact that privately-owned EVs can charge more economically-efficient, since the grid capacity is not considered in their charging optimization.

The increase in total charging costs with the proposed system is more considerable when looking at other charging strategies of privately-owned EVs. These higher overall charging costs are caused by an increase in charging costs of privately-owned EVs, which do not have the opportunity to use V2G in these charging strategies and thus have less options for cost-optimization. This is in contrast to combined cost-optimization of shared and private EVs, where privately-owned EVs can use V2G functions.

Impact of shared EV adoption rate, VKT reduction and transformer capacity

With higher adoption of shared EVs, the share of shared EVs in the total number of charging sessions occurring in a LV grid increases. Since shared EVs have a longer average connection time to the charging station compared to privately-owned EVs (see Figure 4.2), there is more room to move charging to moments with low ToU-tariffs. This results in lower overall charging costs with higher shared EV adoption. The difference in charging costs between the reference case and the charging scenarios for privately-owned EVs which do not consider V2G (blue and red bars in Figure 4.4) decreases with higher shared EV adoption. In these scenarios, only shared EVs use V2G and the share of the total EV fleet that cost-optimizes their charging demand without V2G thus decreases with higher shared EV adoption.

Overall charging costs and the rise in charging costs when using the proposed system increase slightly with higher reductions in VKT when adopting a shared EV. The lower number of shared EVs required to meet the travelling demand of shared EV users with higher VKT reduction causes that less shared EVs are available as a flexibility resource, resulting in less-efficient mitigation of grid congestion. This also explains why the model is infeasible at low EV adoption rates with high VKT-reduction rates; too little shared EVs are connected to the grid to bring the transformer peak load below the transformer capacity, as was also seen in Figure 4.3.

Mitigating grid congestion using shared EVs in a grid with a 250 kVA transformer leads to higher overall charging costs (+8%) when charging in the day-ahead market, since more deviations from the economically-optimal charging schedule are required when mitigating grid congestion compared to a 400 kVA transformer. Besides, the

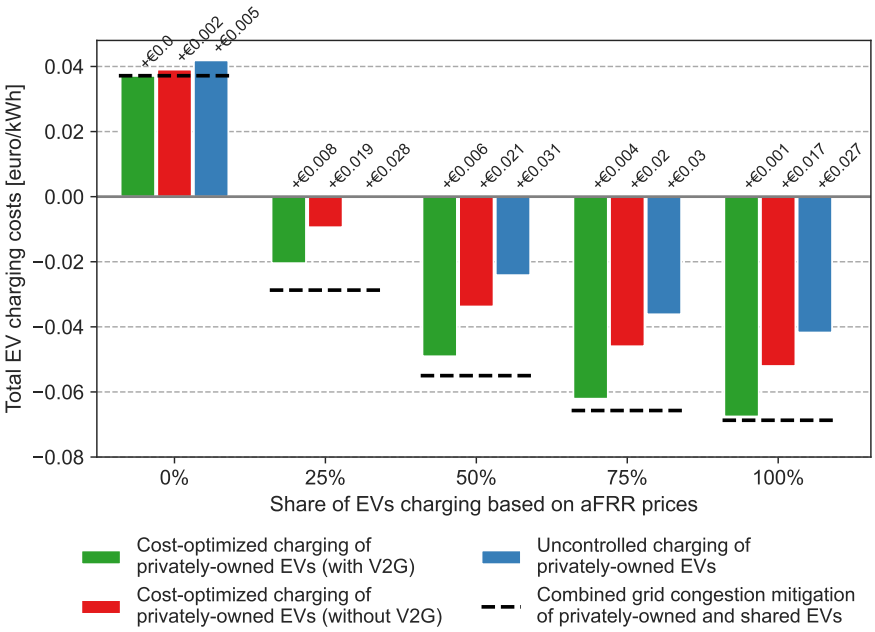


Figure 4.5: Combined average EV charging costs (electricity costs in the day ahead and aFRR markets and battery degradation costs) of privately-owned and shared EVs when different shares of the EV fleet charge based on aFRR prices using the proposed system. Results are presented for a grid with a 400 kVA transformer, a 50% EV adoption share and a VKT reduction of 40%. The dashed lines represent the average charging costs of a reference case with combined grid congestion mitigation of privately-owned and shared EVs. The values above the bars present the cost-increase of using the proposed system compared to the reference case in euro/kWh.

cost increase compared to combined grid congestion mitigation of privately-owned and shared EVs is slightly higher with a 250 kVA transformer, in particular at low shared EV adoption rates. With a 250 kVA transformer, more efforts from shared EVs are required to mitigate charging peaks caused by privately-owned EVs, providing less room for them to charge economically at moments with beneficial ToU tariffs.

Impact of selected pricing scheme

To assess the impact of considered electricity market on the economic viability of the proposed system, a sensitivity analysis has been performed in Figure 4.5. In this figure, aFRR market prices are used for the optimization of charging schedules for varying shares of the EV fleet. Day-ahead electricity market prices are used for the remainder of the EV fleet. The price volatility in the aFRR market is substantially higher compared to the day-ahead market, which explains why EV charging costs decrease and even become negative with increasing shares of the EV fleet participating

in the aFRR market.[10]

The difference in charging costs between the proposed system and the reference case of combined grid congestion mitigation of shared and privately-owned EVs increases when considering aFRR prices for a share of the EV charging sessions, although the difference between the reference case (dashed line) and the scenario of cost-optimization of privately-owned EVs using V2G (green bar) remains below 0.01 €/kWh in all cases. The connection time of shared EVs is generally longer (see Figure 4.2d) and therefore shared EVs can benefit most from the high price volatility in the aFRR market. Since transformer congestion is only considered in the charging schedules of shared EVs in the proposed system, transformer congestion cannot be mitigated using shared EVs charging in the day-ahead market only and shared EVs charging in the aFRR market are required to deviate from their cost-optimal charging schedules. This is in contrast to the reference case of combined grid congestion mitigation of shared and private EVs, where most transformer congestion problems can be mitigated by only adjusting the charging schedules of private and shared EVs participating in the day-ahead market. When considering aFRR prices for higher shares of EV charging sessions, deviations from the cost-optimal charging schedules of shared EVs participating in the aFRR market are also required in the reference case to avoid transformer congestion. As a consequence, this cost difference decreases when considering aFRR market prices for higher shares of the EV fleet.

4.6 Discussion

4.6.1 Implications and limitations

This work should be regarded as an exploratory study, presenting the theoretical techno-economic potential of using shared EVs for the mitigation of transformer congestion. The calculated benefit is an over-estimation of the one to be expected in reality, as this study assumed perfect foresight for different aspects, including the grid load, EV charging demand, electricity prices and the arrival and departure times of EVs, while there is uncertainty on these aspects in practice. One of the main benefits of using shared EVs, namely their more predictable departure times via the usage of a reservation system, was not considered, causing shared EVs to be charged less conservatively compared to private EVs in practice. Therefore, the increase in charging costs when using the proposed system approach will be lower in practice, further pronouncing the economic viability of this system.

The results in this analysis indicated that a 20-30% shared EV adoption rate is required in a specific LV grid to be able to mitigate all transformer congestion

[10]As explained in Section 4.4, the aFRR pricing scenario represents an extreme case to test the robustness of the economic analysis, reflecting the theoretical maximum cost savings under ideal conditions. In reality, this is not achievable, as aFRR prices are set in real time based on system imbalances and cannot be reliably forecasted.

problems. In 2020, around 6.6% of the Dutch population with a driving license made use of a car sharing platform [282], [283], while the share of the population that fully shifted to car sharing is substantially lower. A 20-30% adoption rate of shared EVs on a national level is therefore not realistic in the short term. However, shared cars are increasingly considered in densely-populated urban areas as a solution to reduce the land use of parking spaces. This is illustrated by different newly-constructed urban districts, in which all parking spots can only be used by shared cars [284], [285]. Therefore, it is realistic that the minimum required adoption rate of shared EVs is met relatively soon in an increasing number of urban LV-grids.

Important to note is that a well-functioning remuneration system is crucial for successful implementation of the proposed system. The proposed system can lead to unfair allocation of costs and benefits between car sharing companies and private EV owners, since charging costs for car sharing operators increase if they adjust their charging schedules to mitigate grid congestion, while charging costs of private car owners decrease since they do not need to consider grid congestion when scheduling their EVs. For this reason, the development of a fair remuneration scheme or local electricity market which provides financial incentives to car sharing operators to participate in such system should become a priority for grid operators. The local electricity market design under coordination of a community manager (e.g., the grid operator) proposed in [286] could serve as a blueprint for a fair allocation mechanism for costs and benefits between all involved stakeholders.

High quality forecasts of the grid load are a prerequisite for high effectiveness of the proposed system architecture. Forecasting errors can lead to transformer overloading or to imbalance costs to operators of car sharing schemes if shared EVs need to deviate from their optimal charging schedules to correct for forecasting errors. For this reason, grid operators should invest in monitoring equipment for LV grid data and should invest in the development of advanced forecasting methods to achieve more accurate forecasts. Also, investments in communication infrastructure are mandatory for a well-function system.

This study made use of a rich data set of charging sessions of shared EVs. Since all charging sessions in this study are from a station-based car sharing scheme in an urban area, the results cannot be generalized to other types of car sharing schemes. New user groups could adopt shared EVs with higher adoption of car sharing, which potentially results in higher utilization rates of shared EVs and different arrival times or lower connection times of shared EVs. In contrast, it can be expected that an overcapacity in the number of shared EVs will always remain to assure availability of shared EVs to users, causing the flexibility in charging demand not to change considerably with higher shared EV adoption.

4.6.2 Future research

Next to mitigating transformer congestion, EVs can also be used to mitigate cable congestion or other power quality issues, including voltage issues and voltage fluctuations [63]. Future research could adapt the proposed system to analyze its potential in mitigating other LV grid problems using shared EVs only. In addition, future research could further enhance the proposed system by suggesting methods on how to allocate the responsibility of mitigating grid congestion among car sharing operators when two or more car sharing operators charge shared EVs in the same LV grid. Lastly, the lower uncertainty about the departure time of shared EVs compared to privately-owned was not considered in this research. Future studies could quantify this lower uncertainty and consider this in optimization models, in order to fully capture the added value of mitigating grid congestion problems using shared EVs only.

4.7 Conclusions

This study proposed a novel system approach for mitigating transformer congestion in LV grids using shared EVs and assessed its techno-economic potential in reducing transformer peak loads. Extensive simulations were performed using high-resolution EV charging session data of both privately-owned and shared EVs. The results showed a promising future potential role for shared EVs in the mitigation of transformer congestion problems in LV grids if the adoption of shared EVs continues to rise. Shared EVs are able to avoid all grid congestion problems in grids with a 400 kVA transformer at relatively low adoption rates. However, high adoption rates of shared EVs are required in grids with 250 kVA transformers. The techno-economic assessment indicated that the extra charging costs when mitigating grid congestion using shared EVs only are negligible compared to the reference case with combined grid congestion mitigation of privately-owned and shared EVs. Shared EVs can alleviate barriers for using EV smart charging to grid problems and this study showed that transformer congestion can be mitigated using shared EVs only at relatively low shared EV adoption rates and at negligible extra costs. Therefore, further stimulation of car sharing by governments is not only attractive from an environmental perspective, but also from a grid management perspective.

Chapter 5

Forecasting for scheduling electric vehicle charging

This chapter is based on the following publication, with minor edits for coherence within the thesis and in response to committee feedback:

N. Brinkel, L. Visser, W. van Sark, & T. AlSkaif (2023).

A novel forecasting approach to schedule aggregated electric vehicle charging.

Energy and AI, 14, 100297.

Summary

To schedule the charging demand of an electric vehicle fleet using smart charging, insight is required into different charging session characteristics of the considered fleet, including the number of charging sessions, their charging demand and arrival and departure times. The use of forecasting techniques can reduce the uncertainty about these charging session characteristics, but since these characteristics are interrelated, this is not straightforward. Remarkably, forecasting frameworks that cover all required characteristics to schedule the charging of an electric vehicle fleet are absent in scientific literature. To cover this gap, this study proposes a novel approach for forecasting the charging requirements of an electric vehicle fleet, which can be used as input to schedule their aggregated charging demand. In the first step of this approach, the charging session characteristics of an electric vehicle fleet are translated to three parameter values that describe a virtual battery. Subsequently, optimal feature and hyperparameter sets are determined. These serve as input for the last step, in which the virtual battery parameter values are forecasted. The approach has been tested on a real-world case study of public charging stations, considering a high number of features and different forecasting models (Multivariate Linear Regression, Random Forest, Artificial Neural Network and k-Nearest Neighbors). The results show that the different virtual battery parameters can be forecasted with high accuracy, reaching R^2 scores up to 0.98 when considering 400 charging stations. In addition, the results indicate that the forecasting performance of all considered models is somehow similar and that only a low number of features are required to adequately forecast aggregated electric vehicle charging characteristics.

Highlights

- Novel approach to forecast all required aspects to optimize charging of an EV fleet.
- The effectiveness of the approach is tested using real-world EV charging session data.
- Results report high forecasting performance, especially for large EV fleets.
- Forecasting performance is similar for different forecasting models.
- Only a low number of features is required for a good forecasting performance.

5.1 Introduction

5.1.1 Problem definition

The rapid introduction of Electric Vehicles (EVs) in different countries increases the number of distributed energy assets in the energy system. Due to the high charging power and long connection time of EVs, the potential to shift their charging demand over time is high [54]. This high charging flexibility can serve a wide range of applications if EV smart charging is deployed. From a customer perspective, smart charging can considerably reduce costs and emissions [77], [287]. From the perspective of electricity grid operators, implementation of EV smart charging is the most cost-effective option for mitigating the increasing number of grid congestion problems [202], [288]. In addition, EV smart charging can be used to solve power quality issues [63], [289] and to provide balancing reserves to Transmission System Operators (TSOs) [278], [290].

One of the main problems hindering the large-scale deployment of EV smart charging is the wide range of uncertainties faced when optimizing the charging schedules of an EV fleet. These uncertainties include the number of charging sessions occurring in the scheduling timeframe, their charging demand, charging power, arrival time and departure time.

These uncertainties can be reduced by forecasting those EV charging session characteristics. Typically, EV smart charging sessions are controlled by an energy aggregator. In all cases, the aggregator needs to forecast the departure time and energy demand of an EV when optimizing the charging session, to assure that the charging demand of an EV is met at departure. However, when participating in electricity markets using an EV fleet, an aggregator needs to extend their forecasts. In addition to forecasting the departure time and charging demand of each charging session, it also needs to forecast the number of charging sessions during the bidding period, their arrival time and maximum charging power. This is because the Gate Closure Time (GCT) of most electricity markets (i.e., the last moment until market parties can make bids) is well before actual operation (e.g., 12-36 hours before operation for the day-ahead market in Europe [291]). An incorrect forecast could force aggregators to deviate from their accepted bid to the electricity market, resulting in high imbalance costs.

Two challenges complicate the forecasting of those different EV charging session characteristics. First, the number of charging sessions in the assessment timeframe is unknown at the moment of scheduling for different smart charging applications. Hence, it is complex to forecast the charging session characteristics (i.e., arrival/departure time, charging power and charging demand) with an unknown set of charging sessions. Second, the different charging session characteristics are highly interrelated (i.e., a higher charging demand is likely to result in a longer connection time). For this reason, alternative forecasting frameworks are required for scheduling

an EV fleet when the values of critical parameters are unknown.

5.1.2 Literature review

Surprisingly, a low number of scientific studies have looked into developing methods to perform comprehensive forecasts of all EV charging characteristics that are required to schedule an EV fleet. A large number of studies have proposed a wide variety of methods to forecast the load of one or multiple charging stations when EVs charge in an uncontrolled manner (e.g., [292]–[295]). These forecasts are valuable for grid impact studies of EV charging, but do not provide insight in the required aspects to optimize the charging schedules of an EV fleet using smart charging (i.e., number of charging sessions, arrival/departure time, charging demand and maximum charging power).

Another group of papers proposes forecasting approaches that only consider some of the aspects that are required to schedule an EV fleet, as summarized in Table 5.1. Aabrandt et al. [296] propose a method to forecast the connection time of an EV to a charging station. Markov Chains were used to account for the uncertainty in EV availability by Iversen et al. [297], Sundström et al. [298] and Wan et al. [299]. Bikcora et al. [300] forecast the availability and maximum charging power of single EVs, and Islam et al. [124] forecast the arrival State-of-Charge (SoC) distribution for an EV fleet. Habibifar et al. [301] forecast the charging demand and departure time of individual EV charging sessions, but this study did not consider the uncertainty in the total number of charging sessions. Since the forecast approaches proposed in these studies do not cover all relevant aspects required to schedule an EV fleet, these methods can only be used to a limited extent when implementing EV smart charging for an EV fleet. Huber et al. [123] use quantile forecasts of the charging demand and connection time of individual charging sessions to identify the charging sessions with the highest flexibility. Giardano et al. [302] estimate the number of charging sessions, arrival time, departure time and energy demand for an individual EV, using clustering methods. Similarly, Aguilar-Dominguez et al. [125] use clustering techniques to forecast the connection hours of individual EVs. To guide users in finding an available charging station, Majidpour et al. [305] forecast the available charging capacity for a charging station.

Instead of using forecasting techniques, some studies (e.g., [120] & [121]) propose to ask for user input, such as the expected arrival and departure time and the expected arrival SoC, to reduce uncertainty when optimizing EV charging schedules. However, this is generally undesirable for different reasons. First, different studies have shown that adding complexity to users reduces their willingness to participate in smart charging [115], [306]. Second, it is questionable whether users are able to provide detailed and accurate charging information hours in advance of actual operation, i.e., 12-36 hours ahead in case of bidding into the day-ahead market.

Paper	Considered charging session characteristics for scheduling an EV fleet					Used forecasting method	Considered features
	Number of sessions in assessment timeframe	Arrival time of charging sessions	Departure time of charging session	Charging demand of charging sessions	Charging power of charging sessions		
[296]	✗	✓	✓	✗	✗	Statistical modelling using historical data	Historical parameter values
[297]	✗	✓	✓	✗	✗	Markov decision process	Historical parameter values
[298]	✗	✓	✓	✓	✗	Markov decision process	Historical parameter values
[299]	✗	✓	✓	✓	✗	Markov decision process	Historical parameter values
[300]	✗	✓	✓	✗	✓	Generalized linear models	Historical parameter values
[124]	✗	✗	✗	✓	✗	Maximum likelihood estimation	Historical parameter values
[301]	✗	✓	✓	✓	✗	Autoregressive models	Historical parameter values
[123]	✗	✗	✓	✓	✗	Quantile regression, Multivariate conditional kernel density estimator	Historical parameter values
[302]	✓	✓	✓	✓	✗	Clustering using k-medoids technique	Historical parameter values
[125]	✗	✓	✓	✗	✗	Gradient Boosting	Historical parameter values

Table 5.1: Overview of relevant literature on the forecasting of charging session parameters for every individual charging session.

Paper	EV aggregation parameters considered in forecast: Total daily charging demand	Hourly max. charging power	Hourly max. aggregated charging energy	Hourly min. aggregated charging energy	Used forecasting methods	Considered features	Conducted forecasting analyses
[127]	✓	✓	✗	✗	Seasonal autoregressive model	Historical parameter values	Model performance of aggregation parameters
[303]	✓	✓	✓	✗	Autoregressive model	Historical parameter values	Model performance of one aggregation parameter
[304]	✓	✓	✓	✓	Autoregressive model	Historical parameter values	None
[126]	✓	✓	Partly	✓	Autoregressive model	Historical parameter values	Model performance of aggregation parameters for different EV fleet sizes
This work	✓	✓	✓	✓	Multivariate Linear Regression, Random Forest, Artificial Neural Network & k-Nearest Neighbors	Temporal data, Historical parameter values & Weather forecasts	Model performance of aggregation parameters for different EV fleet sizes & forecasting models, feature importance, optimal hyperparameter sets

Table 5.2: Overview of relevant literature on the forecasting of parameters associated with aggregated EV modeling and an overview of the aspects covered in this work.

To facilitate the scheduling of an EV fleet, different aggregation methods are proposed in scientific literature. An aggregation method combines the charging characteristics of a set of EV sessions into a few parameters for scheduling their aggregated charging schedule. Aggregation methods for EV fleets are presented in different forms, but all aggregation methods consider the temporal (i.e., arrival and departure time of individual EVs) and energy dimensions (i.e., charging demand and maximum charging power of individual EVs) of the charging flexibility of the respective EV fleet. Lilliu et al. [307] and Pedersen et al. [308] present the FlexOffer approach, in which the charging flexibility of an EV fleet is illustrated by two sets of constraints: (i) constraints on the usable amount of energy at each timestep and (ii) total energy constraints. Schlund et al. [309] describe the total flexibility by identifying the time and energy flexibility. The most common aggregation methods are to aggregate the charging session characteristics of an EV fleet by identifying the dispatchable region of the charging energy over time [304], [310] or by transforming these charging session characteristics to a virtual battery (e.g., [311], [312]). In this latter approach, all charging session characteristics are reduced to a set of three parameters for each timestep; (i) a minimum aggregated charging energy, (ii) a maximum aggregated charging energy and (iii) a maximum total charging power.

The reduction in the number of parameters through aggregation simplifies the incorporation of uncertainty into the scheduling of an electric vehicle fleet. This can be done by considering the uncertainty in the parameter values in the scheduling process. Many studies used simplified approaches to account for the uncertainty of aggregation parameters. Lilliu et al. [307] and Bessa et al. [313] assumed unverified probability density functions for different aggregation parameter values when scheduling an EV fleet. Similarly, González Vayá and Andersson [314] added noise around the actual parameter values in their model. Yan et al. [315] considered simplified scenarios to account for uncertainty. Ruelens et al. [316] generate scenarios using Markov chains and simulated EV data, without considering forecasting techniques.

Despite the use of an EV aggregation method as an efficient way to schedule an EV fleet, the integration of forecasting techniques into aggregation methods has received little attention, as visible in Table 5.2. Visser et al. [127] use forecasts of the daily aggregated charging demand and 15-minute forecasts of the total available charging power of all EVs to schedule the charging patterns of an EV fleet. Similarly, Bessa and Matos [303] forecast the total charging requirement for each day and the maximum charged energy and power at each hour. Although the methods proposed in both studies cover most aspects that should be considered for aggregated scheduling of an EV fleet, they do not account for the minimum aggregated volume that should be charged at each timestep in the assessment timeframe. This minimum aggregated charging volume assures that the charging demand of EVs that depart during the assessment timeframe is met at their departure. Visser et al. also did not consider the maximum aggregated charging demand at each hour of the day, which should be considered to account for the fact that the charging demand of EVs cannot be known

until their arrival moment at the charging station.

5.1.3 Contributions

The previously introduced virtual battery approach considers both the minimum aggregated volume that must be charged and the maximum aggregated charging demand at each timestep, which are missing aspects in prior studies. To the best of our knowledge, only Zhou et al. [304] & Pertl et al. [126] applied forecasting techniques to an aggregation method that considers all required aspects to schedule an EV fleet. However, the main focus of these studies is not on forecasting and they did not attempt to maximize the forecasting performance. Hence, the insight into the forecasting potential of an EV aggregation approach that considers all required aspects to schedule an EV fleet is currently very limited.

As highlighted in Table 5.2, this study addresses this literature gap by presenting the first work that comprehensively analyses the forecasting potential of all required parameters to schedule an EV fleet. The presented forecasting approach adopts the virtual battery approach and can be applied to any scheduling timeframe, EV charging session data set and EV smart charging application. In this analysis, different forecasting models are compared, including machine learning methods, and insight is provided into the optimal feature sets to maximize the forecasting performance. In addition, the impact of the considered EV fleet size on the forecasting performance is analyzed. A case study of real-world charging data from a large number of charging stations in Utrecht, the Netherlands is used for the analysis.

The contributions of this work can be summarized as follows:

- An approach to forecast all required parameters for scheduling the charging of EV fleets aimed at reducing uncertainty by providing insights into the expected values of critical parameters;
- An in-depth assessment of the forecasting potential of parameters associated with an EV aggregation method;
- A comparison between the performance of different forecasting models for varying EV fleet sizes;
- An analysis of the most relevant features when forecasting all parameters associated with the EV virtual battery method.

This work is structured as follows. The concept of an EV virtual battery is explained in Section 5.2. This is followed by the methodology in Section 5.3, which introduces a generic approach to forecast EV virtual battery parameters. Section 5.4 introduces the considered case study and describes the considered forecasting models and considered features. The results are presented in Section 5.5. The discussion and conclusion in Sections 5.6 & 5.7 are the last two sections of this work.

5.2 EV virtual battery method

As proposed by [314] and [169], the aggregated charging demand of an EV fleet can be optimized for various objectives by modelling it as a virtual battery. Using this method, the characteristics of a set of charging sessions are reduced to a set of three virtual battery parameters for each timestep: the minimum and maximum aggregated charging energy since the beginning of the assessment timeframe ($E_{ch,min}$ & $E_{ch,max}$, respectively) and the maximum aggregated charging power ($P_{ch,max}$). These parameters are determined as follows:

- $E_{ch,min}$: This parameter represents the minimum required charged energy since the beginning of the assessment timeframe to assure that the charging demand of EVs departing during the assessment timeframe is met. The parameter values of $E_{ch,min}$ at each timestep are determined by summing the total charged energy since the beginning of the assessment timeframe in a '*latest charging*' scenario for all considered charging sessions. This scenario represents the case in which the charging of an EV is delayed until the latest possible moment that the charging demand of an EV can be met before departure. Hence, to assure that the charging demand of all considered EVs is satisfied before departure, the aggregated charging energy since the beginning of the assessment timeframe should be higher or equal to $E_{ch,min}$ at all timesteps. The mathematical formulation of $E_{ch,min}$ is as follows:

$$E_{ch,min,t} = \sum_{n}^{N} \sum_{\tau=0}^{t} P_{ch,latest,\tau,n} \Delta t \quad \forall t \in \mathscr{T}. \tag{5.1}$$

  In this equation, $\mathscr{N}$ represents the set of EV charging sessions, indexed by $n = 0, 1, \ldots, N$, $\mathscr{T}$ represents the set of timesteps in the assessment timeframe, indexed by $t = 0, 1, \ldots, T$, τ represents a timestep between the start of the assessment timeframe and timestep t, $P_{ch,latest,\tau,n}$ represents the charging power of charging session n at timestep τ in a *latest charging* scenario and Δt represents the duration of one timestep.

- $E_{ch,max}$: This parameter poses an upper limit to the total charged energy since the beginning of the assessment timeframe. It is introduced to account for arriving EVs during the assessment timeframe, whose charging demand can only be met after their arrival. The parameter values are determined by summing the total charged energy since the beginning of the assessment timeframe in a *charging on arrival* scenario for all considered charging sessions. A *charging on arrival* scenario represents the case in which an EV charges at the maximum available charging power directly after arrival until the charging demand is met. Hence, $E_{ch,max}$ represents the maximum possible aggregated charged energy since the beginning of the assessment timeframe at each timestep,

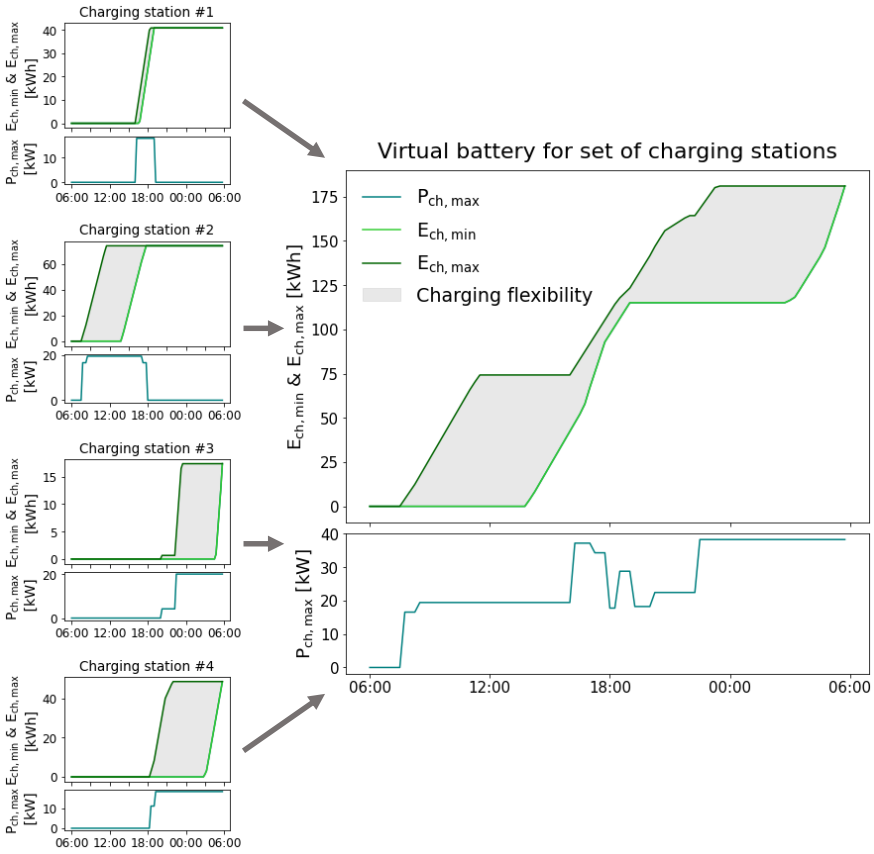


Figure 5.1: Example of EV virtual battery parameters for a set of four charging stations for an assessment timeframe of one day, with a start/end time of 06:00.

and the aggregated charging energy since the beginning of the assessment timeframe should be lower or equal to $E_{ch,max}$ at all timesteps. The mathematical formulation of $E_{ch,max}$ is as follows:

$$E_{ch,max,t} = \sum_{n}^{N} \sum_{\tau=0}^{t} P_{ch,coa,\tau,n} \Delta t \quad \forall t \in \mathcal{T}, \tag{5.2}$$

where $P_{ch,coa,\tau,n}$ represents the charging power of charging session n at timestep τ in a *charging-on-arrival* scenario.

- $P_{ch,max}$: This parameter defines the maximum total charging power at a specific timestep. The parameter value at a specific timestep is determined by summing the maximum charging power for all EVs connected to a charging station at

the considered timestep:

$$P_{ch,max,t} = \sum_{n}^{N_t} P_{max,n} \quad \forall t \in \mathcal{T}, \tag{5.3}$$

where N_t represents the set of ongoing charging sessions at time t and $P_{ch,max,n}$ represents the maximum charging power of charging session n.

When scheduling an EV fleet, the aggregator must assure that the aggregated charging demand since the beginning of the assessment timeframe stays between $E_{ch,min}$ and $E_{ch,max}$, and that the combined charging power does not exceed $P_{ch,max}$. The EV virtual battery method can be applied for different scheduling timeframes and is generic for any EV charging session data set. Figure 5.1 presents an example of the EV virtual battery method for an assessment timeframe of one day. Since $E_{ch,min}$ and $E_{ch,max}$ represent the minimum and maximum aggregated charging energy since the beginning of the assessment timeframe, their parameter values increase over the course of the assessment timeframe. The difference between $E_{ch,min}$ and $E_{ch,max}$ (highlighted in grey in Figure 5.1) is an indicator of the EV charging flexibility: a large difference means that there is considerable room to shift the EV charging demand over time. At the end of the assessment timeframe, $E_{ch,min}$ and $E_{ch,max}$ should converge to assure that the charging demand of all considered charging sessions is met at their departure.

5.3 Methodology

This section presents an approach to determine the optimal forecasting performance, optimal sets of features and the feature importance for EV virtual battery parameter forecasts. The approach is described in a generic manner, to assure it can be applied to any EV charging session data set, scheduling timeframe, feature set, forecasting model and EV fleet size. Section 5.4 discusses how this generic approach was applied to the specific case study studied in this chapter.

Figure 5.2 provides an overview of the required methodological steps to make optimal EV virtual battery parameter forecasts. In this approach, $E_{ch,min}$, $E_{ch,max}$ and $P_{ch,max}$ are forecasted separately. Hence, the steps in Figure 5.2 are repeated for all considered forecasting models and for all considered EV virtual battery parameters. Each step is outlined below.

5.3.1 Step 1: Generating virtual battery data

This step converts EV charging session data from an EV fleet to a time-series of EV virtual battery parameter values. This is done using the methods outlined in Section 5.2. This EV virtual battery data serves as input data for the forecasting models. The

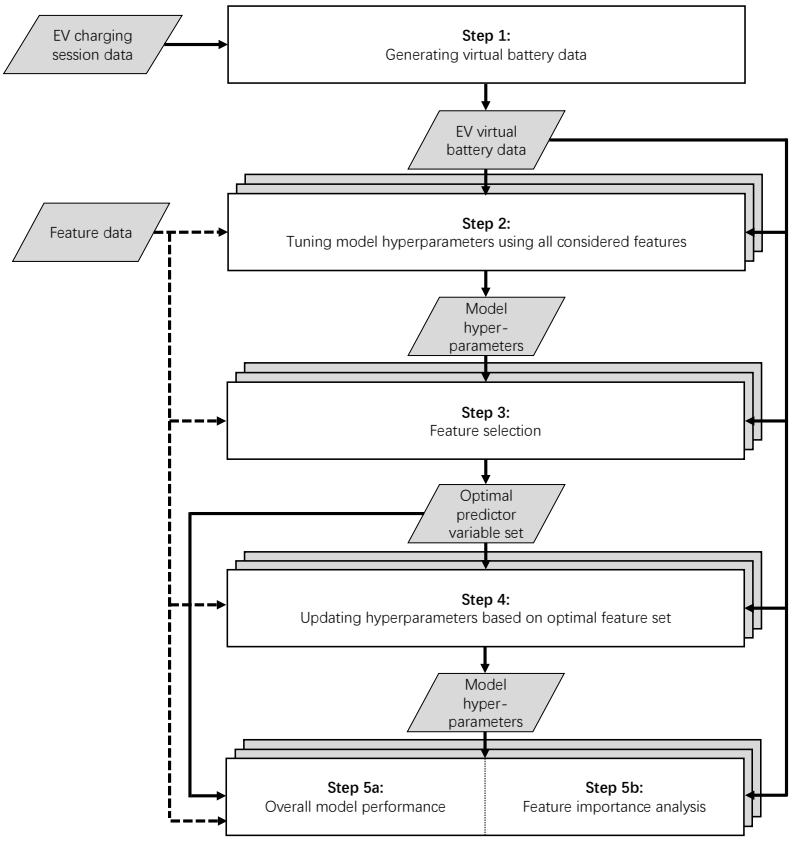


Figure 5.2: Overview of methodological steps in the analysis.

number of EV charging sessions that are combined into one virtual battery depends on the desired scheduling timeframe. For instance, if the scheduling timeframe is 24 hours, EV virtual batteries are generated for 24-hour periods and all charging sessions that start within the same 24-hour period are considered for one EV virtual battery.

The selected start and end time of each scheduling timeframe for an EV virtual battery should depend on the specific charging characteristics of an EV fleet. As discussed in Section 5.2, $E_{ch,min}$ and $E_{ch,max}$ should converge at the end of the scheduling timeframe. This is only possible if the charging demand of each EV charging session can be met before the end of the scheduling timeframe. Therefore, the time of the day that provides the maximum number of charging sessions with the opportunity to meet their full charging demand should be selected as the end time of each scheduling timeframe. In case the charging demand of an EV charging session cannot be met before the end of the scheduling timeframe, the charging demand of the specific

charging session should be reduced to the maximum possible charging energy during the assessment timeframe. The remaining charging demand could be considered for the next scheduling timeframe.

5.3.2 Step 2: Tuning model hyperparameters using all considered features

The learning process of different machine learning forecasting models is controlled by their hyperparameter values. Since these values affect the forecasting performance of a specific model, hyperparameter values of all considered forecasting models need to be tuned.

In this step, the optimal hyperparameter values are set for each considered model and for each EV virtual battery parameter when considering all features. This can be done by evaluating the model performance on a large number of hyperparameter sets, and by selecting the hyperparameter set with the best model performance. This process is repeated for each model and each EV virtual battery parameter. To avoid overfitting of the forecasting model, the virtual battery data should first be split into a training and testing set. Next, the training set is used to compute the optimal hyperparameter values using k-fold cross-validation [317].

The performance of the forecasting model can be assessed using R^2 (i.e., the coefficient of determination) as an evaluation metric. Since R^2 is a normalized score between -1 and 1, it allows for a comparison of the forecasting model performance of different virtual battery parameters and a varying number of charging stations.

5.3.3 Step 3: Feature selection

In some cases, features can have a negative impact on the performance of a forecasting model, for instance due to multicollinearity [317]. Therefore, the optimal feature set for each considered forecasting model and each considered virtual battery parameter should be determined.

The most common methods to select the optimal feature set are backward or forward sequential (floating) feature selection, as explained in [318]. To avoid model overfitting, it is recommended to apply one of these methods to the training data set while using k-fold cross-validation. Subsequently, the forecasting performance with a different number of features can be determined by applying the trained model to the separate testing data set. These steps can be repeated multiple times in order to increase the robustness of the results. The feature set with the highest average performance on the testing data set should be selected as the optimal feature set.

5.3.4 Step 4: Updating hyperparameters based on optimal feature set

Since the optimal hyperparameter set could change with a different number of features, Step 2 should be repeated for each forecasting model and for each virtual

battery parameter using the optimal feature set determined in Step 3.

5.3.5 Step 5a: Overall model performance

To evaluate the overall performance per forecasting model, each virtual battery parameter and every model should be trained with a training data set, using the optimal feature set from Step 3 and the optimal hyperparameter set from Step 4. The trained models should be applied to the testing data set to determine the model performance using the R^2.

5.3.6 Step 5b: Feature importance analysis

A feature importance analysis evaluates the impact of each feature on the forecasting performance. A permutation importance analysis can be used in this step. In this analysis, each model is trained using the training data set, and a reference model performance is determined using the testing data set. Subsequently, the values of one feature in the testing set are permuted (i.e., randomly shuffled), and the model performance with this one set of permuted feature values is determined. This should be repeated multiple times for each feature to increase the robustness of the results. The feature of which the permutation of its values results in the largest decrease in model performance compared to the reference model performance can be considered as the feature with the highest impact on the results.

5.4 Analysis outline

To provide insights into the performance of different forecasting models and their most important features when forecasting EV virtual battery parameter values, the approach from Section 5.3 has been applied to a case study. In this analysis, a 24-hour virtual battery timeframe is considered, which allows for bidding to the day-ahead electricity market. This section will introduce the case study, discuss the considered forecasting models and features and provide details on the model simulations.

5.4.1 Case study introduction

This study used historical EV charging session data from public stations operated by charge point operator *We Drive Solar*. These charging stations are located in residential areas in the city of Utrecht, the Netherlands and are located on-street. The charging stations can be used by any EV owner, and no specific subscription was required to be able to use the charging station. Users paid a fixed tariff per kWh and uncontrolled charging was applied to the considered charging stations. The considered charging stations allowed for charging up to a charging power of 22 kW. Hence, fast charging was not possible at these locations. In the used data,

the arrival time, departure time, charging demand and maximum charging power of each charging session is logged. This charging session data is logged between 9 January 2019 and 1 December 2021. During the course of this period, the number of charging stations operated by this company grew considerably. Also, during a large share of this period, the Netherlands faced numerous lockdowns due to the COVID-19 pandemic, which had a considerable impact on EV charging patterns [319]. In order to provide a realistic insight into the ability to forecast EV charging patterns under normal circumstances, the main analyses in this study were conducted using charging session data from between 9 January 2019 and 12 March 2020, during which no COVID-19 restrictions were imposed. During this period, charging data was available from 20 charging stations. Charging data from these charging stations was considered in the analysis. The average daily number of charging sessions for the considered set of charging stations equaled 30.3 during the considered time period, while the average daily charging demand during this time period equaled 519.4 kWh for the considered charging stations.

To get insight into the impact of the EV fleet size on the forecasting performance (see Section 5.5.1), data from additional EV charging stations is required. For this analysis, charging data from between 28 April 2021 and 12 November 2021 was used, during which relatively few COVID-19 restrictions were in place in the Netherlands. A total of 405 charging stations were operating throughout this whole period and data from these charging stations was used to conduct an analysis of the impact of the considered EV fleet size on the forecasting performance.

5.4.2 Forecasting models

This study compares the performance of five different forecasting models. The selected models are commonly applied in other forecasting studies and cover different categories of forecasting models. The following models are considered in this study:

1. *Multivariate Linear Regression*: This linear regression model predicts the target parameter values (i.e., $E_{ch,min}$, $E_{ch,max}$ and $P_{ch,max}$) by determining the optimal coefficients of each considered feature.

2. *Random Forest*: This is an example of an ensemble-based regression method. It creates a set of independent decision trees, considering a random subset of the training data points and features in each tree [320]. The forecast is generated by averaging the outcomes of all decision trees.

3. *Artificial Neural Network*: This forecasting method is based on deep learning and builds a nonlinear relationship between the target parameters and the different features [321]. It connects the input data to one or multiple hidden layers, each consisting of multiple nodes. Each node uses an activation function and weight to process the data and generate an output value. The output value

Table 5.3: Overview of the considered features for the forecasting of EV virtual battery parameters.

Category	No.	Explanation	Short notation	Source
Temporal	1.	No. of hours since start of optimization timeframe	Hour	-
	2.	Whether the considered day is a weekend day	Weekend	-
	3.	Whether the considered day is a school holiday	SH	-
	4.	Whether the considered day is a public holiday	PH	-
Historical	5.	Parameter value week ago at the same time	H:W-1	-
	6.	Parameter value day ago at the same time	H:D-1	-
	7.	Parameter value 2 days ago at the same time	H:D-2	-
	8.	Parameter value 3 days ago at the same time	H:D-3	-
	9.	Average parameter value at the same time during the last week	H:W-AV	-
	10.	Average parameter value at the same time at the same weekday during the last month	H:M-AV	-
Weather forecasts	11.	Forecast of average daily temperature	W:AT	[323]
	12.	Forecast of daily precipitation volume	W:PV	[323]
	13.	Forecast of daily average windspeed	W:WS	[323]
	14.	Forecast of daily number of sunshine hours	W:SH	[323]

is fed to each node in the following layer, where the forecasted value presents the output value of a single node in the last layer.

4. *k-Nearest Neighbors*: This is a non-parametric forecasting method, meaning that equal weight is given to all features. This model considers the Euclidean distance function to locate the k most-similar data points in the training data set, and takes the average value of these data points as the forecast [322].

5. *Persistence forecast*: This serves as the reference forecasting model. This study considered the value of one week before the considered timestep as the persistence forecast, due to the observed high simultaneity in EV charging characteristics between weekdays.

5.4.3 Features

Three main categories of features are considered to forecast EV virtual battery parameters. The first category considers temporal features, such as time of the day and the type of day (weekend day, school holiday and public holiday). Second, historical data are used as features. These features consider historical values of the forecasted parameter, such as the parameter value one/two/three days before at the same time of the day or the average parameter value at the same time of the day during the past week. The third category consists of features based on day-ahead weather forecasts (average daily temperature, daily precipitation volume, daily average wind speed and daily number of sunshine hours), since people's choice of transport mode depends on the weather conditions [324]. Day-ahead weather forecast data for the city of Utrecht

from ECMWF [323] was used in this analysis. An overview of all 14 considered features is presented in Table 5.3.

5.4.4 Data pre-processing and model simulation setup

In the data pre-processing step, the feature values were determined for each data point in the input data. Subsequently, all parameter and feature values were normalized to the maximum observed value in the assessment timeframe for the considered parameter or feature.

This study used the scikit-learn [325] library in Python version 3.8.5 to perform EV virtual battery parameter forecasts for the different considered forecasting models. An AMD EPYC 7451 core with 5.333 GB of memory was used to generate the forecasts. Forecasts were generated for a 15-minute time resolution. The training data set and testing data set covered 80% and 20% of the input data, respectively, and consisted of randomly-sampled days from the input data. Due to the relatively short time period covered in the input data (see Section 5.4.1), the tested data set was generated using random sampling of days, instead of using a consecutive time period as the testing data set, to assure that all periods of the year are covered in the training and testing data set. 5-fold cross-validation using randomly-sampled days was used in hyperparameter tuning and feature selection. The feature selection was performed using sequential floating backward feature selection, using the MLxtend Python package [326]. To increase the robustness of results, the feature selection analysis was repeated 10 times for each parameter value and each forecasting model, while the overall model performance analysis and feature importance analysis were repeated 100 times. The required time to train the model and perform the forecast differed between the considered forecasting models. The average running time equaled 0.01 seconds for the *Multivariate Linear Regression*, 4.79 seconds for the *Random Forest* model, 2.46 seconds for the *Artificial Neural Network* model and 1.28 seconds for the *k-Nearest Neighbors* model.

A separate analysis is performed to determine the impact of the considered number of EV charging stations on the forecasting performance. This analysis is repeated 100 times for each considered number of EV charging stations, each time considering a different set of charging stations when generating the virtual battery data. Given the large computational burden that comes with hyperparameter tuning and feature selection, the optimal parameter and feature set of the main analysis were used in this analysis.

The selected start and end time of the forecasting timeframe is 06:00, as the largest share of the EV charging demand in the considered case study (98%) can be met when using this time as the start/end time of one EV virtual battery. In the rare case that the charging demand of an EV charging session can not be met before the end of the scheduling timeframe, the charging demand is reduced to the value that

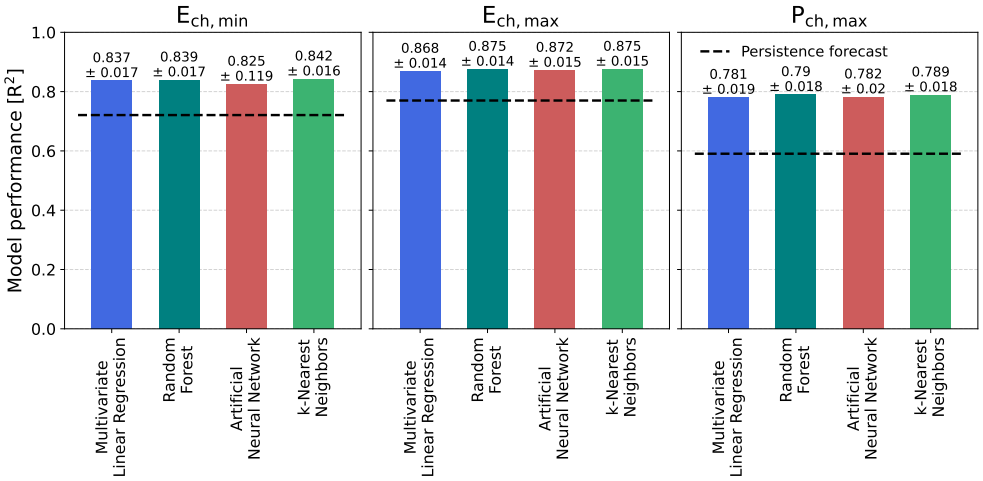


Figure 5.3: Average forecasting performance (expressed as the R^2 value) and standard deviation (±-values) of all model runs of the different considered forecasting models for the different EV virtual battery parameters when considering EV virtual batteries based on charging data of 20 charging stations. Persistence forecasts are based on the parameter value one week ago at the same time of the day.

can be met at the end of the scheduling timeframe to assure that $E_{ch,min}$ and $E_{ch,max}$ converge at the end of the assessment period (see Section 5.2).

5.5 Results

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5.5.1 Overall model performance

Figure 5.3 presents the model performance of the considered forecasting models for each EV virtual battery parameter, which were determined using the optimal hyperparameter sets in Appendix 5.A and the optimal feature sets in Table 5.5. The models show a relatively good forecasting performance for all EV virtual battery parameters, with an average R^2 score ranging between 0.78 and 0.88 for all models and virtual battery parameters. The model performance of all considered forecasting models is considerably better than the reference case of using persistence forecasts, which indicates that the use of forecasting models is highly recommended when forecasting EV virtual battery parameters. This can also be observed from Table 5.4, which reports the model performance using the Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and the Weighted Absolute Percentage Error (WAPE)[11]

[11]The WAPE has been used over the commonly-used Mean Absolute Percentage Error (MAPE), since the MAPE can take infinite or extreme values if the realized parameter values are equal or close to zero [327], which is regularly the case in this analysis. WAPE, defined as the total absolute error divided by the total actual values, provides a more stable and scale-invariant error measure in such situations.

Table 5.4: Average forecasting performance of all model runs of the different considered forecasting models for the different EV virtual battery parameters when considering EV virtual batteries based on charging data of 20 charging stations. Persistence forecasts are based on the parameter value one week ago at the same time of the day.

		Multivariate Linear Regression	Random Forest	Artificial Neural Network	k-Nearest Neighbors	Persistence Forecast
$E_{ch,min}$	*Mean parameter value*			*128.6 kWh*		
	MAE	38.1 kWh	36.6 kWh	38.4 kWh	35.9 kWh	47.6 kWh
	RMSE	54.6 kWh	54.1 kWh	56.5 kWh	53.6 kWh	70.8 kWh
	WAPE	29.6%	28.4%	29.8%	27.9%	37.0%
$E_{ch,max}$	*Mean parameter value*			*252.8 kWh*		
	MAE	56.6 kWh	53.9 kWh	55.1 kWh	53.1 kWh	70.1 kWh
	RMSE	78.8 kWh	76.7 kWh	77.8 kWh	76.7 kWh	103.5 kWh
	WAPE	22.4%	21.3%	21.8%	21.0%	27.7%
$P_{ch,max}$	*Mean parameter value*			*85.3 kW*		
	MAE	20.9 kW	20.3 kW	20.6 kW	20.3 kW	27.4 kW
	RMSE	27.7 kW	27.1 kW	27.6 kW	27.2 kW	37.9 kW
	WAPE	24.5%	23.8%	24.2%	23.8%	32.2%

as performance metrics.

A comparison between the different EV virtual battery parameters shows that the R^2 values are generally lower for $P_{ch,max}$ compared to $E_{ch,min}$ and $E_{ch,max}$. As explained in Section 5.2, $E_{ch,min}$ and $E_{ch,max}$ are continuously increasing over the assessment timeframe, while $P_{ch,max}$ is more volatile. Hence, $E_{ch,min}$ and $E_{ch,max}$ are better predictable than $P_{ch,max}$, explaining the differences in the forecasting performance between the different virtual battery parameters. On the contrary, it is evident from Table 5.4 that the WAPE scores are highest for the forecasts of $E_{ch,min}$. This phenomenon can be largely attributed to the nature of $E_{ch,min}$, which has a relatively low parameter value for most of the day and increases towards the end of the assessment timeframe (see Section 5.2 and Figure 5.4). As a result, the average parameter value for $E_{ch,min}$ is comparatively low. This lower average parameter value directly contributes to higher WAPE values, as the mean absolute forecasting error is divided by the average parameter value when calculating this metric score.

The difference in forecasting performance between all considered models is negligible. Although Multivariate Linear Regression is the worst-performing forecasting model in all considered cases, the minor difference with the other considered models indicates that EV virtual battery parameters do not necessarily need to be forecasted using more advanced machine learning models.

Figure 5.4 compares the forecasted EV virtual battery parameter values of the considered forecasting models with the realized values for three arbitrarily chosen consecutive days for one of the model runs. It shows that the models generally seem to be able to forecast the main trends of $E_{ch,min}$ and $E_{ch,max}$ during the course of the day. The forecasting models do not seem to be able to capture the fluctuations in the values of $P_{ch,max}$ during the day. It is visible from Figure 5.4 that some of the forecasted EV virtual battery parameter values are infeasible. For instance, some models forecasted negative values for $E_{ch,min}$ and $E_{ch,max}$ for some timesteps. Similarly, the forecasts of $E_{ch,min}$ and $E_{ch,max}$ do not always converge at the end of the assessment timeframe

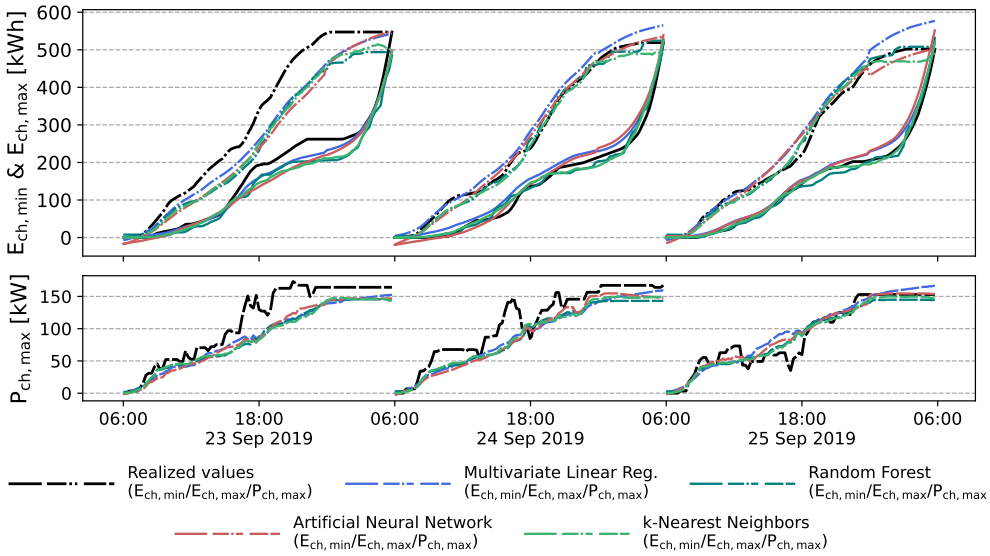

Figure 5.4: Realized EV virtual battery parameter values (i.e., actual parameter values in historical data at considered time step) for three consecutive days and the forecasted values for these considered days for 20 charging stations for different forecasting models for one model run.

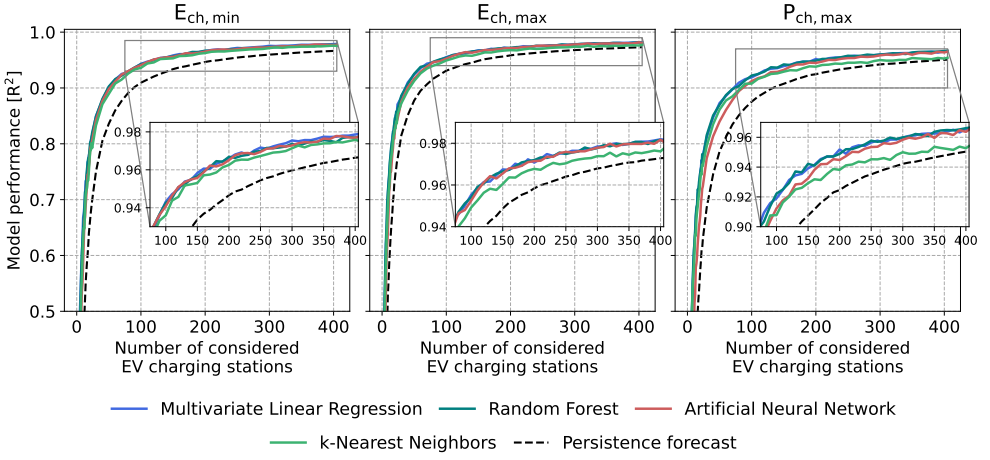

Figure 5.5: Average forecasting performance (expressed as the R^2 value) of all model runs for different forecasting models when considering EV virtual batteries based on charging data of a varying number of charging stations. Persistence forecasts are based on the parameter value one week ago at the same time of the day.

Table 5.5: Optimal feature sets for the considered forecasting models for different EV virtual battery parameters. Green values are included in the optimal feature set. The used abbreviations for the features are introduced in Table 5.3.

		Features													
		Hour	Weekend	SH	PH	H:W-1	H:D-1	H:D-2	H:D-3	H:W-AV	H:M-AV	W:AT	W:PV	W:WS	W:SH
$E_{ch,min}$	Multivariate Linear Regression	✓	✓	✓	✓	✗	✓	✗	✗	✓	✓	✗	✗	✗	✗
	Random Forest	✓	✓	✓	✓	✓	✗	✓	✓	✓	✓	✗	✓	✗	✓
	Artificial Neural Network	✓	✓	✓	✓	✓	✓	✓	✗	✓	✓	✗	✓	✓	✓
	k-Nearest Neighbors	✓	✓	✓	✗	✗	✓	✓	✗	✓	✓	✗	✗	✗	✗
$E_{ch,max}$	Multivariate Linear Regression	✓	✓	✓	✗	✗	✗	✗	✗	✓	✓	✗	✓	✗	✓
	Random Forest	✓	✓	✓	✗	✗	✗	✗	✗	✓	✓	✗	✗	✗	✗
	Artificial Neural Network	✓	✓	✓	✓	✗	✓	✗	✗	✓	✓	✓	✗	✗	✓
	k-Nearest Neighbors	✓	✓	✗	✗	✗	✗	✗	✗	✓	✓	✗	✗	✗	✗
$P_{ch,max}$	Multivariate Linear Regression	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
	Random Forest	✓	✓	✗	✗	✗	✗	✗	✗	✓	✓	✓	✗	✗	✗
	Artificial Neural Network	✓	✓	✓	✗	✓	✓	✗	✓	✓	✓	✗	✗	✗	✓
	k-Nearest Neighbors	✓	✗	✓	✗	✗	✗	✗	✗	✓	✗	✗	✗	✗	✗

and in rare cases the forecasted value of $E_{ch,min}$ is higher than the forecasted value of $E_{ch,max}$, which is technically not possible. The latter two effects are caused by the fact that $E_{ch,min}$ and $E_{ch,max}$ are forecasted separately.

As the size of the EV fleet in the EV virtual battery increases, the forecasting performance of all models improves considerably. This is outlined in Figure 5.5, which presents the average forecasting performance of all considered models when considering different numbers of EV charging stations. R^2-scores up to 0.98 are reached when considering more than 400 EV charging stations. The arrival and departure of EVs are less stochastic when considering a larger EV fleet, which decreases the volatility in the EV virtual battery parameter values and thus results in better EV virtual battery parameter value forecasts. Considering a larger EV fleet size when forecasting EV virtual battery parameters also increases the performance of the persistence forecast and decreases the relative added value of using forecasting models.

5.5.2 Feature selection and importance

The optimal feature set per forecasting model for each EV virtual battery parameter is presented in Table 5.5, while Figure 5.6 provides insight into the most important features for each considered forecasting model and for each EV virtual battery parameter. The hour of the day ('Hour'), the weekly average parameter value at the considered time ('H:W-AV') and the monthly average parameter value at the considered time and day of the week ('H:M-AV') seem to be the most influential features; these features are present in almost all optimal feature sets and show the highest feature importance in Figure 5.6. The features linked to the type of day, in particular to weekend days and school holidays ('Weekend' and 'SH'), are included in almost all optimal feature sets,

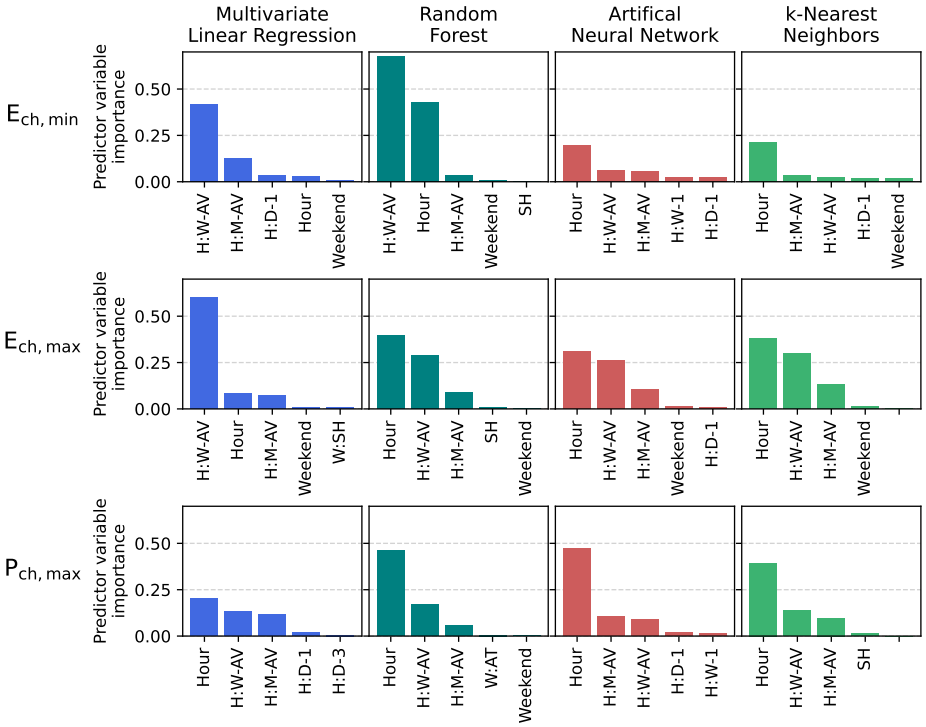

Figure 5.6: Feature importance for the five most important features for each considered forecasting model and for each EV virtual battery parameter. The feature importance is defined as the average reduction in the R^2 score when permuting the feature values. Note that in some cases the optimal feature set only consists of four features. The used abbreviations for the features are introduced in Table 5.5.

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but seem to have limited impact on the model outcomes in Figure 5.6. Furthermore, features related to weather forecasts and using historical parameter values of 1-3 days or one week before the forecasted timestep seem to have little impact on the forecasting outcome. Therefore, only a few features are needed to produce reliable forecasts of the EV virtual battery parameters.

5.6 Discussion

This study proposed a novel forecasting approach to forecast all required parameters to schedule an EV fleet. A comprehensive analysis of the effectiveness of this proposed approach has been conducted using a real-world case study. The results indicated that when using the EV virtual battery method, very good forecasting performance can be reached, especially when considering large EV fleets. This is particularly interesting for aggregators, who generally consider a large number of EVs for smart charging applications, including electricity market bidding. These aggregators can use the

proposed forecasting approach to reduce uncertainty when scheduling these EV fleets, mitigating the risk of potential imbalance costs.

The results of the analyses applied to the considered case study showed that only a limited number of features are required to forecast EV virtual battery parameter values and that the difference in forecasting performance between different forecasting models is minor. We encourage others to adopt our methodology and test the EV virtual battery forecasting approach on other data sets, for locations with different climates and mobility patterns.

From the results of this study can be seen that the performance of the *Multivariate Linear Regression* and *k-Nearest Neighbors* (when considering a high number of charging stations) models was minimally lower than the performance of the other considered models, although these models scored best in terms of running times. Their inferior model performance can be attributed to the fact that these models are not able to capture non-linear relationships between the features and the forecasted parameter values [328]. A superior performance of tree-based or deep-learning forecasting models has been observed in other energy domains as well, including photovoltaic generation [329], wind generation [330] and load forecasting [331]. In addition, the results section showed that the forecasting performance for $P_{ch,max}$ is lower compared to the forecasting performance of $E_{ch,min}$ and $E_{ch,max}$, since the values of $P_{ch,max}$ are more-erratic and thus harder to forecast. Future work should address how the forecasting performance for this parameter could be improved, for instance by using more-advanced forecasting models (e.g., Gradient Boosting [332] or Extreme Gradient Boosting (XGboost) [333]) or by including details about the EV fleet composition (e.g., EV model, maximum charging power of EV models) in the input data.

As the three EV virtual battery parameters were forecasted separately in this study, it could occur that the forecasts of $E_{ch,min}$, $E_{ch,max}$ and $P_{ch,max}$ are not perfectly aligned (see Section 5.5.1). For this reason, the forecasted values should be post-processed before using them for EV scheduling. This problem could potentially be reduced by forecasting the flexibility (i.e., the difference between $E_{ch,min}$ and $E_{ch,max}$) and by adding/subtracting the forecast of the flexibility to/from the forecast of respectively $E_{ch,min}$ or $E_{ch,max}$. Another way to potentially improve the forecasts is by forecasting each timestep separately, using only the historical data of the considered timestep when training the model. Hence, further research should look into such ways to finetune the forecasting approach proposed in this research to increase forecasting performance.

This study considered a scheduling timeframe running from 06:00 to 06:00 the next day, which does not align with the bidding period for most day-ahead electricity markets (i.e., 00:00 to 00:00 the next day). Using 00:00 as the start and end time of the forecasting timeframe would result in a large number of charging sessions in the considered case study of which the charging demand cannot be met during this timeframe, due to EVs arriving home in the late evening. To account for this

discrepancy, one can use the optimized charging schedules between 06:00 and 00:00 to bid in the day-ahead market for one day, and use the charging schedules between 00:00 and 06:00 for the day-ahead market bids for the next day. Also, it should be noted that market bids can be updated in intraday markets.

It should be highlighted that the results when using an EV virtual battery to optimize the charging schedule of an EV fleet show a minor difference compared to the aggregated EV charging schedule when optimizing individual charging sessions [202]. This can be attributed to the fact that $P_{ch,max}$ is based on the aggregated maximum charging power of all connected EVs to the grid, without considering the fact that EVs that already met their charging demand cannot charge anymore. Therefore, the total aggregated charging power at specific timesteps in the virtual battery model could be higher than physically possible. Future research could look into ways to reduce this discrepancy, for instance by considering a reduction factor for the forecasts $P_{ch,max}$ when optimizing an EV fleet using the virtual battery approach.

Lastly, after determining the aggregated charging schedule using the virtual battery approach, this aggregated charging schedule should be disaggregated to individual charging sessions at the moment of real-time operation. Different disaggregation approaches have been proposed. For instance, Vandael et al. [311] propose to prioritize charging sessions with the highest urgency to charge when allocating the aggregated charging power among charging sessions. Danner et al. [334] compare cost-optimal, probability-optimal and proportional disaggregation strategies.

5.7 Conclusions

The forecasting of EV charging session characteristics for EV smart charging is complex due to the wide range of charging characteristics that need to be forecasted. A forecasting approach that tackles the complexities associated with forecasting for EV smart charging is practically absent in scientific literature. This study is the first work that presented a forecasting approach that considers all required EV parameters for EV smart charging. It uses the EV virtual battery method and requires separate forecasts of only three parameters: $E_{ch,min}$, $E_{ch,max}$ and $P_{ch,max}$. The proposed approach is generic and can be applied to any scheduling timeframe or any EV fleet.

The approach was tested on a real-world case study to create 24-hour forecasts, considering a total of four forecasting models and a reference persistence model. When considering charging session data from 20 charging stations, the average R^2 score ranged between 0.78 and 0.88 for different forecasting models and virtual battery parameters. The forecasting performance considerably increases when considering a larger EV fleet, reaching very high R^2 scores of at least 0.96 for all virtual battery parameters. From the results, it can be concluded that adopting the proposed approach to forecast EV virtual battery parameter values significantly improves the forecasting performance compared to using persistence forecasts. The difference in

performance between the considered machine learning forecasting models is negligible. Results also showed that only a low number of features impacts the forecasting results.

Overall, from this study can be concluded that EV virtual battery parameters can be forecasted with very high accuracy, in particular with large EV fleets. This means that the uncertainty associated with the available charging flexibility of EV fleets when applying EV smart charging can be reduced drastically. Hence, the risk of additional costs (e.g., imbalance costs in electricity markets) is reduced, facilitating the rollout of EV smart charging.

Appendix

5.A Optimal hyperparameter sets

The optimal hyperparameter sets for each considered forecasting model for each EV virtual battery parameter are presented in Table 5.A.

Table 5.A: Optimal hyperparameter sets for the considered forecasting models for different EV virtual battery parameters.

	Forecasting model	Optimal hyperparameter set
$E_{ch,min}$	Random Forest	Max.tree depth: 5 (tested values: 0, 1, 2, 3, 4, 5) Min. no. of samples at leaf node: 2 (tested values: 1, 2, 3, 4, 5) Min. no. of samples to split an internal node: 2 (tested values: 2, 3, 4, 5) Considered. no. of features: total no. of features (other option: square root of total no. of features) No. of trees in forest: 75 (tested values: 25, 50, 75, 100, 150, 200, 250, 300, 500, 700, 900)
	Artificial Neural Network	Activation function: rectified linear unit function (other options: hyperbolic tan function, logistic sigmoid function and no-op activation) L2 regelurization term: 0.01 (tested values: 0.01, 0.001, 0.0001, 0.00001) No. of hidden layers: 3 (tested values: 1, 2, 3, 4) Number of neurons per layer: 14, 10, 7 (tested values: values between 5 and 54) Solver: quasi-Newton (other options: stochastic gradient descent and 'adam')
	k-Neirest Neighbors	Number of neighbors: 169 (tested values: values between 1 and 500) Power parameter for Minkowski metric: 2 (tested values: 1 and 2) Used weight function in prediction: uniform (tested values: 'uniform' and 'distance')
$E_{ch,max}$	Random Forest	Max.tree depth: 5 (tested values: 0, 1, 2, 3, 4, 5) Min. no. of samples at leaf node: 4 (tested values: 1, 2, 3, 4, 5) Min. no. of samples to split an internal node: 2 (tested values: 2, 3, 4, 5) Considered. no. of features: square root of total no. of features (other option: total number of features) No. of trees in forest: 150 (tested values: 25, 50, 75, 100, 150, 200, 250, 300, 500, 700, 900)
	Artificial Neural Network	Activation function: hyperbolic tan function (other options: rectified linear unit function, logistic sigmoid function, no-op activation) L2 regelurization term: 0.001 (tested values: 0.01,0.001,0.0001,0.00001) No. of hidden layers: 2 (tested values: 1, 2, 3, 4) Number of neurons per layer: 7,7 (tested values: values between 5 and 54) Solver: quasi-Newton (tested values: stochastic gradient descent and 'adam')
	k-Neirest Neighbors	Number of neighbors: 139 (tested values: values between 1 and 500) Power parameter for Minkowski metric: 1 (tested values: 1 and 2) Used weight function in prediction: distance (tested values: 'uniform' and 'distance')
$P_{ch,max}$	Random Forest	Max.tree depth: 5 (tested values: 0, 1, 2, 3, 4, 5) Min. no. of samples at leaf node: 4 (tested values: 1, 2, 3, 4, 5) Min. no. of samples to split an internal node: 2 (tested values: 2, 3, 4, 5) Considered. no. of features: square root of total no. of features (other option: square root of total no. of features) No. of trees in forest: 500 (tested values: 25, 50, 75, 100, 150, 200, 250, 300, 500, 700, 900)
	Artificial Neural Network	Activation function: rectified linear unit function (other options: logistic sigmoid function, hyperbolic tan function, no-op activation) L2 regelurization term: 0.0001 (tested values: 0.01, 0.001, 0.0001, 0.00001) No. of hidden layers: 3 (tested values: 1, 2, 3, 4) Number of neurons per layer: 28, 10, 7 (tested values: values between 5 and 54) Solver: quasi-Newton (other options: stochastic gradient descent and 'adam')
	k-Neirest Neighbors	Number of neighbors: 362 (tested values: values between 1 and 500) Power parameter for Minkowski metric: 2 (tested values: 1 and 2) Used weight function in prediction: uniform (tested values: 'uniform' and 'distance')

Chapter 6

Addressing paused and delayed charging problems

This chapter is based on the following publication, with minor edits for coherence within the thesis and in response to committee feedback:

N. Brinkel, T. van Wijk, A. Buijze, N. Panda, J. Meersmans, P. Markotić, B. van der Ree, H. Fidder, B. de Brey, S. Tindemans, T. AlSkaif & W. van Sark (2024).

Enhancing smart charging in electric vehicles by addressing paused and delayed charging problems.

Nature Communications, 15(1), 5089.

Summary

Smart charging of electric vehicles can alleviate grid congestion and reduce charging costs. However, various electric vehicle models currently lack the technical capabilities to effectively implement smart charging since they cannot handle charging pauses or delays. These models enter sleep mode when charging is interrupted, preventing resumption afterwards. To avoid this, they should be continuously charged with their minimum charging power, even when a charging pause would be desirable, for instance with high electricity prices. This research examines this problem to inform various stakeholders, including policymakers and manufacturers, and stimulates the adoption of proactive measures that address this problem. Here, we demonstrate through technical charging tests that around one-third of tested car models suffer from this issue. Through model simulations we indicate that eliminating paused and delayed charging problems would double the smart charging potential for all applications. Lastly, we propose concrete legal and practical solutions to eliminate these problems.

Highlights

- One-third of EVs tested cannot resume charging after a pause or delay, limiting smart charging potential.
- The impact of EVs' inability to handle charging pauses is quantified across various smart charging applications.
- Smart charging becomes half as effective for cost reduction and congestion mitigation if EVs do not support paused or delayed charging.
- Charging pauses drop downward flexibility by 34%, reducing EVs' role in providing grid balancing services.
- Lack of regulation and standards adoption is a key barrier to solving paused/delayed charging issues.

6.1 Introduction

With the growing adoption of Electric Vehicles (EVs), our transportation and electricity systems are becoming increasingly intertwined. Initially, a network of petrol stations provided the energy requirements to fulfil our road transportation needs. However, the electricity grid infrastructure increasingly takes over this role through EV charging [48], [335]. This transition brings new challenges to the electricity system, particularly to the grid infrastructure. Most EV charging occurs in Low-Voltage (LV) grids at home or on-street charging stations [336], and the majority of these grids were designed decades ago without the concept of EV charging in mind. The charging power of an EV is significantly higher than the typical peak-time power consumption of a household, and since most EV users tend to arrive at their charging station at a similar time, concentrated charging moments are expected in residential LV grids [54], [337]. As a result, EV charging is likely to cause grid congestion [87], [196], [338].

Grid reinforcements could serve as a solution, but their feasibility is hindered by the exorbitant costs (see Chapter 2) and a shortage of qualified personnel to execute these reinforcements [67], [68]. Another approach to alleviate grid congestion is to move away from uncontrolled charging, where EVs charge at maximum power upon arrival until their demand is met. For most EV charging sessions, the connection time to a charging station considerably exceeds the required time to meet their charging demand. This provides ample opportunities for EV smart charging. With smart charging, EV charging sessions are optimized for different objectives by aligning the charging moments and charging speed over time with user preferences and current market or grid conditions [336], [339].

EV smart charging can benefit both grid operators and EV users and can facilitate the ongoing energy transition. Different studies showed that the application of smart charging could support grid operators in mitigating grid congestion and power quality problems (e.g., [201], [219], [340], [341]). Similarly, smart charging can be applied for the provision of balancing reserves to Transmission System Operators (TSOs) [342], [343]. It can also help EV users reduce their charging costs by taking advantage of moments with low electricity market prices when considering static or dynamic Time-of-Use (ToU) pricing schemes [72], [344]. Lastly, the roll-out of smart charging can accelerate the energy transition by shifting the charging demand of EVs to moments with excess renewable generation [79], [80], [345], thereby reducing the dependency on fossil-based energy resources and mitigating the intermittency challenges associated with renewable energy sources. If vehicle-to-grid (V2G) functions are considered, EVs could even act as a mobile storage medium for excess renewable energy, which can be used to meet the electricity demand during periods of renewable energy shortage.

However, it is not widely known that the current deployment of smart charging is hindered by the technical capabilities of EVs. As this research will show, a significant

share of EV models (both Plug-in Hybrid EVs (PHEVs) and Battery EVs (BEVs)) is unable to perform paused or delayed charging. In paused charging, the charging process is interrupted after the EV was previously charging, while in delayed charging, the start of the charging process is postponed after the EV arrives at the charging station. Both processes cause a substantial portion of the EV models in the market to switch to sleep mode. This makes them unresponsive to charging signals after the pause or delay, posing a risk of unmet charging demand at their departure from the charging station. To avoid this, EVs need to be continuously charged with at least their minimum charging current [346], even when this is not desirable, for instance at moments with a high electricity price or grid load. Consequently, the paused and delayed charging problems of EVs reduce the potential impact of smart charging.

Remarkably, the technical problems associated with EV smart charging have hardly been addressed in scientific literature and the media, leading to low awareness about these issues among different stakeholders, including policymakers, EV manufacturers and grid operators. This is evident from several factors. First, as this research will show, a notable portion of newly-introduced EV models cannot perform paused or delayed charging, indicating that EV manufacturers may not be aware of this issue. Second, almost all smart charging studies fail to consider that a considerable share of the EV fleet cannot perform paused or delayed charging, resulting in an overestimation of the smart charging potential. Third, no legal or policy initiatives appear to address this problem.

In this work, we shed light on these problems to raise awareness among relevant stakeholders (e.g., grid operators, EV manufacturers and policymakers) about the prevalence of technical smart charging problems and their impact on the effectiveness of smart charging. We present the results of large-scale technical charging tests, which indicate that around one-third of the 43 tested EV models in the market cannot handle charging pauses or delays. Moreover, this study presents the results of model simulations that quantify the impact of EVs' inability to perform paused or delayed charging on three different applications for which smart charging can be used, namely: (i) charging cost reduction, (ii) mitigation of grid congestion, and (iii) offering flexibility products to grid operators. The outcomes of these model simulations show that the potential impact of smart charging is halved for all applications if paused or delayed charging cannot be considered. Lastly, the current international regulations and standards on this topic are discussed, and options to eliminate paused and delayed charging problems are analysed.

6.2 Results

6.2.1 Technical smart charging tests

The technical performance of new EV and charging station models is evaluated using charging tests at the Testlab of ElaadNL, a knowledge centre on EV charging

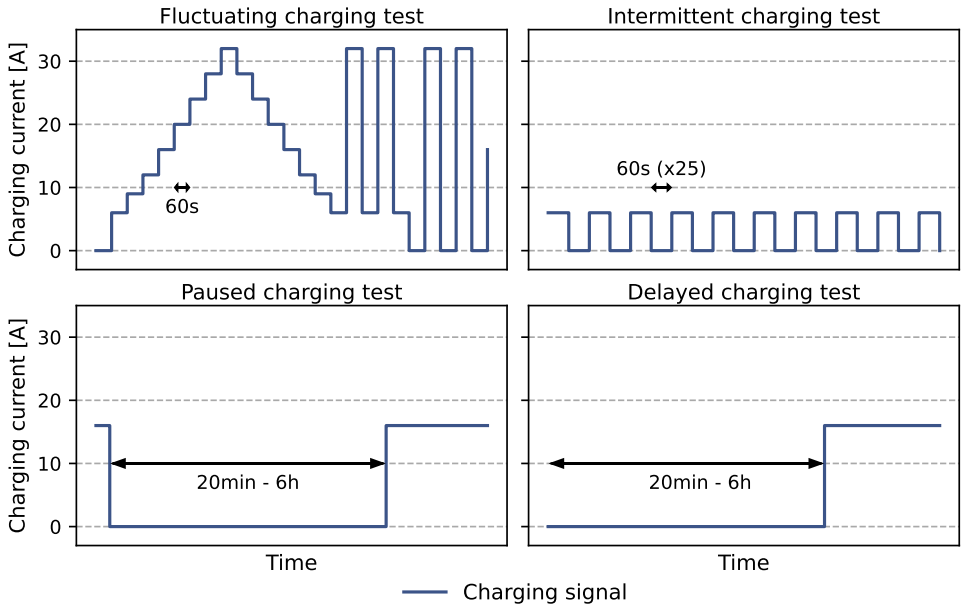


Figure 6.1: Overview of the charging signals for the different smart charging tests in the charging protocol at the ElaadNL Testlab.

established by Dutch grid operators. Manufacturers of EVs and charging stations are invited to test the technical performance of their products. They are tested on their interoperability, impact on power quality and ability to perform smart charging [347] using a standardized testing protocol to ensure comparability of results between charging tests for different EV models. The charging tests have been performed on a large share of the PHEV and BEV models on the Dutch market and manufacturers can use the results of these tests to improve the technical performance of their products. This section focuses on the charging test results related to different smart charging applications. It is important to note that some manufacturers have rectified the charging issues after undergoing the charging tests through the installation of software updates.

The smart charging tests conducted at the Testlab aim to evaluate the EV's response when exposed to various charging patterns that could occur with different applications of smart charging. The parameters of the charging tests have been determined in consultation with different stakeholders, such as grid operators and EV manufacturers. The fluctuating charging test assesses whether an EV can handle smart charging applications with high fluctuations in the charging signal, such as solar charging (i.e., directly linking the charging power to the solar generation of photovoltaic (PV) systems). As shown in Figure 6.1, this test considers a fluctuating charging signal between 6 and 32 amperes at a 60-second interval. These current

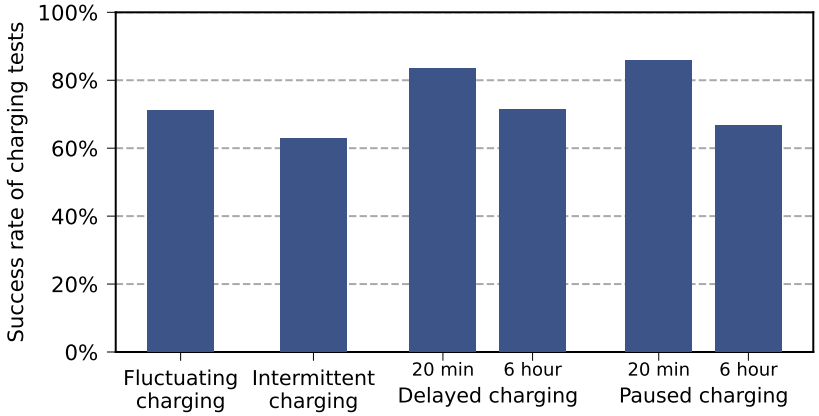


Figure 6.2: Results of the conducted charging tests at the ElaadNL Testlab between 1 June 2020 and 1 January 2023. Results are presented for fluctuating charging tests on 52 EV models, intermittent charging tests on 43 EV models, 20-minute paused and delayed charging tests on 42 models and 6-hour delayed and paused charging tests on 21 models.

values correspond to the prescribed minimum and maximum charging currents for EV charging, as defined in the International Electrotechnical Commission's communication standard for EV charging [133]. The intermittent charging test evaluates the EV's response to a charging session with a high number of charging pauses, which is for instance relevant when applying smart charging for load balancing at car parks (i.e., quickly alternating the charging power between charging stations to reduce the peak charging power of the car park). In this test, the charging signal is switched 25 times between 0 and 6 amperes at 60-second intervals. The last set of tests analyses the EV's response to paused and delayed charging. These tests are relevant for smart charging applications that require longer periods without charging, such as smart charging to reduce charging costs with static or dynamic ToU tariffs or smart charging to mitigate grid congestion. The paused and delayed charging tests have a similar setup. The paused charging tests assess the EV's ability to properly react to the charging signal after a charging pause, which is implemented after the vehicle has been charged for a brief period. The delayed charging tests also consider a charging pause, which starts directly after the EV arrives at the charging station. Both tests are conducted with pauses of 20 minutes and 6 hours.

Figure 6.2 presents the results of smart charging tests that were conducted with 52 EV models (cars, vans and motorcycles) between 1 June 2020 and 1 January 2023. A charging test was labelled as unsuccessful if the tested EV model ceased charging or if its charging current violated the current limits specified in the EV charging standards by exceeding the charging signal by at least 0.5 amperes [133]. The latter problem only occurred with the fluctuating and intermittent charging tests. The success rate of the fluctuating charging test equals 71% for the tested EV models. The share of tested

models that can follow the intermittent charging profile is lower and equals 63%. In both cases, charging problems were observed in both PHEVs and BEVs, with the majority of failed tests attributed to violations of current limits. These results indicate that a large share of the tested EV models is unable to perform smart charging for applications at which the charging power could fluctuate rapidly. These issues appear to be caused by the software settings of certain EV models, which identify charging stations with high fluctuations in the charging signal as faulty without considering that the application of smart charging may cause these fluctuations.

The share of EV models that can deal with paused and delayed charging profiles depends on the pause duration. When considering a charging pause of 20 minutes, the success rate for the tested EV models equals 86% and 83% for paused and delayed charging, respectively. When the pause duration is extended to 6 hours, the share of tested EV models that successfully pass the charging test reduces to 71% and 67% for paused and delayed charging, respectively. These problems manifested with both PHEVs and BEVs. These issues are also software-based: to prevent the 12-volt battery that powers the vehicle's electrical systems from draining, the EVs switch to sleep mode if no charging signal is received for an extended duration.

6.2.2 Impact on smart charging's charging cost reduction potential

The inability of EVs to perform paused or delayed charging can diminish the effectiveness of different smart charging applications, including smart charging for participating in an electricity market that considers static or dynamic ToU tariffs (e.g., day-ahead electricity market) [157], [348], [349]. Charging costs can be reduced by shifting the charging demand from moments with high prices to moments with low prices. While longer charging pauses may be desirable at specific moments, for instance at moments with high electricity prices, they cannot be implemented into EV charging schedules as some EV models will shift into sleep mode and will become unresponsive to charging signals. Since the EV model is not specified in the current communication protocols between the EV, the charging station and the back-office of the charge point operator [119], [133], charging pauses are generally not considered for all EVs, regardless of whether they are able to perform paused and delayed charging or not. The only way to reduce the impact of EV charging at the moments at which this is desired is by charging with the lowest possible current of the charging system, which is typically 6 amperes [133]. Figure 6.3 illustrates how this reduces the effectiveness of smart charging. It reports the charging schedules for one charging session when considering different charging regimes (uncontrolled charging, smart charging without paused charging and smart charging with paused charging) for a simplified cost-optimization problem. This figure shows that if smart charging is applied without considering charging pauses, still a considerable share of the charging demand (50% for the charging session in Figure 6.3) has to be fulfilled at moments with medium or high prices. This is in contrast to smart charging with

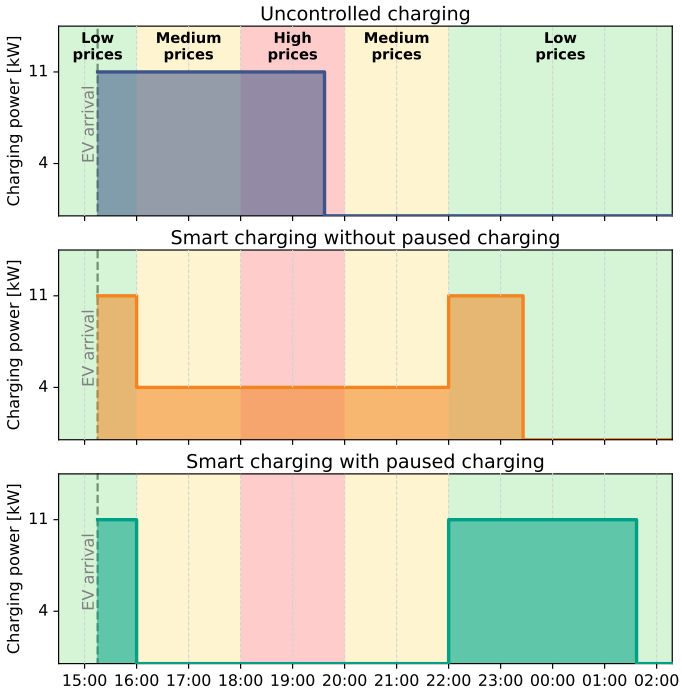


Figure 6.3: A comparison of charging schedules of one charging session with a simplified cost-optimization approach for different charging regimes. Charging session characteristics are an arrival time of 15:15 (dashed line in Figure), a departure time of 08:00, a charging demand of 48 kWh and a minimum and maximum charging power of 4 kW and 11 kW, respectively.

paused charging, where the charging demand can be completely fulfilled at moments with low prices in this example.

Model simulations are performed to quantify the impact of the paused and delayed charging problems on the cost-reduction potential when using smart charging for electricity market bidding. Figure 6.4 presents the charging costs for a large EV fleet when participating in the day-ahead market in different European countries with perfect foresight. Three charging scenarios are considered in the model simulations: (i) uncontrolled charging, (ii) cost-optimization without considering paused or delayed charging and (iii) cost-optimization considering delayed or paused charging. The results in Figure 6.4 indicate that the inability to perform paused or delayed charging almost halves the cost-reduction potential of smart charging. When charging pauses can be considered, the cost-reduction potential compared to uncontrolled charging equals 14-35%, depending on the country. For all considered countries, the cost reduction potential is approximately half as high when no paused or delayed charging can be considered. This is because EVs are forced to charge with the minimum current of 6 amperes at times of high prices and cannot benefit from lower prices since their charging demand is fulfilled before those times arrive.

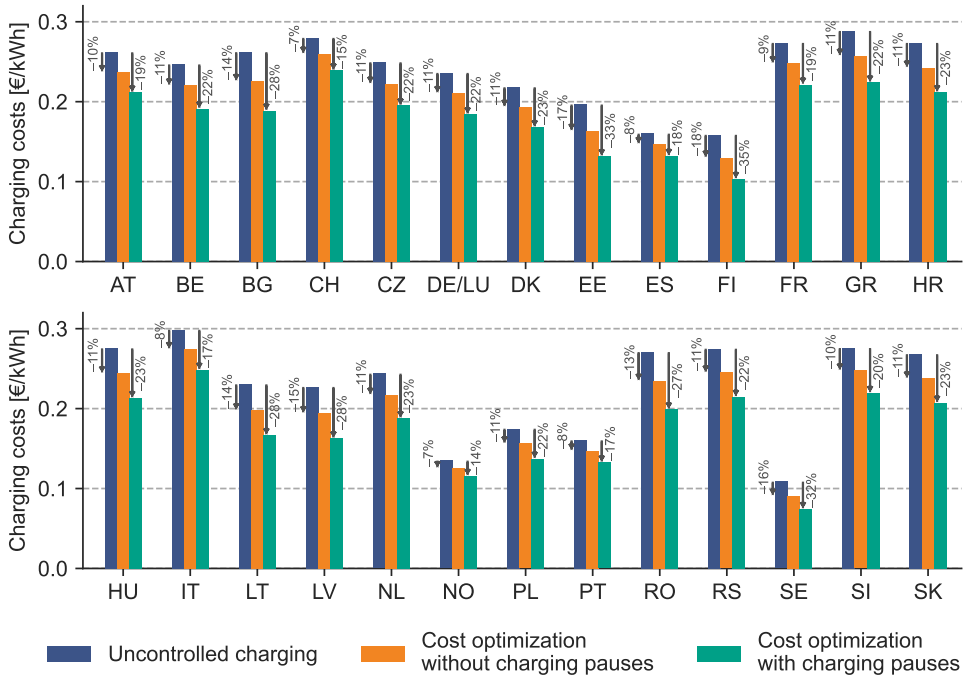


Figure 6.4: Average EV charging costs for three different charging strategies in the day-ahead market of different European countries. Results are presented for 322 public charging stations in residential areas for an assessment timeframe of one year between 1 February 2022 and 1 February 2023. Percentage values represent the cost decrease compared to uncontrolled charging (blue bars). For countries with multiple bidding zones (DK, NO, SE & IT), the average charging costs for all bidding zones are reported. As Germany and Luxembourg comprise one bidding zone, the results for these countries are reported together.

6.2.3 Impact on smart charging's grid congestion control potential

Smart charging can also be used to address grid congestion problems induced by EV charging by shifting the charging from moments with high local grid load to moments with low local grid load [350], [351]. When charging pauses cannot be considered, EV charging cannot be completely shifted away from peak hours. Consequently, grid congestion problems will manifest at lower EV adoption levels when deploying smart charging without paused or delayed charging compared to the deployment of smart charging with these features.

Model simulations were conducted using a transformer peak load minimization algorithm for EV charging to investigate the impact of the paused and delayed charging problems on the potential for mitigating grid congestion through smart charging. Simulations were performed for both transformer peak load minimization with and without considering paused and delayed charging.

Figure 6.5 presents the transformer peak load values (i.e., the sum of the non-EV

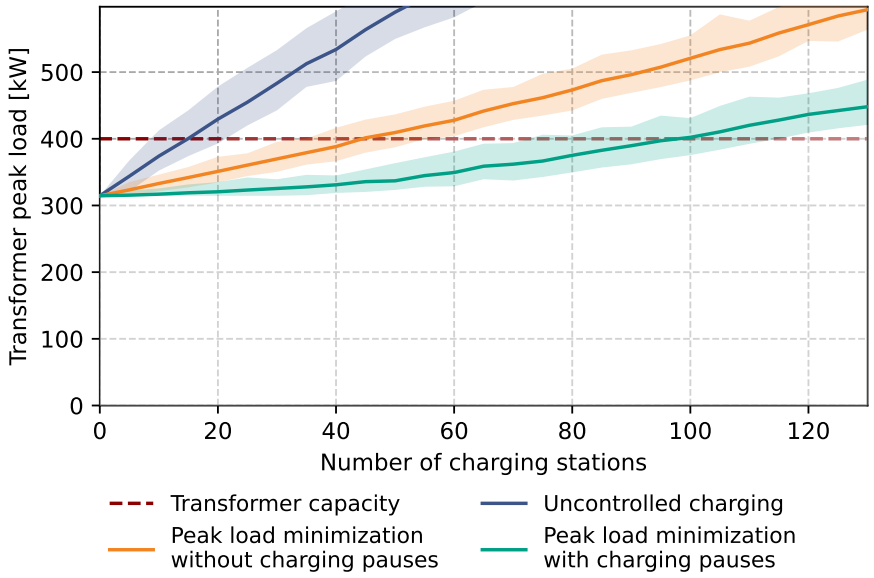


Figure 6.5: Peak transformer load values in a one-year assessment timeframe when applying a peak transformer load minimization algorithm to a different number of installed on-street charging stations in one residential LV grid in the city of Utrecht, the Netherlands. The analysis is repeated 100 times for each considered number of EV charging stations, with a randomly sampled subset of EV charging stations in each run. The line shows the average outcome for all model runs and the shaded area shows the 95% confidence interval.

load and EV load) for a varying number of on-street charging stations connected to one LV grid. From this figure, one can determine the maximum number of EV charging stations that can be theoretically hosted in one LV grid without causing transformer congestion. The results show that the number of charging stations that can be installed in the considered grid without exceeding the transformer capacity is approximately twice as high when charging pauses can be implemented in the charging schedules. Transformer congestion problems will occur in the studied grid if it hosts between 35 and 55 charging stations, a peak load minimization algorithm is applied and charging pauses and delays cannot be implemented. This increases to a range of 75 to 115 charging stations when paused and delayed charging can be considered.

6.2.4 Impact on smart charging's flexibility services potential

Moreover, smart charging can be applied to offer flexibility services to grid operators, for instance by supplying balancing reserves (e.g., frequency restoration reserves) to TSOs for restoring the balance between supply and demand [290], [352]–[354]. Additionally, DSOs have been experimenting with local flexibility markets to address

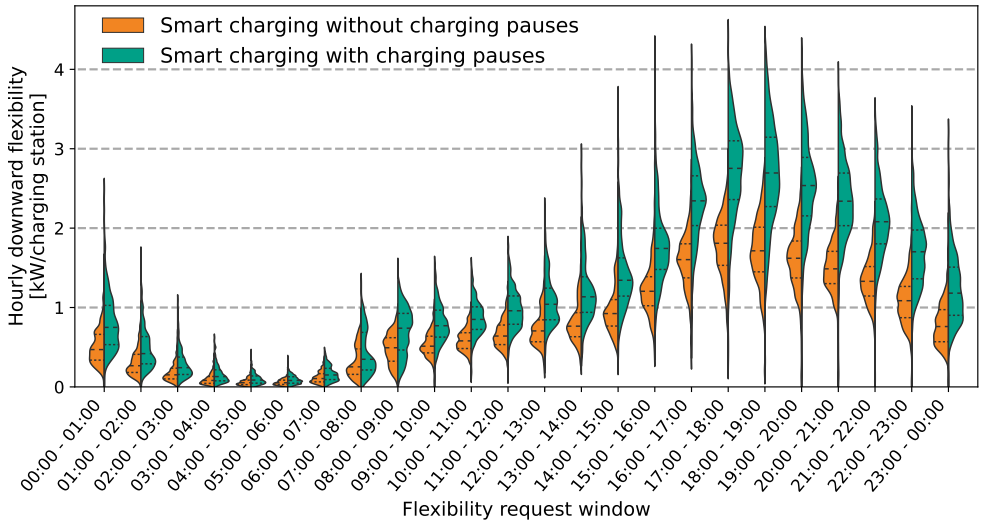


Figure 6.6: Violin plot with the distribution of the available downward flexibility of an EV fleet for each hour of the day during the assessment timeframe of one year when considering the uncontrolled charging profile as the reference charging profile. Results are compared for the case with and without paused and delayed charging. Model simulations are performed using historical charging data from 322 on-street charging stations located in the city of Utrecht, the Netherlands. The dashed and dotted lines in the violins represent the 25%, 50% and 75% quantile values.

grid congestion issues [355]. The paused and delayed charging problems affect the amount of downward flexibility (i.e., a reduction in charging power from the reference charging schedule) that can be provided using smart charging. This was demonstrated through the final series of model simulations, which compared the available downward flexibility of an EV fleet under two scenarios: one that does not consider charging pauses and another that does. In these simulations, the maximum reduction in charging power from the reference charging schedule (uncontrolled charging in this case) is determined while ensuring that the charging demand of every session is met at departure.

The violin plot in Figure 6.6 presents the distribution of the hourly available downward flexibility throughout one year for both considered cases. It shows that the available downward flexibility is higher during early evening hours. This is because more EVs are typically charging during this time in residential areas, resulting in a higher potential for charging power reduction. As visible in Figure 6.6, the inability to perform charging pauses reduces the available downward flexibility, since EVs that cannot handle charging pauses cannot fully ramp down their charging power to provide downward flexibility and must keep the charging current above the minimum charging current. On average, 34% less downward flexibility can be offered when no charging pauses can be considered (95% confidence interval: 24-44%).

6.2.5 Options for eliminating charging problems

The previous sections emphasized the necessity of EV car models to be able to perform paused and delayed charging. This section examines existing international regulations and standards on this issue and explores solutions to avoid such problems in the future.

Two standards for EV charging currently address the delayed and paused charging problems. However, EV manufacturers are not obliged to comply with them. IEC 61851 [133] is a set of standards that contains use cases for EVs and charging stations on how to wake up EVs that shifted to sleep mode after a charging pause. This standard also contains safety standards, and manufacturers of EVs and charging stations that comply with it are deemed to comply with the Low Voltage Directive (LVD) [356]. This directive applies to all electrical equipment traded within the EU and aims to safeguard the health and safety of persons, animals and property (art. 1 LVD). It is based on self-assessment, and there is no notified body that intervenes with the conformity assessment procedure. For EVs and charging stations, compliance with IEC 61851 leads to the presumption of compliance with the LVD (art. 12 LVD). By complying with this standard, EVs are able to perform paused and delayed charging. However, EV manufacturers do not need to use this standard to comply with the LVD; as long as the safety standards in the LVD are met, the product can be traded on the EU market. Since the ability to handle charging pauses is of limited relevance for product safety, EVs are able to comply with the LVD without complying with IEC 61851.

Secondly, the paused and delayed charging problem is addressed in a newly-developed standard for communication between EVs and their charging station. The ISO 15118-20 standard [109] has been developed to enable bidirectional EV charging through V2G technology and has been implemented in a small number of EV models. It includes a use case to re-establish communication with an EV in sleep mode by sending a wake-up trigger. While the implementation of this standard would likely eliminate the paused and delayed charging problems for compliant EVs, there is no legal requirement for manufacturers to incorporate it in their models. As a result, the paused and delayed charging problems might persist for some EV models since manufacturers might not be incentivized to implement the standard in models that are unable to perform V2G functions.

If the public sector, including governments and regulatory agencies, deem that the paused and delayed charging problems are too severe to be resolved without intervention, there are multiple enforcement or stimulation methods available. First, these organizations could stimulate manufacturers to comply with the existing standards that address this issue. This can be done by taking an active role in informing manufacturers about the importance of EVs being able to handle paused and delayed EV charging. Alternatively, the public sector has the option to establish an EV model certification program, where EV models that successfully completed a set of EV smart

charging tests are granted a certificate, which could make the specific EV model more appealing to consumers.

The public sector can also enforce the elimination of paused and delayed charging problems by implementing regulations on this topic. This could be modelled after the type-approval system that is currently in place. Before getting access to public roads in the EU, all car models need to acquire type-approval [357], issued by a national approval authority. The type-approval tests assess whether the car models meet EU safety rules (e.g., crash tests) and noise and emission limits. Expanding these tests to include an evaluation of the technical charging capabilities of EVs would ensure that only EV models meeting technical charging standards are permitted on the road. If the public sector prefers not to incorporate technical charging tests into the type-approval process, they could introduce legislation that makes compliance with standards that address the paused and delayed charging problems, such as ISO 15118-20, compulsory, either through self-assessment or by requiring testing and approval by a national approval authority. Ideally, all discussed enforcement or stimulation methods should be implemented at an international level, within entities such as the EU, to enhance efficiency and maintain consistency in policies across different nations.

As long as the paused and delayed charging issues are not resolved, smart charging operators can use workaround solutions to identify whether a specific EV can handle charging pauses. A pause can be introduced to a charging session of each EV. If the EV responds properly to this pause, paused and delayed charging can be applied to it. However, this method increases system complexity and could lead to user discomfort if the EV does not respond properly to the pause.

Finally, consumer demand may compel manufacturers to address the paused and delayed charging problems. EV users could become increasingly aware that the cost-saving benefits of smart charging are diminished if their EV model is unable to deal with charging pauses. This may influence their decision when purchasing a new model, incentivizing manufacturers to resolve these issues.

6.3 Discussion

EV smart charging is widely acknowledged for its potential to reduce charging costs and address grid-related issues. However, it is lesser known that its potential is currently limited by technical problems related to EV smart charging. In this work, we shed light on these problems by presenting the results of large-scale EV technical charging tests and by conducting model simulations to quantify the impact of the technical limitations that are currently in place for smart charging on its effectiveness. The results of large-scale EV technical analyses showed that around one-third of the tested EV models cannot handle longer charging pauses. To prevent the EVs from shifting to sleep mode, they should continuously be charged with a minimum charging

current of 6 amperes after connecting to the charging station. Model simulations showed that the potential to reduce charging costs, mitigate grid congestion and offer flexibility services using smart charging is approximately halved when charging pauses cannot be considered.

Although this research indicated that it is important that EVs are able to deal with paused and delayed charging, it should be acknowledged that actual implementation of paused and delayed charging could trigger range-anxiety issues among EV users. When scheduling the charging of an EV, its departure time from the charging station has to be estimated through user input and/or by applying forecasting methods. If an EV departs from the charging station before the anticipated departure time and the vehicle has continuously been charged with a charging current of at least 6 amperes, it is ensured that the EV has at least partly been charged. However, with the application of paused and delayed charging, there is a risk that the EV will receive a minimal charge if it departs before the expected departure time. Therefore, smart charging operators must exercise caution regarding the uncertainties in their models when using paused and delayed charging scheduling. The reader should bear in mind that this additional uncertainty was not considered in this work's model simulations for paused and delayed charging. Nevertheless, it should be realized that this real-world challenge may be largely mitigated by actively requesting user information about their charging sessions (e.g., expected departure time & charging demand). This could be achieved, for instance, through a mobile application (e.g., [113], [358]), either by setting user-defined defaults with opt-outs or by requesting per-session preferences.

To mitigate the problem of range anxiety among EV users when implementing smart charging solutions, various local governments and municipalities have imposed minimum charging current requirements for public charging stations within their jurisdiction [359], eliminating the option to implement charging pauses. While this approach can help to alleviate range anxiety concerns, these authorities need to recognize that it significantly constrains the potential of EV smart charging.

In addition, it should be recognized that the model simulations in this research exclusively focused on quantifying the impact of the EV's inability to perform paused and delayed charging. The results of the technical smart charging tests indicated that fluctuating or intermittent charging problems also occur frequently. This could harm the roll-out of different smart charging applications, including renewable-based charging, in which the EV charging power depends on the output of a PV system or wind turbine. Implementing renewable-based charging systems has the potential to boost the self-consumption of renewable energy and enhance the integration of renewable energy technologies into the grid [79], [80], [345]. This approach helps mitigate the intermittency of renewable energy generation and reduces dependence on fossil fuels to fulfil electricity demand. For this reason, policy addressing technical charging problems for EV smart charging should also encompass the resolution of technical charging problems related to fluctuating or intermittent charging signals.

Overall, this work showed the inability of different EV models to handle charging pauses causes highly inefficient operation of smart charging, resulting in unnecessary and costly grid reinforcements and a considerable increase in charging costs. Despite the major impact of the paused and delayed charging problems, no binding legislation is currently in place to eliminate this issue. If the public sector considers these problems to be problematic, legislation that sets a minimum technical charging performance for EV models should be introduced.

Appendix

6.A Methods

6.A.1 Technical smart charging tests

The Testlab of ElaadNL in Arnhem, the Netherlands, invites EV manufacturers to test the technical charging performance of their products in their lab. All EV models undergo the same standardized charging procedure, which consists of four tests:

1. Interoperability tests: Assesses whether the tested EV model is able to charge at different charging station models;
2. Power quality emission tests: Assesses whether the charging of the tested EV model causes disturbances in the grid voltage;
3. Power quality immunity tests: Assesses whether the tested EV model can cope with fluctuations and disturbances of the grid voltage;
4. Smart charging tests: Assesses whether the tested EV model responds to different smart charging profiles.

The manufacturers are informed of the test results, which they can use to enhance the technical charging performance of their products.

A large majority of the sold EV models (both PHEV and BEV models) in the Netherlands have undergone the technical charging test procedure at the Testlab. This study reported the results of the technical smart charging tests that were conducted at the Testlab between 1 June 2020 and 1 January 2023. In this timeframe, 52 EV models have undergone the fluctuating charging test, 43 models have undergone the intermittent charging test and 42 models have undergone the 20-minute paused and delayed charging tests. The 6-hour delayed and paused charging tests have only been introduced since April 2021. Hence, the number of EV models that have undergone these tests is lower: 21 models have undergone these charging tests.

A charging test was considered unsuccessful if the EV did not continue to charge when exposed to the tested charging profile or if the charging current was at least 0.5

amperes higher than the communicated charging current in the charging signal. It should be noted that the EV manufacturers could have used the test results to resolve any technical charging issues with their model.

6.A.2 Model simulations — charging models

Three sets of model simulations were conducted in this work, considering three different charging models: (i) a charging cost minimization model, (ii) a peak grid load minimization model and (iii) a model to determine the flexibility volumes that can be offered to grid operators. Each charging model will be outlined below.

The cost minimization model is a deterministic model that can be applied to a set of EV charging sessions to determine the theoretical minimum charging costs that can be achieved in a specific electricity market. In this work, it is used to compare the charging costs with and without considering charging pauses. The validity of this model has been confirmed through real-world application [105] and the model is formulated as follows:

$$\min_{p_{\text{ch}},\,\phi_{n,t}} \quad \sum_{n=0}^{N} \sum_{t=\text{t}_{\text{arr},n}}^{\text{t}_{\text{dep},n}} \pi_{\text{el},t}\, p_{\text{ch},n,t}\, \Delta\text{t} \tag{6.1a}$$

$$\text{s.t.} \quad \sum_{t=\text{t}_{\text{arr},n}}^{\text{t}_{\text{dep},n}} p_{\text{ch},n,t}\, \Delta\text{t} = \text{E}_{\text{dem},n} \quad \forall n \in \mathcal{N}, \tag{6.1b}$$

$$0 \leq p_{\text{ch},n,t} \leq \phi_{n,t}\text{P}_{\text{ch,max},n} \quad \forall n \in \mathcal{N},\ \forall t \in \left\{\text{t}_{\text{arr},n}\right\}, \tag{6.1c}$$

$$\phi_{n,t}\text{P}_{\text{ch,min},n} \leq p_{\text{ch},n,t} \leq \phi_{n,t}\text{P}_{\text{ch,max},n} \quad , \quad \forall n \in \mathcal{N},\ \forall t \in \left[\text{t}_{\text{arr},n} + \Delta\text{t}, \text{t}_{\text{dep},n}\right], \tag{6.1d}$$

$$\phi_{n,t-1} \geq \phi_{n,t} \quad \forall n \in \mathcal{N},\ \forall t \in \left[\text{t}_{\text{arr},n} + \Delta\text{t}, \text{t}_{\text{dep},n}\right], \tag{6.1e}$$

$$\phi_{n,t}\,\{0,1\} \quad \forall n \in \mathcal{N},\ \forall t \in \left[\text{t}_{\text{arr},n} + \Delta\text{t}, \text{t}_{\text{dep},n}\right]. \tag{6.1f}$$

The objective of this optimization model in equation 6.1a is to minimize the total charging costs of all charging sessions in the set of charging sessions $\mathcal{N}$, indexed by $n = 0 \ldots N$. In this equation, $p_{\text{ch},n,t}$ represents the charging power in kW of charging session n at time t, $\pi_{\text{el},t}$ represents the electricity tariff at time t (€/kWh), Δt represents the timestep duration in hours and $\text{t}_{\text{arr},n}$ and $\text{t}_{\text{dep},n}$ represent the arrival and departure time of the considered charging session, respectively. Constraint 6.1b assures that the charging demand ($\text{E}_{\text{dem},n}$) of each charging session is met at departure. The charging power is constrained in equations 6.1c and 6.1d. The minimum charging power is not considered at the first timestep after arrival (see equation 6.1c) for each EV charging session to avoid model infeasibility, which is caused by the fact that the charging demand of some charging sessions can not be exactly met when considering 15-minute timesteps and a minimum and maximum charging power. In constraint 6.1d, the binary variable $\phi_{n,t}$ makes sure that $p_{\text{ch},n,t}$ stays between the minimum

required charging power ($P_{ch,min,n}$) and the maximum charging power ($P_{ch,max,n}$) of the considered charging session, or is 0 otherwise. Constraint 6.1e assures that once an EV stops charging, it does not restart charging later. This constraint can be neglected if charging pauses can be considered.

The peak load minimization model aims to minimize the peak transformer loading in a specific LV grid when considering a set of EV charging sessions. The nature of this model is also deterministic, assuming perfect foresight in the charging session characteristics and the non-EV load. This model can provide an understanding of the maximum potential to lower the peak transformer load when considering a given set of EV charging sessions. It is formulated as follows:

$$\min_{\substack{p_{ch},p_{grid},\\ p_{grid,peak},\phi}} \quad p_{grid,peak} \tag{6.2a}$$

$$\text{s.t.} \quad p_{grid,t} = P_{non\text{-}EV,t} + \sum_{n=0}^{N} p_{ch,n,t} \quad \forall t \in \mathcal{T}, \tag{6.2b}$$

$$p_{grid,t} \leq p_{grid,peak} \quad \forall t \in \mathcal{T}, \tag{6.2c}$$

$$(6.1b) - (6.1f)$$

The objective of this model in equation 6.2a is to minimize the peak transformer loading of the transformer ($p_{grid,peak}$). In constraint 6.2b, $p_{grid,t}$ represents the transformer loading at timestep t. This is equal to the sum of the non-EV load in the considered LV grid ($P_{non\text{-}EV,t}$) and the total charging demand of all charging sessions at the considered timestep. In equation 6.2c, it is defined that the transformer load should be lower or equal to the peak transformer load at all timesteps. Lastly, the constraints in 6.1b-6.1f are considered in this model.

The last optimization model determines the available downward flexibility of an EV fleet during a specified flexibility request window. This deterministic model is based on [354] and formulated as follows:

$$\max_{\substack{p_{ch},\phi,\\ p_{ch,tot},p_{flex}}} \quad p_{flex} \tag{6.3a}$$

$$\text{s.t.} \quad p_{ch,tot,t} = \sum_{n=0}^{N} p_{ch,n,t} \quad \forall t \in \mathcal{T}, \tag{6.3b}$$

$$p_{flex} = \min_{t \in T_{flex}} \left(P_{ch,ref,t} - p_{ch,tot,t} \right), \tag{6.3c}$$

$$(6.1b) - (6.1f)$$

This model's objective in equation 6.3a aims to maximize the downward flexibility (p_{flex}) that can be offered using an EV fleet during all considered timesteps in the flexibility request window. The variable $p_{ch,tot}$ represents the realized aggregated charging power at timestep t, as visible in equation 6.3b. Constraint 6.3c defines p_{flex}

as the minimum difference between the charging power with the reference charging schedule ($P_{ch,ref}$, exogenous model input) and the realized aggregated charging power. The reference charging power depends on the reference charging strategy, e.g. uncontrolled charging or day-ahead market optimization. Constraint 6.3c only applies to the set of timesteps in the considered flexibility request window (T_{flex}). Lastly, this model also considers constraints 6.1b-6.1f.

6.A.3 Model simulations — simulation outline

All model simulations in this work were conducted using an assessment timeframe of one year, between 1 February 2022 and 1 February 2023, considering 15-minute timesteps. The charging cost optimization model was applied to the whole set of considered EV charging sessions in the assessment timeframe. The hourly day-ahead market prices for different countries in Europe were used as price inputs in this optimization model. For every considered country, the optimization model was run for the scenarios with and without paused and delayed charging. In the model simulations without paused and delayed charging, charging pauses are not considered for all charging sessions to account for the fact that the operator does not know the respective EV model in the current communication protocol [119]. For countries with multiple bidding zones, the analysis is repeated for every bidding zone and the average charging costs for all bidding zones are reported. For comparison, the charging costs are also determined for uncontrolled EV charging, in which the EVs charge with maximum charging power directly after arrival until their charging demand is met. In the model simulations, it is assumed that the charging demand of EVs with a connection time to the charging station of more than 24 hours will be fulfilled within one day, by setting a virtual departure time of 24 hours after the time of arrival. This is done since it is not reasonable to assume that the charging demand of EVs can be delayed over multiple days, due to the unpredictable departure times of EVs. The model simulation timeframe is one day longer than the assessment timeframe to allow EVs that arrive close to the end of the assessment timeframe to complete their charging session.

The peak load minimization model is run for a varying number of considered EV charging stations. A subset of the charging stations in the EV charging session data is randomly selected for each number of considered charging stations. The model simulations include all sessions that occurred at the selected subset of charging stations during the assessment period. This process is repeated 100 times for each considered number of charging stations. Similar to the model simulations with the charging cost optimization model, the simulations were conducted considering both the case of no charging pauses and the case that considers charging pauses, as well as uncontrolled charging. The simulations also considered a virtual departure time of 24 hours after the time of arrival and a model simulation timeframe of one day longer than the assessment timeframe.

The downward flexibility model was used to determine the available downward flexibility for each hour for each day in the assessment timeframe. All charging sessions of the total charging session set that were connected to the charging station during the considered hour in the assessment timeframe were included in the model simulations. An uncontrolled charging profile was considered as the reference charging profile in these model runs. Both the cases of delayed and paused charging and no delayed and paused charging were considered in the model simulations.

All model simulations were performed in Python v3.9.12 [188] and Gurobi v9.5.2 [189] on the DelftBlue [360] and Eejit [246] high-performance computing (HPC) clusters.

6.A.4 Model simulations — data inputs & preparation

Three data sources were considered in these simulations. Historical EV charging session data was used as input for all three simulation models. This study considered EV charging data from public charging stations of charge point operator 'We Drive Solar'. Fast chargers are not included in this charging data. In this charging data, each charging session's arrival time, departure time, car ID, charging card ID, charging station ID and charging demand (kWh) is logged. Similarly, the maximum charging power for each charging station is logged at a 10 or 20-minute interval, depending on the considered charging station. The maximum charging power during each charging session has been derived from this. This maximum charging power has been considered for all timesteps in the model simulations.

All model simulations only considered charging session data from public, on-street charging stations located in the city of Utrecht, the Netherlands. These stations were accessible to both PHEVs and BEVs. Charging stations that were predominantly used by EVs in car-sharing schemes (>50% of the charging sessions were from shared EVs), that were not located in residential areas (determined using visual inspection of the charging station location) and that were not active during all months of the considered assessment period were excluded from the analysis. This resulted in EV charging data from 322 charging stations, each with 2 charging sockets.

Prior to running the model simulations, the EV charging session data underwent several data preparation steps to address any data logging errors. Charging sessions that were infeasible due to data errors (i.e., the charging demand that cannot be met with the logged maximum charging power during the connection timeframe) were removed from the data. Similarly, charging sessions with a charging demand of less than 1 kWh, a maximum charging power of less than 0 kW or more than 23 kW or a connection time to the charging station of less than 15 minutes were omitted from the charging session data. Some charging sessions in the data had exactly the same arrival time (to the nearest second) and were registered at the same charging station ID. Due to the small probability of this occurring, these charging sessions were identified as erroneous. If the charging sessions with the same arrival time and

charging station ID also had the same charging card ID, the first charging session was kept. Otherwise, both charging sessions with identical arrival times and charging station IDs were removed. The arrival and departure time of all charging sessions was rounded down to the previous 15-minute timestep. For the few sessions that became infeasible due to this rounding, the charging volume was set equal to the maximum possible charging volume in the adjusted connection time to the charging station. On average, the volume of these sessions changed by 0.6 kWh. Out of all the charging sessions, 2.7% were eliminated during the data preparation process, leaving 179,374 sessions in the considered assessment timeframe.

The maximum charging power of each session was used to determine whether the EV was charging using one or three phases. EVs with maximum charging power below 7.5 kW were classified as one-phase, while all other EVs were classified as three-phase. With a minimum required charging current of 6 amperes, the minimum charging power of EVs classified as one-phase equals 1.38 kW (1 phase × 0.23 kV × 6A). The minimum charging power for three-phase EVs equals 4.14 kW (3 phases × 0.23 kV × 6A). For a low number of charging sessions (0.4%), the minimum charging power of a charging session exceeds its maximum charging power. For those sessions, the minimum charging power is set as equal to its maximum charging power to avoid model infeasibility.

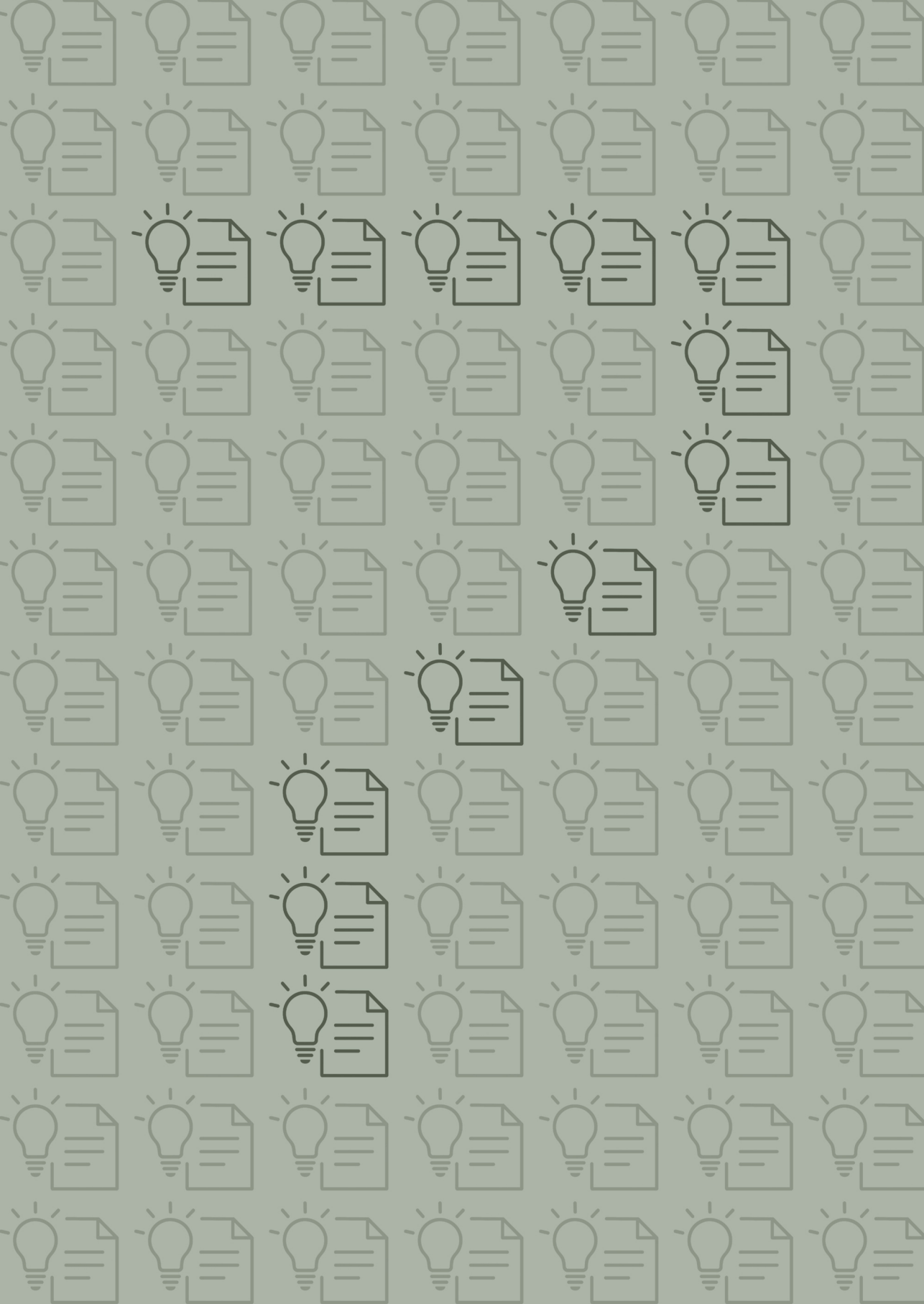
The cost-minimization model also considered day-ahead electricity price data. This data was obtained from [165]. Transformer load data was used as input for the peak load minimization model. This study used transformer load data from one LV transformer located in a residential area in the city of Utrecht, the Netherlands. The transformer has a capacity of 400 kW and the transformer load was measured at a 15-minute resolution. The non-EV loading at each timestep was determined by subtracting the loading of the registered charging stations connected to the transformed from the measured transformer loading. The peak non-EV transformer loading during the considered assessment timeframe equalled 314.5 kW.

6.B Data availability

Source data for Figures 2 and 4-6 are available from [361]. The EV charging session data from *We Drive Solar* and transformer load data from *Stedin* that served as input for the model simulations are not publicly available due to the inclusion of privacy-sensitive information and their commercial value for these organizations. Sample data for these data inputs are provided in the data repository that was created for this work [361]. Full data access can be requested from the corresponding author. Price data that were used as inputs for the model simulations are publicly available from [165].

6.C Code availability

The code used to conduct model simulations in this work is available from [361].



Chapter 7

Conclusions and recommendations

7.1 Overview of thesis objectives

The objective of this thesis, as defined in **Chapter 1**, was to develop a more nuanced understanding of the value of smart charging to mitigate grid congestion issues while also laying the foundation for further optimization of smart charging systems. To achieve this aim, the thesis addressed the following main research question:

What is the value of EV smart charging in mitigating grid congestion problems, and how can this value be effectively realized?

To comprehensively address this main research question, it was broken down into two sub-questions to structure this thesis:

1. **What is the system value of different mechanisms that grid operators can use for mitigating grid congestion using EV smart charging?**
2. **What strategies can address barriers to the effective deployment of EV smart charging for mitigating grid congestion?**

This chapter synthesizes the findings of the thesis, addresses the research questions and provides actionable recommendations for future research, policy development, and the practical implementation of EV smart charging systems.

7.2 Contributions to research questions

Sub-question 1: What is the system value of different mechanisms that grid operators can use for mitigating grid congestion using EV smart charging?

This thesis has explored three different mechanisms that could be deployed to effectively mitigate grid congestion using EV smart charging. The analysis in **Chapter 2** considers a capacity-limitation system in which the grid operator limits the available grid capacity for EV charging. Additionally, **Chapter 3** examined how alternative grid tariff structures can incentivize CPOs to implement smart charging in ways that reduce grid congestion and improve system efficiency. **Chapter 4** explores a system where a company, specifically a car-sharing company operating a fleet of shared EVs, applies smart charging to its EV fleet under a capacity-limitation system.

As the cases studied in these chapters differ significantly, their effectiveness cannot be directly compared. Nevertheless, the findings demonstrated that all mechanisms can help reduce grid expansion costs. **Chapter 2** showed that in the considered case study, no transformer upgrades are required to be able to meet all EV charging demand when applying a capacity-limitation system. **Chapter 3** took a system-wide approach, demonstrating that alternative grid tariff structures can lower grid expansion costs,

but that they cannot fully mitigate them. Similarly, **Chapter 4** found that a relatively small number of shared EVs can prevent transformer upgrades when they are used to mitigate grid congestion.

The chapters also examined other system impacts of these mechanisms. **Chapters 2 and 3** found that, in most cases, smart charging results in a net reduction in system costs, as the savings from lower grid expansion costs outweigh the additional costs for CPOs in electricity markets. EVs that are less constrained by transformer capacity can optimize their charging schedules more effectively in electricity markets, resulting in electricity cost savings. However, Chapter 2 showed that the annualized costs of upgrading a transformer station are at least twice as high as these savings. When cable reinforcements are also considered, the costs of grid expansion increase further, amplifying the overall system cost impact. The chapter also highlights that introducing an EV smart charging system for mitigating grid congestion is, in most cases, also beneficial from a system emissions perspective if emission-based optimization is considered. Similarly, **Chapter 3** demonstrated that most alternative grid tariff structures can lower system costs by up to 5% compared to traditional tariffs, depending on the EV adoption rate and the specific tariff structure applied. This cost reduction occurs because the savings in grid expansion costs outweigh the additional costs incurred in electricity markets. **Chapter 4** found that using a company fleet to mitigate grid congestion, specifically a shared EV fleet of a car-sharing company, results in only a modest increase in overall charging costs compared to using both shared and private EVs.

There are conceptual differences between each of the considered mechanisms, and each mechanism offers distinct advantages and drawbacks. A capacity-limitation system provides the grid operator with most direct control, as they implement hard limits which may not be exceeded, providing them with assurance that congestion will be avoided. However, the implementation of such a system could face challenges in terms of social acceptance and regulatory approval, as the grid operator's control over maximum EV charging power could be perceived as overly-authoritative or restrictive. The introduction of alternative grid tariff structures only provides incentives to influence user behavior and mitigate congestion, offering less certainty to grid operators about actual congestion outcomes. Nonetheless, this thesis shows that it leads to partial congestion mitigation and a fairer distribution of grid costs among users. Lastly, the mechanism of using company fleets to mitigate grid congestion is about which groups should be targeted to achieve efficient congestion management. This thesis shows that applying smart charging to a subset of EVs has significant potential for mitigating grid congestion, but is viable only in areas with sufficient company EVs connected to charging stations. The future smart charging system could also consist of a combination of these mechanisms.

Sub-question 2: What strategies can address barriers to the effective deployment of EV smart charging for mitigating grid congestion?

This thesis has addressed two main barriers that hinder the large-scale and efficient roll-out of EV smart charging and has proposed solutions for mitigating them. First, **Chapter 5** aimed to reduce the uncertainties that one faces when applying EV smart charging in practice. These uncertainties often lead to conservative smart charging practices to ensure user charging needs are met. The chapter introduced a forecasting framework that encompasses all the necessary elements for scheduling the charging of a group of EVs, which is based on aggregation and translates an EV fleet's charging characteristics into three key parameters that can be forecasted. The results demonstrate that high forecasting accuracy (R^2 scores up to 0.98) can be achieved for these parameters, particularly for larger fleets, enabling aggregators to better manage uncertainties and improve smart charging effectiveness.

Second, this thesis has looked into the technical barriers that currently prevent the efficient implementation of smart charging. **Chapter 6** demonstrated that a considerable portion of EVs on the market are unable to handle pauses or delays in charging, which makes it impossible to apply full charging pauses during periods of high grid load or electricity prices. Model simulations revealed that these technical limitations halve the potential benefits of smart charging, including its potential to reduce charging costs, alleviate grid congestion and provide grid balancing services. The chapter proposed different solutions, including requiring EVs to meet smart charging standards for approval and establishing a certification program for compliant models.

Main research question: What is the value of EV smart charging in mitigating grid congestion problems, and how can this value be effectively realized?

The different chapters of this thesis showed that EV smart charging is an essential solution for the efficient mitigation of grid congestion problems. Three mechanisms for using EV smart charging to address congestion were analyzed and the findings illustrated that all studied mitigation mechanisms avoid or delay the need for grid expansions with growing EV adoption rates. The results also indicated that the implementation of these mechanisms has only a limited effect on the overall charging costs or emissions, making them, in most cases, advantageous from both an overall system cost and emissions reduction perspective. This means that relying solely on traditional grid reinforcements to address congestion would be economically inefficient and hinder the energy transition. It is, therefore, imperative that policymakers and grid operators make the implementation of these mechanisms a top priority.

The chapters of this thesis demonstrated that smart charging can offer substantial value across other functions than mitigating grid congestion, including reducing charg-

ing costs, lowering emissions, and offering grid balancing reserves. When deciding which smart charging mechanisms to implement, regulators and grid operators must take a system-level approach that considers these additional benefits. Furthermore, they should assess how these mechanisms contribute to promoting fairness in the distribution of grid costs among grid users.

To implement a smart charging system that effectively mitigates grid congestion, it is crucial to address the barriers hindering its adoption. Smart charging operators need to implement frameworks that reduce the uncertainties associated with smart charging, such as the framework presented in **Chapter 5**. These frameworks are essential for enhancing the effectiveness of smart charging without compromising EV drivers' comfort. Moreover, technical smart charging problems currently occur in a substantial subset of EV models available in the market, hindering the effective implementation of smart charging. These issues should be addressed to improve the system's overall effectiveness, for instance by introducing technical smart charging requirements as part of the road approval process for EVs.

7.3 Research recommendations

While this thesis has contributed to filling gaps in the literature, there are still opportunities for further exploration. This section presents specific recommendations for future research.

A key direction for future research is to study the role of EV smart charging in mitigating grid congestion from a more holistic perspective. This involves different aspects. First, this includes examining the impact of EV smart charging on higher grid levels, such as MV and HV grids. Most existing research focuses on the impact on LV grids, but congestion often starts at higher grid levels before affecting LV grids, as illustrated by current grid congestion problems at MV and HV grids in the Netherlands [60]. In line with this, the *netbewust laden* system in the Netherlands, which sets capacity limits based only on LV grid load [362], should be evaluated for its effectiveness at higher grid levels, with future systems accounting for MV and HV grid conditions.

Similarly, future research could explore the effectiveness of combining the different considered mechanisms to gain a more comprehensive understanding of smart charging's role in mitigating grid congestion. While this thesis has examined various mechanisms, it has focused solely on their isolated effects. Importantly, grid operators may implement these mechanisms in combination, where their interactions and mutual influences could significantly impact outcomes. Additionally, future studies should investigate how these mechanisms interact with other grid services enabled by EV smart charging, such as the provision of balancing services.

The analyses in this thesis used charging session data from public charging stations, but, as shown in Figure 1.3 in **Chapter 1**, most future charging stations are expected

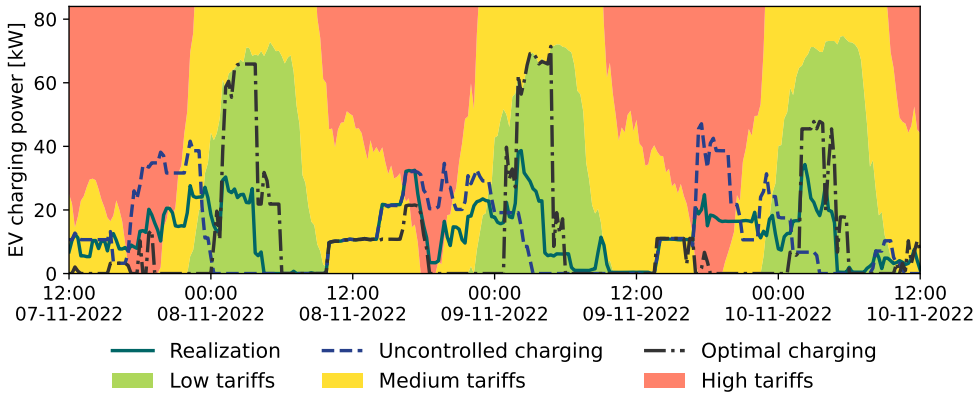


Figure 7.1: Realized charging profiles from the FLEET smart charging pilot [366] for 10 charging stations in one LV grid and their modelled uncontrolled and cost-optimal charging profiles over three example days. Charging was optimized using day-ahead market prices and dynamic grid tariffs. For this group of charging stations, specific capacity was available at each timestep for the low, medium, and high grid tariffs, represented by green, yellow, and red backgrounds, respectively. Adapted from [105].

to be privately-owned home chargers. Charging sessions at home chargers typically exhibit a different charging flexibility [363], which could affect their potential to mitigate grid congestion using smart charging. Additionally, home chargers share a grid connection with household loads, potentially influencing how EV smart charging can be applied under these mechanisms, in particular if heat pumps and/or PV systems are also connected behind the smart meter. Future research should explore the implications of these factors for grid management in areas with many home chargers. Furthermore, it should study the effectiveness of these mechanisms in mitigating grid congestion problems induced by other DERs, such as heat pumps and PV systems. To gain a more holistic view of smart charging's potential in mitigating grid congestion, future research should also consider the role of fast charging stations and the electrification of light and heavy-duty vehicles and buses. These factors could create significant charging demands, potentially impacting grid congestion levels [364], [365].

A pitfall in many studies in this field, including those in this thesis, is that they often adopt a technical perspective that assumes that individuals act rationally. Deviations from rational decision-making are often overlooked in existing models. Similarly, a smart charging system can only be successfully implemented if it is accepted by current and future EV users. Future studies should investigate how user preferences, perceptions, and potentially irrational behaviour of both current and future EV users influence the effectiveness of smart charging systems.

Lastly, different of the research problems addressed in this thesis were inspired by practical problems encountered during real-world smart charging pilots I participated

in throughout my PhD. Figure 7.1 presents the realized charging profiles from one such pilot, alongside the modelled optimal and uncontrolled charging profiles. This comparison highlights a significant gap between the realized and optimal profiles, which can be attributed to various practical issues which are neglected in model simulations. Addressing this gap should be a key focus of future research. Therefore, I strongly encourage researchers to collaborate closely with stakeholders in the field, for instance by engaging in research pilots and participating in transdisciplinary research activities. This approach offers two key benefits: it ensures the research directly contributes to shaping future smart charging systems with tangible social value, and it helps avoid the common pitfall often found in the existing literature of studying systems that are unrealistic for real-world implementation and provide limited practical value.

7.4 Policy and practical recommendations

As concluded when answering the research questions, this thesis has indicated that it is imperative that policymakers and grid operators prioritize the implementation of smart charging systems that aim to mitigate grid congestion problems. This section provides different specific recommendations for successfully implementing such systems.

This thesis examined three mechanisms that grid operators can use to unlock EV charging flexibility for mitigating grid congestion, showing that all can reduce the need for grid reinforcements. Determining which mechanism to implement in practice is not straightforward. However, reforming grid tariff structures to move away from fixed tariffs is strongly recommended, as current tariffs unfairly distribute grid costs between households and CPOs. Since **Chapter 3** demonstrated that alternative tariff structures only partially reduce grid costs, additional measures, such as capacity-limitation systems, may often be necessary. Before introducing such measures, it is essential to evaluate their systemic impact, as was done throughout this thesis. Also, grid operators should invest in digitalizing their grid to enhance real-time load monitoring and provide signals through congestion-mitigation mechanisms that accurately reflect local grid conditions.

While I strongly recommend that grid operators prioritize implementing mechanisms to support smart charging, I also stress the importance of maintaining a focus on grid reinforcements. This is essential since grid congestion problems in the Netherlands are so severe that these mechanisms alone are unlikely to fully resolve them. Additionally, without grid reinforcements, more rigorous application of smart charging may be needed, potentially discouraging EV adoption and increasing overall system costs due to distortionary effects. The current congestion problems in the Netherlands serve as a warning for other countries, where similar issues could arise in the coming years. These countries should proactively invest in the required

infrastructure to enable the introduction of smart charging mechanisms and make timely grid investments.

To support the large-scale implementation of mechanisms that promote smart charging for mitigating grid congestion, policymakers should actively address technical issues related to EV smart charging. **Chapter 6** highlighted that some EV models face technical smart charging problems, limiting the effectiveness of smart charging. Policies requiring compliance with smart charging requirements as a market entry criterion for EV models are recommended. For instance, adherence to the ISO 15118-20 [109] standard could resolve these issues while also providing benefits such as EV model and battery SoC communication, further improving the effectiveness of smart charging. Updating current communication standards, such as OCPP [134], is recommended to ensure that full-power charging is not required before a charging session is registered. This adjustment would help alleviate grid congestion during peak times.

Similarly, the technical charging capabilities of EV models also hinder the implementation of smart charging systems that consider V2G functions. **Chapters 2 and 4** have shown that V2G has the potential to further enhance the effectiveness of smart charging in mitigating grid congestion, yet few EV models currently support it. To encourage the development of V2G-capable vehicles, governments could consider introducing temporary incentives, such as tax reductions for V2G-capable EV models. A large-scale roll-out of such vehicles will also require grid operators to adapt the different congestion mitigation mechanisms to be able to deal with electricity injection via V2G.

To reduce barriers to participation in smart charging mechanisms, policymakers and grid operators should work on standardizing these mechanisms and their associated communication protocols across different grid operators and even countries. Such harmonization will reduce transaction costs by simplifying the implementation and operation of smart charging systems across different regions and grid operators. A strong example of this is the Open Charge Point Protocol (OCPP) [134], which enables seamless communication between EV charging stations and service providers through a single, globally recognized standard. In line with this, it is recommended to stimulate the sharing of grid and market data, which would enable more accurate analyses of the effectiveness of smart charging mechanisms and would support market participants in developing products that can contribute to mitigating grid congestion.

Lastly, it is crucial to involve users in designing smart charging systems for mitigating grid congestion. As discussed in this thesis, addressing this issue requires behavioural change and potentially a paradigm shift from various user groups, including businesses and households. The failure of *road pricing (rekeningrijden)* in the Netherlands, primarily due to negative user perception [367], showed that economically superior solutions can fail without user support. User comments on various online news articles about smart charging further reveal that public perception of this

concept is not always favourable.[12] Therefore, to avoid implementation issues, it is crucial to prioritize clear communication regarding the benefits and consequences of implementing smart charging systems. Furthermore, to improve system acceptance, these systems should offer direct incentives, such as discounts for EV drivers that offer flexibility. In addition, involving users in the design process can further help to identify overlooked flaws and ensure the system aligns with the real-world situation.

7.5 Epilogue

The ongoing grid congestion problems in the Netherlands are, alongside the energy transition, among the most pressing challenges the country has faced in recent decades. These problems have far-reaching social and economic consequences, including disruptions to businesses, households, and broader sustainability goals. Given the large scale and major consequences of these problems, addressing this problem should be envisioned as the next Dutch *Delta Works* projects. However, unlike the original Delta Works of 1950s-1990s, which relied primarily on engineering solutions to protect the country from devastating floods, resolving grid congestion demands more than technical innovation. It requires institutional reforms and coordinated actions across all stakeholders, from policymakers and grid operators to businesses and communities. For this reason, it is important to view this challenge not just as an engineering project but as a societal transformation. This transformation is both complex and exciting, offering opportunities for rapid, large-scale innovation. I truly enjoyed working on this inspiring topic throughout my thesis, and although my research has primarily a technical nature, I hope I have managed to maintain a broader perspective. I also hope my work has made a modest contribution to advancing understanding and offering insights into how we can collectively tackle these critical issues.

[12] See for instance (in Dutch) https://www.nu.nl/klimaat/6312112/laadpaal-uit-bij-vol-stroomnet-slimmer-laden-helpt-al-een-boel.html and https://www.nu.nl/nu-klimaat/6179160/je-elektrische-auto-kan-straks-ook-een-kleine-elektriciteitscentrale-worden.html

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About the author

Nico Brinkel was born in 1994 in Capelle aan den IJssel in the Netherlands. He earned a Bachelor's degree in Science and Innovation Management from Utrecht University, followed by a Master's in Energy Science at the same university. During his Master's, he was awarded a scholarship from the Energietalenten program of the *Topsector Energie*. He also completed two internships during his Master's. At TenneT TSO, he contributed to the annual TenneT Market Review, which provides insights into the developments in electricity markets. In addition, he combined his MSc thesis with an internship at the Dutch DSO Stedin, where he studied the impact of rapid PV generation fluctuations on grid stability.

He joined the Copernicus Institute of Sustainable Development at Utrecht University as a Junior Researcher in May 2019 and later transitioned into a PhD candidate role. During his PhD, he researched the impact of EV charging on electricity grids and explored the role of smart charging in mitigating these effects. He was involved in three different research projects: Smart Solar Charging, FLEET, and ROBUST. For the latter two projects, Nico was responsible for managing the real-world smart charging pilots, in which different smart charging systems for mitigating grid congestion were deployed at approximately 400 public charging stations. In the FLEET project, he was also responsible for overall project management. Nico has presented his research findings in various webinars, as well as at both scientific and industry conferences. Furthermore, he was invited to share his insights with multiple grid operators and at the national smart charging initiative *Slim laden voor iedereen*, and has been featured in several news articles and a podcast about smart charging.

Between September 2023 and June 2025, Nico worked as a postdoctoral researcher at the same institute, where he was involved in the Horizon Europe SCALE project. This project focused on the European rollout of smart charging and V2G.

As of June 2025, Nico works at TenneT TSO in the Energy System Planning - Market Analysis team as an Electricity Market Analyst. In this role, he is responsible for setting up electricity market models. He conducts market simulations and translates results into reports and presentations, used to guide investment planning and future infrastructure development.

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