Optimisation of smart- and Vehicle-to-Grid charging strategies in distribution networks

by

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Vehicle-to-Grid

Integration and optimisation of smart-charging and Vehicle-to-Grid charging strategies in distribution networks based on charging behaviour analysis

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Preface

First I would like to express my gratitude towards the supervision I received from both Rudi Hakvoort and Maarten Kroesen from the TU Delft. I also would like to acknowledge and emphasise the excellent supervision I have received from Jelle Wijnja during the execution of this graduation project. Our weekly meetings resulted in valuable new insights and most of all kept me on track. The municipality of Amsterdam and the Hogeschool van Amsterdam receive graditude for providing and maintaining respectively the charging session data set. I also would like to declare this work originated from within myself and was made possible to endorse by the network company Liander, whom recently initiated a Vehicle-to-Grid pilot project in Amsterdam.

Abstract

Currently in the energy system of the Netherlands, lower level consumer demand flexibility is rather obsolete due to sufficient capacity limits of the distribution network and supply of capacity mechanisms by large industrial actors. However, in the upcoming 10-20 years, the power system is in transition to become decentralised with a higher share of renewable energy sources and significant increase in consumption. An operational control structure in the power system, where private consumers provide flexible capacity, is an effective and economical efficient approach to make sure the regulated process of electricity generation to supply at consumers is secure and reliable. Currently as a result of the EU Energy Efficiency Directive of 2012, an institutional base is presented for development initiatives of demand response in Europe [17]. Technical and regulatory standards now enable demand response flexibility to be offered on the wholesale and retail energy market and allow for consumer participation [34]. Demand response schemes are usually distinguished by the various motivation methods offered to the participating consumers. Programs include in general two control methods, centralised direct load control or time-based and incentive-based DR. Because these schemes rely on demand response decision-making by means of a centralised (multi) aggregator perspective, direct load control can be precisely adjusted to technical (local) grid constraints [69]. Practically, the objective of DR in this research is used to reduce congestion in distribution grids by moving part of BEV energy demand from (evening) peaks to the afternoon or night with direct control. By achieving these measures potential benefits arise, including the most profound in the distribution grid [29]:

- Optimising local grid assets by increasing the utilisation factor, and thereby maximise asset efficiency and subsequently decrease costs, which is beneficial for the DSO
- Scheduling of peak charging demand to aid congestion in distribution grids.

The modelling of the demand response charging strategies in Amsterdam fills the knowledge gap towards handling congestion for the DSO. It also provides a new study that addresses the potential to postpone future distribution grid investments by using charging strategies specifically for Amsterdam. The main research question that this study addresses is therefore:

What is the value of demand response management in a Vehicle-to-Grid network and does it provide increased benefits to smart charging for consumers and the distribution system operator in Amsterdam?

In order to grasp the subject of congestion prevention withing the time limits of graduation, the scope of this study is limited to assess the first mentioned item by modelling charging demand, and subsequently simulate optimal demand response charging strategies for a case study in Amsterdam's local power grid. The motivation for this study is

threefold. Firstly, providing insight and recommendations in Amsterdam's BEV charging demand to compute the potential to provide demand flexibility by making use of a large-scale charging sessions data (2017-2018). Literature that uses such a vast data set for Amsterdam is scarce. Therefore, typical demand behaviour for daily and seasonal variation or periodicity is assessed by using a method of time series analysis and local regression analysis to derive time- and load-flexibility parameters. These parameters describe the measures for which demand response is generally defined. Secondly, a linear programming model is developed that optimises charging demand of smart charging and V2G charging strategies for demand response purposes to aid congestion at local feeders in the distribution grid of Liander. Lastly, an information-task exchange protocol is described from the perspective of a multi-aggregator to perform coordinated DR.

Further investigation about the usable amount of flexibility is simulated with linear programming for charging strategies (smart charging and V2G charging) to aid in local feeder congestion. In this research a case study is performed on data of a low-voltage feeder under different congestion situations, and a range of different number of BEVS connected to explore future distribution grid implications. Results show that the model's performance works especially well during peak demand periods throughout the day. In addition, the V2G strategy outperforms charged prices per kWh in almost every simulation compared to the uncontrolled scenario, by both charging during periods of low prices and discharging during periods of high prices even though the LP model does not optimise on prices. Thus, the V2G strategy allows the DSO to postpone grid investments in a number of cases while simultaneously the consumer almost always receives remuneration for its delivered services. The V2G strategy therefore provides a significantly added value over a smart charging strategy, by allowing electric vehicles to be charged whenever the feeder exhibits congestion. Future work includes analysis towards the value of DR in a liberalised system regarding the subject of the split-incentives challenge. Who initiates demand response (consumer, retailer, aggregator, DSO) and how should the benefits be divided along the supply chain. Handling an optimisation problem of DR for holds strong requirements for an global system balance in which neither participating actors are discriminated and the whole system benefits. An assessment of relational dependencies between participators in DR should be incorporated in designing charging strategies.

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List of abbreviations

BEV	Battery Electric Vehicles
PHEV	Plug-in Hybrid Electric Vehicle
ICE	Internal Combustion Engine vehicle
DEG	Distributed Energy Generation
REG	Renewable Energy Generation
DR	Demand Response
V2G	Vehicle-to-Grid
SOC	State-Of-Charge
TSO	Transmission System Operator
DSO	Distribution System Operator
BRP	Balance Responsible Party
CPO	Charge Point Operator (Aggregator)
PDF	Probability Density Function
CDF	Cumulative Density Function
LP	Linear Program

Nomenclature

Indices

n	BEV user [n]
h	hourly time step indicator [h]

Parameters and decision variables

H	Time window for optimisation in hours [h]
$P^c_{n,h}$	Load charging demand [kW]
$P^d_{n,h}$	Load discharging [kW]
E_{max}	Maximum available battery capacity [kWh]
SOC_{min}	Minimum available battery capacity [kWh]
N	Total number of BEVs in the optimisation time window
H	Total number of time slots in the optimisation window
t_{start}	Start date & time of the optimisation window [yyyy-mm-dd hh:mm:ss]
t_{end}	End date & time of the optimisation window [yyyy-mm-dd hh:mm:ss]
$c_{t,h}$	total costs (dis)charging during optimisation window [€]
$p_{c,h}$	electricity purchasing price [€/kWh]
$p_{d,h}$	electricity selling price [€/kWh]
$T_{Flex,t}$	Time flexibility [h]
$P_{Flex,up}$	Load flexibility up [kW]
$P_{Flex,down}$	Load flexibility down [kW]

1. Introduction

During the last decade, electrical mobility received an increase in appeal in response to technological developments, governmental subsidies, and a strict environmental policy for the near future that advocates an environmental and sustainable energy outlook for the near future. Reasons for this rise in popularity is denoted to consumer operational cost efficiency as alternative to conventional vehicles, while exhibiting promising characteristics in decreasing GHG emissions and increasing utilisation of renewable energy resources. Evolving policies resulting from the Dutch Electricity Act changed the organisation of electricity production and distribution due to disintegration of the energy market. Increasing distributed generation facilities of renewable energy appear to be economic competitive and supported by (local) governments. However, due to the stochastic characteristics of wind and solar, energy generation is difficult to predict and hence more complex to control. In addition, growing energy demand resulting from an increase in electric vehicles, electrical housing estate heating, and other modes of electrification might impose operational difficulties in the power system due to increasing peak power and intermittent generation. Therefore, the near future will impose implications to maintain reliable, efficient and secure energy transmission and distribution operations in the power system. The ongoing electrification also opts for cost effective methods to postpone large capital grid investments. This research therefore, aims to aid in local grid congestion by coordination of electric vehicle charging operations through smart-grid and V2G charging strategies. In addition an assessment of the DR capabilities for smart charging and Vehicle-to-Grid from a distribution system operator perspective is elicited to investigate the benefits for smart charging and Vehicle-to-Grid charging.

Due to increasing decentralised generation an increase in electricity consumption, and changing market structure, energy market-clearing mechanisms may no longer fit the developed technology standards and consumer roles [23], [30]. Subsequently, the need for energy market-clearing mechanisms that match decentralised supply with growing demand is in the near future a necessity. There is a requirement for consumer-side demand response - back-up for flexible power generation- to mitigate local grid overload (congestion) and match energy flows in the power system. These requirements are a cause of controlling an increasing amount of distributed generation sources while governing a central control strategy. In contrast, use of Renewable Energy Generation (REG) in distributed local grids has the potential to increase with use of local storage options or controllable consumer consumption - one of the applications of a demand response strategy. However, if development of distributed generation hampers due to slow transition of the top-down control approach this storage potential to stabilise the (local) grid is dissipated. If demand response potential benefits are to be exploited completely, a bottom-up control strategy is more effective.

Future expectations about the growth in the market share of BEVs in the Netherlands are positive and significantly large such that contingent energy demand can impose local distribution grid congestion problems. On the contrary, charging electric vehicles can also be controlled to provide flexibility for DR, which is one of the approaches to alleviate grid congestion. Electric vehicles are potentially an effective local grid DR approach, because of two fundamental characteristics, i.e. the spatial mobility to disperse an energy source over a region any point in time, and the fact that it can store electricity. Furthermore, research pointed out the flexibility BEVs have to defer energy demand due to longer connection time spans than theoretically necessary, and their inherent energy storage capabilities which at later times can be fed back in the grid when necessary. Due to new charging technologies, i.e. smart charging and Vehicle-to-Grid charging, which are presently slowly integrating in the Dutch power system infrastructure, real-time grid information and communication between energy system actors and consumers can be shared to jointly arrive at an effective and efficient management of energy operations and curtailment on a local distribution level.

While these challenges have been put forward rigorously in international literature, only disperse or limited research is available that elicits impact and DR potential of electric vehicles in the local distribution grid of Amsterdam. In addition, system-level comparison between smart charging and V2G is generally not addressed in literature. Therefore, in collaboration with (Al)Liander, the DSO of Amsterdam, this study addresses the notion to solve congestion problems at consumer demand level in Amsterdam for both charging strategies. This work provides the reader with an exploratory assessment on the methods to integrate electric vehicles in a direct demand response approach and statistically analyses patterns in historical charging session data. Furthermore, a model is developed that optimises planning of BEV charging sessions, by adoption of smart charging and Vehicle-to-Grid charging strategies to reduce network peak electricity flows. Furthermore, this study develops a dynamical energy pricing tariff that expresses a charge for energy demand and flexibility as a competitive market price, and assesses the benefits in charging costs of the charging strategies compared to the uncontrolled charging. The motivation of this research is to ameliorate implications of uncontrolled BEV charging effects by aiming to relief grid loads and decrease additional capital expenditures. Therefore, the main research question driven by the need for sustainable and economical efficient energy management for electric vehicles is:

What is the value of demand response management in a Vehicle-to-Grid network and does it provide increased benefits to smart charging for consumers and the distribution system operator in Amsterdam?

Under the principle of consumer self-participation in demand response programs and the motivation of this research, an active participation in the electricity system by consumers contribute to market clearing and could receive remuneration for their provided service, while the power grid simultaneously benefits. Forthcoming sustainable objectives set by the Dutch coalition advocate an economical and operational efficient energy system emphasised by increasing renewable energy generation initiates this research.

Practical relevance

From power generation, transmission and distribution to electricity consumption at consumers, electricity flows in the system become more difficult to predict with growing renewable energy generation and increasing consumption. Due to the uncertainties in predicting the stochastic behaviour of solar and wind, while fossil fuel power generation facilities In addition, increased consumption puts local distributional grids under stress, which consequently can overload local distribution assets, such as low-voltage cables and feeders. A potential result is unreliable, inefficient and costly distribution of electricity to consumers [75, 39]. However, while this problem is currently not apparent for Amsterdam's distribution grid, it is nonetheless a future challenge.

Optimisation of energy consumption and (local) distributed generation is one of the objectives of enabling smart grid technologies. It is an approach to reduce energy losses during production, transmission and distribution, and most importantly in this research, demand during peak hours. A key mechanism described in the literature is an active approach to plan, control, and monitor local energy consumption by performing demand response [19, 64, 66, 75, 84] with electric vehicles. Demand response is considered one of the solutions in a smart grid system to alter or reschedule consumers demand (profiles) incentivised by for example real-time electricity tariffs, to make it match technical grid constraints and generation. For example, in times of high demand, higher electricity prices in response can induce incentives for consumers to temporarily lower electricity use.

The main goals of demand response aim to aid blackouts, reduction of operational costs, increasing efficiency of the whole energy system [17, 75]. It is considered a cost-effective and reliable solution for alteration of demand profiles for both consumers and the power grid.

Theoretical relevance

Existing literature shows insufficient research on prediction of electric vehicle charging demand and the potential for smart charging and V2G charging in Amsterdam by using direct control schemes to coordinate charging of electric vehicles and complying to multiple energy actor's interests. An important note is to attain satisfactory BEV consumer charging service requirements. If the BEV consumers are not ensured with sufficient charging energy, it is likely that either they will not allow their BEV to be used for DR purposes and they may switch from charging point operator (aggregator) [69]. The grid services that can be offered through using V2G enable attractive energy products for the consumer in the Dutch liberalised energy system, but have to comply to other energy system actor's interests as well. It is therefore important to address what actors need to cooperate in the whole power system to enable demand response services to alter consumer loads precisely to distribution grid constraints.

This study therefore aims to fill the knowledge gap by proposing a coordinated information exchange framework that addresses the interactions between power system actors and prosumers necessary to assess the potential of demand response with V2G charging optimisation for the DSO and consumer. Furthermore, BEV charging demand predictions are necessary that are used to to model non-intrusive load levelling further downstream in the distribution grid to aid in congestion problems. The modelling of the demand response charging strategies in Amsterdam fills the knowledge gap towards handling congestion for the DSO. It also provides a new study that addresses the potential to postpone future distribution grid investments by using charging strategies specifically for Amsterdam.

Centralised congestion management

Congestion management is achieved by controlling the charging-discharging rate of electric vehicles. In order to reduce peak power demand, load scheduling decisions have to account for DSO imposed grid constraints, consumer preferences, applied pricing structure and the availability of scheduling flexible and inflexible loads.

Specifically applied for managing energy demand of BEVs in the existing distributional grid, the main goals of demand response are directed to adjust load shapes by shifting demand to off-peaks hours to reduce peak demand. A method to enhance grid reliability and delay investments by reducing (peak) demand in a period of time to maintain electricity flows within technical boundaries. The motivation of this research is to investigate local grid congestion problems in Amsterdam due to increasing BEV electricity consumption, and applies demand response with two different charging modes. It is the first study carried out for Amsterdam that quantifies flexibility of BEVs under their current charging behaviour. It furthermore incorporates a Real-Time pricing scheme that reflects the electricity curtailment prices on an hourly basis of the wholesale day-ahead market, which entail a fair cost of electricity on nearly real-time.

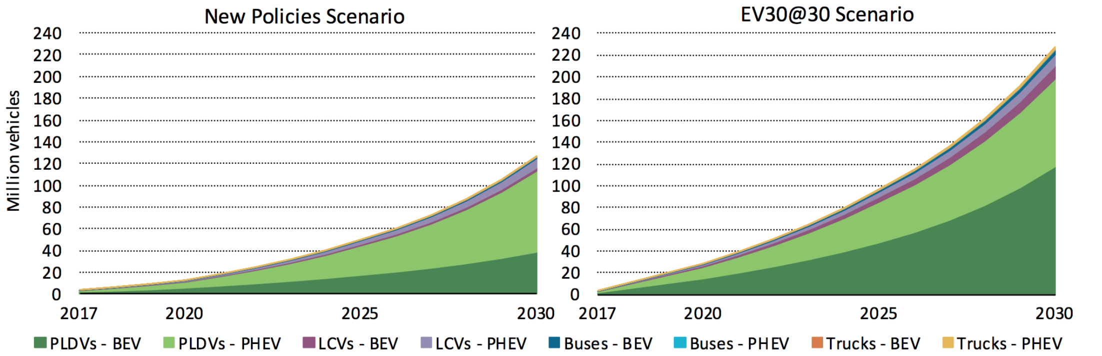
Potential of electric vehicles

While the power system deals with increasing (BEV) consumer demand, local grids in Amsterdam can subsequently endure peak loads jeopardising grid operation [14]. Demand response with BEVs in the light of recent charge point innovations, is considered one of the solutions to improve local grid conditions under increasing demand. DSOs and Liander in specific elicit research in the area of congestion prevention for their local grids in order to suspend additional grid investments by performing demand response with BEVs. Liander's Vehicle-to-Grid pilot project in Amsterdam shows potential to mitigate local congestion by use of electric vehicle demand response, but requires a rigour assessment of its feasibility with real world BEV charging data. The benefits of BEV demand response through Vehicle-to-Grid charging from the DSO perspective are not yet captured for the urban area of Amsterdam in the current BEV penetration scenario and near future scenarios. The next section, therefore, makes assumptions for short-term and long-term scenarios which will be used in the calculation of the charging strategies.

Scenarios

An increasing trend of sold BEVs in the Netherlands is observed while consumers are increasingly supported by a growing accessibility to a charging infrastructure and electric vehicle procurement subsidies amongst others. Moreover, the governments most recent coalition report advocates that every new car sold in the Netherlands should be zero-emission by 2030 at the latest [79]. This entails the necessity for a responsible charging infrastructure development to meet consumer's energy demand. Therefore, in order to foresee any power system related implications of this growing need for BEV energy, short-term and long-term realistic scenarios are investigated that denote future BEV market share penetration. Furthermore, the market share of electric vehicles on the road indirectly relates, next to the total demand, also to the potential BEVs exhibit to participate in charging strategies for demand response. Thus, to derive near future power system demand and potential influence of DR charging strategies on peak power moments through time, the near future outlook for electric vehicle market share is derived. However, the short-term and long-term scenarios are the most extreme expected scenarios for the near future, though in the case study in paragraph 7.4, a varying penetration rate is adopted to provide more insight in the V2G charging strategy's capabilities.

As more countries, such as the Netherlands follow similar environmental objectives as is constituted in the Paris Agreement, the global outlook for penetration growth of BEVs, as is analysed by [29], up to 2030 and their expected number is depicted in figure 1. These numbers can be roughly translated to the expected market share globally of 10% in 2020 and 75% in 2030 of all vehicles on the road.



Notes: PLDVs = passenger light duty vehicles; LCVs = light commercial vehicles; BEVs = battery electric vehicles; PHEV = plug-in hybrid electric vehicles.

Figure 1: Global amount of electric vehicles on the road [29]

The following realistic scenarios are developed according to the figure above and the most recent policy measures advocated in [79]:

- Short-term scenario - 2020: The Dutch Ministry of infrastructure and Water management advocates goals in which 50% of all new passenger cars sold will be driven by electric energy. At least 30% of that percentage will amount to fully electric vehicles [79]. This means contingent changes in electric vehicle penetration over all vehicles in the Netherlands is estimated to be equal to 10% market share in 2025, otherwise similar to approximately 175.000-200.000 BEVs according to [35, 65, 29, 79].
- Long-term scenario - 2030: The Government exerts a mandate to completely stop the sale of cars with internal combustion engines (ICE). All new passenger cars sold will produce zero CO2 emission. The total BEV penetration is estimated to grow to approximately 75% depending on realistic scenarios [29, 16].

1.2. Research objective

The goal of this research is to investigate how BEV charging can aid congestion problems in the local grid of the DSO by considering BEV demand response possibilities utilised in smart charging and Vehicle-to-Grid charging strategies. The aim is to show that within current smart grid technologies electric vehicles can complement instead of burden Amsterdam's local distribution grid by directly altering consumer's consumption habits. Therefore, the strategies' objective is to deliver the maximum amount of required energy to the electric vehicles while ensuring the local grid to operate within technical limits. Within a V2G charging infrastructure, electric vehicles can facilitate on local power system-level demand and supply energy flows by charging during off-peak hours and discharging during peak hours, through which consumers can sell back energy to the grid [17, 75]. The direct load control method is analysed in this research and subsequently modelled due to the recent developments in Dutch institutional frameworks (USEF) that make integration of BEV DR relatively easily [1].

By performing an assessment on the potential benefits of BEV demand response with a market-driven approach, the feasibility of both smart charging and Vehicle-to-Grid charging is investigated. An algorithm is developed that computes the effect of time- and load- shifting of individual charging sessions within their session window, to ascertain mutual benefits to both the DSO and the consumers. Therefore the objectives of this study are:

1. Providing insight in the current power system and the implementation of demand response explicitly for BEVs to derive their present and future role in the local distribution grid of Amsterdam. Subsequently to develop a framework that focuses on a centralised control approach where multiple power system actors participate simultaneously and influence charging schedules for grid operations. In addition, the most important demand response value flows for the DSO are elicited.

2. Time-based assessment on prediction of BEV charging behaviour in Amsterdam for public charging points to quantify temporal trends, potential flexibility to utilise for demand response, and impact on specific feeders throughout Amsterdam for which data is available.

3. To develop a proof-of-concept linear programming model that optimises BEV demand profiles in terms of congestion minimisation and associated charging/discharging costs, for aim to relieve local grid congestion problems.

1.3. Research questions

The following research questions follow logically from the objectives set in this research: *What is the value of demand response management in a Vehicle-to-Grid network and does it provide increased benefits to smart charging for consumers and the distribution system operator in Amsterdam?*

1.3.1. Sub questions

1. How could the distribution power network (in Amsterdam) benefit from application of demand response from BEVs?
2. What are the trends and periodicity that can be distinguished in BEV charging behaviour and how does this relate to impact on the grid and potential time- and load- flexibility to be utilised in demand response?
3. How to optimally schedule BEV charging demand in Amsterdam for smart charging and Vehicle-to-Grid charging strategies to mitigate congestion and minimise grid operational costs for both the distribution system operator and consumer?
4. How much peak load can be deferred by BEV vehicles at the existing distribution grid now and in future scenarios for smart charging and Vehicle-to-Grid charging strategies to tailor grid congestion requirements?

1.4. Methodology

The general approach for this research is carried out in three parts, and also visually depicted in figure 2:

1. A statistical assessment is performed to derive mostly temporal characteristics of current BEV charging behaviour from a real-world data set of recorded charging sessions in Amsterdam.
2. Demand response is modelled by the making use of the scaled BEV charging sessions from the former assessment. The model schedules BEV sessions to lower peak demand periods within their predetermined charging window to minimise local grid congestion and is solved by making use of linear programming.
3. A business value proposition scheme from a DSO perspective is proposed that aims to highlight the logic of an electric vehicle DR business system and the interrelations necessary to create value flows. Accordingly, the widely used business model literature by [54] is adopted. By assessing different near future scenarios with varying penetration rates of BEVs, the value of demand response is computed in terms of the total peak load shed relative to the uncontrolled case, and associated charging costs.

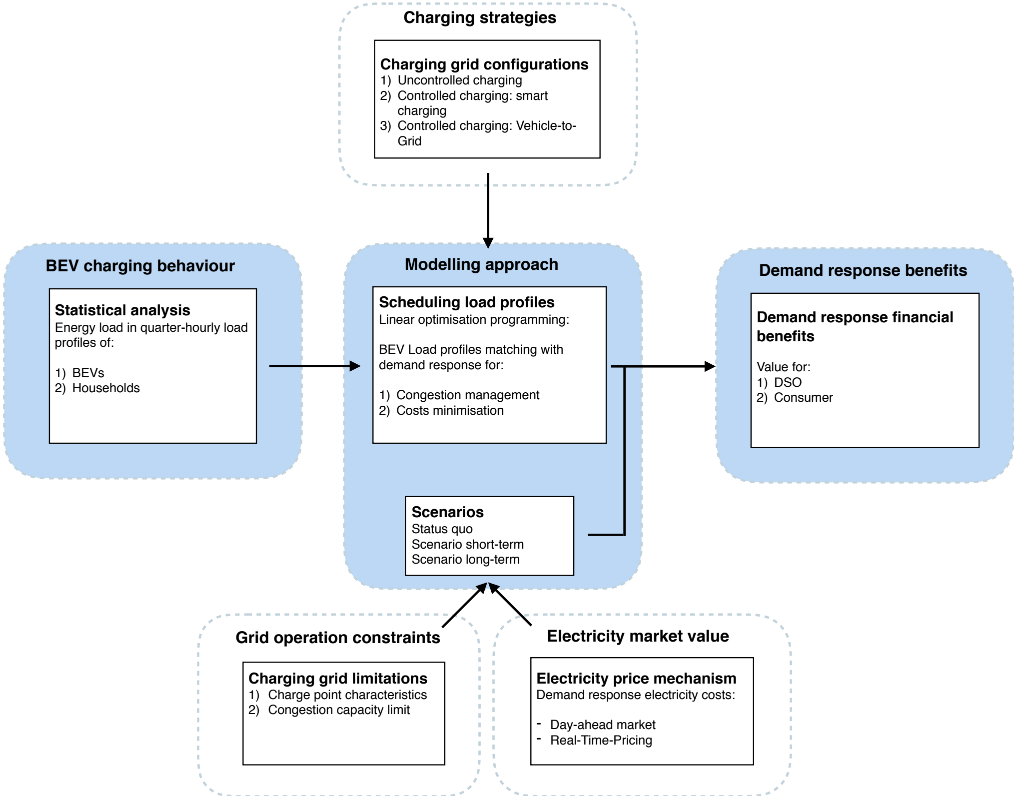


Figure 2: Conceptual framework of the methodology used in this study

Energy demand data mining

Characterising behaviour of BEV charging by analysing recorded charging sessions is necessary to understand their potential in smart grids. To characterise power demand over time, real-world charging sessions are statistically analysed using R-language to transform the data into comprehensible information structures. Its assessment is to derive exploratory information about BEV charging behaviour of individual charging sessions in terms of spatial and temporal measures. The distributions of the most focal session characteristics, i.e. arrival-departure, charging demand, charging time, reveals information regarding the available time- and load-flexibility that is qualitatively described. Furthermore, time series measures are obtained by making use of the statistical models local regression (LOESS) and auto-correlation. These models perform statistical operations on the (univariate) time series data to capture the underlying characteristics such as trend, seasonality, periodicity, and serial correlation.

Modelling approach

Demand response operational control mechanisms can generally be divided into direct (controllable) and indirect (price-based) approaches. Either control method forward similar objectives; lower systems costs and relief the local grid of peak loads. Two of those capabilities are defined in the literature as congestion management and costs minimisation. The applications for BEV demand response in the energy system are diverging, whereas the focus is to investigate direct congestion control for local grids. In paragraph 4.3 a thorough discussion about the control mechanisms is provided, including a proposed information exchange protocol to determine optimal charging schedules. The model expresses prior mentioned objectives in a linear mathematical formulation and uses linear programming to optimise the utilisation of direct load DR for different charging strategies. This approach schedules the demand, i.e. charging-discharging rate, for aggregated charging sessions to avoid peak demand while complying to consumer needs and grid constraints.

Demand response Benefits

A growing importance of business model evaluation for the DSO in the context of intelligent charging, such as smart charging and V2G charging, is deemed essential for large scale adoption of electric vehicles. Therefore, the business model in the perspective of the DSO is conceptualised according to [54] into four essential building blocks (and nine interrelated blocks) that serve to identify the essential model issues of V2G charging. The model is subsequently only partly evaluated on value flows by using an extensive real-world data set and simulated charging strategies.

Benefits for the DSO of the simulated strategies are expressed in the percentage of peak demand that is minimised and the increased number of vehicles that can be connected simultaneously as opposed to uncontrolled charging scenario. The benefits for consumer are computed by making use of a competitive pricing scheme, in which dynamic changing prices throughout the day are derived from the Dutch EPEX Day-ahead energy market. The tariff structure used in this research is called real-time pricing (RTP) that lists the electricity price per hour of the day.

1.5. Research outline

This thesis is organised as follows. Chapter 2 provides this thesis with an explanation of power system developments and electric vehicles to provide background information, where chapter 3 explores the notion of demand response in the current Dutch system. Chapter 4 discusses characteristics of the demand response application for BEVs in the energy system and explores implementation of demand response in a smart grid context by designing a DR protocol for centralised control. Chapter 5 subsequently introduces a general business model for a DSO that is developed in the context of centralised DR for electric vehicles. Next, the focal driver in the business model for DR with BEVs in this research is peak demand minimisation that can be approached by a linear mathematical framework, which is presented in chapter 6. Chapter 7 analyses the effects and impact on the grid of BEV charging and household demand in temporal- and spatial means. Subsequently, this chapter builds forth on the former results and introduces a discussion concerning the results of the simulation. The conclusions will be presented in chapter 8. Finally, future remarks and recommendations for this study can be found in chapter 9.

2. Distributed energy network developments and electric vehicles

Current environmental and political contingencies in the power system of the Netherlands, urge associated actors to adapt and redefine operational structures of the current power system and market. A large-scale adoption of sustainable energy generation is pushed by global environmental awareness about salient effects of greenhouse gasses and incentivised by governmental organisations. The Dutch policy's objective for its energy outlook in the near future aims for an energy generation portfolio that contains at approximately two-thirds renewable generated energy based on a 37% reduction target of greenhouse gas emissions by 2030 in the electricity-transportation sector [15]. As a result an increase is noticed in decentralised renewable production sources by both public and private actors (households). Furthermore, the energy transition is also denoted by a rapid increase in the adoption of electric vehicles. On that account, the institutional arrangements of the Electricity Act of 1998 (see appendix A) is outdated in our decentralising power system that now also allows for private consumer participation in the energy market under the recent EU Energy Efficiency Directive of 2012. Although, emergence of demand response policies is still limited due to amongst others high costs of associated technology and infrastructure.

Therefore, this chapter provides the reader with knowledge about the current operational state of affairs of the Dutch power system. The power system actors and their roles within the electricity sector are briefly described in 2.1 which is essential information leading up to the necessity for demand response. In addition, the current state of affairs for the electric vehicle outlook is provided in 2.2 for a prospective view on the near future.

In the scheme below (3) the governance energy market structure is depicted that originated after the Electricity Act of 1998 (background about the development of regulatory power system arrangements can be read in A). This scheme allows non-discriminatory access to government regulated transmission and distribution by third parties through separation of transmission, distribution and production. Particularly, local distributed energy generation (DEG) is gained access to the market favoured by the Dutch government in an act to offer electricity security and a diversifying portfolio of generation.

Currently, both the transmission system operator (TSO) and the distribution system operator (DSO) are operated under governmental regulation preventing it from becoming a natural monopoly. The distribution System Operator (DSO) came under state regulation after the Electricity Act of 1998, to ensure reliable and secure power delivery from the Transmission System Operator to consumers. These operations must meet requirements for power quality, such as: specific voltages, frequency balance, real and reactive power flows amongst others [34, 76]. However, both generation and retail currently operate under privatised sectors to allow for free competition. Operating in a competitive market, and the fact that from 2004 on households could choose their energy provider, enabled competitive pricing for energy.

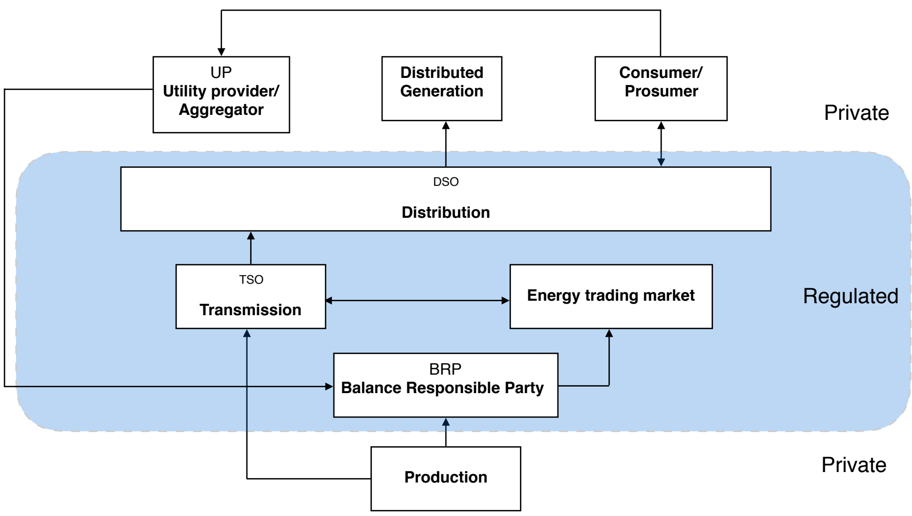


Figure 3: Energy system control structure after Electricity Act of 1998 [3, 36, 42, 50]

In these privatised sectors, a few large commercial and industrial consumers with constant energy demand make contractual agreements with generators, that can extent for years. Smaller-scale consumers in the residential sector for example, operate on the energy market through their utility provider. Generators therefore offer their estimated production of energy on the market for a price per volume. In turn, the balance responsible party (BRP) is tasked to maintain balance in demand and supply of its portfolio by making a balanced energy planning for the TSO on a national level. This planning contains the dispatching amounts, information of production and consumption, and international trade contracts.

In response to rising DEG and REG the vulnerability of a balanced power system increases if the market does not ensure sufficient supply [6]. Multiple benefits are attached to distributed generation such as an increase in zero-emission renewable energy generation. Also, if distributed generation is connected closer to consumption sources, transmission and distribution require significantly reduced investments due to local consumption-generation control [1, 42]. On the contrary, distributed systems also endure larger frequency fluctuations compared to centralised power systems. Therefore, to allow these sources to develop and increase their penetration, capacity mechanisms are frequently considered to cover energy demand when distributed sources are temporarily not sufficiently available [6]. Capacity mechanisms are referred to as policy measures that ensure sufficient investment in generation capacity, which will lead to an efficient energy market operation [6]. These capacity mechanisms, e.g. ancillary services are out of the scope of this research and will therefore be left out. Further downstream at the distribution level, congestion control is one of the methods to alleviate peak demand that may be introduced by unanticipated high demand or low supply. The section below presents a brief description about congestion control.

2.1.1. Congestion Management

If more energy is produced and offered at the energy market than the grid could transport at a certain period, there is a phenomenon called congestion, overload on the distribution/transmission grid. Vice versa, when demand exceeds technical grid constraints congestion also exists. The imposed tasks of the DSO are directed to deliver electricity through a reliable, secure and cost efficient distribution grid to its end-consumers. The above described capacity mechanisms can also be applied further downstream in the distribution grid, by contracting aggregators for example [6]. This mediating actor couples the consumers (prosumers) that provide flexibility for the DSO or BRP.

Deployment of demand response flexibility for congestion management allows the DSO to operate between the capacity constraints of the grid [32]. DR offers significant benefits to the DSO, mainly to reduce both capital- and operating expenditures such as delayed investments in grid reinforcements [34, 50]. As such, these measures also decrease the possibility for a power failure and reduces peak demand. The next section introduces the relevance of electric vehicles both as a means to transportation and the growing impact they may have on the power system by having the possibility to actively cooperate with the DSO to prevent congestion in local grids.

2.2. Market trends of electric vehicles

Technology development of the transport sector to achieve climate goals has become imperative. The automotive transport sector has grown steadily in size the past decades and will keep on growing in the future. Increasing harmful gas emissions impose negative implications related to this increase in mobility demand. While oil resources still fuel the majority of the automotive sector, related emissions make up for 23% of the total global energy related emissions. In addition, the transport sector has not developed the same decline in emissions as other sectors have [1]. As agreed in the Paris agreement global concerns address the importance to decarbonise the transport sector and propose solutions by integrating electric vehicles [72]. Associated GHG emissions dependent on the BEV market share and emissions of power generation. Based on economic and environmental improvement for a low-emission automotive sector, consumers could benefit from innovated infrastructures for alternative energy sources, decreased usage costs, and low emission electric vehicles [26, 63].

The development and uptake of electric vehicles on the road in the Netherlands has risen to a total of 26.000 BEVs and 98.000 Plug-in Hybrid Electric Vehicles (PHEVs) on the road by April 2018. In contrast with the total amount of passenger cars in the Netherlands, 8.373.200, this is a mere 1.5% BEV penetration approximately [9]. Electric vehicles statistics for Amsterdam in [52], show a sharp increase in environmental friendly vehicles since they started collecting data collection in 2013. By the first measurements only 3505 PHEVs and 573 EVs were present, while in 2017 the total compiles to 5242 PHEVs and 5014 EVs, that is 4.4% of the total vehicles in Amsterdam [52]. The increase of the penetration rate of BEVs in general can be accounted to multiple factors. Mostly used measures that explain penetration are environmental objectives and subsidies of governmental organisations, and technological standards. These latter consist of infrastructural developments in charging points, or BEV typical innovations that decrease battery costs, increase range, and enable to charge through different charging technologies [29]

However, this increase in BEV penetration is not without implications for the energy system that endures increasing electricity demand. Estimated global electricity demand from electric vehicles has increased 21% from 2016 to 2017 and is forecasted to increase in the near future under the current (global) policies. In order to accommodate the increasing requirement for energy the charging infrastructure ought to grow contingently to the BEV market share. In the figure below typical values are predicted for the amount of BEVs per electric vehicle supply equipment (charging point) now, and with the EU 2020 target:

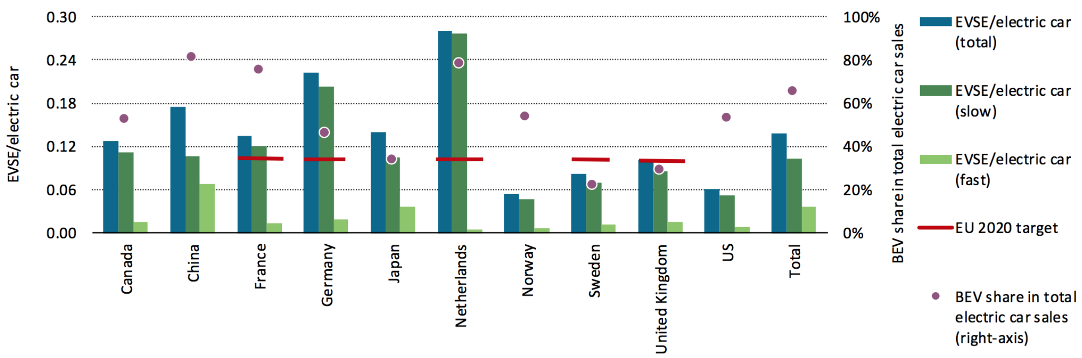


Figure 4: Ratio public charging points per BEV [29]

The EU 2020 target assumes that under the EU AFI Directive, member states have ensured that every charging point at most covers ten BEVs within sufficient proximity. This ratio may be lower than expected because of the faster uptake of BEVs than deployment of charging points, as is now apparent in Norway. If the ratio decreases, the average occupancy may increase that causes an increase in charging demand. This however is probable for the Netherlands as well [23]. According to [23], however, it is reasonable to assume this ratio can be achieved by 2020. Although, if average charging point occupancy increases the potential of electric vehicles to be used as flexibility source decreases. This effect can be explained by the fact that there exists merely flexibility if an electric vehicle exhibits a connection time greater than its theoretical required charging time, which dissipates if average occupancy per charging point increases. More about the current ratio of charging time to connection time can be read in appendix C.

2.2.1. Implications for the distribution grid

Concluding, in response to rising DEG and REG the vulnerability of a balanced power system in-creases if the market does not ensure sufficient supply, which remains a challenge due to the uncertainty in prediction of REG. Furthermore, due to the electrification of households and mobility, congestion overloads can be expected in the future in local distribution grids. Therefore, a possible candidate to control demand from the bottom-up (from the prosumer side) might be a cost efficient solution to aid in congestion problems. Deployment of demand response flexibility for congestion management allows the DSO to operate between the capacity constraints of the grid [34]. DR offers significant benefits to the DSO, mainly to reduce both capital- and operating expenditures such as delayed depreciation of distributional grid assets [36, 52].

3. Demand Response management

Implementation of bottom-up controlled electricity demand and delivery in real time is currently being adopted in the Dutch power system and is usually denoted as: smart grids. The use of smart-grid technologies in the power system introduces opportunities for effective operation of electricity distribution that are pushed by economical and technological, and political pillars. While an increase in DEG, REG, BEVs penetration rate is observed, operation of electricity in distributed grids is significantly affected. Providing reliable electricity supply to consumers will be a challenge in the near future and calls for a requirements of flexible storage while dealing with limiting distribution capacities. One of the promising and cost effective methods enabled by smart grids, is to control electricity demand from the bottom-up, i.e. demand load alteration induced by consumers in respond to prices or exerting direct load control by an aggregator. In very short time spans, this can result in meeting network capacity constraints [75, 17, 22, 64, 76]. A recent application of demand response in the Netherlands incorporating home energy management systems in households that react to energy system operating states, was temporarily implemented as a pilot project to assess the technical and economical viability. The general market framework that couples participating actors reliant on and participating in demand response is the USEF, which is a collaboration between multiple energy market actors. This framework potentially provides a promising starting point to include electric vehicles in DR and is shortly addressed in the last paragraph of this chapter.

In the first two paragraphs of this chapter, paragraph 3.1 reviews the possibilities concerning implementation and the efficacy of general demand response in our current power system through a so-called smart-grid interface. Dynamic pricing tariffs in DR are seen as the engaging market mechanisms to allow distributed electricity control, which are presented in 3.2. Paragraph 3.3 describes the USEF framework, that is potentially a base for demand response with BEVs.

3.1. Energy market developments and the decentralisation paradigm

Private investments in distributed energy resources, renewables specifically, has mainly been driven the past years by governmental support and tax incentives [79]. Benefits of distributed generation is clearly present in a higher implementation of renewables, decreased transmission losses, and lower investments in transmission and distribution networks [64, 19, 33]. While small-scale distributed generation is made accessible for the consumer's public, an increase in active participation of the energy supply side with conventional energy actors will result in improved cost competitiveness for both the consumers and other related actors in the energy market. A change in a consumer participation movement that continues to accelerate by decreasing investment costs for distributed resources [34]. Now that consumers have the possibility to participate in the electricity market as producers and adjust their demand according to prices and generation, new markets and new products emerge such as 'smart-grids' and 'demand side management' [66, 14, 64, 33, 75]. However, it is still believed demand response potential in the EU energy market remains underutilised as of today, while it presents promising applications.

Smart grids

Today's energy decentralisation paradigm calls for the introduction of so-called 'smart grids', an interoperable way to integrate control over electricity consumption and delivery in real-time to interactive and responsive consumers. Smart grids are realised with smart metering installations and ICT communication technologies to be worthwhile for distributed electricity management. In smart grids consumers (prosumers) can modify their demand behaviour according to (price) incentives and thereby realise improvement of electricity reliability and energy-cost efficiency [64]. In practice home energy management systems (HEMS) receive real-time information regarding pricing tariffs (that can be day-ahead, peak power loads) that incentivise efficient and effective use of electricity demand by an aggregator or consumer. The communication standards relevant for DR implementation are not further discussed in this research, but can be found in [26, 64].

As an intro, prior to the review for demand response opportunities specifically tailed for BEVs (in 4.3) the general definition of DR is given below that confers the benefits in the power system. In the context of increasing distributed electricity resources and growing electricity demand, reliable supply requires a back-up for flexible power generation given limited transmission and distribution capacity. A mechanism denoted as demand response ensures changes in consumer's demand patterns by delivering time- and load- flexibility though intermediaries on a local scale to enhance system electricity coordination, and is usually quantified with four parameters [63, 17, 75]:

1. Direction of flexible capacity (upward or downward)
2. Size of capacity
3. Time at which the demand response service is required, and the duration of the provided demand response
4. Location

Usually, demand response is deployed through use of different resource types, such as home energy management systems, storage (BEVs), and distributed generation (renewable sources) to mainly lower peak loads (both demand and supply) in local grids or to provide DR in ancillary services to balance deviation. Consumers can interact through intermediaries known as aggregators that enable offers of flexibility on one of the wholesale electricity markets. On the contrary, consumers can also be approached indirectly through price-mechanisms that induce incentives to lower electricity costs. Participation at the demand side has various benefits in the energy system, the most noteworthy can be summed up to but are not limited to [66, 39, 40]:

- Consumers have the ability to shift loads in periods of peak demands where high prices are charged, to periods of low demand and hence low prices.
- Shifting loads result of aggregated consumption to relieve the local grid from overloads, and reduces overall electricity transportation/distribution costs.
- Minimisation of electricity consumption costs
- Production companies are limited in their market power due to higher system competition.
- Higher exploitation of renewable energy generation by matching demand with generation

Demand response schemes are distinguished by the various motivation methods offered to the participating consumers. Programs include in general two control methods, centralised direct load control (possibly with multi-aggregators) or time-based and incentive-based DR. Depending on the type of customer, the former is often used for private, residential consumers, while the latter suits large industrial consumers but is not limited to that particular type. Methods for centralised approaches comprise of direct load control by directly modifying consumption of consumers [75, 17, 44], to sustain power system reliability.

On the other hand, incentive-based DR programs are driven by power system stress and consequently produce a price signal to consumers in order to restore the system requirements. Therefore, the system stress is correlated to time-varying prices accordingly, and introduces incentives to consumers to lower electricity use. These programs are market-based, as a DSO, aggregator, retailer or other actor can place offers or bids of flexibility on either the wholesale or retail market. In turn, consumers receive remunerations according to their performance of reducing an amount of electricity demand by their retailer beforehand. Consumer participation is promoted by inducing a voluntarily choice to react to price signals for which they can lower their bills. [44]. However, a vision where the consumer is its own manager of energy consumption, or potentially generation, does not necessarily solve grid technical implications that correspond with the interests of energy actors as of today [21]. Therefore, to enable substantial modification in consumption behaviour, compensation schemes are required that integrate dynamic-based electricity tariffs for either consumption or provision of flexibility back into the grid. The following section describes the most frequently used tariff structures in the literature.

3.2. Dynamic demand response pricing

Currently, consumer electricity prices are are set by the utility provider into uniform consumer tariffs and charged the amount of demand that is acquired (€/kWh) and can be distinguished into simple tariff, flat rate tariff, two part tariff, maximum demand tariff, etc. These tariff structures do not reflect a fair pricing mechanism, because they consist of preset prices and do not take account for real-time market related electricity charges [66, 39]. In demand response programs, consumers are considered price-takers who exhibit the means to adjust their demand by being allowed to place bids for energy on the retail market. Mediated by an central aggregator or utility provider. As of today, the UTP charges the consumer through one of the simple tariff structures earlier mentioned, while within a smart grid network prices may need to be coherent to the nature of the costs (time dependent) [33, 34].

On the retail energy market offers and bids for capacity regulation are usually priced in relation to the volume of capacity. This does not ensure fair electricity prices in a system that is denoted by a growing share of renewable energy generation. The results of [66, 34] are in accordance with this statement, where the authors assessed the effectiveness of conventional bids for capacity on the day-ahead market with different characteristics.

The results suggest conventional price-volume bids are more often declined and leave a fraction of the total required energy unsatisfied, compared to demand-shifting bids. The latter is more effective in both cost of consumption and management of unsatisfied demand. Demand shifting is becoming increasingly used to balance low-level demand response by use of households and BEVs, which makes a similar price system particularly suitable.

Several electricity tariffs can be implemented for either control mechanisms, that are responsive to to changes in wholesale electricity prices over time. The most adopted schemes for residential and BEV consumers include:

- Real-time-pricing (RTP) - the utility provider announces the electricity pricing on a quarter-hourly/hourly basis
- Time-of-use (TOU) - preset prices for time periods during the day
- Critical peak pricing (CPP) - utility provider can set higher prices in times of high demand to incentivise load decrease.
- Peak-time rebate PTR - consumers are incetivised to react to on top of their standard tariff, receive a rebate for load reduction they provide.

Two of the most frequent used pricing schemes, time-of-use and real-time-pricing, are elaborated on below. Time-of-use pricing is frequently used to induce a change in consumption patterns for distributional grid purposes, for two apparent reasons. 1) Due to its relative low requirements to implement in the energy market, as usually only at two peak times during the day prices are increased, and 2) because these prices explicitly reflect distributional grid states. The authors of [32] & [44] implement actual TOU schemes that are combined with separate demand and energy charges , although this scheme requires less communication due to its preset prices, but on the contrary does not reflect real-time fair prices, and also possibly discriminates prospective consumers based on varying prices for peak stress in the distribution grid on a specific location and time [75].

On the other hand in a Real-Time-Pricing scheme, electricity prices are based on day-ahead energy prices, usually in hourly periods, multiplied by a specific factor to resemble the variation in price, whereas the average price equals the traditional charged tariffs. These prices best reflect the costs incurred by the UTP/retailer to charge their consumers [33]. This scheme relies on a near real-time communication flow between the consumers and the UP. While some large industrial consumers use this scheme, household consumers are careful in adaptation due to higher risk in price volatility due to a negative tendency to make system related decisions [75]. As opposed to these associated drawbacks, centrally activated DR could diminish these risks and potentially offer fair retail prices in respond to short periodic changes of the wholesale price. That is, the higher the participation, the higher the reduction in costs. For RTP on the day-ahead market, as used in this research, aggregators (consumers) make schedule decisions to procure expected electricity consumption from the retailer according to prices every hour for the next day (max 24h) prior to the energy market closing time, i.e. 12:00. During the auction day, the retailers' bids are matched and the day-ahead price for the predicted consumption is charged. One of the possible drawbacks that occurs due to uncertainty in demand prediction, may lead to deviation in the day-ahead schedules, for which energy is charged based on real time electricity rates. Case studies from multiple literature sources as reviewed in [75] show DR benefits in decreased demand and power losses and a lower peak-to-peak distance by incorporation of this tariff-scheme.

3.3. Demand response facilitating USEF framework

USEF is a collaborative foundation between Liander, Stedin, IBM, ICT Group, ABB, DNV-GL. USEF describes a standard for unlocking the value of energy flexibility by making it a tradeable commodity, delivering a new market structure with associated mechanisms and rules to make flexibility trading effective. These demand response mechanisms allow prosumers to alter their consumption patterns and contribute to actively decrease system demand and help restore grid imbalance during power deviations or congestion [31]. Drivers for participation are dynamical electricity prices and remunerations for load reduction. Control of DR in the USEF role model requires a new actor, called an aggregator, who acts as third party to connect consumers/prosumers into the energy system with either the DSO or BRP to deliver flexibility [23]

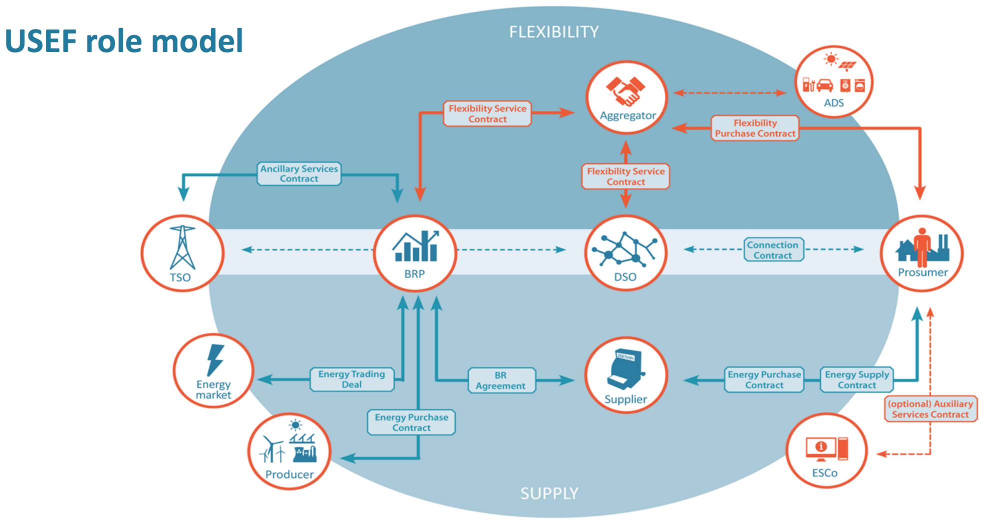


Figure 5: USEF flexibility market structure [74]

The USEF is a mere framework to facilitate the aggregator in selling flexibility from prosumers to DSO/BRP parties for maintaining grid constraints on wholesale and balancing markets. Research by [1] showed how the BRP can use flexibility to trade on the unbalance Day-ahead market to benefit from both a decrease in cost of electricity and restore balance in the power system. For participation in the energy markets and to place capacity bids, rules restrict capacity bids below a threshold, an aggregation of individual consumers is necessary to be in compliance with the market bidding rules. Due to smart grid technologies, active participation from the prosumer side could now be facilitated.

For example, if a demand peak occurs either the DSO or the BRP call to order for flexibility from the aggregator. In this process the aggregator is required to make forecasts for the amount of flexibility that can be offered for bids on the Day-Ahead/Intraday market. Subsequently the aggregator operates under two strategies, 1) by controlling smart appliances in Home Energy Management (HEM) systems according to meet the required power arrangements with DSO/BRP, 2) or by forecasting the expected residential consumption, that inherently has a load forecast error and hence is to be balanced with required flexibility. The forecast error either contributes or opposes flexibility dependent on the sign of the error [31].

Results show that Liander's electricity distribution grid in the municipality of Amsterdam is expected to experience increased congestion at local grid connections, due to increased PV solar generation, BEV penetration and household heat pumps [1]. Liander expects additional grid reinforcement costs, on national level, to be accounted for 2-5% every year up to 2030, and 7% every year from 2030-2050. Furthermore, while demand response curtails grid overloads, gross capital investments can save up to €700M up to 2050. However, a thorough investigation where electric vehicles are introduced to participate in this framework by utilising new charging technology standards is not performed, hence the following chapter complements with approaches for BEV integration.

3.4. Implications for demand response management

Application of demand response in a distribution network is currently one of the methods to increase economic efficiency and effectivenes of grid operational controls. The trend towards using hourly pricing tariffs can incentivise the BEV owner's demand request to be shifted towards hours with low electricity prices and hence also less energy demand. Therefore, to enable substantial modification in consumption behaviour, compensation schemes are required that integrate dynamic-based electricity tariffs for either consumption or provision of flexibility back into the grid. The most focal benefits o fDR that potentially arise in the distributional power system include:

- Shifting loads result of aggregated consumption to relieve the local grid from overloads, and reduces overall electricity transportation/distribution costs for the DSO
- Minimisation of electricity consumption costs for the consumer
- Higher exploitation of renewable energy generation by matching demand with generation

The recent developed USEF energy market framework allows for application of demand response by making flexibility a tradeable commodity on energy markets. Furthermore, while demand response curtails grid overloads, gross capital investments in local distribution grids can save up to €700M up to 2050 for Liander's network. Thus, this research focusses on a (multi-aggregator) centralised approach of directly controlling and optimising the consumers' energy demand by introducing a planning protocol that may be integrated in the USEF framework.

4. Demand response with smart charging and V2G charging in local grids

Demand response resource types are, broadly speaking, control schemes that either manage energy consumption by delay, or use energy storage devices to temporarily capture capacity. The battery of a BEV is essentially a flexible storage unit, and although its use is transportation, the battery can be utilised for ancillary grid functions. The inherent potential of zero-emission vehicles as an alternative to Internal Combustion Engine (ICE) vehicles can only be fully ensured if BEVs are charged with REG resources, having a well-to-wheel emission of zero. However, BEV energy demand may be out of synchronisation with REG generation unable to use this generated energy decreasing its economical benefits. In addition, when BEV market share grows an increase in energy demand is expected that may potentially enlarge peak loads during existing peak demand hours. [13] predicted in their real-time modelling approach, under an increase of BEV penetration from 16% to 63%, significant voltage deviations, high power losses and expensive costs in ancillary generation. If as a consequence capacity mechanisms have to be used to cover the demand that is usually generated by fossil-fuel based units, this potential is waisted [6]. Additionally downstream in the distribution grid, capital asset expenditures require an expansion in this situations as well.

The structure of this chapter therefore serves as a constructive review that describes the approach to incorporate a management control strategy in which electric vehicles play a role in providing grid operational aid. After the introduction in paragraph 4.1, a review is provided that highlights the distinction in demand forecasting methods for different classes of data, for which each class may serve a specific application in the energy system. Paragraph 4.3 addresses DR control methods and gives the information exchange protocol between the prosumer, aggregator, and DSO for a centralised DR approach to unlock flexibility from electric vehicles.

4.1. Electric vehicle demand management

Managing growing BEV energy demand can significantly reduce grid investments and additional generation capacity, as well as an increase of REG. Currently as a result of the EU Energy Efficiency Directive of 2012, an institutional base is presented for development initiatives of demand response in Europe [17]. Technical and regulatory standards now enable demand response mechanisms to curtail flexibility on the wholesale or retail energy market and allow for prosumer participation for which its purpose is to serve economically efficient and environmental friendly operational grid measures. Demand response also serves as a coupling method between wholesale and retail markets (background about energy markets is described in B) that allows fair electricity pricing in a competitive system. As described in the previous paragraph (3.1) energy market actors developed a framework to facilitate DR between the prosumer and DSO/BRP that will serve as a basis for the control and business model of electric vehicles demand response. Practically, DR in this research is used to reduce congestion in distribution grids by moving part of BEV energy demand from (evening) peaks to the afternoon or night. By achieving these measures potential benefits arise, including [29]:

- Optimising local grid assets by increasing the utilisation factor, and thereby maximise asset efficiency and subsequently decrease costs, which is beneficial for the DSO
- Reduce the need for expensive additional generation capacity and to increase use of renewable energy, by spreading the charging loads throughout the day while price arbitrage opportunities can take place. This is both beneficial for the BRP, prosumer and aggregator.

The charging technology standards, briefly introduced below, make application of DR possible. However, in order to operationalise DR with BEVs it is imperative to know the charging demand characteristics to assess impact on the power system. The next paragraph reviews different models used in the literature that assess and predict charging demand.

4.1.1. Charging technology characteristics

The Dutch Ministry of Economy, Climate, and Infrastructure of the Netherlands has addressed budgetary outlay of 7.2 million Euro the past five years to stimulate development and uptake of charging infrastructure in the Netherlands [61]. The amount of charging points is increasing at a steady rate up to 17.500 public and 17.400 semi-public charging points in 2018. The amount of private charging points is estimated to be 84.000. This research applies a case study to analyse BEV charging behaviour for the municipality of Amsterdam for which a historic data set of charging sessions from 1832 charging points is recorded. In contrast Amsterdam currently resides 3761 public and semi-public charging points. In the upcoming near future, technical standards develop to potentially become a mature and economical part of the infrastructure, increasing the importance to direct research towards implementation of smart-charging or V2G charging points.

In Europe the charging standard IEC 62196 is adopted, that proposes three different modes of charging, to be distinguished into slow-fast charging and with-without communication availability to control the battery management and charging rate. The charging strategies considered in this research are:

- *Regular uncontrolled charging*
  Uncontrollable charging is the strategy generally considered as the standard, where charging occurs immediately when BEVs connect to the charging point until the battery reached its requested capacity while the charging rate is constant and depends on the charging point class.
- *Smart-charging*
  Smart charging is a unilateral charging strategy in which there is an indirect- or direct control with the BEV prosumer possible to schedule consumption to current local grid and electricity cost parameters. This is considered an unidirectional charging strategy, where regulation up- & down can be enabled by either increasing or decreasing the charging rate [47]. Regulation up- & down refers to the under- or over-estimation of energy supply respectively, inverted reciprocal to the demand.
- *Vehicle-to-Grid*
  Vehicle-to-Grid charging strategy is similar to smart charging but additionally involves bilateral power flow between the BEVs and charging points [26]. The efficacy of V2G is expected to increase the provision of flexibility to the grid in charging-discharging as compared to unidirectional charging. With V2G more percentage of load shed can be realised than with smart charging, because peak energy flows can not only be re-scheduled, but also be decreased by discharging [47].

4.2. Classification of models for BEV charging behaviour and consumption pattern forecasting

Understanding BEV charging behaviour in terms of user's energy demand in an urban charging infrastructure is imperative to assess impact on a network level. Combined electricity consumption behaviour by residents at certain periods throughout the day that coincides with BEV consumption can temporarily lead to a shortage of distribution capacity due to local peak demands [41, 2, 82, 64]. It is found in [22] that depending on the charge point output, a BEV usually has a demand more than twice as large as a residential demand. The near future scenario about the electrification of the society imposes realistic challenges to manage a significant increase in energy demand. The importance of forecasting future electricity consumption of BEVs cannot be stressed enough although the implications on the local distribution grid are not explicitly apparent currently. Therefore, the following section of this paragraph shortly explores forecasting techniques for BEV demand with different classes of data and different purposes.

Charging session forecasting techniques

Literature about works of demand response for electric vehicles exists in abundance in which many of those works address mathematical modelling approaches to predict electric vehicles use patterns based on influential variables such as connection time, charging point occupancy, charging demand economic factors etc. Literature is roughly divided into deterministic and stochastic load forecasting [5, 26] to either design long-term policy measures or use short-term forecasts for grid operational measures. Because the variables exhibit stochastic randomness, to be able to fully capture and forecast the charging behaviour and generate energy consumption profiles, most commonly applied techniques are classified in the categories statistical and artificial intelligence based modelling, dependent on the applications in the energy system and the time window for which the forecast application serves[33]:

- Statistical based modelling: Multiple regression analysis, Auto Regressive, Moving average, State space, Kahlman filter, exponential smoothing
- Stochastic time series: Monte Carlo, Markov chain
- Time series decomposition, auto-correlation
- Artificial intelligence: Artificial Neural Network, fuzzy logic
- Heuristic optimisation based on knowledge

The distinction in performance of modelling of the two categories lies between the formulation of the mathematical equations. For statistical modelling, mathematical equations are generally linear and tend to neglect the natural non-linearity of the data, whereas artificial intelligence based models have the ability to deal with this non-linearity and predict with more accuracy energy demand requirements [82, 30, 12, 30].

Annual long-term forecasting models for policy measures

Early mathematical models that assess charging behaviour impact on the grid for different deployment scenarios, can be summarised by annual vehicle use and car ownership of conventional ICE vehicles. Usually its application lies in development of long-term policy measures, such as GHG emmission outlook and energy security analyses. Unfortunately, metropolitan travel survey data do not capture the difference in effect of charging demand on infrastructural factors and travel patterns specifically for BEVs [11]. Assuming travel patterns remain unchanged raises concerns about the applicability in describing BEV charging behaviour due to the fact that BEVs have range limitations and are confined in limited charging possibilities [11, 82]. However, an increasing amount of real-world electric mobility data enables a classification of forecasting methods along a finer grained time dimension resulting in accurate predictions.

Short-period demand forecasting models

The purpose of short-period models is to forecast peak loads or congestion phenomena. This is key in the determination for operation and loads planning in a power system for utility providers or grid operators. Short period modelling uses smaller time resolution data of for example daily activity travel schedules and daily mileage driven (of conventional vehicles) which are better usable constructs to assess demand behaviour. With these assessments, demand behaviour prediction can be used for operational tasks and planning of energy in a power system[33]. However, this kind of statistics data about conventional travel demand for arrival times and distance travelled, strongly limits the accuracy to model BEV use for operational grid planning tools due to inaccurate data that don't resemble usage behaviour of electric vehicles. In the work of [44] for example, the authors use arrival time statistics of conventional vehicles and translate those parameters to charging tendencies of individual vehicles. Although they fit a regression model to the distributions of correlated variables, their accuracy in representative prediction of BEV use lacks replicability and rigor because averaged values for charging demand are used. This is a natural consequence in using fixed or preset factors for charging demand, charging output and battery capacity.

Currently, due to the availability of a growing amount of short-period BEV charging session data in urban areas, attributed with temporal-spatial measures, BEV patterns can be explicitly derived from individual charging sessions that truly capture the characteristics [62, 56]. These finer grained period models exhibit information to forecast BEV's associated load demand on local grid level and allow expansion to network level.

Other methods model electric vehicle demand describing the sequence of states a BEV resides in, for which the probability of the current state depends solely on the previous state. A state can be defined by driving, idling, or charging. Assumed that probability of every state is based on SOC, average driving distance. For example, the studies of [55, 82, 31, 5] model a probabilistic decision making process (e.g. Markov chain) by prediting when a BEV should be charged. In some situations, the arrival SOC may be high enough and the charging session periodicity frequent such that planning of charging demand is facilitated by making the decision not to charge. According the parameters of SOC and future trip predictions, the current level of SOC ought to suffice for these trips. Usually, the data used is based on non-gaussian multivariate distributions, describing the correlation between the charging session variables. Despite the ability to generate consistent BEV patterns over long time periods, these models neglect the state responsiveness to dynamic electricity tariffs and other non-predetermined behaviour. Thus limiting in implementation for grid operational energy planning.

By using real-world charging session data most research converges to solve the following general planning challenges for operators that manage energy demand[12, 67, 64]:

- Assess if current electricity generation is sufficient to provide for the additional BEV demand
- Evaluate marginal electricity costs for smart charging/V2G charging BEV demand for various ancillary services
- Assess if growing demand due to increasing BEV penetration can create congestion and voltage deviations at local grids
- Evaluate the benefits of DR by prediction of BEV charging profiles

4.3. Electric vehicle flexibility control strategies

Different grid operational aiding tasks can be enabled through either central or decentralised energy scheduling approaches, each with its inherent pros and cons. Approaches are generally distinguished in two classes of optimisation goals, i.e. 1) maximising (operational) benefits of the grid-side, and 2) maximising charging cost benefits at the BEV-side [47]. DR flexibility can only be enabled by models that assess decisions tools concerning management of energy in a local distribution grid. Therefore, the scheduling problem of charging sessions is modelled as an optimisation problem where the formulation of objective functions depend on a threefold of demand response model characteristics. That is, 1) prosumer interaction, 2) optimisation method, and 3) time-scale [19].
The first characteristic describes the prosumer interaction and is either decentralised, meaning individual prosumer response without coordination, or centralised where cooperative prosumers are controlled by a multi-aggregator. The second characteristic differentiates between deterministic approaches that assume the current prosumer state depends only on the previous state, and stochastic approaches that consider real-world phenomena to be stochastic of nature when the samples are large enough [4]. The third and last characteristic relates to the time-scale required for the optimisation and is either day-ahead or real time.

As both grid-side and BEV-side objectives are modelled in this research, the next section in the paragraph below is a brief review on the different control approaches to manage charging of BEVs for grid operational tasks and the abstraction into mathematical modelling required to describe and manage aforementioned goals.

Charging control models

The most frequently adopted optimisation models or algorithms in current literature that are capable of coordinated BEV charging in a distribution network are summarised below and are ranked according to increasing computation time, problem complexity, and problem convexity (optimal/sub-optimal solutions).

- (Integer) linear programming
- Markov chain
- Mixed integer programming (fast computation time, global optimum)
- Non/-/convex optimisation problem (able to handle complex systems)
- Quadratic programming
- Non-linear programming (large computation time)
- Heuristic neural network models
- Game theory (interaction between different sources of DR in coordinated applications)
- Multi-agent systems

The most focal challenges surrounding planning of energy requirements of the prosumers can be distinguished into the following terms: *interoperability, scalability, behaviour, security and privacy,* [33]. While the scope of this research is limited to the first three challenges, a study towards security and privacy is therefore not included. Dependent on the models mentioned above and the control structure of DR, each approach scores differently on these terms. The section below reviews the pros and cons of the control method to enable flexibility at BEVs.

More research effort is currently dedicated to tackle distribution grid related problems where DR approaches for electric vehicles can roughly be distinguished in centralised and decentralised optimisation strategies [86, 44, 19, 22], as been shortly introduced in the previous chapter. Main objectives in DR at the grid-side comprise of minimising costs of supply, enhance economical- and technical distribution of grid operations and maximising integration of thermal-, wind-, & solar plants to accommodate for stochastic generation uncertainty and thereby enhance utilised renewable generated energy. On the prosumer-side of the market, participation in DR can be motivated by objectives that aim for a minimisation of charging costs, increasing user convenience and minimising GHG emissions [38, 37, 59, 8, 25, 47].

In decentralised planning, [86] proposed a decentralised random access framework in which smart agents reschedule their own charging independently, according to information about grid and costs status received from the DSO (to aid congestion). Although they claim their model does not need accurate predictions on BEV load or arrival time, it is complex to extend its scale for high BEV penetration, due to the lack of a priori prosumer and distribution grid parameters. It may be that decentralised control decreases the privacy concerns prosumers have by letting their BEV charging be controlled by an aggregator, but prosumers are currently not actively engaged in the smart grid [21, 47].

A centralised control as opposed to decentralised control requires high level control of decisions for which low level (prosumers) demand is explicitly in the hands of the central actor. Subsequently, this leaves the central actor with the choice to provide the flexibility for a specific purpose and actor in the energy system. While those purposes can roughly be distinguished into up-stream (high-voltage network, TSO) or down-stream (low-voltage network, DSO) services, either incurred provision of DR can be in conflict with operational tasks of the different actors in power system. Hence, a coordination strategy that incorporates multi-objectives is required if demand response is executed, because some V2G services can have conflicting interests [26, 70]. A conflict arises when two actors need the flexible load capabilities from the BEV for conflicting services, such as frequency control and peak shaving/shifting which can cause implications in a part of the power system [70]. A prioritised service list will be required when dealing with multiple actors, but is not used in this research.

Not only conflicting services must meet a trade-off prior to DR, a fair compensation scheme ideally needs to describe a maximisation of benefits from both the system operators and prosumers perspective [44]. While prosumers adopt solely cost saving strategies, as potential consequence the shifted demand may define new energy demand peaks during times with low prices. However, only a few literature works developed models that consider the optimisation of both system operators load deviation and prosumers charging costs simultaneously. The works of [44, 75, 81] stress the importance of modelling the relations between the actors' strategies to optimise a balanced system that provides a Pareto optimal solution. The model developed in [44] opts for such an approach in which the authors found a global system optimum that satisfies both the prosumer, aggregator and DSO. They formulate a Mixed Integer Linear (MILP) problem where weights are assigned to conceptualise ranks and create mutual benefits. The authors simulate the relations between strategies for each participating actors. Although this algorithm suggests a distribution grid optimisation simultaneously with driver needs (costs effective) by scheduling charging loads, this model omits uncertain conditions in the power system such as congestion network constraints.

In short, the authors of the work [60] explicitly compared a local decentralised and centralised charging strategy in distribution networks and found that local control can accommodate a larger penetration of BEVs on a feeder while requiring a smaller communication infrastructure, but suffers to keep demand within distribution grid constraints. Whereas with a centralised strategy, network constraints can be retained on an acceptable level as a more accurate schedule can be produced due to the information of both BEVs and the grid. Due to the direction of this research, in which optimising energy demand within distribution grid constraints as the most important objective, a centralised control charging is modelled.

4.4. Information exchange scheme for centralised load control

The optimisation problem of V2G charging in an existing institutional framework as of today, requires aside from energy exchange also vast amounts of information exchange between the BEV, aggregator (CPOc), supplier, and the DSO. An already established communication infrastructure allows two way information exchange to offer a service related DR V2G mechanism, the actual charging demand and allocated billing according to the electricity tariff-scheme. However, research has shown signs of integration complexity in using a decentralised control for DR that can mainly be addressed by the dependency on prosumer participation and inherent uncertainty in predicting the stochastic nature of driving and charging [60, 26, 75]. Hence, in compliance with current system innovation in the energy system (USEF), as a responsible, easy to integrate, and scalable approach, this research adopts a direct control approach for multi-aggregators to trade energy an the USEF flexibility market, but differs slightly in the task protocol. This section, therefore, describes an information exchange protocol to enable DR from an aggregator perspective.

One of the direct control (centralised) methods of demand response is through aggregation of BEVs by aggregators, to perform adequate operational management and the ability to integrate various grid-providing services. The process to manage energy demand between these actors is expressed by the joint service and information relationship between the prosumer, aggregator, and DSO. The successive steps and relationships are exemplified in the scheme below. The scheme also shows the tasks that need to be executed in the process of demand response within the time window where flexibility from BEVs is required to aid in congestion control by influencing charging schedules:

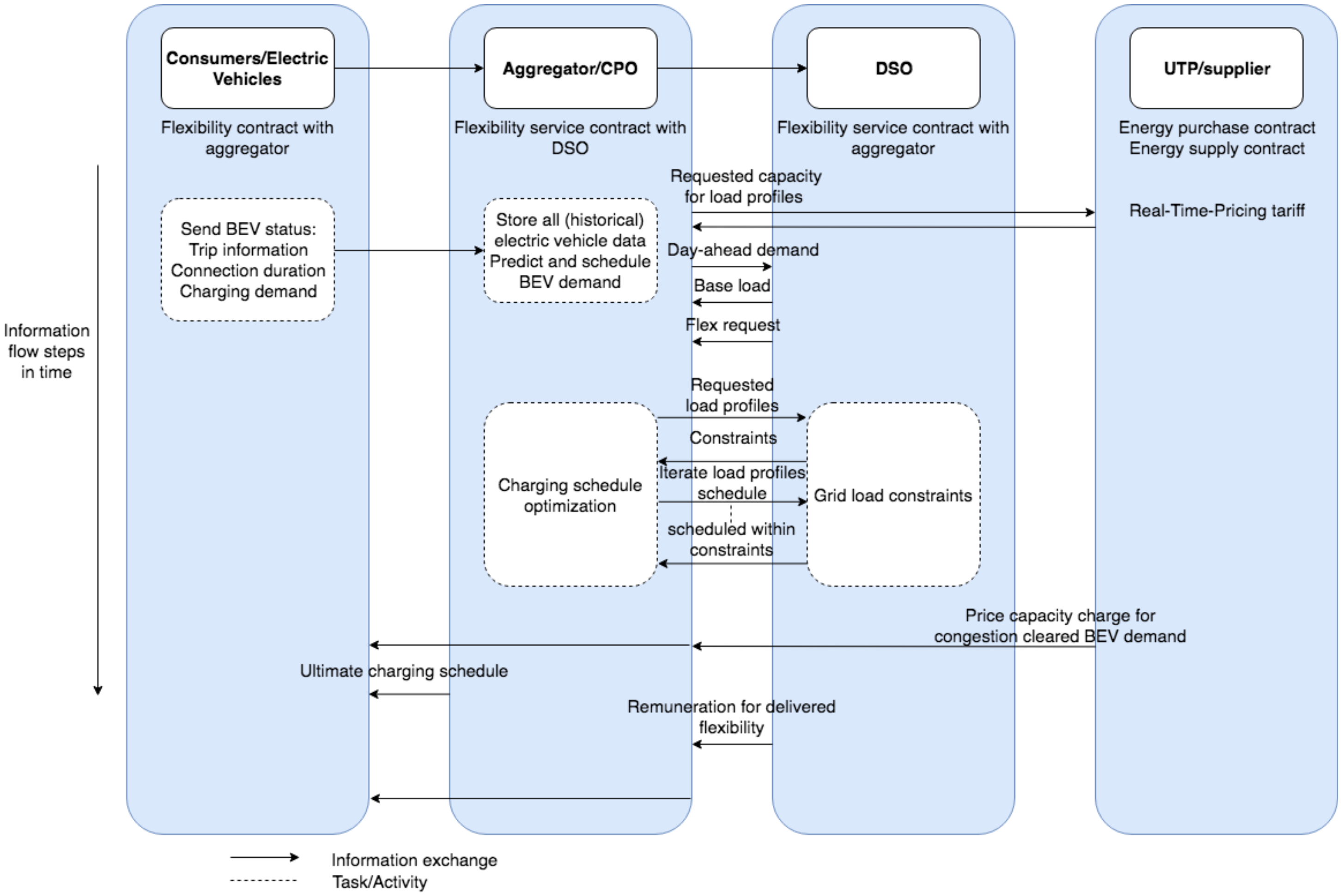


Figure 6: Direct load control

- *Data collection*
  In practice, the BEV user sends information to the aggregator regarding the charging demand, initial SOC, required SOC and departure time when it is connected to the grid at a certain location at the beginning of each hour. To design the appropriate charging schedule, the aggregator sends a request for information about grid base loads and feeder asset load boundaries to the DSO and requires day-ahead electricity pricing information from the supplier.

- *Electric vehicle demand prediction*
  The scheduling optimisation problem requires additionally a prediction of future BEV energy demand such that flexibility can be exploited and planned a priori before arrival of new BEVs. According to historical data and current connected BEVs, charging behaviour is predicted that includes the variables mentioned above. This increases the operational planning capabilities of demand such that the aggregator can optimise associated charging costs a priori according to the hourly day-ahead prices and takes prospective BEV demand into account [32]. After day-ahead demand predictions are made, this schedule is sent to the DSO, which subsequently assesses the expected periods for congestion. In addition for every successive, newly connected BEV, the charging point extracts the unknown BEV energy demand characteristics, initial SOC and updates the DSO with the energy usage to compute the potential flexibility capacity.

- *Charging schedule optimisation*
  The aggregator is responsible for charging all individual BEVs while it is the responsibility of the DSO for retaining efficient and reliable grid operation within the system constraints. Every beginning of each hour, the aggregator optimises BEV charging schedules to minimise peak loads in the local grid - based on the base load input of the DSO - and respects BEV prosumers' energy needs while simultaneously minimising the charging associated energy costs for both the prosumer and CPO until an equilibrium is achieved. The details of each optimisation step are as follows:

  1. The first step in this process requires an optimisation problem that uses the supplier's day-ahead pricing information to minimise charging costs by scheduling charging rates of all connected BEVs while taking into account future predicted BEV demand. Hence, chapter 7 assesses a prediction of BEV demand behaviour. Although, actual price minimisation is not considered in this research, the resulting electricity costs in the charging schedule optimisation are analysed for the simulated case studies by using the RTP tariff scheme.

2. Moreover, the second step includes sending these BEV demand profiles to the DSO that performs a check whether the determined BEV profiles and it's own baseline demand prediction fall within the grid constraints. If by newly connected BEVs or an unanticipated high base load the grid constraints are not in compliance with the limits, the DSO can offer a request for flexibility. If accepted by the aggregator, this task is the second optimisation that iterates until the scheduled profiles are in accordance with the grid constraints and simultaneously uses 'cheap' hours for charging/discharging as the second constraint. Meaning that the aggregator determines the charging/discharging rates to fulfil the flexibility offer for maintaining grid operations, for which it receives monetary compensation from the DSO and uses day-ahead pricing to lower associated charging costs.

3. For the last step, the aggregator submits hourly electricity offers to in accordance with their BEV demand predictions and sends this information to the supplier. Next, for each receding hour the supplier receives the demand request from the aggregator and charges energy costs equal to the marginal electricity price on the energy market. Finally, the resulting charging schedules are communicated back to the BEV. In addition this reduces the congestion that is a result of misalignment in the energy curtailed by the aggregator from the supplier and the actual consumed energy. If the aggregator remains with flexibility after complying to the DSO's requirements, it can be offered to the BRP or TSO for balancing services. [47, 1].

In conclusion, this direct load control approach is for the most part complementary to the operations expected from an aggregator in the context of the USEF framework. The difference in this control protocol is the aggregator's electricity pricing information request from the supplier. Although, the aggregator is decoupled from actual energy supply that is governed by the UTP/supplier, a day-ahead pricing request allows for cost minimisation for the aggregator where it balances the difference in variation of its predicted- and actual demand schedule. According to this "shared" actor objective optimisation, the value of demand response shall be shared between the prosumer, aggregator and DSO which mainly serves the purpose to delay expansion of the distribution grid and minimise electricity costs. The next chapter introduces the business model from a DSO perspective that conveys the possible value of V2G charging.

4.5. Implications for model design

Potential economic and power system impacts of demand response integration for BEVs is studied for various applications in the energy system. Whether controlled charging and discharging strategies are applied to provide ancillary balance power further upstream in the energy system (to improve REG integration), or applied to aid congestion on a local level, all strategies are beneficiary to the grid's operation and the prosumer.

- Reliability, stability, security of electricity in decentralised grids are all grid operational objectives in which demand response is an effective method to realise these objectives.
- Thus, to accurately analyse urban BEV charging demand behaviour, reliability and consistency of prediction increases if large-scale data sets are used for analysis of typical trends in energy demand.
- Application of BEV flexibility in demand response schemes is highly dependent on the specific task it will be utilised for, and hence its value proposition is diverging for different actors in the energy system, which can be dealt with by value-stacking.
- In addition, if active prosumer participation in the energy system remains a reverse salient, indirect or incentive price-based schemes could hamper the full utilisation of the flexibility BEVs potentially have. Therefore, a centralised direct load control method is currently in the Dutch smart grid environment easy to integrate together with a RTP pricing scheme to reflect fair electricity tariffs.
- The various options in strategies to provide demand response in different parts of the power system induce potential conflicting interests between energy actors (i.e. TSO, DSO, CPO, prosumer). Within a given conflicting situation demand response should be activated for operations with higher priority. However, this research limits the scope to applications of BEV demand response for separate system operator congestion prevention and charging cost minimisation, and does not further elaborate on conflicting situations.
- Various studies developed operational control models of DR with BEVs for different actors in the energy system with balanced objectives. Focussing on the gap between multiple interests of system operators and BEV prosumers simultaneously, ensures a mutually beneficial equilibrium. Different actor states are compared and their strategies related by weighting functions. Because this falls out of the scope of this study, further research on concerning this subject is necessary.

5. Demand response smart charging and V2G charging economics

Management of charging processes of electric vehicles is generally considered to be a forthcoming and promising method in support of grid operations for a distributed power system. The economical value for provision of demand response for such operations - which are diverging for different required grid services of the power system - is for consumers and aggregators market driven while system operators are confined to regulated non-commercial purposes, and hence twofold in its benefits. Remuneration for grid-stabilising flexibility is paid by the DSO and ought to be shared among the consumers and the aggregators that control the dispatched flexibility. Simultaneously, the aggregator communicates with the supplier to receive hourly day-ahead electricity prices to further reduce charging costs by designing an economically efficient charging schedule. In the Dutch privatised energy sector, costs for electricity charges, network charges and taxes are separately defined and, therefore, induce multiple objectives.

A business value proposition scheme from a DSO perspective is proposed that aims to highlight the logic of an electric vehicle DR business system and the interrelations necessary to create value behind this former mentioned process. The value of DR ought to be divided among the participation of each actor in the supply chain. The following section in this chapter is dedicated to explain the business case surrounding integration of a V2G infrastructure, and the structure how value is added by incorporating a bilateral charging service to provide aid in grid congestion.

5.1. Business case for the Distribution System Operator

Recent investments in charging infrastructure, currently initiated by municipality of Amsterdam, is largely focused on design of public charging programmes, by realising investment in new charging technology standards to maximise prosumer contribution to demand response. The various DR strategies mentioned in 4.3 comment the promising benefits in monetary compensations for prospective prosumers that allow electric vehicles to be used as a buffer and thereby decrease peak load and supply in local grid through new charging standards, i.e. smart charging, V2G, and tariff-schemes. After all, vehicles are merely used for a small proportion of the day, and if connected to a charging point poses the excellent capability to return energy to the grid when it is ought to be necessary.

This paragraph elicits a business model analysis that delivers a pictorial scheme of all building model elements that constitute costs and benefits for a V2G charging infrastructure from a DSO perspective. The value flows in the schematic overview presented in paragraph 5.1 are assessed on a preliminary level in 7.4 due to uncertainties concerning the underdeveloped market conditions for DR and management of compensation schemes that come in a large variety with different cost and revenue structures [17, 8]. Remuneration to prosumers in return for delivered flexibility can be approached by adopting a variety of value flows, i.e. different contractual agreements or tariff mechanisms.

While it is assumed that prosumers are price-takers, participation in DR is significantly dependent on charging costs, and therefore imposes uncertainties on the outcome of the added value. These assumptions result in a large variance of the expected benefits. In addition, it can be argued that the aggregator as a DR enabling actor deals with so-called value-stacking challenge, where it may need to propose a trade-off between selling flexibility for differing grid operational tasks. The aggregator is a profit maximising entity as it operates in a competitive market and as a result chooses to deliver flexibility to the actor that compensates the most. Subsequently, the DSO develops a potential competitive advantage to the supplier by forming strategic alliances with the aggregator, because it has the ability to adapt prices in temporal and spatial means [68]. Whenever congestion is expected, the utility provider charges high prices just because energy demand is high. However, if the DSO during these peak moments requests an offer for flexibility, the aggregator shifts and schedules energy demand to unlock flexibility by coordination and information exchange of the DSO and supplier. The incurred costs of energy demand that is subsequently not purchased from the supplier means less revenue, while the aggregator becomes a supplier due to its offerings of electricity to the DSO. Interactions between these power system actors becomes unavoidable, and remains a subject for future research. The value of DR should be divided along the complete value chain to all participating actors in order to avoid unwanted value asymmetry. Despite a growing literature on business models that investigate V2G opportunities, the main focus for the business cases consider V2G charging for applications in the regulation market and not so much on the subject of congestion flexibility from the perspective of the DSO [8].

5.2. Vehicle-to-Grid business model

The widely applied business model ontology of [54]; Osterwalder, serves the purpose to characterise future performance indicators of a business' success, by dissecting all relevant elements of a business case, i.e. V2G system relations, components and participating actors in electric vehicle demand response. These elements are called building blocks in [54] where the author uses as an all encompassing business characterisation that describes a business case according to four essential and nine smaller interrelated building blocks (depicted in figure 7). These building blocks serve the purpose to measure and monitor key performance indicators beyond merely financial indicators. In the section below, each of these nine elements are described. Furthermore, the business model is financially evaluated for prosumers in paragraph 7.4, and the opportunity costs of Captial expenditure (CAPEX) for investment on distribution grid assets are considered for the DSO. Modelling of multiple future scenarios with different local grid peak demands allow to inspect whether the scheduled charging strategies allow more vehicles to be connected simultaneously.

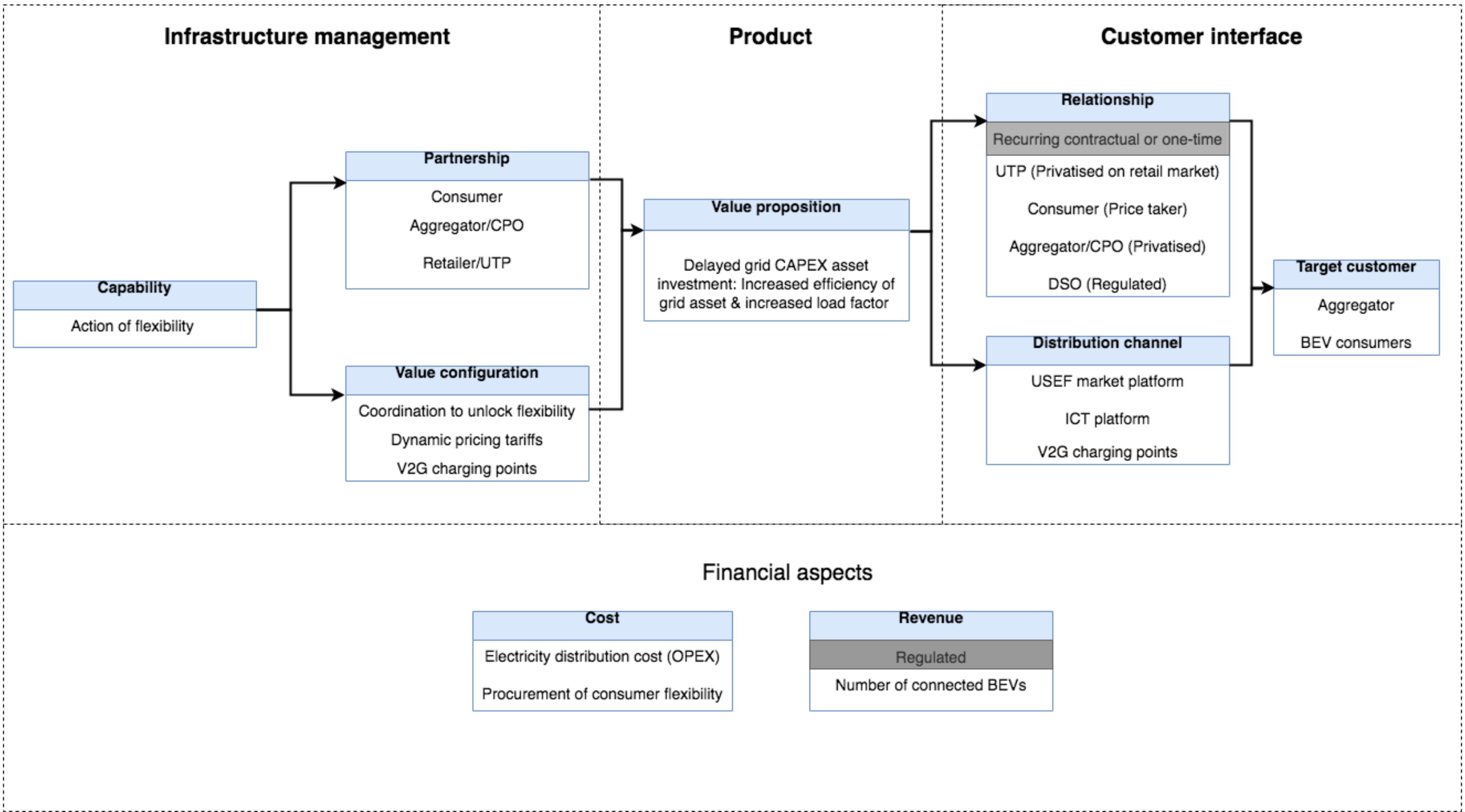


Figure 7: Business model framework

Product/Innovation perspective

Demand response is characterised by a complex network dependent mechanism, unlocked by the growing ICT infrastructure and increased prosumer connectivity. Co-management of service dependent DR is the hart of unlocking a value-added business model. The *value proposition* element, as conferred in the business model ontology of [54] can be explained by the benefits that the DSO delivers to the target customer, i.e. the aggregator, for enabling an offer for flexibility on the USEF based flexibility market. Value transfer is defined in terms of price/kWh delivered flexibility which is paid for by the DSO. The prosumer (participator), and hence the aggregator are therefore considered as price-takers. To put it simply, flexibility offers on the market as item of value for the DSO can be described as a regulated product offering whereas the government prohibits the DSO from altering market processes for suppliers [17]. Regulation of consumer prices prevents the DSO to develop as a natural monopoly (see appendix A), which is necessary because flexibility settlement may discriminate between location and time, inducing beneficial asymmetries for different customers [17].

The intermediary actor, i.e. the aggregator has the ability to pursue other demand response services for different actors in the power system and therefore potentially establishes competitive advantage in the V2G scenario. It operates in a competitive privatised market and, therefore, competes with other aggregators. However, when offers for flexibility are made, the aggregator is bound to fulfil its accepted offers on the day-ahead market and delivers the contracted capacity. While in the current system, energy is delivered by the supplier, that if due to acting of the aggregator fails to meet its energy portfolio can get penalised. Penalties may be induced that prioritise DR flexibility for specific grid operational tasks that require priority to prevent endangering security and reliability of electricity supply, which constituted in governmental regulations. As already has been discussed, a prioritised DR list needs to be constructed to deal with multi-objectives from different actors to design appropriate shared compensations schemes.

Customer interface

The building block of the customer interface contains three elements, i.e. *target customer*, *relationship*, and *distribution channel*, that define how and to whom the DSO delivers its value proposition under a specific type of relationship with its customers, either contract-based or one-time. The aggregator and the DSO must beforehand agree on the amount of flexibility that is required to prevent congestion, either long-term contractual agreement or on single basis. BEV prosumers are the actual provides of the flexibility and may enter into recurring long-term contracts or enter on a single basis with the aggregator. The profits of delivered flexibility ought to be distributed along the supply line. The *distribution channel* through which the prosumers are billed can be integrated in the USEF framework to utilise the existing communication infrastructure [1].

Infrastructure management

[54] describes three building blocks for the delivery and retaining prosumers in the value system configuration, i.e. *capability*, *partnership*, and *value configuration*. *Capability* refers to the repeated long-term offering of flexibility for prospective customers. This flexibility, defined as the *value configuration*, can be enabled by scheduling BEV charging demand, which is facilitated by instalment of charging infrastructure and a market framework to realise energy curtailment from aggregators and provide charging for the prosumer. The crucial actor that creates the value flows is essentially the aggregator who mediates between the prosumers and the DSO. Therefore, a strategic long-term *partnership* with the aggregator to access the target customers enhances potential value creation and realises certainty. Value configuration is subsequently dependent on the amount of prosumers that participate in V2G DR services and need to be made aware on their capabilities to provide aid in congestion while being compensated.

Financial aspects

In order to enable the core capability of V2G charging electric vehicles, the government and CPO make the necessary investment in the smart- and V2G charging infrastructure. For the DSO this means that costs incurred by additional investment in distribution grid assets should surpass the cost incurred by purchase of flexibility. The DSO's opportunity costs depend on the *cost* and *revenue* elements [54]. The *revenue* element is in this situation not actual revenue, but denotes deferred costs in the procurement of flexibility against additional grid investment. The value configuration has a large dependency between the *costs* of the 1) local grid operational efficiency, 2) procurement of delivered flexibility (amount and when is flexibility ordered) and 3) additional grid investment. Whereas an equilibrium point should be calculated according to sensitivity analyses of the former three mentioned cost- and value flows, to investigate whether investment in V2G flexibility outweighs additional grid investment. Therefore the *revenue*, or rather opportunity cost stream is directly correlated with the amount of BEVs that deliver flexibility, and thus determine the delay in grid asset investments. On the other hand, the price of flexibility and the over- or underestimated amount of flexibility only slightly influence total value configuration [1].

5.2.1. Implications for the distribution system operator

Concluding, the business case as conveyed proceeds on an already existing but unproven communication infrastructure, market framework, and an intermediary actor that has real-time access to all BEVs. This model provides insight in prospective value configuration for the DSO, for which procurement of delivered flexibility should weigh up to additional grid reinforcement costs. As described in the model above, the value flow for the DSO is significantly dependent on the size of BEV enabled flexibility, and hence on the size of the connected BEV fleet. Therefore, to investigate this value flow, a comparative simulation between smart- and V2G charging is elicited for the amount of flexibility (capacity) that can be utilised for congestion prevention. These result are subsequently expressed in percentage of feeder load shed and maximal amount of BEVs that can be connected while retaining grid limits for different future scenarios. Other financial elements influencing value configuration, i.e. operational efficiency, CAPEX investment, can be integrated in the linear model of chapter 6 in future research.

6. Model design smart charging & Vehicle-to-grid

The insights from the literature reviewed in the previous chapters are bundled together and used to make a proposition for a smart-charging and V2G charging model that reduces local peak loads and aids in congestion. In general, for all BEV charging sessions the charging starts immediately after connection, and usually ends long before vehicles depart from the charging point. Within the connected time window there often appears to be a period where no charging activity occurs. The charging profile scheduling problem proposed in this research simulates how, using a historic data set, charging profiles can either be moved in time or reversed (discharged) within this 'idling' period to aid grid congestion and lower associated charging costs. In order to minimise consumption, the central aggregator that is responsible for scheduling the BEVs load profiles, must receive information beforehand regarding the energy consumption and connection times in the ideal situation. However, in real life scenarios this assumption is concerned with privacy and security anxiety of consumers as is described in paragraph 4.3. To propose charging schedules used to predict behaviour of connected BEVs, this research therefore first forecasts the most probable aggregated distributions of charging demand scheduling that BEV sessions from the data set exhibit. Secondly, this research delivers a proof-of-concept linear programming model that optimises demand response by using two charging strategies aimed to minimise peak demand.

The first paragraph of this chapter introduces the design criteria for the model. Paragraph 6.2 briefly introduces the scheduling problem as a linear program approach to model smart- and V2G charging strategies. Next, paragraph 6.3 describes all the components in the model and its input, before defining the model's objective functions and describing it in mathematical form. Figures 9 & 10 show a schematic overview of the models input and simulation steps. In paragraph 6.4 a formulation is provided for quantification of the charging strategies in percentage of total peak demand shed within the optimisation window and charging costs.

6.1. Design criteria

This subsection shortly addresses the criteria attached to provision of BEV demand response within the constraints addressed by the distribution system operator. Application of demand response in a smart grid environment has a clear distinction in the task it is used for and in what part of the power grid. The main criteria in this research for assessing the potential of BEV's in grid overload alleviation, is the *control in demand rate and storage* to minimise local grid loads and prevent local grid congestion while charging the BEVs as fast as possible.

Energy stored in BEV fleet

To study the effects of smart charging and Vehicle-to-Grid charging strategy it is required to compute aggregated BEV fleet battery characteristics in which the following terms are considered: characterised by a vector $(SOC^{n,initial}, SOC^{n,departure}, P_n^h, SOC^n)$, where n is the vehicle ID, $SOC^{n,initial}$ & $SOC^{n,departure}$ the arrival and departure State-Of-Charge, P_n^h required consumption, and SOC^n denotes the BEV battery capacity.

There is no data available in the set that contains information about the BEV type and its battery capacity, this parameter will henceforward be computed by making a distribution of the battery capacities from the top five and top ten most sold BEVs, the fraction of charging time related to the connection time, and capacity charged for each BEV. Furthermore, due to battery limitations, the charging-discharging power is set equal and is computed with the algorithm of [41] whom integrate, among others battery specific characteristics and charging point power rate.

Criteria of the low-voltage distribution grid in Amsterdam

The low-voltage feeder and its components considered in this research have technical component boundaries, i.e. maximum allowable power load, which are significantly higher compared to other low-voltage grid assets in Amsterdam. Subsequently, other local feeders throughout Amsterdam endure usually higher loads and lower technical limits. In order to prevent peak loads in both cables and feeders and provide congestion control, the maximum load values specify the constraints for which power flows should fall within this particular range. In accordance with professionals at the DSO Liander, the case study models the load on a specific feeder in Amsterdam Nieuw-West that is capable to endure maximum loads of 115kW, in either positive or negative direction. However, the assumption is made not to use previously mentioned limit, but to vary the limit of the feeder according to the maximum feeder base load to realise a practical and more realistic case for other feeders located in Amsterdam.

An increasing amount of studies apply research on methods to quantify cost revenue structures for BEV charging to meet travel needs and optimise V2G grid balancing. One of the implications concerning V2G balancing is increased charging cycles imposed on the battery. Battery wear is an irreversible process and a known cause of driving patterns, amount of charging cycles, and depth of discharge amongst others. [80, 71].

Results from the study [80] point to the contrary. The authors performed a quantitative analysis on real-world data to assess the battery degradation impacts for peak load shaving and frequency regulation and decouples these impacts to a scenario of uncontrolled charging and driving. They found a low correlation between accelerated degradation from provision of grid services and regular calendar ageing plus driving and charging. This only amounts to an additional average capacity loss below 1% for a simulation of 10 years. [71] developed a comprehensive battery degradation model which they subsequently validate with real-world usage cycles. Their model has been integrated with algorithms to simulate V2G charging strategies in order to minimise battery degradation. Results show battery operation, both for driving mode SOC and V2G SOC, is best kept within a fixed range to ameliorate the life cycle of the battery. An improvement over uncontrolled charging. In addition, large depth of charge-discharges within the maximum physically possible ranges of the battery are correlated with an increase in battery degradation. According to [69] a general battery SOC operation range should be within: $SOC \in [0.2, 0.9]$ to avoid early degradation and capacity loss.

6.2. Modelling approach for optimal scheduling of charging sessions

Charging decisions are made through predefined objective functions to optimally utilise the effectiveness of the flexibility for the scenarios. By building forth on the results of the charging behaviour as described in the data mining chapter, an optimisation through linear programming is carried out that schedules BEV load profiles according to the strategies mentioned earlier[1], [2]. Optimisation is based on the amount of capacity that can be delayed or provided within the constraints of the BEV owner (minimal SOC at departure), the time available to provide these services (offering flexibility), the system operator's reference load curve (max. load) and lastly, the duration or period in which flexibility can be offered [63, 17, 75]. The algorithm performs the simulation under the objective function to minimise the subtraction of the absolute differences between BEV charging demand and the feeder load while capacity limits are respected. Furthermore, this model aims to ensure to not minimise a change in the original energy consumption and charge BEVs as fast as possible. However, whenever grid constraints are exceeded, the linear model will find a solution that violates the consumer requirements as little as possible. This means if grid constraints are in conflict with BEV demand, the total consumption of BEVs might be lower than with uncontrolled charging.

6.3. Modelling components - Input and Objective functions

The problem to solve is a discrete-time system that takes on the form of objective functions, which are expressed into linear aggregated demand functions to minimise energy peak demand and compute an optimal solution for scheduling sessions. The base of the model described in [83, 68] is adopted and rewritten to be applied for the BEV scheduling problem. The goals of scheduling the charging sessions are twofold, aimed to minimise local distribution loads and assess the financial costs of power supply for the consumers. In the optimisation window charging sessions are iteratively solved each time slot in a horizontal time receding approach. This is done by controlling each BEV's battery power and keeping the battery at a required reference SOC, i.e. $E_{t,ref}$. The reference SOC equals the maximum allowable energy for each BEV to intend the fastest charging upon arrival for consumer satisfaction. Therefore, to pose this problem as an objective function, it can be defined as a non-linear expression by minimising the absolute term of the BEV battery energy and given reference BEV energy at time step h. This problem will in a later section be rewritten into a linear programming model.

$$\underset{P_n^h}{\text{Minimise}} \quad \sum_{n=1}^{N}\sum_{h=1}^{H} |E_{n,h} - E_{n,h,ref}| \tag{1}$$

6.3.1. Model input

This section describes the expressions and constraints used to model the smart charging and V2G strategies.

Time window

To capture the electric vehicle load sessions, the demand profiles are discretised in hourly slots $h \in H = [1, 2, ..., H]$ for an optimisation window with a length of the earliest BEV arrival to the latest BEV departure, which is defined by a start time slot t_{start} and an end time slot t_{end}. For each charging session or user (n) a column vector is created $n \in N = [1, 2, ..., N]$ that represents the charging demand vector from start-to-end of each individual session $\delta t = [t_n^d, t_n^a]$ within the optimisation window $[h_{start}, h_{end}]$:

$$P_n^h = \begin{bmatrix} P_1^h, & P_2^h, & ..., & P_N^h \end{bmatrix}^T \tag{2}$$

The model is described in such a way that the control task is assigned to the aggregator, who models aggregated BEV fleet loads according to the maximum and minimum energy and battery power boundaries of all BEVs, defined as $E_{max/min}, P_{max/min}$ respectively. Both the uncontrollable and controllable electric vehicle charging demands are modelled separately, for which the charging- and discharging power rates as well as the battery energy boundaries are specified by the set of charging profiles according to the following expression:

$$E_{min} < E_{n,h} < E_{max} \tag{3}$$

Constraint 3 is the energy level of the BEV, which is bounded for the minimum and maximum value. Minimum state-of-charge energy level required before it can discharge represents whether the BEV can immediately start charging or discharging throughout its interconnection. Furthermore, note that the charging and discharging efficiency is assumed to be similar for both trajectories and equal to 100%. The motivation behind this assumption is that efficiency depends on the charging rate and charging profile, which is out of the scope of this research. However, the maximum and minimum charging output for each charging point is computed by the algorithm of [41] that includes exogenous and BEV characteristic battery values and influence the theoretical charging rate.

1. *Uncontrolled charging demand* Whenever a BEV connects with an expected charging duration no longer than its total connection time to ensure the battery is sufficiently charged (assumed a SOC of 100%), its total connection period is used for recharging. The charging rate and energy boundaries have no flexibility. For uncontrollable charging demand, only the charging power rates are used. The uncontrolled battery charging boundary is mathematically expressed as:

$$P_n^c(h) = \begin{cases} 0 & h \leq t_n^a,\, h > t_n^d \\ P_{n,h,max} & t_n^a < h \leq t_n^d \end{cases} \tag{4}$$

2. *Controlled charging demand* An electric vehicle with an expected connection duration longer than the necessary charging time, exhibits flexibility in charging and discharging rates. Therefore as considered for smart charging points, the battery output power can be adapted dynamically, such that the battery charging boundaries can be defined for smart charging described in expressions 5 & 7, and for vehicle to grid charging 5, 6 & 8. The indices c & d denote either charging or discharging. The boundaries are given by:

$$P_{n,h}^c = \begin{cases} 0 & h \leq t_n^a,\, h > t_n^d \\ P_n^c & t_n^a < h \leq t_n^d \end{cases} \tag{5}$$

$$P^d_{n,h} = \begin{cases} 0 & h \leq t^a_n,\ h > t^d_n \\ P^d_n & t^a_n < h \leq t^d_n \end{cases} \tag{6}$$

$$0 \leq P_{n,h} \leq P^c_{n,h,max} \tag{7}$$

$$P^d_{n,h,min} \leq P_{n,h} \leq P^c_{n,h,max} \tag{8}$$

Distribution network power boundaries

1. *Power constraints on distribution feeder*
   In accordance with professionals at Liander, the considered feeder in this case study has a varying capacity limit of 100-90-80-60-50% of the maximum base load in both positive and negative direction, which can be expressed as a constraint:

$$|P_{f,h,min}| = P_{f,h,max} \leq limit \tag{9}$$

   Next, the network minimum and maximum power output constraints of the grid can be expressed in a relationship with the minimum and maximum battery power constraints for every electric vehicle. The grid power constraints determine whether either charging or discharging at a specific time step is possible for each BEV separately. The grid power constraints for smart charging and Vehicle-to-Grid can be computed from 10, and are expressed below in 11 & 12, where $P_{b,h}$ denotes the base load on the feeder:

$$P_h = \begin{cases} P_{h,min} = -P_{f,h,max} - P_{b,h} \\ P_{h,max} = P_{f,h,max} - P_{b,h} \end{cases} \tag{10}$$

2. *Smart charging minimum and maximum power demand*
   The minimum power output for smart charging is limited to zero as no discharging is possible in this unilateral charging strategy. The sum of the charging rates of all BEVs should remain within the boundaries, and expressed as:

$$0 \leqslant \sum_{n=1}^{N} P_{n,h} \leqslant P_{h,max}, \quad \forall h \in H, \forall n \in N \tag{11}$$

3. *Vehicle-to-Grid minimum and maximum power demand*

$$P_{n,h,min} \leqslant \sum_{n=1}^{N} P_{n,h} \leqslant P_{h,max}, \quad \forall h \in H, \forall n \in N \tag{12}$$

Electricity costs

The costs associated with (dis)charging are calculated by integrating a RTP day-ahead pricing scheme, and henceforward uses hourly rates of the electricity price on the day-ahead market. Charging costs are, therefore modelled through use of a dynamic retail price tariff incorporating day-ahead price variation. To propose a feasible variable tariff, the hourly variation in the day-ahead price is multiplied by a coefficient such that the averaged price over the time interval shadows the conventional used charging electricity cost (during this research the price equals 0.32 €/kWh). This price is charged to the consumer by the UTP. The total electricity cost for the following day per hour for all BEVs is calculated by taking the product of total load consumption in a particular time slot and the RTP pricing tariff (in the same time slot):

$$c_h(P_n) = (p_{c,h} \cdot P_h^c \cdot \Delta t) - (p_{d,h} \cdot P_h^d \cdot \Delta t) \tag{13}$$

With $p_{c,h}$ & $p_{d,h}$ are the respectively charging- and discharging electricity prices for each BEV derived from the EPEX day-ahead market prices and can be seen in the appendix B. The constructed the RTP-tariff is depicted in figure 8. P_h^c & P_h^d are the charging and discharging power for each BEV specific, and Δt the length of the time interval.

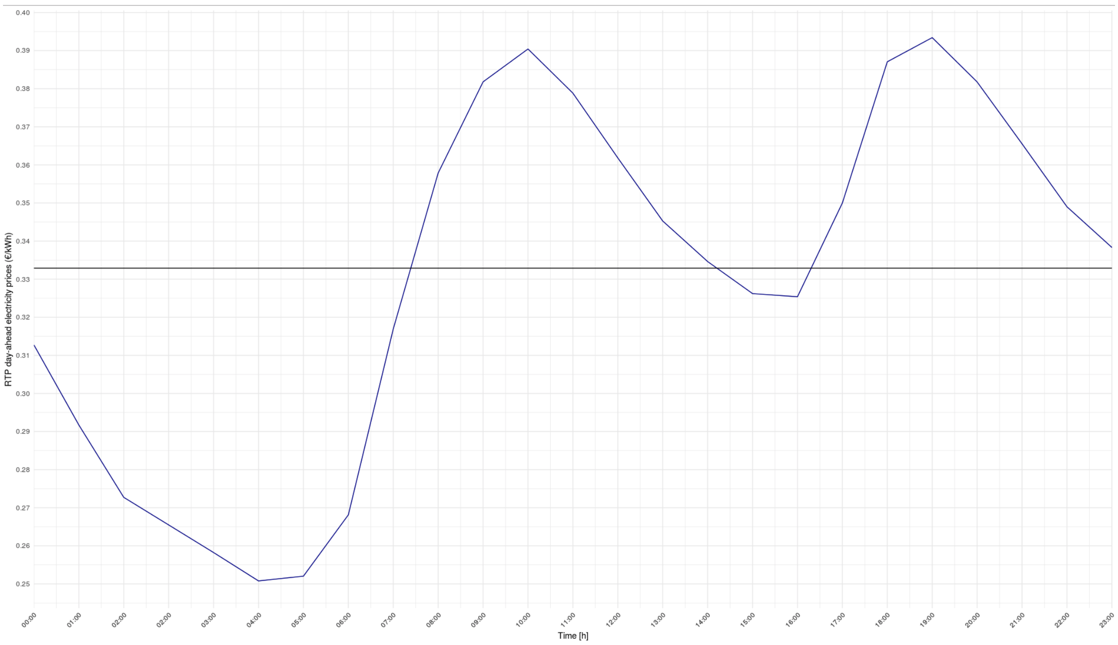


Figure 8: Averaged Real-Time-Price tariff derived from EPEX-day-ahead market prices for 24 hour [18]

6.3.2. Optimisation formulation

Each charging session n is combined with the system load vector of households as described in the previous section, and subsequently included in the charging demand vector to determine the total allowable load on the system feeders. The optimisation problem is written below in standard form. However, while this problem imposes a nonlinear formulation that expresses the minimisation of the absolute energy differences, it is necessary to decompose this problem into linear constraints prior to solving [24]. After this operation it is possible to formulate the problem into linear programming. This process involves the introduction of dummy or auxiliary variables for each BEV session: $\overline{E_n}$ in the constraints. This means that the absolute value of equation 1 can be rewritten into the single variable $\overline{E_n}$ by substitution of two variables into the original constraints, i.e. $\overline{E_n} = E_{n,h,ref} + E_{n,h}$, and $\overline{E_n} = E_{n,h,ref} - E_{n,h}$.

Furthermore, the linear program used in this research attempts to approximate the constrained optimisation problem with an unconstrained problem, after which it computes the solutions. By adding a term to the objective function that attaches a large penalty value to the violation of the constraints, approximation can be accomplished. Basically, this converts the optimisation problem with inequality constraints into an unconstrained problem. This is formally defined as the barrier method that favours solutions, which are in the feasible region over those near the constraint [20]. Thus, may requirements unable to be satisfied, this method will find a solution that minimises the violation of the constraints as little as possible. In addition, whenever no feasible solution can be computed for the charging strategies, a desirable behaviour of the optimisation is to still find a solution to meet the required BEV demand and grid constraints. According to the barrier method, the variable P_{over} is introduced and given a large penalty weight: $c \gg \overline{E_h}$.

Smart charging strategy

Taking into account the linearisation and the barrier function, the linear demand optimisation problem can finally be written as:

$$\underset{E_{n,h},P_{n,h}}{\text{Minimise}} \quad \sum_{n=1}^{N}\sum_{h=1}^{H} \overline{E_h} + c \cdot P_{over} \tag{14}$$

Subject to:

$$\begin{aligned}
&\overline{E_n} + E_{n,h} \geqslant E_{ref} \\
&\overline{E_n} - E_{n,h} \leqslant E_{ref} \\
&E_{min} < E_{n,h} < E_{max} \\
&E_{n,h+1} - E_{n,h} + P_{n,h,over} \geqslant 0 \\
&E_{n,h+1} - E_{n,h} - P_{n,h,over} \leqslant P_{n,h,max} \\
&E_{n,1} = E_{n,start}
\end{aligned} \tag{15}$$

V2G charging strategy

The objective equation 14 is similar for the V2G strategy as conveyed above, but depends on different constraints:

$$\underset{E_{n,h},P_{n,h}}{\text{Minimise}} \quad \sum_{n=1}^{N}\sum_{h=1}^{H} \overline{E_h} + c \cdot P_{over} \tag{16}$$

Subject to:

$$\begin{aligned}
&\overline{E_n} + E_{n,h} \geqslant E_{ref}\\
&\overline{E_n} - E_{n,h} \leqslant E_{ref}\\
&E_{min} < E_{n,h} < E_{max}\\
&E_{n,h+1} - E_{n,h} + P_{n,h,over} \geqslant P_{n,h,min}\\
&E_{n,h+1} - E_{n,h} - P_{n,h,over} \leqslant P_{n,h,max}\\
&E_{n,1} = E_{n,start}
\end{aligned} \tag{17}$$

Model input and simulation diagram

The optimisation can be schematically depicted as in the figures below.

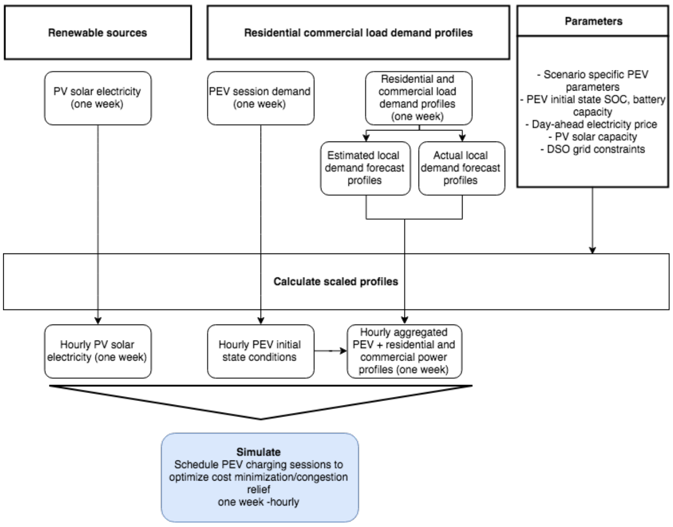


Figure 9: Model input

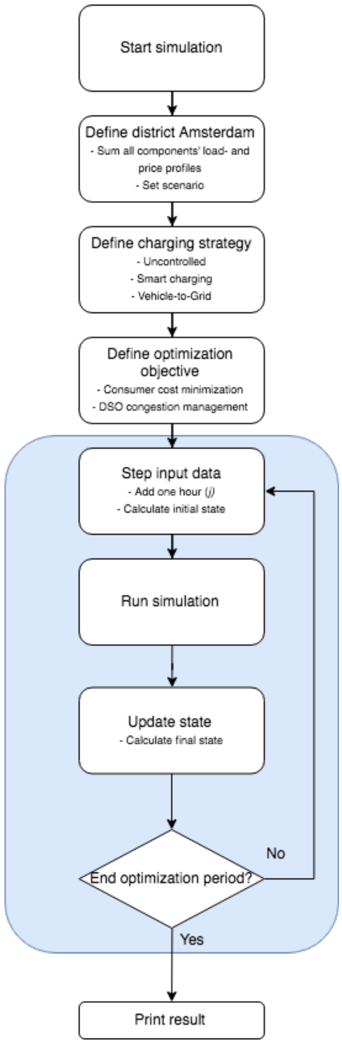


Figure 10: Diagram for the optimisation simulation

6.4. Charging strategies quantification

This study provides exploratory insight into the potential of different charging strategies towards impact on grid load impacts for different actors in the system. The linear program is simulated for different near future use cases for which the BEV penetration and feeder load parameter values will vary. To demonstrate the potential of the conveyed smart charging and V2G charging strategies, the percentage of total peak shed is computed from the results of the optimisation given by the ratio of the scheduled demand against the unscheduled demand for every hour in the optimisation window:

$$PeakShed = (1 - \frac{\sum_{h=1}^{H} P_{V2G,h}}{\sum_{h=1}^{H} P_{uncontrolled,h}}) \cdot 100\% \tag{18}$$

Furthermore, associated potential charging costs are computed for the strategies in price per kWh according to the electricity tariff proposed in 6.3 and subsequently compared to the electricity price in the uncontrolled scenario.

7. Predicting trends and periodicity in charging behaviour & Simulation

In this research a large-scale data set is collected that is comprised of BEV charging sessions, acquired from 1832 public charging points located throughout the area of Amsterdam. The municipality of Amsterdam recorded 682,476 usable charging sessions that span a full year, 2017-03-01 - 2018-03-01.

The focus of this research is to investigate typical trends and impacts of BEV charging behaviour demand on Amsterdam's distribution grid. In this case study, the potential of BEV flexibility is derived that can have the purpose to serve for demand response strategies to relieve the local grid from congestion and to minimise charging costs. Both smart charging and V2G charging strategies are modelled for DR and subsequently compared on their performance and benefits to the DSO and the consumer.

This chapter is structured by starting with a brief introduction in paragraph 7.1, which presents the data sets used in this study and refers to the normalisation and scaling of charging sessions into usable load profiles. Subsequently, paragraph 7.2 delivers a statistical assessment of these charging profiles to explore distinct stochastic behaviour and trends in temporal-spatial measures. Demand response related factors are computed that describe the availability and amount of flexibility at different periods throughout the year. Furthermore in paragraph 7.4, the charging strategies are simulated under the objectives to minimise both congestion (over consumption or supply) and associated charging costs by using the results from the previous assessment on predicting behavioural BEV demand trends. To realise a solvable optimisation window the proposed charging schedule optimisation is performed for a maximum period of 36h with an hourly time step resolution. Both the period can be shortened and the resolution can be adapted to finer time steps to gain solution accuracy.

7.1. Data collection and preparation

Dataset electric vehicle charging sessions

The BEV charging session dataset, already shortly addressed in the introduction of this chapter, is provided by the municipality of Amsterdam, in which they recorded individual charging sessions. Each uniquely recorded charging session is attributed with transaction ID, Charging point ID, and Location ID keys, and contains measured parameters as shown in table 1.

Table 1: Example of keys and attributes of the recorded sessions

Parameter	**Explanation**
Charge session key	Individual key for each session
Start connection	Date and time a session
End connection	Date and time a session ended
Connection time	Connection time of a session in hours
Idle time	Time connected and not charging
Charging time	Charging time of a session in hours
kWh	Capacity charged/Power consumption
Charging point ID	ID code of a charging point
Location ID	Postal code of charging point
Latitude	Latitude coordinate of charging point
Longitude	Longitude coordinate of charging point
P_h^c)	Charging point demand

To provide insight in the temporal and spatial effects of charging sessions in the data set, various plots are depicted that show distributions over time for different variables on time- or interval scales. On forehand, assumptions are made which sessions to omit in the analysis denoted as outliers that negatively influence validity of the assessments:

- Sessions that have charged less than 1 kWh, because these small charge capacities usually mean a faulty recording (deleted 69,917 sessions)
- Sessions that have a longer connection time than 72h are discarded, because these excessive sessions indicate a heavy-tailed distribution and influence the distributions of the data (deleted 41,140 sessions) Furthermore, these data sessions are not representative for commuter charging behaviour as compared to the complete distribution.

To analyse the characteristics of sessions, the following variables are calculated that further describe charging behaviour, and are formally expressed as:

$$Connection\, time \equiv t_{departure} - t_{arrival} \tag{19}$$

$$Idle\, time \equiv t_{connection} - t_{charging} \tag{20}$$

Data set feeder load of household-, BEV, REG load

To analyse the effects of BEV charging on the local grid, Liander provides this research with a low-voltage feeder data set containing load profiles of 40 connected households with- or without REG, and two BEV charging points. This feeder is located in district Nieuw West in Amsterdam. For further visual specification and graphs see appendix C A. The feeder load profiles, as well as the other load profiles, are scaled to hourly time intervals to match with BEV load profiles. The model simulates total load impact on this specific feeder by integration of different BEV charging strategies, and can be conceived as a proof-of-concept for these mentioned strategies.

Data set Vehicle-to-Grid

During this research two V2G charging points originating from the City-zen pilot project V2G are taken into operation from 2018-05-07 on, and are connected to the same feeder as described above. Data is collected of the total power load, both consumption and generation. Power load graphs can be found in appendix D and serve the purpose to provide insight in bilateral charging effects on feeder loads. Note however, the discharging profiles are activated when the battery SOC is above a specified value and furthermore are not optimised in any way. In contrast to the results of this data, the charging profiles which are simulated with the model of chapter 6 are optimised to the feeder load.

7.2. Analysis of trends and seasonality in Electric vehicle session characteristics in Amsterdam

By performing a statistical assessment on spatial and temporal effects of charging in Amsterdam from the sessions that are recorded, insight is gained to understand the probability distributions of factors that comprise charging demand and flexibility behaviour. Distributions of arrival-departure times and charging demand, which influence available time- and load-flexibility are analysed for typical recurring behaviour. Global measures are obtained by making use of the statistical models local regression (LOESS) and auto-correlation. These models allow statistical operations on the (univariate) time series data to capture the underlying characteristics such as trend, seasonality, periodicity, and serial correlation [10]. The results of this assessment on behaviour can be used for aggregators to make preliminary predictions about the expected BEV demand characteristics throughout the day and year. The next section describes the method that is adopted to analyse the time series variables.

Times series method - Trend and seasonality

Abstraction of the stochastic nature of charging session characteristics shows insight in the components of these time series that have recurrence in short cyclical nature, and makes it possible to characterise patterns. Usually univariate time series are abstracted or decomposed to forecast their parameters into trends, seasonality periodicity, and residuals (remainder). Trends are defined as long-term changes in the mean of the time series, whereas seasonality is the periodicity of the series over fixed intervals (e.g. month of the year). [10] proposed a model to work with finer grained time resolution steps of, for example one day to show oscillatory effects that can be analysed by the seasonal-trend decomposition method based on (non-parametric) local regression. This method assumes the time series data is an additive series that is composed of: trend (T), seasonality (S), and remainder ($Y_t^{'}$), which can be mathematically expressed as:

- *Original data*

$$Y_t = T_t + S_t + Y_t^{'} \tag{21}$$

- *Decomposed trend*

Let X_t be the de-trended data with the following computation:

$$X_t = Y_t - T_t \tag{22}$$

- *Decomposed seasonality*

Let Z_t be the de-seasonalised data:

$$Z_t = Y_t - S_t \tag{23}$$

- *Decomposed remainder*

Let $Y_t^{'}$ be the remainder data:

$$Y_t^{'} = Y_t - T_t - S_t \tag{24}$$

To specify the terms in the equations above, a model is fitted to the data measurements. For non-parametric data as used in this research, local regression or LOESS builds forth on classical models such as linear regression, but instead of defining a global function to fit all data points it formulates polynomial functions for 'smoothed' localised subsets of the data points. Most distributions of the variables used in this research (see 7.2) are not normally distributed, show high heteroscedasticity. Hence in cases with significant skewness and kurtosis, general predefined distributions do not fit the data well. With a LOESS approximation data points are fitted using the standard linear regression least squares method, however only applied to the nearest neighbour algorithm. Hereby allowing a straightforward way to model the seasonal component and trend.
Suppose x_i from $i = n$ for all n are the measurements of the variable. Let $g(x)$ be the LOESS smoothing curve, than an integer q is selected of x_i, which is the nearest to x based on the distance from x. Subsequently, the neighbourhood weight for any x_i is computed. Now the tricube weight function can be expressed by the following equation from [10]

$$W(u) = \begin{cases} (1 - u^3)^3 \& \quad for \; 0 \leq u \leq 1 \\ 0 \qquad\qquad\qquad\qquad\qquad\qquad u \geq 1 \end{cases}$$

where u is the distance of a measurement from the point on the curve that is fitted. To decompose the time series, the number of observations per seasonal cycle has to be determined. The model is specified by daily seasonal observations for every week of the year, due to the expected daily periodicity in driving and charging behaviour during daytime. 95% of all charging sessions have mean connection times of 8.05 hour, and are therefore assumed to periodically recur in charging frequency each successive day. In addition the larger Figures 14, 16, and 21 show the result of fitting LOESS to decompose the time series.The plots in one window show the original time series at the top, followed by the seasonal component, the estimated trend (third), and the irregular remainder component at the bottom. The length of the bars at the right side express the relative magnitude of the decomposed effects on the same span in the y-axis. A larger bar means a variation attributed to one of the decomposed terms has a small influence on the data, and vice versa for small bars.

Although the LOESS model returned smoothed patterns of seasonal periodicity, it can merely be used for visual inspection, whereas to explain the characteristics of the time series, a measure of the strength of the trend, seasonal, and periodicity components is required. Furthermore, as a formal measure of strength, all component's influence in the original series can be reviewed on their contribution to the overall series variance (squared standard deviation). Equation 25 below computes seasonal influence by calculating the relative variance of the remainder with the decomposed seasonal component. Equation 26 computes trend influence by taking the relative variance of the remainder with the trend component, and lastly, the influence of the relative variance of the remainder with the original series in equation 27:

$$1 - \frac{Var(Y_t^{'})}{Var(Z_t)} \tag{25}$$

$$1 - \frac{Var(Y_t^{'})}{Var(X_t)} \tag{26}$$

$$1 - \frac{Var(Y_t^{'})}{Var(Y_t)} \tag{27}$$

The statistical auto-correlation is a tool to find repeating patterns or periodicity in a time series for which successive values in time, at certain lags, correlate with each other. In other words, it computes randomness in the data for which the auto-correlation factor is (near) zero if there is no correlation and thus randomness, and (near) 1 for a perfect auto-correlation [27]. It finds, by using equation 28, the similarity, i.e. Pearson correlation, between values as a function of itself but lagged in time.

$$ACF(s,t) = \frac{E[(X_t - \mu t)(X_s - \mu s)]}{\sigma_t \sigma_s} \tag{28}$$

Where time 't' is discretised in daily intervals for the value X. Then the same holds for the lagged version for time step 's'. E is the expected value computed by subtracting the mean from the value at 't' or 's'. Positive correlations are strong indications of long runs of several consecutive observations above or below the 5% significance level . Negative correlations indicate low incidence of such runs. In the correlograms of the charging session variables below, the values that exceed the significance level have a dependence with successive values in time but are lagged for a certain period. Thus, the ACF values indicate how much correlation lagged values have with each other where the lag is the period for which the successive values correlate. Expected is that between adjacent days the lag the correlation is the largest.

The next sections of this paragraph provide the reader with an analysis of the stochastic distributions of the charging session variables to provide insight in the behaviour. For the most important variables, which are used in the simulation of the proposed linear program, a time series decomposition using LOESS is performed.

7.2.1. Frequency of charging sessions

A first overview of charging characteristics in Amsterdam is given by analysing the frequency of sessions that took place throughout the total time span of the data set. A distinction is made between districts in Amsterdam to see how non-residential aggregated demand is spatially dispersed. The districts can be seen in the left mapping of figure 11, in which the small black dots represent the locations of all charging points in the data set. First observations of this graph show relative minor deviations between frequencies for different weekdays in comparison to the location of those session. In weekend days however public charging points are less occupied and show overall decreasing session frequencies. Locations such as the city's centre and southern part (agglomeration of large business ventures) show the highest amount of sessions. The charging point occupancy, measured in number of sessions per charging point, and charging demand is highest for the city's centre.

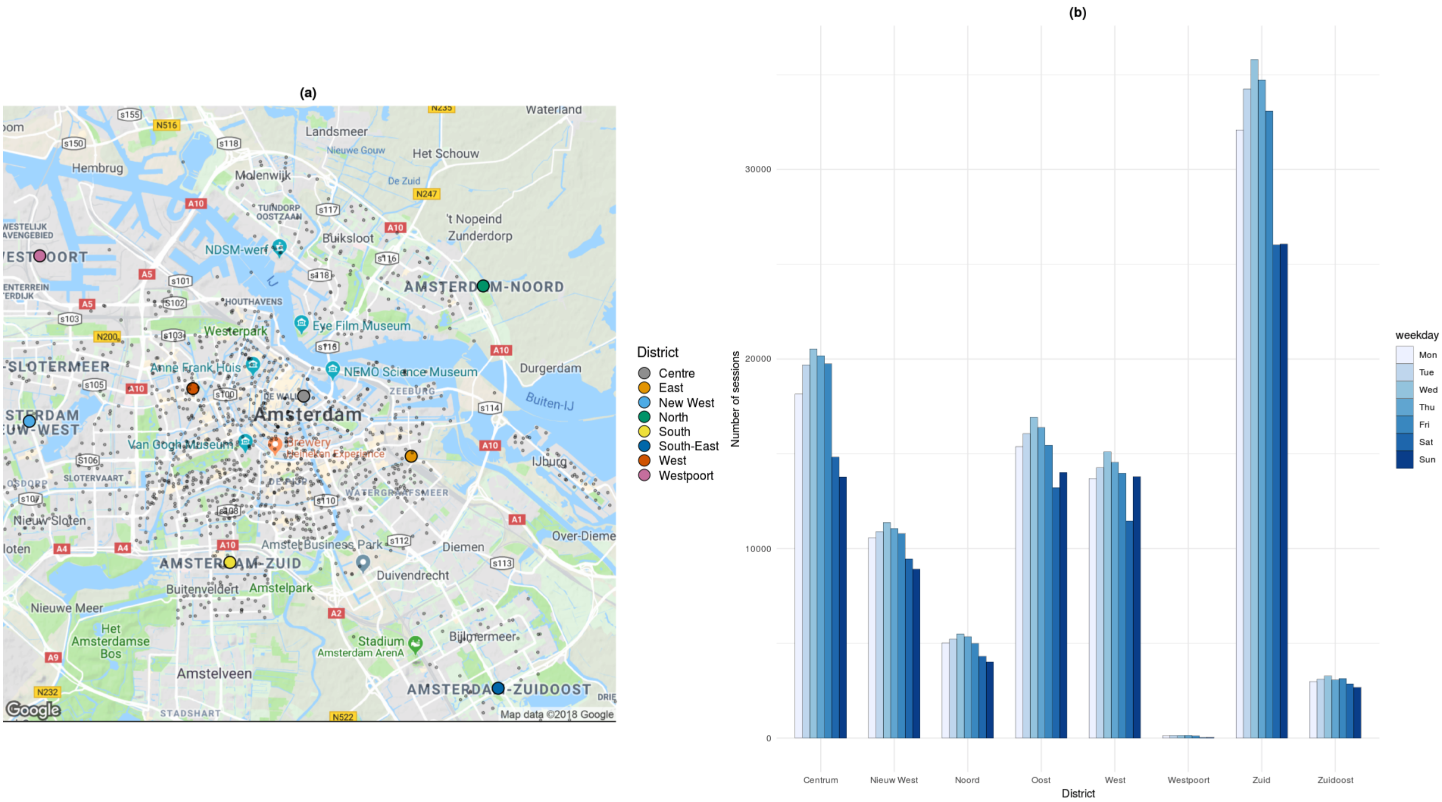


Figure 11: Contour plot of charging sessions' frequency

Table 2: Charging points and session frequency per district in Amsterdam

District	# of charging points	# of sessions	Charging Demand [MWh]
Centre	187	126,886	1110,39
New West	151	73,045	928,060
North	117	34,403	394,078
East	203	107,421	1022,418
West	187	96,843	887,502
Westpoort	2	728	7,05309
Zuid	370	222,033	1908,542
Zuidoost	58	21,117	198,417

7.2.2. Analysis of arrival-departure times

Temporal effects of charging sessions that take place during the day are depicted for a complete year, distinguished by different seasons to show overall trends of sessions. A quick glance at figure 12 (a) and (b) in appendix C shows minor seasonal shifts in arrival- and departure time respectively, while there is a larger deviation observed between the frequency of arrival sessions for the summer. Because this dataset solely comprises recorded sessions from public charging points and hence mostly used by commuters, an explanation can be accounted to summer holidays where people don't commute to work.

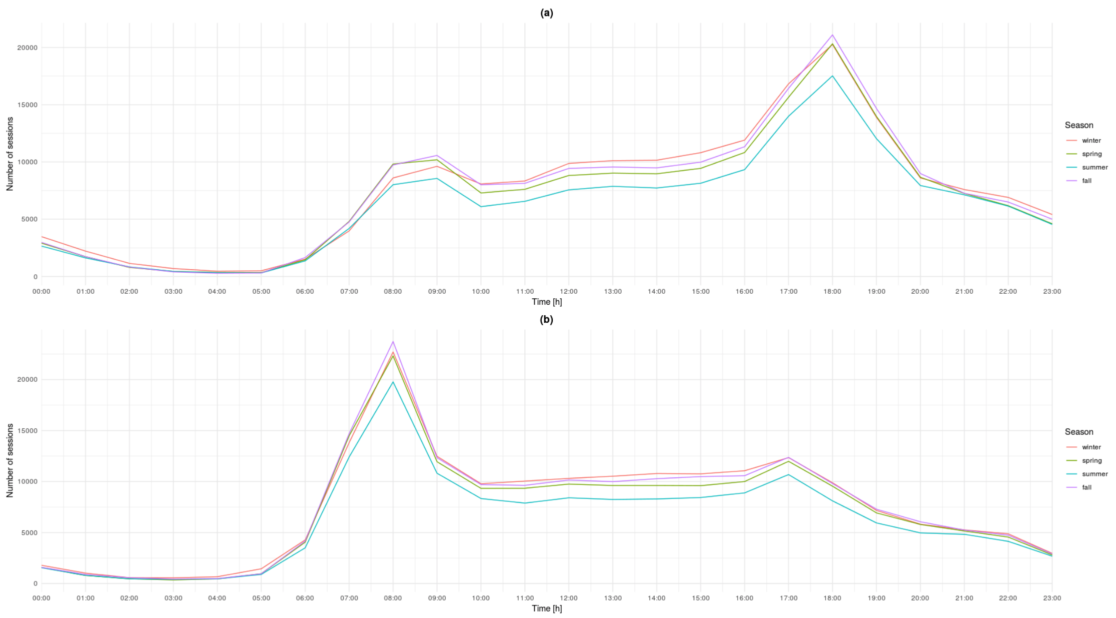


Figure 12: Count of charging sessions' arrival (a) and departure (b) over time of day with seasonal differences

Arrival time

A more refined plot in figure 13 shows labelled peak and valley characteristics for the frequency distribution of arrival time during week days and weekend days.The week days and weekend days comprise 76% and 24% of the sessions respectively. In the literature charging behaviour in terms of arrival-departure times is usually categorised into residential charging, park-to-charge (or shopping), and commuter charging [63, 82]

Distinct arrival times during the day show peaks at 8:45 and 18:15 during weekdays. Making the consideration that most sessions coincide with typical workday hours in the Netherlands, these peaks can be denoted to mainly commuter charging behaviour. Charging sessions in the weekend indicate a deviant behaviour from the weekdays, where the lower plot of figure 13 shows negative kurtosis due to a larger spread in in the arrival times indicating the mass of the BEV distribution arrival times connect their BEV preferably at later periods of the day.

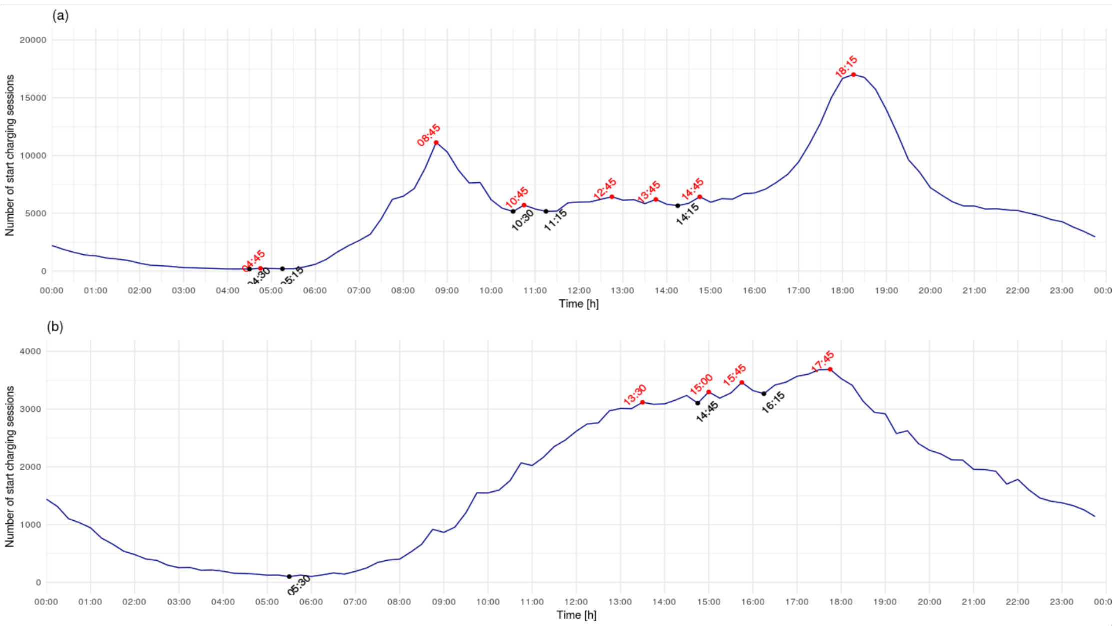


Figure 13: Count of charging sessions' arrival time during week days (a) and weekend days (b)

Described below is the analysis of the time series by fitting a local regression model and calculation of the auto-correlation values to assess seasonality, trends and periodicity in arrivals.

Table 3: Measure of each components influence of relative variance on total time series variance of arrival time

	seasonal	trend	remainder
Arrival	0.3340263	0.4978265	0.1272259

The decomposed plot of 14 shows a varying trend denoted by two large valleys at weeks 24 and 45, which have a larger influence on the variation in the original data (0.498) compared to the daily seasonal influence (0.334). Only a small variance in the data is explained by daily seasonal effects, and the magnitude of relative variation in trend imposes the largest influence on the data. What is clear from examining the remainder component are the irregular negative outliers at week 9, 13, 42, 45 and positive outliers at week 52. Furthermore, as apparent from the figure 13 in paragraph 7.2 weekdays and weekend exhibit dispersion (with two distinct peaks) in arrival times, which can have an influence on the magnitude of the seasonal and trend component.

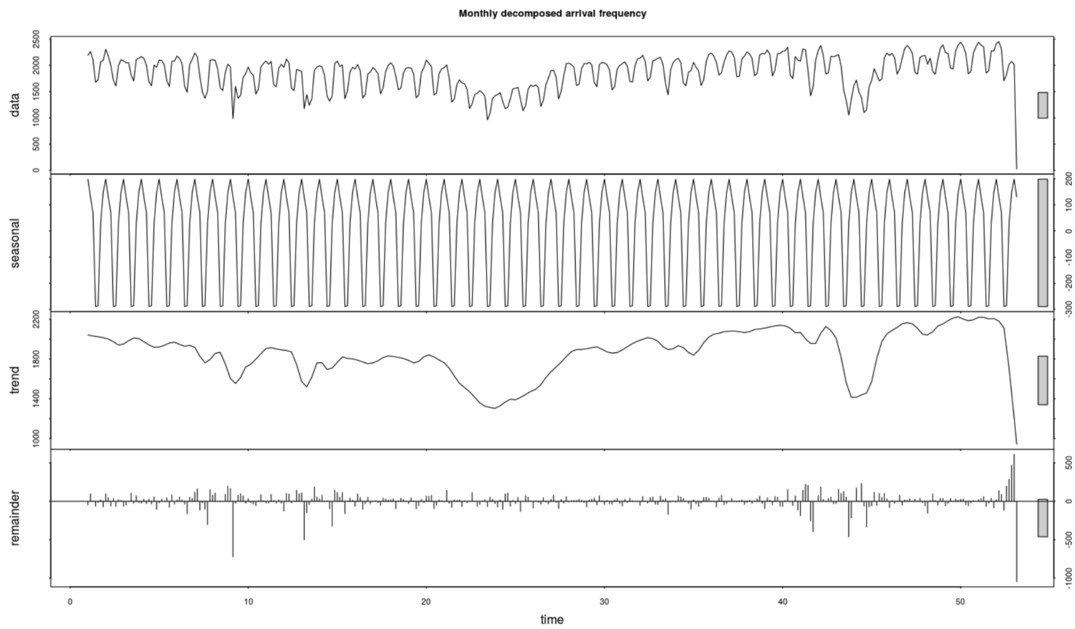


Figure 14: Decomposition of daily observations in weekly patterns for arrival time

Similarly to the previous case, only minor variations between seasons can be inspected that influence the departure time. In figure 15 plots are depicted of departures during a whole week, in which one can notice a majority of the departures during weekdays occur at 8:15, with an additional smaller peak occurring at 17:15. A possible explanation for this distribution is the cross-correlation between the arrival-departure times of commuter drivers and work hours in the Netherlands as been said before. Figure 15 (b) indicates similar behaviour to be recognised for weekend days being positively skewed and having a large variance in time.

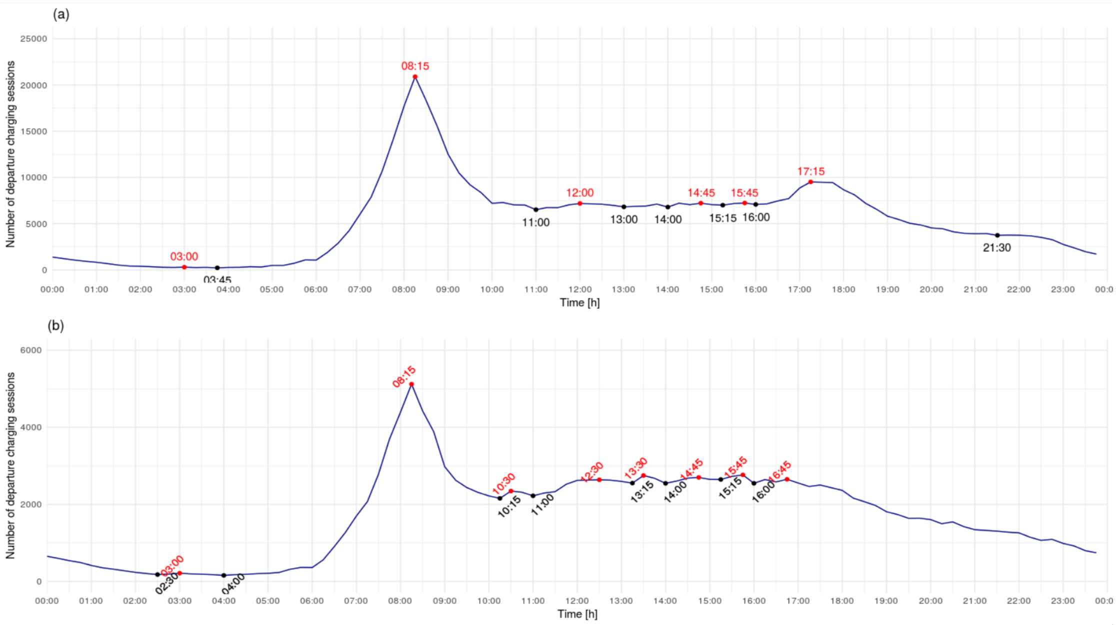


Figure 15: Count of charging sessions' departure time during week days (a) and weekend days (b)

Table 4: Measure of each components influence of relative variance on total time series variance of departure time

	seasonal	trend	remainder
Departure	0.4239381	0.4304912	0.1100280

Decomposed time series curves and auto-correlation results are have similar shapes as the arrival decomposed time series, as can bee noticed from figure 16. A logical explanation resides in the fact that 95% of all charging sessions have mean connection times of 8.05 hour, and are therefore periodically recurring in charging frequency each day. In addition the larger seasonality factor - 0.424 - compared to the factor of the arrival -0.334 - can be induced from the distribution of frequencies in figure 15 in paragraph 7.2 that show larger distinct peaks at 08:15, thus imposing a stronger periodicity. This premise is in accordance with the larger auto-correlation factors in figure 18 (b) compared to (a).

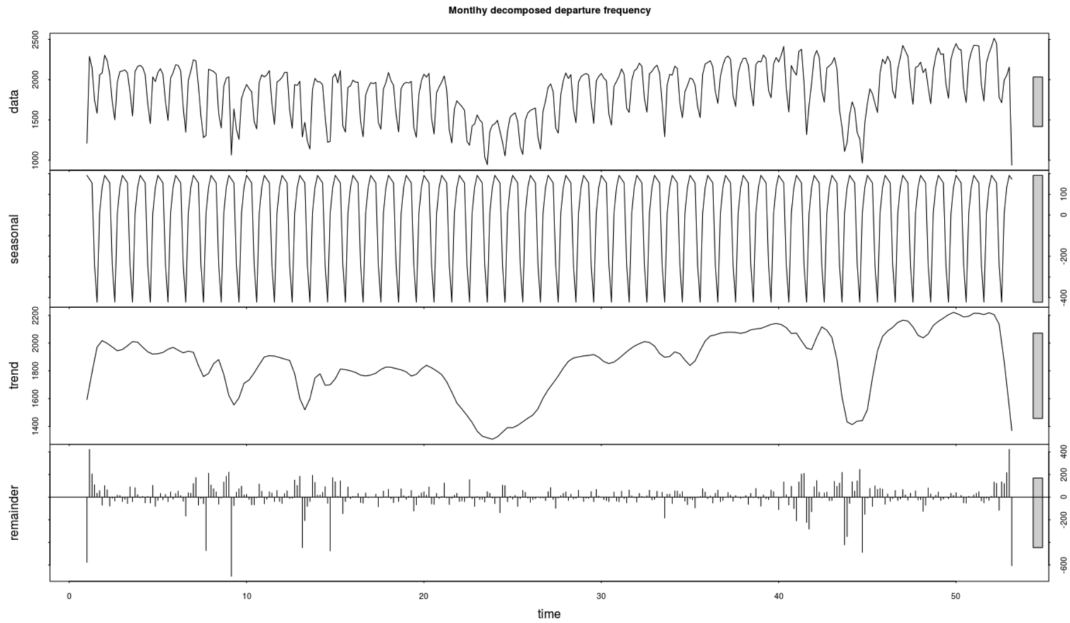


Figure 16: Decomposition of daily observations in weekly patterns for departure time

7.2.3. Analysis of interconnection session characteristics

Consumer tendencies for charging are statistically analysed in terms of arrival time and interconnection times. In order to estimate apparent patterns or trends, frequency and probability plots are modelled and shown in appendix C together with a decomposition of the time series and auto-correlation. Periodicity in connection time are of great importance to the aggregator, because further inference in predictions are more accurate when BEV demand together with the flexibility potential is required to be known. The sessions used for analysis exhibit for the majority longer interconnection times than what theoretically is required. Figure 33 in appendix C exemplifies this trend by calculating the ratio of charging time (according to capacity charged) relative the total connection time for each session. The lower the ratio, the more idle time within sessions. As an example, 65% of the charging sessions have a ratio score below 50%. The ratio score of 50% means that connection time is twice the required charging time. This trend enables the possibility to utilise the fact that BEVs, while connected to the grid, can provide flexibility in scheduling their charging. The section below continues the analysis of the trends and periodicity in connection times for over a year.

Connection time

Based on the sessions' connection time distributions a minority of the sessions (<7%) have connection times that exceed 24h, see summarised values in table 5. BEVs with longer connection times than 24h have multi-model distributions showing distinct peaks at subsequent 24 hour periods, sessions are sub-clustered according to connection time of 0-24, 24-48, 48-72h to analyse weekdays and seasonal influences. From figure 35 (a) in appendix C - representing more than 77% of sessions in the data set - it can be concluded that during weekdays, the connection time is usually 1.5h shorter than in weekend days. For the remaining clusters (48h and 72h) mean connection times differ 44 min and 37 min respectively for weekdays and weekend days, but offer significantly longer connection times between the clusters.

Table 5: Summary of average and standard deviation of connection-, idle-, and charging time clusters

	Sub-clusters	Fraction of clusters	Mean connection time	Mean idle time	Mean charging time
	0-24h	77.45%	8h 2 min	6h 11 min	1h 50 min
Weekday	24-48h	3.406%	36h 22 min	34 h 13 min	2h 9 min
	48-72h	1.176%	61h 3 min	58h 59 min	2h 6 min
	0-24h	18.00%	9h 32 min	7h 32 min	2h
Weekend	24-48h	1.964%	35h 38 min	33h 31 min	2h 7 min
	48-72h	0.4049%	60h 26 min	58h 11 min	2h 14 min

In general daily seasonal variations have significant effects on the averaged connection times during the day, while between weekdays and weekend days more variation in the distributions is visible. Although, the former decomposed time series show a relative low seasonality variance effect in the original series, the connection time series is emphasised by a daily seasonality cycle with a coefficient of 0.632. The trend component however, explains only 0.117 of the relative series variance, and shows no long term increase nor decrease. The large standard deviation is a sign of the peaks and valleys in the trend curve.

Table 6: Measure of each components influence of relative variance on total time series variance of connection time

	seasonal	trend	remainder
Connection time	0.6320452	0.1171437	0.2109484

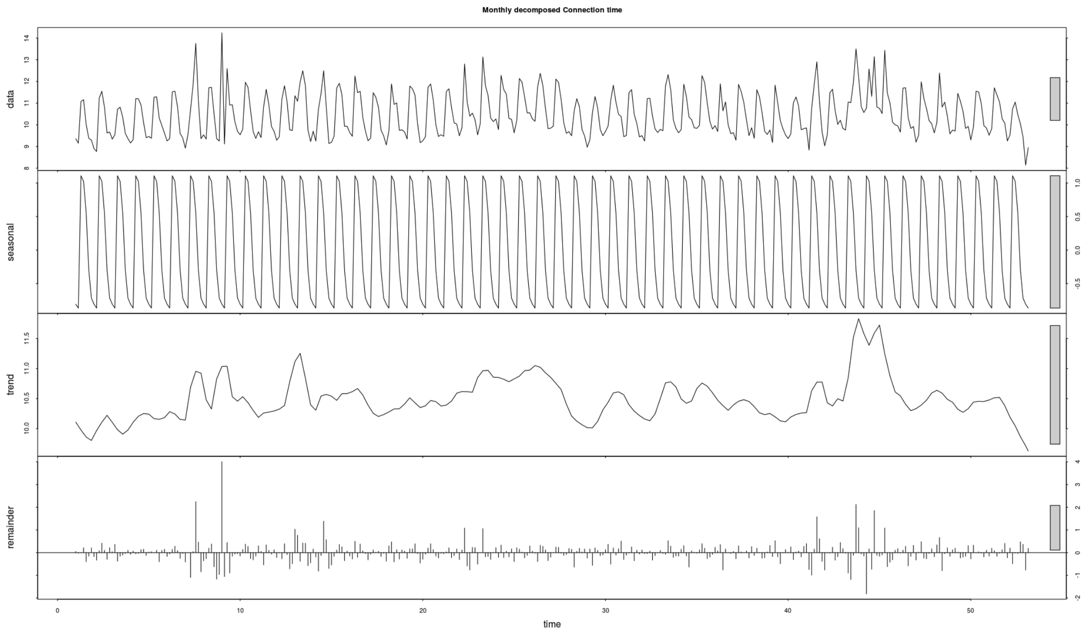


Figure 17: Decomposition of daily observations in weekly patterns for connection time

Idle time

The idle time construct is the time interval between completion of charging and departure time. It is essentially inefficient to exhibit long idle times if one takes infrastructure use into consideration. If for example, the future ratio of charging points per BEV is taken into account, a low to null idle time is desired to optimally use the charging point for BEVs in its proximity. However, most research, similar to this study, found approaches to make effective use of this idle time. In the sections below, the idle time - one of the four measures in demand response - is used to calculate potential flexibility What can be noticed from table 5 is that while average charging time for the clusters only differ at most 20 min, the difference between idle time for the subsequent clusters are on average approximately one complete day (24h).

Periodicity of time series temporal related variables

Now that all temporal session variables are presented, the periodicity can be calculated. In figure 18 (a) & (b), auto-correlation values for arrival and departure are almost identical. The major peaks at ACF(1) = 0.6, ACF(2) = 0.5, ACF(3) = 0.4 apart correspond to a dependence between frequency of BEV arrivals each day, 2 days and 3 days respectively. A similar statement can be elicited for the departures, that show even a slight stronger auto-correlation. In the night, the values fall back within the significance bars, due to low charging activity. The oscillatory pattern can be explained by the fact that recurring arrival times each day are dispersed across time and show strong seasonality effects. ACF for departure time is even more correlated in terms of increased ACF values. In short, the arrival and departure time series are not random and show strong periodicity. Plots (c) & (d) appear also similar (what can be noticed from the distributions in figures 34 & 36) and show also high auto-correlation values for every adjacent day up to three days ahead. In accordance with the time series analysis of the connection time. When the lag-axis is proportioned to represent weeks, a similar phenomenon is observed in periodicity. Negative values can be a sign of anti-correlation of connection- and idle-time during the night which means the observations are scatted and dispersed without any pattern. In general if an observation has an above average value, is it likely that the next observation has a below average value.

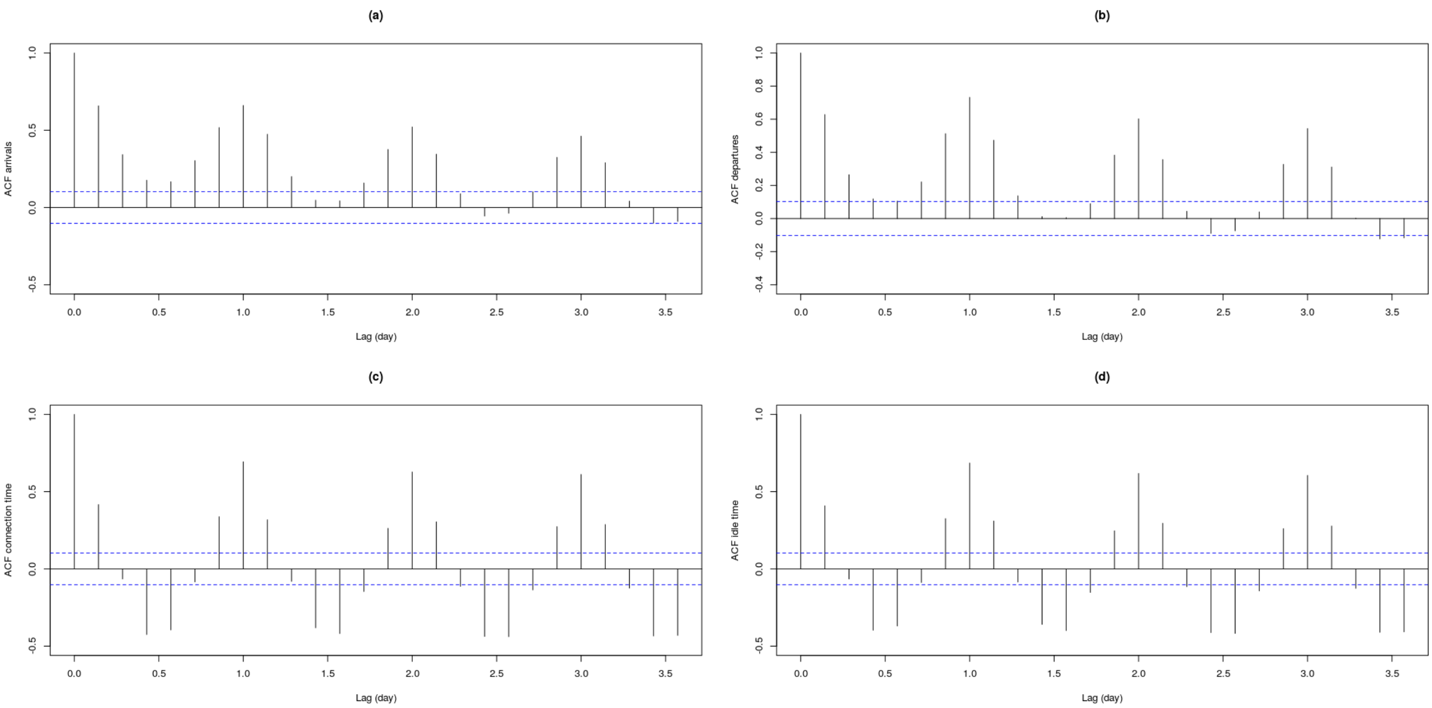


Figure 18: Auto-correlation function of (a) arrival time, (b) departure time, (c) connection time, (d) idle time

7.2.4. Analysis of charging demand

For the calculation of charging demand at the points, the duration a BEV charges is affected by multiple variables that in the article of [41] are distinguished into environmental effects, charge points effects, and BEV characteristic effects. The authors have proposed an algorithm that incorporates these variables in a computation to determine actual charging time and demand of all charging sessions. This research adopts this charging algorithm for an accurate calculation of charging demand for the sessions in the data set. Furthermore, in this research a day is discretised into hourly intervals, as this sample time stamp is a general parameter used in the electricity sector. Each charging session demand profile is scaled into 1 hour time slots from $[t_{start}, t_{chargingcomplete}]$ and added to sessions that fall within the same charging interval. These scaled sessions represent the actual charging point's output demand where BEVs start immediately with charging when they arrive. Afterwards, the total demand in every time slot is averaged for every hour of the day to inspect for weekday and seasonal variation, depicted in figure 20 (a) and (b) of appendix C.

On average, the mean capacity charged (consumption) in this data set is 10.17kWh and the measure of the variation in the capacity charged, expressed as the standard deviation equals 10.57kWh. The distribution is positively skewed for which approximately 75% of the charging sessions charge less than or equal to 10kWh. Reason for this can be that a large proportion of the data set contains sessions of PHEVs, that have small battery capacities which are driven to their lowest SOC, without imposing any range limitations for the consumer as opposed to BEVs. Aggregated daily charging demand throughout the year is plotted in boxplot 19 below. The smoothing curves is a regressing fitting equation that estimates the mean charging demand conditional on the number of measurements per month. The 25% and 75% quantiles increase during the winter months, indicating a larger spread in the capacities charged, while charging demand increases from August until January.

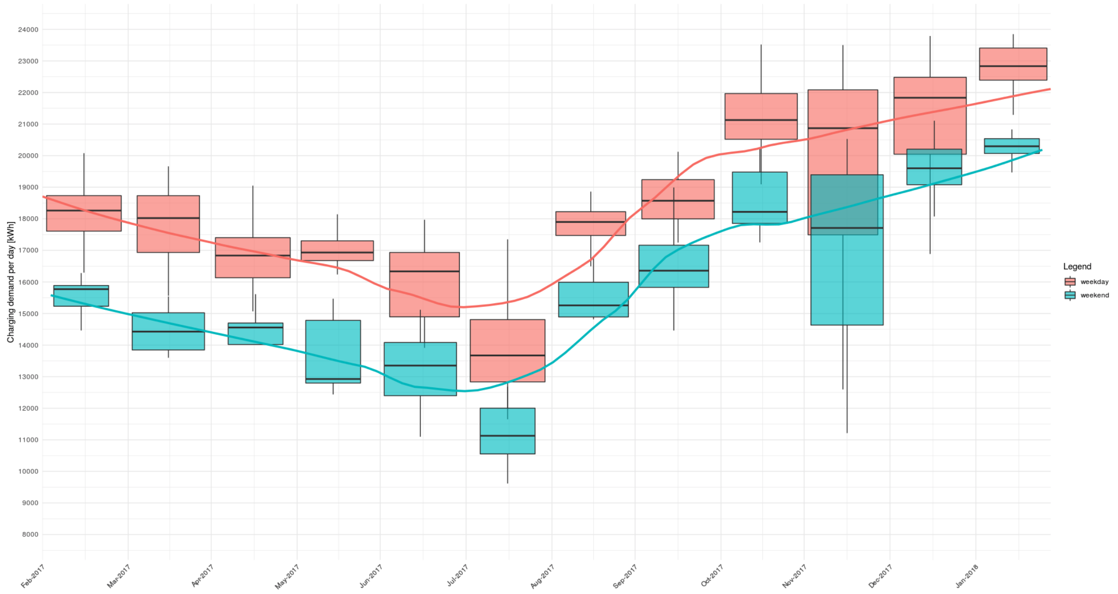


Figure 19: (a) Boxplot of daily charging demand for monthly effects

An explanation for the shape of the demand profile throughout the day is the direct correlation it has with the frequency of BEV arrivals and departures of figure 12 (a) and (b). In figure 20 (a) as suspected, the increase in recorded sessions relates to an increase in charging demand, which is mostly noticeable in the fall and winter. In the study from [85] the authors assessed the dependencies between temperature effects on BEV efficiency, range and charging demand in which they draw the conclusion that cold temperatures and deteriorated weather conditions increase the use of auxiliary equipment. As a consequence more battery capacity is used next to driving that subsequently increases charging demand. The analysis of the time series decomposition also shows this increasing trend. Further inspection of 20 shows a large peak demand around 19:00h that coincides with the peak of BEV arrivals in figure 13, while the departure frequency, figure 15, merely shows a peak that is roughly half of the arrival frequency. Finally, the peaks visible for different days of the week also follow the behaviour of arrival and departure times.

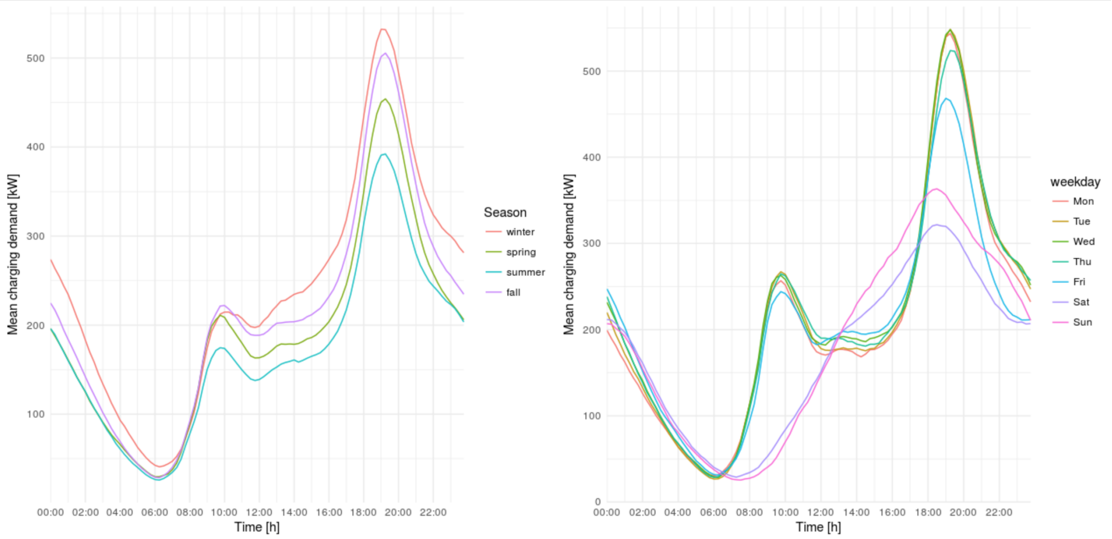


Figure 20: (a) Mean charging demand throughout the day for seasonal variation, (b) mean charging demand throughout the day for daily variation

Table 7: Measure of each components influence of relative variance on total time series variance of charging demand

	seasonal	trend	remainder
Charging Demand	0.1567597	0.6777841	0.1507764

The time series of daily mean charging demand in the plot below is emphasised by the large relative variation of the trend (0.678) in the original series that increases during the winter period, for which a probable explanation is the temperature effect. When temperatures decrease battery efficiency degrades and use of auxiliary equipment increases, such as heating, subsequently a larger demand for energy. The variation attributed to seasonal- and remainder decomposition are much smaller compared to the trend, and thus imposes minor effects on the original series. The charging demand therefore shows only minor seasonality effects.

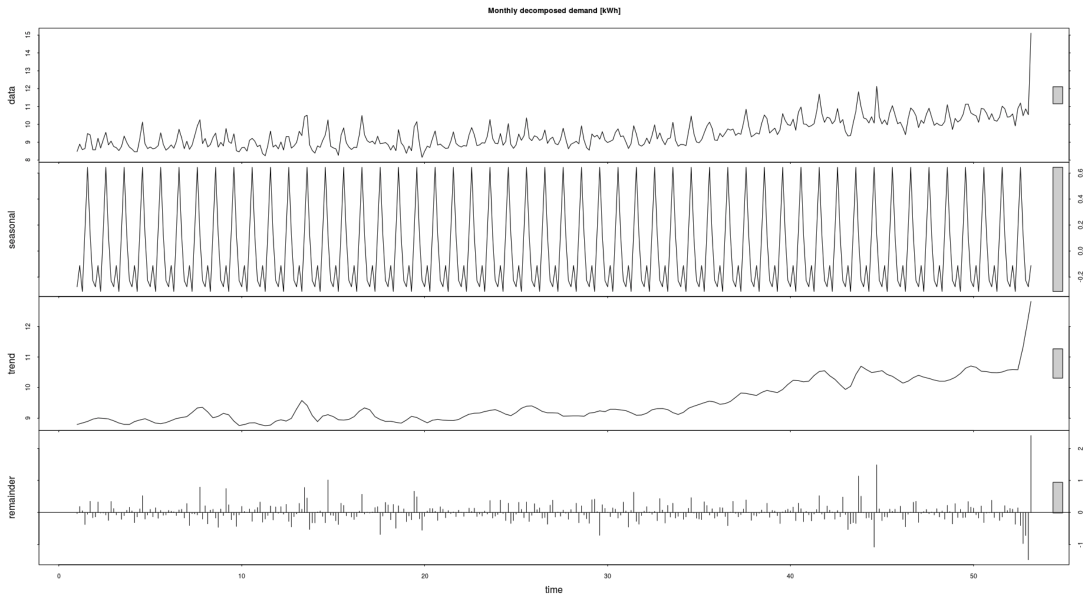


Figure 21: Decomposition of daily observations in weekly patterns for mean charging demand

7.2.5. Analysis of time- & load- flexibility

To properly elicit the difference among charging strategies' potential to aid costs and grid overload, this research distinguishes two measures of flexibility for BEV demand response, i.e. time- and load- flexibility. As mentioned in paragraph 4.1 the usability of flexibility for charging strategies through smart charging or V2G is expressed by three measures [62]:

1. Total amount of capacity that is connected to the grid that can be discharged within the time window constraints of the BEV owner,
2. The moment in time (during the day) to provide these services (offering flexibility),
3. The duration or period in which flexibility can be offered.

Once the potential flexibility is quantified into former three measures, it can be simulated by the demand response strategies. The assessment of these measures is composed of two parts, whereas the first part, described below, investigates the time- and load- flexibility potential in the BEV fleet. Whereas the second part can be found in paragraph 7.4, simulates the charging schedules under the smart charging and V2G strategies. First insight is provided in table 8, in which a summary is shown about characteristic values of averaged individual time- and load-flexibility distributions for each BEV.

Table 8: Summary central tendency of time- & load-flexibility for sub-cluster distributions and 50% IQR values

	Sub-clusters	Median time-flex [%]	IQR time-flex [%]	Median load-flex [kWh]	IQR load-flex[kWh]
	0-24h	0.77	0.34	14.41	20.00
Weekday	24-48h	0.95	0.039	69.90	23.33
	48-72h	0.97	0.020	114.1	17.77
Weekend	0-24h	0.75	0.39	14.50	24.29
	24-48h	0.95	0.038	68.35	23.74
	48-72h	0.97	0.02188628	113.6	23.54

The simplified trajectory of baseline, uncontrolled charging is depicted in figure 22 along with the possibilities to provide demand response within the constraints of the battery limits and connection time.

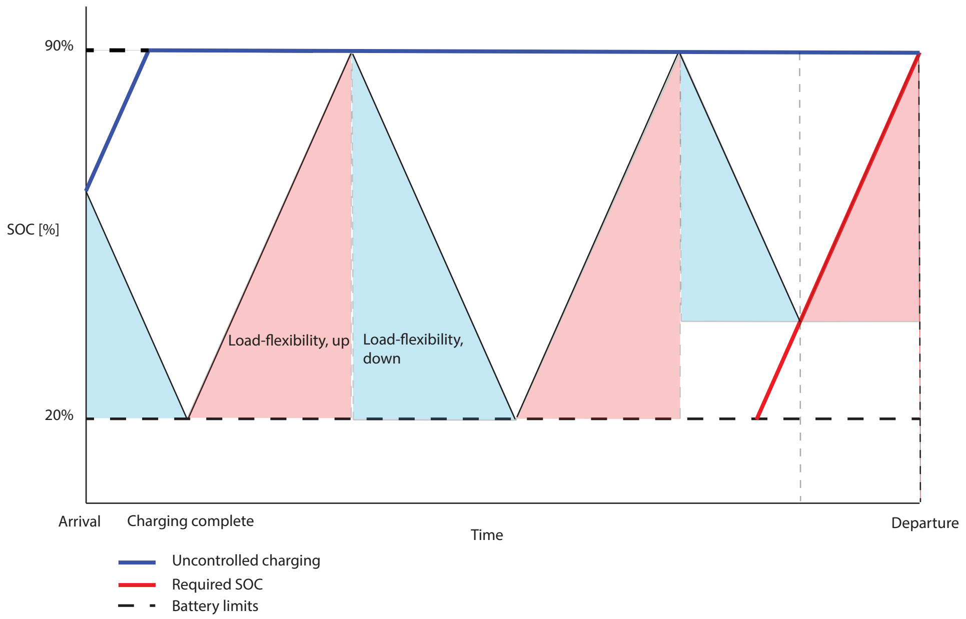


Figure 22: Charging profiles for the baseline and either smart charging and V2G

Time flexibility

The time flexibility depends on the charging time and total connection time of each session. The mean flexibility is calculated for each individual BEV in the data set, plotted to depict daily and seasonal/monthly variations.The ratio is calculated with equation (29) that is expressed in terms of the percentage of available idle time given the complete connection duration; availability of time flexibility:

$$T_{Flex} = \frac{(t_{connection} - t_{charging})}{t_{connection}} \tag{29}$$

The interpretation of the percentages in the equation is as follows. When T_{Flex} approaches 1, it means charging time is near zero in relation to connection time, and time flexibility can be used completely over the connection period of the BEV. On average each BEV charging session in the dataset can be scheduled for over 75% of its connection time.

From the box plot in figure 23, it can be concluded that the time-flexibility distribution for each succeeding month has a negative skew and the interquartile 25% and 75% ranges decrease for time-flexibility. Further investigation behind the reason for this behaviour requires assessment on exogenous related factors. Factors relating to the degree of variation in time flexibility can be weather related, or infrastructure related, such as occupancy of charging points, charging point output, to name a few. The study of [85] examined impacts on BEV energy efficiency and demand for a case study in the U.S.A. on temperature variation. They found a relationship between temporal ambient temperature variation and the range of a BEV. Lower temperatures decreases battery efficiency and increases the use of energy demand for auxiliary equipment, resulting in an increased power demand.However, further analysis of variables that influence time-flexibility are out of scope of this study. Logically, if charging demand increases so does charging time and as a consequence the median of time-flexibility decreases slightly (see figure 37). An explanation of the smaller variations in time-flexibility than those of charging demand can be found in the fact that an increase in charging demand only imposes a relatively smaller part to the idle time part in total connection time.

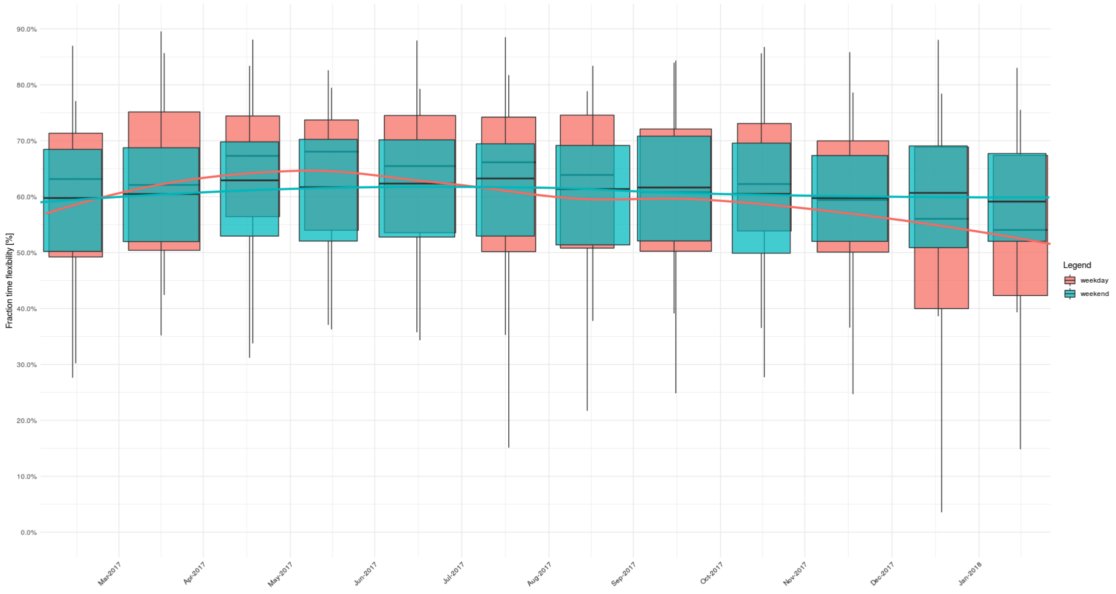


Figure 23: Boxplot of time-flexibility fraction of charging sessions for during every season. [Note: bold black line = median; box = 25-75%; black whiskers inside 99% of the data = minimum and maximum, excluding outliers

Monthly differences are relatively small compared to the differences throughout the day, and from figure 23 a small increase in time flexibility can be observed during the summer months.Furthermore, on average, every day, each BEV has 61.7% of its total connection duration available to reschedule its charging demand. However, the box plot doesn't show when the time-flexibility metric occurs throughout periods of the day, while start- and end- times of the sessions are key in the determination of the benefits for provision of demand response. Therefore, the usability of time flexibility at various times of the day is plotted for seasonal and weekday variations, which is visible in figure 24.

The plot in figure 24 shows the mean of the time-flexibility and its availability at every hour of the day for aggregated charging sessions. Considering charging loads are introduced immediately after a charging sessions starts with uncontrolled charging, the distribution in figures 13 & 15 depict distinct connection times for a typical workday at non-residential charging locations. It suggests a larger fraction of consumers connect their vehicle when they arrive at work and disconnect when they commute back home. Availability of time flexibility (figure 24 (b)) is consequently rising from 13:00-18:00 and, apart from small dips around 19:00-20:00, remains high until 22:00. The odd behaviour of the negative slope from 22:00 - 05:00 can be explained by a decreasing numbers of arrivals and increasing number of departures, which is an indication of decreasing flexibility. Further inspection of seasonality impacts on flexibility backs the earlier mentioned assumptions about the fact that during the winter period charging demand is higher and hence flexibility is lower.

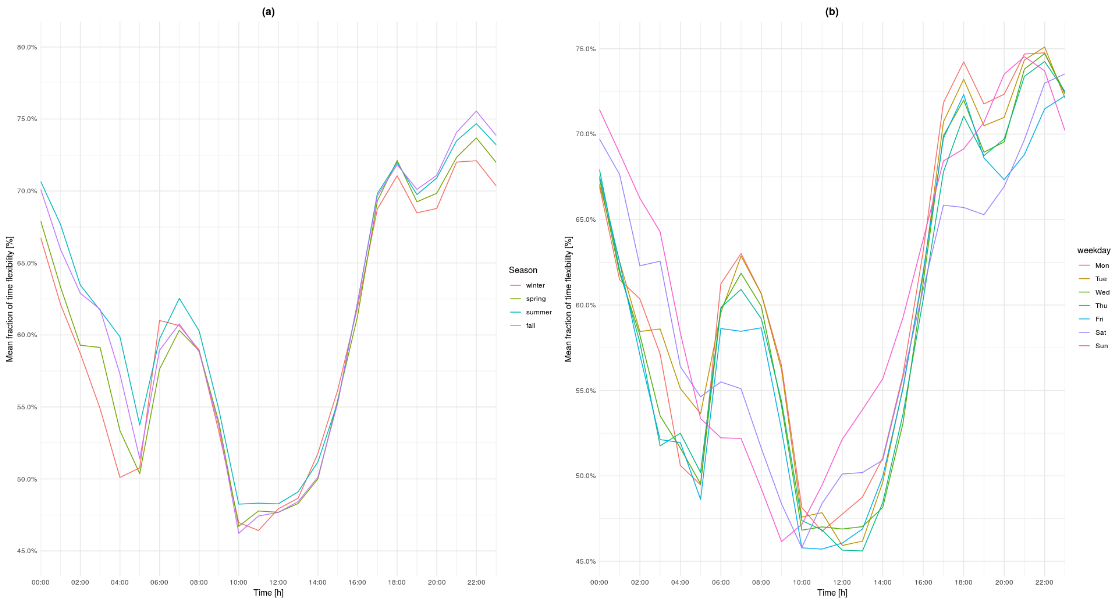


Figure 24: (a) Mean time flexibility per hour of charging sessions throughout the day for seasonal variation, (b) mean time flexibility per hour of charging sessions throughout the day for weekday variation

Load flexibility

The measure for load flexibility is applicable for BEVs that provide demand response under both charging strategies. A distinction is made between provision of load-flexibility for over generation or over consumption in the grid, denoted as $P_{Flex,up}$ and $P_{Flex,down}$ respectively. These measures express the capacity that could be charged or discharged respectively within the connection time window for aggregated sessions. Equation 30 for $P_{Flex,up}$ is a measure for the total rate of energy demand at any time instant that can be decreased within the interconnection period of a charging session in response to low electricity prices (applicable for smart charging). For simplicity and to provide clarification in the amount of energy demand that can be discharged during the total connection time of all BEVs to reach the required consumption, the equation computes to lowest possible charging demand rate, with E_n the original energy consumption:

$$P^{n}_{Flex,up}(t) = \frac{E_n}{\Delta t_{connectiontime,n}} \tag{30}$$

$E_{Flex,down}$ is the capacity that can be offered to the DSO by V2G discharging within the window of all BEV charging sessions for each hour of a day, and is therefore not expressed as power and aggregated. Simply defined, this flexibility can be distinguished into three parts: 1) the arrival- or initial capacity of all BEVs summed, 2) the total connected capacity of all BEVs summed from the moment they are fully charged, and 3) the discharging rate of all BEVs summed for every hour of a day. Distribution plots are made for these three measures that can be used to inspect the flexibility on average for every day of the week. These measures provide expected load-flexibility available on the distribution grid for aggregator DR purposes.

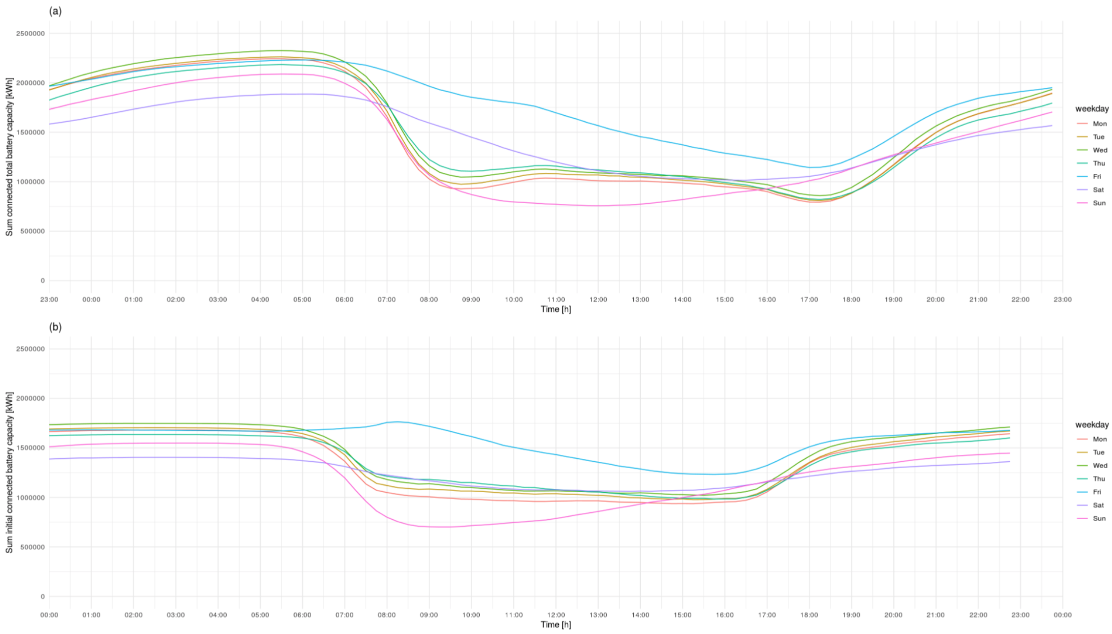


Figure 25: (a) Aggregated total battery capacity per hour of the day for weekday variation, (b) aggregated initial (arrival) battery capacity per hour of the day for weekday variation

The graphs in figure 25 clearly show a large deviation in total connected capacity throughout the day, explained by the characteristics of the arrival and departure frequencies, which were addressed in figures 13 & 15. At around 08:15h the departure rate is 21,000 that levels towards 7,500 at 10:00h. Whereas the arrival rate at 08:45h is only 11,000 that levels towards a rate of also 7,500 between 10:00-16:00h before increasing to 17,000 at 18:15. The curve of the load-flexibility graph at weekdays therefore denotes a sharp decrease in total connected battery capacity of $2.3 \cdot 10^6 kWh$ to $900,000$ around 07:00h and increases again around 17:00 to remain high untill 07:00h. A confirmation of the dependency of load-flexibility behaviour and the arrival-departure frequencies may be explained by the average connection time, i.e. 10h 23 min, that is approximately the length of the valley in the figure. Furthermore, on Fridays the load-flexibility curve decreases with a much lower rate compared to other weekdays. Either a lower departure rate of higher arrival rate after 08:00 explains the curve characteristic. Weekend days also show a deviant behaviour in load-flexibility, for which the sharp decrease of the curve from 06:00-08:00 is characterised by almost zero arrivals and a large peak of 5,000 departures. Afterwards arrivals slowly increase such as for the load-flexibility.

Furthermore, graph (b) depicts the initially connected capacity determined upon arrival of BEVs, and is readily available for the aggregator to provide demand response with. Initial connected capacity is calculated by using the available idle-time of each BEV and its specific charging demand, and thus represents the load-flexibility that can be discharged within that period. The shift of graph (a) is equal to the charging time due to the fact that total battery capacity is available only after the BEVs are fully charged. The daily trend is similar to that of the arrival- and departure peaks, which explains the sharp decline in load-flexibility that starts around 06:00 and increases again around 17:00. The decline in the morning is due to an almost double amount of BEVs that depart compared to BEVs that arrive.

Figure 26 is a derivative of the curves in figure 25, which exhibits the same characteristic curve but defined by the discharging rate. Figure 26 (a) and (b) show the load-flexibility discharging as calculated from the charging rate of the charging points originally in the data set (mean of 5.2kW) , and with a discharging output of 10kW for future V2G charging points respectively. Due to the fact BEVs have the possibility to immediately discharge upon arrival makes them useful for flexibility services during peak demand periods throughout the day, i.e. from 06:00 to 18:30 load-flexibility discharging demand is increasing.

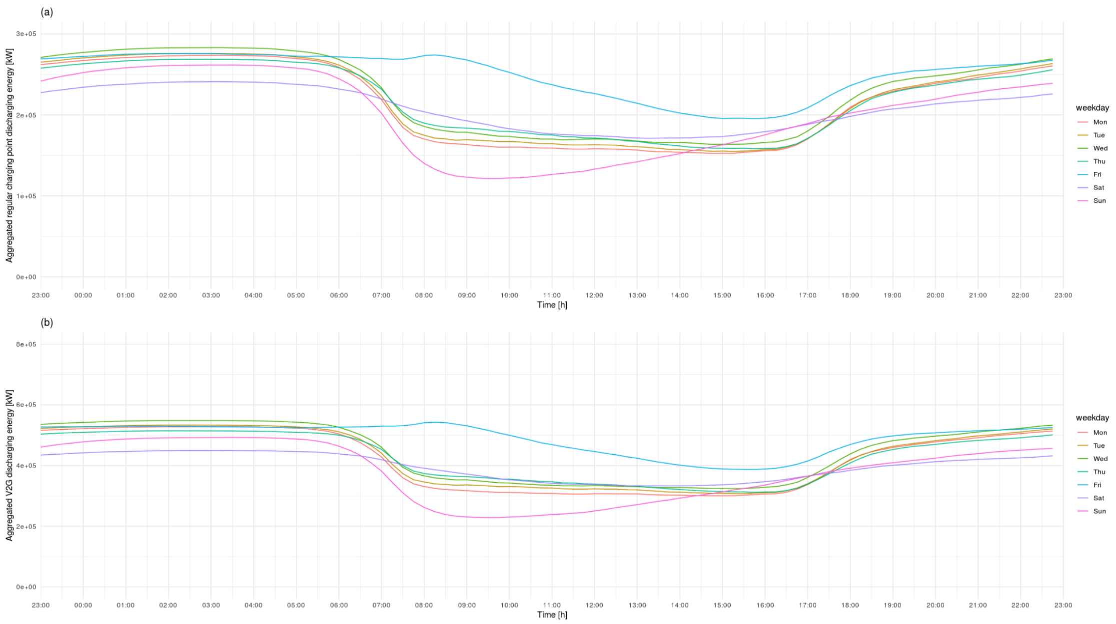


Figure 26: (a) Aggregated discharging rate for regular charging points per hour of the day for weekday variation, (b) aggregated discharging rate for V2G charging points per hour of the day for weekday variation

In addition, the mean load-flexibility is also computed for each individual vehicle to show insight in yearly behaviour, which is presented in the figure below.

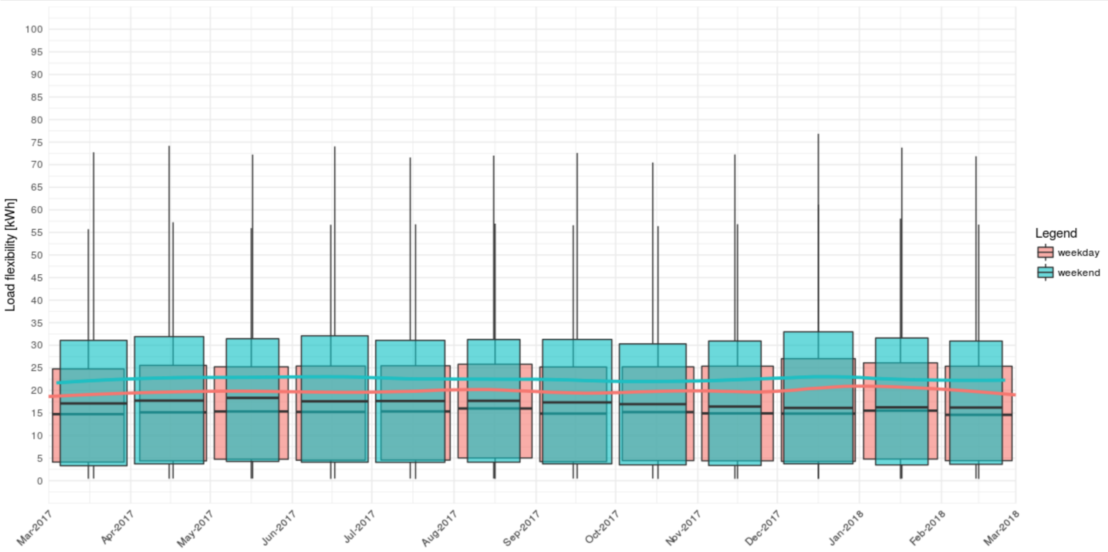


Figure 27: Boxplot of load-flexibility for each individual charging session during every month. [Note: bold black line = median; box = 25-75%; black whiskers = minimum and maximum, excluding outliers;outlier dots = outside 99% of the data]

On average each BEV present in the data set exhibits the potential to discharge 21.03kWh during the week, and 24.68kWh in the weekend during its connection period. Most of the monthly distributions have a positive skew and a slight increase during the winter months. The reason behind this behaviour requires insight in factors that influence load-flexibility. Although charging demand increases during winter months, the load-flexibility shows minor averaged variation during the year, because a large proportion of the data sessions in the set (approximately 75%) charge 10kWh or less while showing recurring behaviour. During fall and winter charging sessions aggregated load-flexibility per hour of the day is higher compared to the summer/spring in figure below. An logical explanation follows from the higher amount of connected vehicles. While charging sessions on average exhibit high time-flexibility percentages, more connected vehicles at the same time instant exhibit coherently also more load-flexibility.

Periodicity of time series demand related variables

The periodicity of the demand related factors provides insight in the recurring behaviour of the impact that loads induce on the distribution grid. Auto-correlation of charging demand in figure 28 is throughout the entire time series strongly auto-correlated, meaning the auto-correlation at any specified lag value is not random. The overal positive lag indicates a high association up to 4 days apart. Especially for the next day (lag = 1) correlations are the largest. Time-flexibility and load-flexibility are derivatives from connection- and idle-time, and therefore, again show similar auto-correlations. While load-flexibility shows more randomness during night time, during day time the flexibility measures can be reasonably accurately estimated for the moment in time they occur.

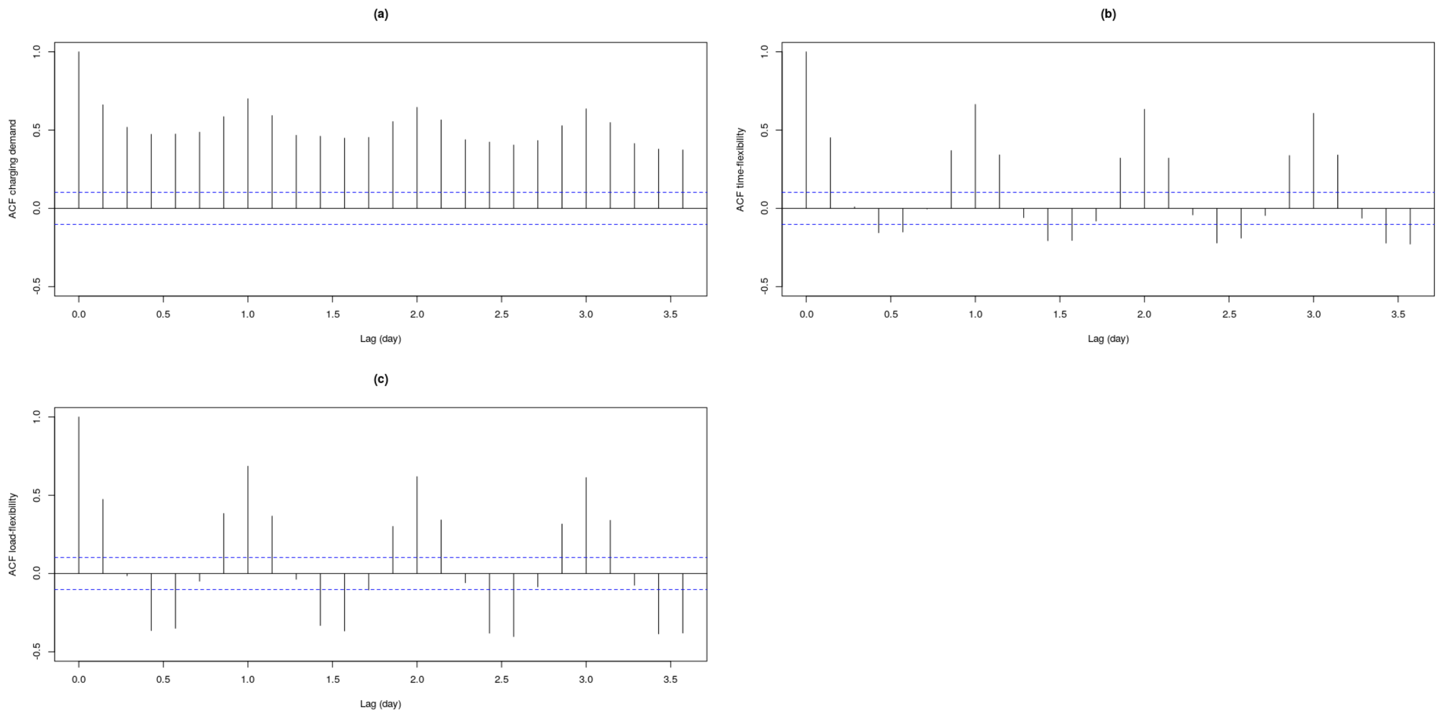


Figure 28: Auto-correlation function of (a) charging demand, (b) time-flexibility, (c) load-flexibility

In summary, the examined urban-level effects of BEV charging with empirical data elicits trends and temporal information of charging session characteristics, such as interconnections, energy demand, and potential flexibility. Paragraph 7.2 provides valuable and up-to-date insight for typical BEV charging demand in Amsterdam. It also quantifies the potential flexibility BEVs can offer at certain hours throughout the day. Whether that is for provision of $P_{Flex,up}(t)$ during low peak demand hours, or $P_{Flex,down}$ during high demand peak hours. It can be concluded that a significant part of the charging sessions show commuter driving behaviour in former mentioned characteristics, for which the interconnection times follow workday related times usually starting at 08:00 and ending at 18:00. Other behaviour can be denoted as park-to-charge, in which BEV drivers connect their BEV not excessively longer than necessary. As a result, time- and load-flexibility is available during standard Dutch work hours. Especially during peak charging demand hours around 07:00-09:00h and 17:00-19:00h time-flexibility for individual BEVs shows significant peaks of 63% and 74% respectively. On average every day, each BEV has 61.7% of its total connection duration available to reschedule 10.17kWh for the smart charging strategy. This equals the regular energy demand as exhibited in the data set but can be rescheduled over the BEVs complete connection time. In terms of load-flexibility on average each BEV present in the data set exhibits the potential to discharge 21.03kWh during the week, and 24.68kWh in the weekend within the individual connection periods. Because the load-flexibility represents the total- and initial- connected battery capacity every connected hour of each BEV, the relation with the time-flexibility has to be drawn carefully. The valleys of time-flexibility at 05:00h and 10:00h mean that the connected vehicles exhibit relatively low idle times but impose a connected battery capacity on the grid. These vehicles contribute therefore only a limited amount of capacity to discharge into the grid. In short, it is demonstrated that BEV charging sessions in Amsterdam on average exhibit sufficient time-and load-flexibility values that can be exploited for effective demand response in districts where charging hot spots occur (Amsterdam south/centre).

The inference of trends and periodicity in the arrival, departure, connection time, and energy demand of the charging sessions in the data set, allow to predict these variables for a few days ahead with reasonable accuracy. The available time- & load-flexibility shows a high auto-correlation coefficient for up to three days ahead for temporal related charging variables and up to four days ahead for energy demand related variables. Subsequently, the aggregator or the DSO are able to predict the periodic recurring behaviour of those former mentioned variables for a few days ahead. This allows for more effective daily operational grid tasks as charging demand can be optimised by taking prospective BEV demand into account.

The next section continues the analysis of charging behaviour impacts on the distribution grid by modelling a case study that simulates the proposed charging strategies. The mean, variance and standard deviation parameters of the sessions analysed in the current section are used to sample sessions that approximate these parameters of all the sessions, and are subsequently used as input for the simulation.

7.4. Case study - Simulation of electric vehicle demand response strategies

The experimental case study in this research proposes mathematical modelling of historical recorded charging sessions at a specific part of a low-voltage distribution grid in Amsterdam Nieuw-West to optimally schedule charging profiles for smart charging and V2G charging strategies. Objective functions as intended to minimise congestion rely on a prediction of BEV energy demand, which is performed in the previous paragraph. Although in reality actual charging characteristics are unknown at the time of scheduling, historic sessions may give an accurate estimation of the demand that is expected, and the capabilities for application of charging strategies

The charging sessions used as input in the simulation are sampled sessions from the complete data set, which are representative for the energy demand that is expected at the specific feeder location. Because the values of the parameters used as input in the optimisation model, i.e. arrival-departure time, charging demand, initial state-of-charge, battery capacity, are assumed to be dependent on each other and thus can be modelled as a multivariate distribution [55, 11]. First, the parameter values are discretised into hourly time intervals for 24 hour, in which the multivariate distribution expresses the covariance of each value's occurrence at a specific time stamp. The correct number of given vehicles for each day, depending on the scenario, are randomly sampled from the multivariate distribution according to the standard deviation, mean and co-variance between the variables of the original data for each session. The charging sessions are then stored as a vector containing: $P^{n}_{consumption}$, $t^{n}_{connection}$, E^{n}_{SOC} , ($t^{n}_{arrival}$, $t^{n}_{departure}$, $L^{n,c,d}$). The parameter values of the samples sessions are shown in table 9 and figure 29. This sampling method realises samples that approximate the whole data set for the standard deviation, mean, and co-variance measures. The reason behind this method is to sample session characteristics according to their probability occurrence as input in the model, in order to make this proof-of-concept reproducible for a larger-scale impact study in the local distribution grid of Amsterdam.

Table 9: Parameter values of the sampled sessions, which are the input of the LP model

Sampled BEVs	Mean required consumption [kWh]	Total battery capacity [kWh]	Mean connection time	Mean arrival time [hh:mm]	Mean departure time [hh:mm]
5	12.7	118	8h 21min	9:48	18:09
10	10.8	178	8h 59min	12:12	21:11
15	12.6	282	8h 52min	09:36	18:28
20	14.1	425	8h 47min	12:21	21:07
25	13.2	482	9h 9min	11:55	21:04
30	13.2	601	9h	14:30	23:30
34	13.8	680	8h 51min	13:57	22:47

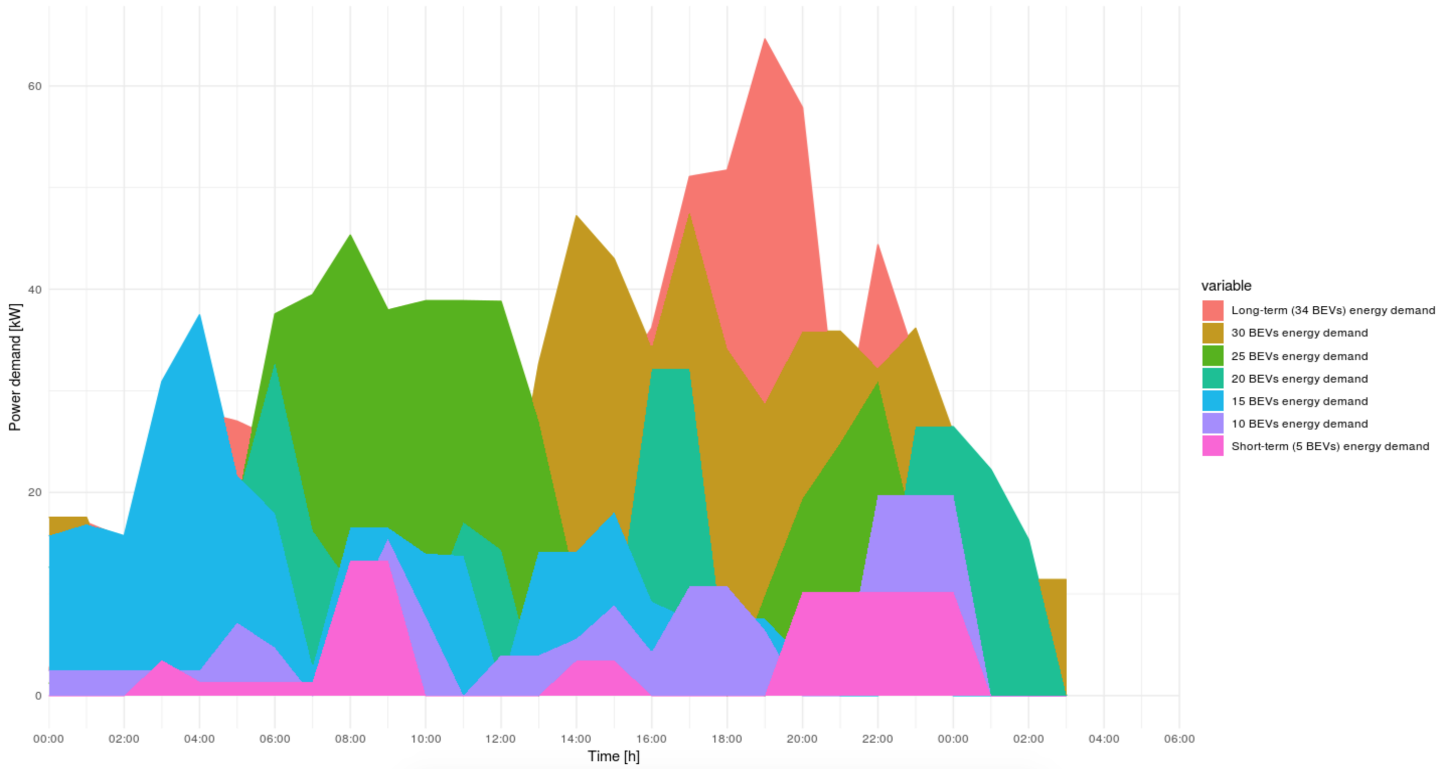


Figure 29: Charging demand of sampled sessions

Due to the fact this specific local grid is robust and developed to handle near future electrification increase, the simulations for different BEV penetration levels are performed for varying feeder capacity limits. In addition, the actual feeder base load is multiplied by a factor of five to be more representative and realistic for other feeders located in Amsterdam. To provide more quantitative insight in the optimisation results for different scenarios, the BEV penetration values will range from the short-term scenario of five BEVs (10% market share), to the long-term scenario of 34 BEVs (75% market share) by steps of five. The linear program is subsequently performed to optimise charging demand of these BEVs for situations in which the feeder's maximum limit is varied at 50%,60%, 70%,80%, 90%, and 100% of its maximum base load, which is 144kW and depicted in figure 30. In this experimental setup of the distribution grid the maximum feeder base load, for all optimisation scenarios, is multiplied with five. This operation is performed to induce optimisation results that are in line with loads on other local grid assets in Amsterdam. These values are determined in collaboration with Liander to mimic actual feeder load values as can be apparent in other parts of the local distribution grid in Amsterdam. Furthermore, demand of uncontrolled charging profiles depends on the charging point equipment for which the rate of each specific point is used from the data set. The smart- & V2G charging points have a rated output of 10kW. The theoretical total maximum aggregated demand of 5 BEVs is 50kW and 34 BEVs is 340kW, and so on. Charging costs are modelled according to the RTP day-ahead tariff and expressed in price per energy (€/kWh). Furthermore, it is assumed that the base load in each receding interval of the day is known.

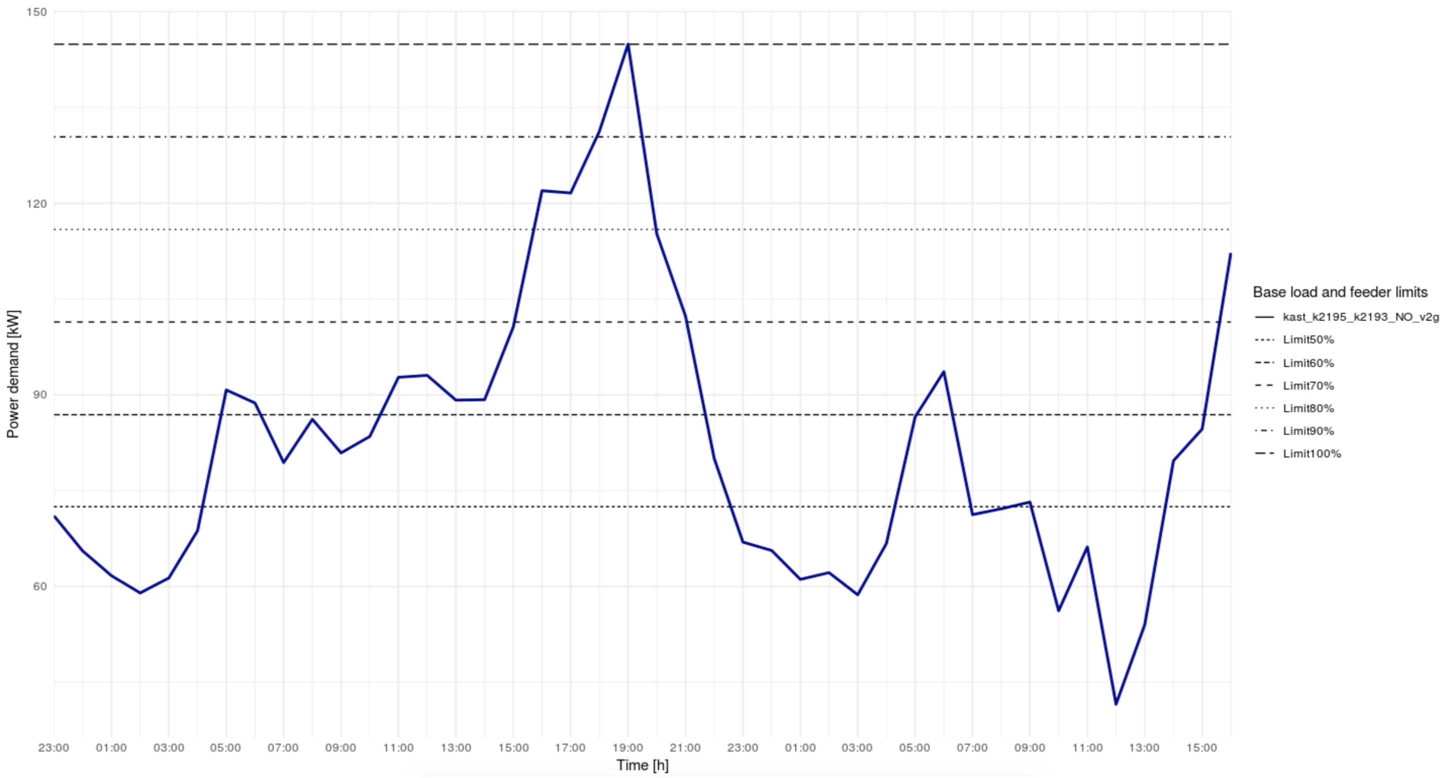


Figure 30: Feeder limit constraints according to base load of 144kW

To solve the LP a non-commercial linear program solver of R is used, i.e. LPsolve. The use of this particular solver is restricted by the privacy disclaimer concerning data duplication prohibition exerted by the data set provider. Results are depicted in a plot of total feeder power load through time for each of the charging modes. According to the total allowable feeder load, the simulated charging strategies show at which penetration rate of BEVs in the local grid, these boundaries will suffice. Benefits for either charging modes are listed for both the DSO (as total percentage of consumption shed) and consumer (as price per kWh).

7.4.1. Analysis of effects on grid congestion

In this section the linear program is simulated on the feeder load with the sampled electric vehicle charging sessions in Amsterdam Nieuw-West as an example. The loads that are optimised in the objective function of 16 depend on the prediction of both household- and BEV power demand, and the varied values of the feeder limit. Although, the power prediction of the household loads are beyond the scope of this research, the prediction of BEV consumption is obtained by performing a time-series local regression analysis and auto-correlation using historical data. Furthermore, the optimisation results of the charging sessions depend significantly on the maximum allowable feeder load. One should bear in mind that all feasible solutions of the LP will be similar to the uncontrolled charging scenario if no grid constraints will be violated, because the LP model always charges each BEV as fast as possible. Also, whenever the induced loads on the feeder exceed the maximum limit, the feeder will encounter a failure and immediately shuts down. Hence, in every simulated case congestion is apparent and the feeder limit is violated if the uncontrolled BEV charging demand is added on top of the base load. Also, the smart charging strategy is not applicable for a feeder limit other than 100%, thus this strategy will merely be used to verify the V2G charging strategy against that smart charging strategy in the simulation with a feeder limit of 100% the base load. The results from this comparison yield similar parameters for both the charging strategies. Furthermore, a simplistic partial validity experiment is set up to test whether the model can replicate reality. This test is empolyed by altering the parameter values such that the real-world values of the uncontrolled charging scenario are modelled. The results show that an optimal solution is found, which entails that the results are an exact replication of the reality, i.e. for uncontrolled charging.

The results of the optimisation runs are presented in the tables below. For each different case, the percentage of peak load shed as well as the average charging costs per kWh are presented, and together provide an overview of possible feeder congestion situations in Amsterdam. Additionally, two tables are provided that describe the possibilities to charge additional BEVs under the V2G optimisation cases and show the energy charged per BEV in comparison to uncontrolled charging. Only the graphs of the long-term scenario are depicted that represent the worst-case as a proof-of-concept visualisation.

Tables 10, 11, 12, 13, 14, and 15 below present the results of the simulation runs for the V2G charging strategy. The columns in the table describe the maximum feeder load, the percentage of average- and maximum peak shed compared to the uncontrolled case, the required energy demand and the energy charged in the V2G strategy. In none of the 50% and 60% feeder limit simulations the V2G strategy was able to decrease the total energy demand below the required feeder constraints, and are therefore not applicable to provide sufficient flexibility to prevent congestion. These results, when applicable, are not presented in the tables under maximum peak shed, but highlighted red. In those simulations, the limit was unable to be sufficed due to either a discharging rate limited by the charging point output, too little battery capacity to discharge, or simply no BEV connected during that period. In addition, the simulations for 5,10,15, and 20 BEVs charging with a feeder limit of 70% show results that are insufficient to meet congestion requirements as well, those are highlighted in red. In all other simulated cases the optimal solution decreased total energy demand to remain within feeder limits, and can be seen in tables: 12, 13, 14, 15. The solutions for which the charged energy in the BEVs is decreased below 90% of the required energy to maintain within feeder boundaries are highlighted in yellow. The results highlighted in green show the solutions that charge more than 90% of the energy as required or with a similar consumption, while not violating the feeder constraint. Furthermore, the maximum peak shed, expressed in percentage and reduced energy demand (kW),is calculated from subtracting the maximum feeder load in the congestion situation (uncontrolled charging) from the V2G load and the base load. The resulting maximum peak shed is an indication for the potential of the V2G strategy at peak demand periods, while remaining within the imposed constraints of the feeder.

Table 10: Optimisation results for 50% (72kW) feeder limit of the maximum base load

BEVs charging	V2G peak shed [%]	BEV energy demand [kWh]	V2G charged energy [kWh]
5	9.97	63	41
10	8.25	108	63
15	14.2	189	81
20	15.2	282	82
25	18.2	332	142
30	20.3	398	39
34	24.8	449	33

Table 11: Optimisation results for 60% (87kW) feeder limit of the maximum base load

BEVs charging	V2G peak shed [%]	BEV energy demand [kWh]	V2G charged energy [kWh]
5	9.97	63	54
10	8.25	108	85
15	14.2	189	97
20	15.2	282	175
25	18.2	332	113
30	20.3	398	171
34	22.4	449	97

Table 12: Optimisation results for 70% (101kW) feeder limit of the maximum base load

BEVs charging	Maximum feeder load	Mean V2G peak shed [%]	Max. V2G peak shed [%]/[kWh]	BEV energy demand [kWh]	V2G charged energy [kWh]
5	155	3.2	-	63	63
10	144	5	-	108	90
15	149	9.4	-	189	141
20	154	12.9	-	282	203
25	164	16.2	38.4/33	332	161
30	188	16.6	46.3/87	398	234
34	203	21.9	50.2/102	449	201

Table 13: Optimisation results for 80% (116kW) feeder limit of the maximum base load

BEVs charging	Maximum feeder load	Mean V2G peak shed [%]	Max. V2G peak shed [%]/[kWh]	BEV energy demand [kWh]	V2G charged energy [kWh]
5	155	2.1	-	63	63
10	144	4.4	19.4/28	108	104
15	149	7.1	22.1/33	189	151
20	154	7.9	24.7/38	282	234
25	164	12.7	29.3/48	332	229
30	188	13.5	38.3/72	398	307
34	203	18.1	42.9/87	449	299

Table 14: Optimisation results for 90% (130kW) feeder limit of the maximum base load

BEVs charging	Maximum feeder load	Mean V2G peak shed [%]	Max. V2G peak shed [%]/[kWh]	BEV energy demand [kWh]	V2G charged energy [kWh]
5	155	1.77	16.1/25	63	63
10	144	3	10/14	108	108
15	149	5.9	12.8/19	189	184
20	154	7.3	15.6/24	282	265
25	164	10.5	20.7/34	332	265
30	188	10.4	30.8/58	398	344
34	203	8.9	36/73	449	365

Table 15: Optimisation results for 100% (144kW) feeder limit of the maximum base load

BEVs charging	Maximum feeder load	Mean V2G peak shed [%]	Max. V2G peak shed [%]/[kWh]	BEV energy demand [kWh]	V2G charged energy [kWh]
5	155	1.7	7.1/11 /	63	63
10	144	2.8	0/0 /	108	108
15	149	5.2	3.4/5 /	189	189
20	154	5.9	6.5/10 /	282	271
25	164	6.7	12.2/20 /	332	290
30	188	8.2	23.4/44 /	398	364
34	203	4.9	29.1/59 /	449	393

In continuation of the subject that addresses the difference in charged energy for uncontrolled charging and V2G charging, this research initially assumed electric vehicles depart with a fully charged battery, while in reality this is not necessarily required. The average distance travelled in Amsterdam equals 22km [51], which requires only a small proportion of the battery capacity. During daily average trips the energy consumption equals 4.4 kWh approximately, according to an inefficient vehicle mobility factor of 0.2 kWh/km, as used in the article of [25]. More so, the sessions analysed in this research show a mean average energy consumption for every session of only 10.17kWh. Based on the prior acquainted results in paragraph 7.2, the energy charged in some of simulated cases, i.e. with a feeder limit of 70%, the V2G charging strategy may impose range limitations as the resulting charged energy is for 25,30,34 BEVs respectively 51%,41%, 55% lower than the required energy demand in the uncontrolled case. This translates to a energy consumption of the values in table 16 for each BEV in the V2G scenario in relation to total energy demand in the uncontrolled case. Although a large concession is made on the energy charged, it may still be sufficient for the average driver in Amsterdam to reach its destination. While this may be a breach on the requirements of the prosumer, this study assumes a satisfactory consumption in the V2G strategy that is between 90% and original required. Again according to the same analogy of the colours, green is 90% or higher, and yellow denotes 4.4kWh or higher.

Table 16: Energy charged per BEV for both uncontrolled charging the V2G charging

BEVs charging	Uncontrolled consumption [kWh/BEV]	V2G consumption 70% limit [kWh/BEV]	V2G consumption 80% limit [kWh/BEV]	V2G consumption 90% limit [kWh/BEV]	V2G consumption 100% limit [kWh/BEV]
5	12.7	-	-	12.7	12.7
10	10.8	-	10.4	10.8	10.8
15	12.6	-	10.4	12.3	12.6
20	14.1	-	11.7	13.3	13.5
25	13.2	6.5	9.2	10.6	11.6
30	13.2	7.8	10.2	11.5	12.1
34	13.2	5.9	8.8	10.7	11.6

By varying the feeder limit, different feeder load circumstances in Amsterdam are mimicked to induce results for a V2G optimisation through a range of different connected electric vehicles. The amount of vehicles that the DSO allows to be charged by application of the V2G optimisation strategy under the congestion situations are derived from the former described tables and shown in table 17 and are the most important results for the distribution grid operator. Again in none of the situations of the uncontrolled BEV charging, the feeder load remained within the imposed constraint boundaries. This means that in each of the proposed cases for uncontrolled charging, the feeder will encounter a failure and breaks down. To provide a fair comparison, only the results of the simulations that attained the imposed constraints, i.e. required energy demand and feeder limit, are shown in table 17. The values represent the amount of vehicles that can be charged with the V2G strategy under varying circumstances of the feeder limit. In conclusion, one can notice that when the feeder limit increases, naturally more BEVs can be connected compared to the uncontrolled case, however at the cost of energy charged (see table 16).

Table 17: Additional BEV connection potential in the V2G optimisation cases

BEVs charging	Uncontrolled Maximum feeder demand	Additional V2G 70% limit	V2G 80% limit	V2G 90% limit	V2G 100% limit
5	155	-	-	5	5
10	144	-	10	10	10
15	149	-	-	15	15
20	154	-	-	20	20
25	164	-	-	-	-
30	188	-	-	-	30
34	203	-	-	-	-

CAPEX opportunity costs

The Capital Expenditure opportunity costs of a distribution grid asset is measured in terms of the best alternative available. As been introduced in paragraph 5.1 the prospective value configuration for the DSO depends on outgoing cash flows that represent costs for procurement of delivered flexibility and grid asset depreciation. Actual data on long-term grid investments is not available for this research. However, the latter costs eventually lead to early grid reinforcement investments that need faster depreciation deduction on the balance sheet, which may be temporarily deferred when V2G charging is applied. As described in the model of figure 7, the value flow for the DSO is significantly dependent on the size of BEV enabled flexibility, and thus can be expressed in the amount of chargeable BEVs under the V2G optimisation, and can be found in table 17. The V2G optimisation for the short-term scenario allows charging of 5,10,15, an 20 BEVs for a feeder limit of 90% and 100% respectively. While these results are significantly dependent on the interconnection time variables of the electric vehicles and their synchronisation with peak base loads, the results from the table provide sufficient proof-of-concept for the possibilities to aid in congestion in Amsterdam for different future BEV penetration rates. In short, for some of the V2G simulation results, for which feeder base loads range from 80% to 100% of its limit, the DSO may still allow BEVs to be charged by using this strategy. For a feeder with a limit of 80% (116kW), a maximum of 10 BEVs can be charged against zero in the uncontrolled charging scenario, which translates to approximately a future scenario in 2021 according to [29]. At a feeder limit of 90% (130kW) the amount of BEVs allowed to charge piles up to 20 that tends to be around 2025. Lastly, with a feeder limit of 100% (144kW) and at a maximum of 30 BEVs, the feeder limited was not violated and congestion is cleared. 30 BEVs corresponds to approximately a scenario in 2028. The exemptions for 25 and 34 BEVs are not included in the total allowable BEVs that may be charged due to the fact that under the V2G strategy these BEVs charged to little energy (still 87% and 88% for 25 and 30 BEVs of the required demand). This may be due a misalignment of interconnection times with peak base loads.

Charging associated costs

The charging costs associated with the simulated sessions are scaled in order to make a fair comparison between the different conveyed strategies. Although the proposed V2G LP model does not handle a minimisation of prices, it checks whether the proposed RTP tariff in paragraph 6.3 produces lower prices after scheduling the charging sessions. The table below depicts the values for price per kWh charged/discharged and the change in percentage of the price/kWh what would have been charged in the uncontrolled case (ignoring congestion) and the price when adopting the V2G strategy. The same colour analogy is applied to this table for which the simulated cases that pass the feeder constraints and the required energy demand are coloured green, yellow if V2G charged energy is less than required energy demand, and red if feeder limits are violated. The cleared V2G optimisation cases in green show a little decrease in costs and in some cases (for 10,15 BEVs charging) even an increase in costs compared to the uncontrolled charging case. This may be due to the fact that the RTP tariff rate is not aligned with the variation in base load, but rather with the wholesale day-ahead prices. However, the optimisation results that display higher charged prices are only marginally larger than the prices in the uncontrolled case, and prices for all other results are significantly lower to the original case.

The costs of charging and discharging are especially low when the constrained limit on the feeder is low, the charging sessions fall within peak periods and are connected for a relatively long time. Most of the results of the V2G simulations. The V2G strategy outperforms in almost every simulation charging in the uncontrolled scenario, by both charging during periods of low prices and discharging during periods of high prices even though the LP model does not optimise on prices. By combining a load-price levelling model, the prices charged to the consumer may be decreased even more [44].

Table 18: Optimisation cost results for varying feeder limits and amount of electric vehicles

BEVs charging	Uncontrolled costs [euro/kWh]	Costs [euro/kWh]/[%] 50% limit	Costs [euro/kWh] 60% limit	Costs [euro/kWh] 70% limit
5	0.344	0.246/-29	0.254/-26	0.282/-18
10	0.339	0.326/-3.8	0.280/-17	0.305/-10
15	0.312	0.241/-23	0.266/-15	0.283/-9.3
20	0.313	0.186/-41	0.257/-18	0.265/-15
25	0.341	0.254/-26	0.251/-26	0.291/-15
30	0.337	-0.131/-139	0.226/-33	0.258/-23
34	0.332	-0.192/-158	0.143/-57	0.251/-24
BEVs charging	Costs [euro/kWh]/[%] 80% limit	Costs [euro/kWh]/[%] 90% limit	Costs [euro/kWh]/[%] 100% limit	
5	0.314/-8.7	0.322/-6.4	0.343/-0.29	
10	0.318/-6.2	0.335/-1.2	0.341/0.6	
15	0.296/-5.1	0.317/1.6	0.320/2.6	
20	0.289/-7.7	0.307/-1.9	0.301/-3.8	
25	0.313/-8.2	0.320/-6.2	0.322/-5.6	
30	0.291/-14	0.314/-6.8	0.327/-2.9	
34	0.289/-13	0.308/-7.2	0.314/-5.4	

In the long term simulation, corresponding to 34 electric vehicles charging under 70% feeder limit of the maximum base load, the optimisation allows to charge all vehicles as fast as possible while remaining close to the feeder limit. Figure 31 shows the most optimal solution for charging the 34 sampled BEVs, for which the colour red is the total feeder load in the uncontrolled case, blue the feeder's base load, green the total feeder load for the V2G optimised solution, and purple to total load that is decreased. The model is designed to charge BEVs between the feeder limits and is consequently in some cases unattainable to meet required consumption because of grid power and connection time limitations. However, what can be noticed from figure 31 is how well the model serves its intended purpose to not violate the feeder constraints, especially during peak base loads from 16:00-22:00. Unfortunately, the V2G optimisation yields a consumption that is 44% lower than the uncontrolled case in order ensure the feeder constraint of 101kW is not violated. Although, this consumption may be sufficient for the average driver in Amsterdam as explained earlier.

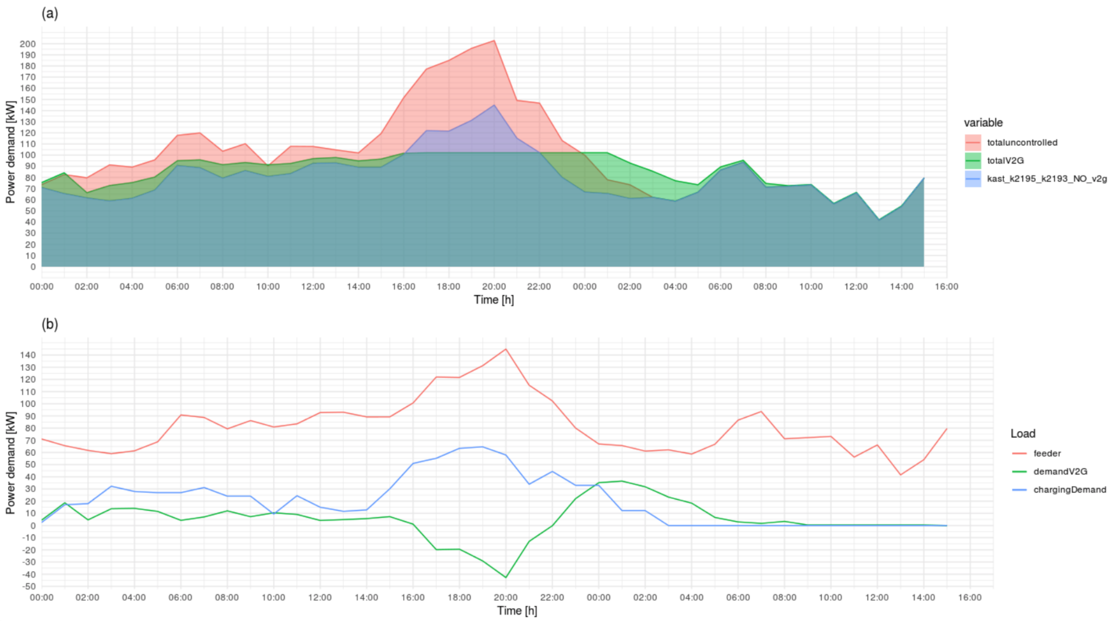


Figure 31: Simulation LP program of the V2G charging strategy for 34 BEVs and a feeder limit of 70% its maximum base load

In conclusion, the coordinated BEV charging for a V2G strategy is shown to cover multiple interests for the prosumer, DSO and aggregator. The DSO may use the unlocked flexibility in the cases shown in table 17 to decrease congestion causing loads and additionally allow more BEVs to be charged while still meeting the imposed feeder limits. For a feeder with a limit of 80% (116kW), a maximum of 10 BEVs can be charged against zero in the uncontrolled charging scenario, which translates to approximately a future scenario in 2021 according to [29]. At a feeder limit of 90% (130kW) the amount of BEVs allowed to charge piles up to 20 that tends to be around 2025. Lastly, with a feeder limit of 100% (144kW) and at a maximum of 30 BEVs, the feeder limited was not violated and congestion is cleared. 30 BEVs corresponds to approximately a scenario in 2028. The exemptions for 25 and 34 BEVs are not included in the total allowable BEVs that may be charged due to the fact that under the V2G strategy these BEVs charged to little energy (still 87% and 88% for 25 and 30 BEVs of the required demand). This may be due a misalignment of interconnection times with peak base loads. Hence, the potential for a V2G charging strategy is significantly dependent on the connection time and feeder limit, and will therefore show significantly increased peak shed percentages if the connection time increases. Also, whenever the induced loads on the feeder exceed the maximum limit, the feeder will encounter a failure and immediately shuts down. Subsequently, the smart charging strategy is not applicable for a feeder limit other than 100%, thus this strategy will merely be used to verify the V2G charging strategy against that smart charging strategy in the simulation with a feeder limit of 100% the base load. The results from this comparison yield similar parameters for both the charging strategies. As been said, the model's performance works especially well during peak demand periods throughout the day, although produces a solution that makes a significant concession for the amount of energy charged in the long-term scenario. Although, none of the optimisation solutions for which the feeder constraint is not violated charge less energy than necessary for the average trip distance in Amsterdam. Furthermore, the V2G strategy outperforms charged prices per kWh in almost every simulation compared to the uncontrolled scenario, by both charging during periods of low prices and discharging during periods of high prices even though the LP model does not optimise on prices.

8. Conclusions

Conclusions

In the near future BEV electricity demand increases significantly, and because BEV prosumers show behavioural tendencies that concentrate at a certain time and additionally exhibit charging session properties that also show periodic characteristics, their demand ought to be controlled to alleviate potential overloading in power system operations. Currently as a result of the EU Energy Efficiency Directive of 2012, an institutional base is presented for development of demand response in Europe [17]. Therefore, to assess potential future incumbent value configuration of BEV demand response, the most focal value flows for the DSO are elicited, that proceed on an already existing communication infrastructure, (USEF) market framework, and intermediary actor that has real-time access to all BEVs. This model provides insight in prospective value configuration for the DSO, for which procurement of delivered flexibility should weigh up to additional grid reinforcement costs.

To be able to provide an answer to the main research question in this study an analysis is performed towards integration of a coordinated direct load control, the trends and periodicity of charging demand and flexibility, and lastly an optimisation scheduling model:

What is the value of demand response management in a Vehicle-to-Grid network and does it provide increased benefits to smart charging for consumers and the distribution system operator in Amsterdam?

This research proposed a (multi-aggregator) centralised approach of directly controlling and optimising the consumers' energy demand by introducing a planning protocol that may be integrated in the existing USEF framework. To be able to control BEV energy demand and remain within distribution boundaries, it is imperative to know BEV charging behaviour. Their impact on the local grid is assessed in terms of potential flexibility throughout the year as to investigate seasonal and daily patterns. It is demonstrated that BEV charging sessions in Amsterdam on average exhibit sufficient time-and load-flexibility values that can be exploited for effective demand response in districts where charging hot spots occur (Amsterdam south/centre). Especially during peak charging demand hours around 07:00-09:00h and 17:00-19:00h time-flexibility for individual BEVs shows significant peaks of 63% and 74% respectively. On average every day, each BEV has 61.7% of its total connection duration available to reschedule 10.17kWh for the smart charging strategy. This equals the regular energy demand as exhibited in the data set but can be rescheduled over the BEVs complete connection time. In terms of load-flexibility on average each BEV present in the data set exhibits the potential to discharge 21.03kWh during the week, and 24.68kWh in the weekend within the individual connection periods. Furthermore, the aggregator or the DSO are able to predict the periodic recurring behaviour of charging demand for three to four days ahead. This allows for more effective daily operational grid tasks as charging demand can be optimised by taking prospective BEV demand into account.

Further investigation about the usable amount of flexibility is simulated with linear programming for charging strategies (smart charging and V2G charging) to aid in local feeder congestion. In this research a case study is performed on load data of a low-voltage feeder. According to the current and near future BEV penetration rate, multivariate sampled charging sessions' load is modelled on the feeder. In conclusion, the coordinated BEV charging for a V2G strategy is shown to cover multiple interests for the prosumer, DSO and aggregator. The DSO may use the unlocked flexibility in the cases shown in table 17 to decrease congestion causing loads and additionally allow more BEVs to be charged while still meeting the imposed feeder limits. For a feeder with a limit of 80% (116kW), a maximum of 10 BEVs can be charged against zero in the uncontrolled charging scenario, which translates to approximately a future scenario in 2021 according to [29]. At a feeder limit of 90% (130kW) the amount of BEVs allowed to charge piles up to 20 that tends to be around 2025. Lastly, with a feeder limit of 100% (144kW) and at a maximum of 30 BEVs, the feeder limited was not violated and congestion is cleared. 30 BEVs corresponds to approximately a scenario in 2028. The exemptions for 25 and 34 BEVs are not included in the total allowable BEVs that may be charged due to the fact that under the V2G strategy these BEVs charged to little energy (still 87% and 88% for 25 and 30 BEVs of the required demand). This may be due a misalignment of interconnection times with peak base loads. Hence, the potential for a V2G charging strategy is significantly dependent on the connection time and feeder limit, and will therefore show significantly increased peak shed percentages if the connection time increases.

As far as the comparison of the smart charging and the V2G charging strategies goes, in all simulated cases congestion is apparent and makes the use of smart charging impossible, the feeder would have failed under congestion without having the possibility to discharge energy. As been said, the model's performance works especially well during peak demand periods throughout the day. In addition, the V2G strategy outperforms charged prices per kWh in almost every simulation compared to the uncontrolled scenario, by both charging during periods of low prices and discharging during periods of high prices even though the LP model does not optimise on prices. Thus, the V2G strategy allows the DSO to postpone grid investments in a number of cases while simultaneously the consumer almost always receives remuneration for its delivered services. The V2G strategy therefore provides a significantly added value over a smart charging strategy.

9. Future work and recommendations

1. More in depth statistical analysis methods, such as cluster density based algorithms, or multi-nomial logit regression could be assessed to derive dependency structures between variables of interest in defining future BEV charging/driving behaviour and to perform validations on the predicted demand. This will allow for a more accurate distinction of typical recurring behaviour, which is, subsequently useful for an aggregators forecast on total power demand in spatial- and temporal terms.

2. In the work of [63] an algorithm is defined that computes the amount of energy and time at which flexibility is used in their charging strategies. They calculate a shift profile in vector form that quantifies the amount of energy shifted to a particular time slot within the optimisation window. This algorithm was initially developed for residential demand response, and can therefore be generalised to any other scheduled optimisation of demand. While the potential to ameliorate congestion at the local grid is explored in this research, information regarding the exact amount and time at which this energy is scheduled provides relevant insight for the DSO's grid operations. Furthermore, using this algorithm the LP program can be validated by results. This means comparing the model's results with real world outcomes, i.e. calculated time- and load-flexibility.

3. The value of DR in a liberalised system should be analysed more on the subject of the split-incentives challenge. Who initiates demand response (consumer, retailer, aggregator, DSO) and how should the benefits be divided along the supply chain. Handling an optimisation problem of DR for holds strong requirements for an global system balance in which neither participating actors are discriminated and the whole system benefits. An assessment of relational dependencies between participators in DR should be incorporated in designing charging strategies.

4. The charging strategies framework as proposed in this research can be expanded to integrate residential, or even larger distributed renewable energy generation, with the objective to charge or store this electricity generation and fully capture green energy by starting control at the consumer-side.

5. Implementation of additional required CAPEX opportunity costs for local grid assets according to future BEV penetration is an important next step to be undertaken to investigate the costs and benefits of building a economical feasible V2G infrastructure.

Appendix

A. Energy market transition

This section provides the reader with context knowledge on the transformation of the Dutch power system and energy markets in reaction to governmental policy arrangements. The global energy systems currently use mainly resources that are oil-, coal- and gas-based to produce energy. The demand of these resources is prospected to grow until 2040, which entails a large reliance on these resources today and in the future [73]. A large share of the worldwide-consumed energy depends on these carbon energy systems defined as a carbon lock-in. This means that many industries and technologies are designed for and reliant on fossil fuels as primary energy resource. They also share the largest percentage equivalent of global gross domestic product. Inevitably, carbon energy resources will remain interdependent on the global economy for many years. It is therefore difficult and expensive to change or displace the current global energy system by better, cleaner alternatives in the very near future [73, 67].

Hence the global energy system is currently subjected to a shift in the energy paradigm that opens up transformational technology- and economical systems for renewable energy production [79, 3, 36]. Subsequently renewable energy resources are thought to be gaining up on conventional resources but remain currently to electricity generation. New technology development in energy systems will impose changes in the economy, policies, investments and mind-set of consumers. Currently the main objective of the current Dutch Ministry is to enlarge the share of renewable energy in the energy mix and invest more in low-carbon energy systems [79]. The new 2017 coalition of the Dutch government describe their target on reaching reductions in greenhouse gas emissions of 49% by 2030 and with that increasing the bar of the 40% level that is elicited by the European Union. 1.5% of that reduction is allocated to measures that include electric vehicles [79].

History reformation Dutch energy market

The original energy grid in the Netherlands has a top-to-bottom hierarchical structure. Its network is built-up with a large number of centralised generating facilities and many vertically disintegrated distribution sectors to provide electricity from a medium- and local sized network, up to the end users. This design dates back to the 19th century imposing significant large infrastructural networks that contribute to the economy of the Netherlands. The energy grids were heavily regulated and owned by the government because it was thought involvement of national authorities would prevent market failures. Regulation is also necessary to protect customers from the natural monopolies that electricity production companies develop.

However, with incentives for market efficiency, the Dutch Ministry of Economic affairs elicited a new sector organisation for stable institutional arrangements in the 1980s. Trends towards liberalisation of the utility market, resulting in a growing need for disintegration between producers and distributors to impose economies of scale for cost savings and improved market efficiency. During 1985-1989 existing market structures were to disrupt and the electricity infrastructure came into a transition that opened up opportunities for free competition that was self-regulated under support of the government. A distinction can be noticed between legal vertical disintegration between the production and transportation sector, and the distribution sector. A reform effort to challenge the production monopoly unbundled the relationships between the producers and distributors, which caused a sharp decline in the amount of production- and distribution companies. The decline was due to merge of local distributors into large concentrated provincial distributors and large distributors geographically related to the four biggest cities in the Netherlands [3, 36].

The Electricity Act of 1989

The new Electricity act of 1989 facilitated new market opportunities for producers that allowed optimisation of production processes to cost criteria instead of political directives. Production became a legal form of private stock companies that used a self-regulation authority, controlled by the government to provide reliable, secure supply and improvement of economic performance. The reform process or liberalisation changed the regulatory role of public authorities by making voluntary agreements between producers and distributors that required minor legal enforcement power [36].

The infrastructure after the integration of the Act appeared not very efficient and cost effective, because distributors were allowed to buy electricity from any regional producer for a state regulated national pooling price (abolition of monopolies) However, under the absence of price differences, resulting from free electricity purchase, this horizontal market structure was not used. Under the Electricity Act, distributors were allowed to produce electricity in small-scale quantities to compete with large producers. Large industrial consumers were not to limited to obligatory use of distributors or national import and subsequently made collaborations with local distributor-producers to build (CHP: Combined Heat Power) decentralised capacity. Later grown in size to 20% of the national production, fuelled by large investments of distributors and partly by large industrial consumers. For environmental reasons, distributors gained societal and political support for their decentralised renewable production.

The Electricity Act of 1998

The electricity act of 1998, allowed not only free competition and unbundling of utility companies, but also free choice of supplier for the largest consumers, and later in phases for medium- and small consumers (phased out in 2004). Distribution came under state regulation to secure a reliable and obligatory utility to consumers. Decentralised trading of electricity was made possible due to the Electricity Act of 1998 on a wholesale market. No longer making use of feed-in tariff structures, the distributors expanded their position in the electricity market [3, 36]. From now on every actor could make use of a fair energy pricing system. Distributed generation however, produced overcapacity in the energy market because of its competitive production methods against the large producers.

B. Wholesale and retail electricity market

Development of open accessible wholesale markets for trading electricity regulated by legal entities is an important factor to maintain a market efficient competitive energy system emphasised by increasing distributed (renewable) generation. In the Netherlands costs of distributed generation are strongly correlated with electricity market rules, therefore regulations alleviate entrance barriers by developing efficient market design for pricing ancillary services, intermittent resource supply, and small consumer access [50, 79, 75, 17]. However, current bid characteristics for trading electricity are not always utilised in an efficient process, which is partly blamed on the rapid technological transition of distributed generation on consumer level. More on that subject can be read in 3.1.

There are multiple energy markets in the Netherlands that facilitate the trading of energy as described in the process above, such as the day-ahead or the unbalance market. On the former market, energy contracts (dispatch amounts) are made between buyers and sellers for every hour of the following day. On the unbalance market every 5 min time stamp energy is dispatched to account for last minute imbalance in supply and demand. These prices are higher than the prices on the day ahead market, owing to the short time period in which energy needs to be dispatched. The electricity wholesale price depends on the generators' offered capacity to retailers for the following day in hourly intervals, in which the price depends on both the volume and time-of-use. Under- or over- estimations in supply and demand are directly related to the electricity prices. Other methods to trade electricity include bilateral contracts for trading parts of the electricity demands, usually applicable to commercial actors. Below depicted are the day-ahead hourly prices for the previous year, that show the historic real-time electricity value on the wholesale market. Some quick observations show higher prices in the during winter and weekend days, for which demand is higher and has more variation.

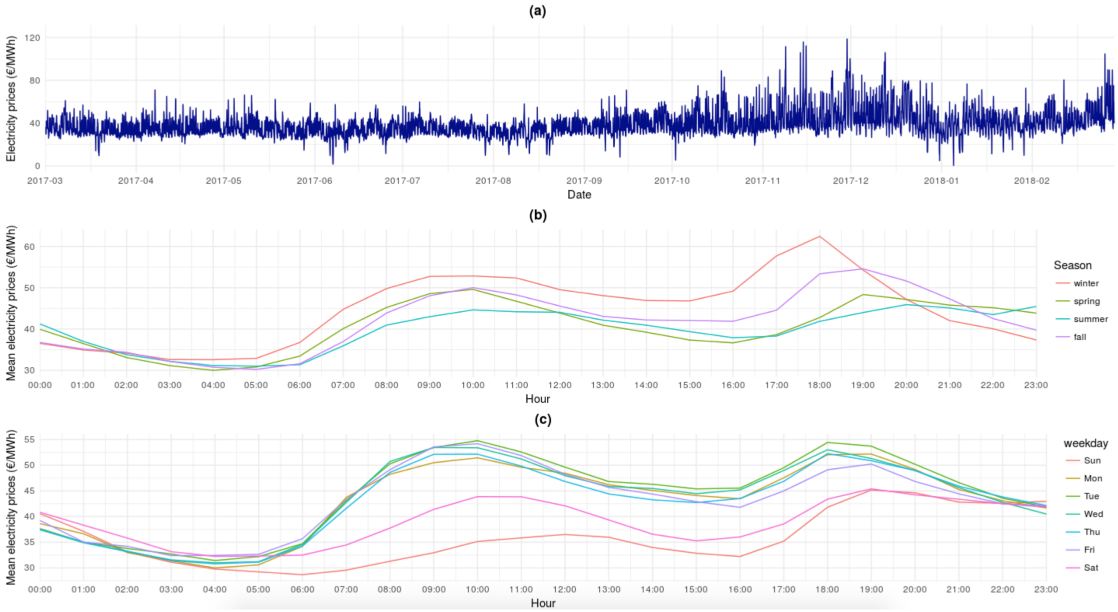


Figure 32: APX spot Day-ahead electricity prices

C. Analysis of distributions of electric vehicle session characteristics

Ratio actual charging time to connection time

A majority of the charging sessions exhibit significant longer connection time than actually required for to suffice charging demand for those sessions. This trend enables the possibility to utilise the fact that BEVs, while connected to the grid, can provide flexibility in scheduling their charging. To further explore how the charging sessions' charging time relative to connection time is distributed, the ratio of actual charging time to connection duration is computed and plotted with a frequency polygon in figure 33 above. The ratio is a measure to calculate the required charging time (according to capacity charged) relative the total connection time for each session. The lower the ratio, the more idle time within sessions. As an example, 65% of the charging sessions have a ratio score below 50%. The ratio score of 50% means that connection time is twice the required charging time. By further graphical inspection, the graph appears to exhibit multi-modal peaks, and is furthermore positively skewed. Skewness is a descriptor that expresses a value for the asymmetry of the distribution, and is derived by inspection of the mean (0.3826) than the median (0.3061). A greater mean than median points out a larger part of the distribution has a ratio score below the median, meaning a trend in connection times longer than the necessary charging times. This statement can be backed by the fact that only a small peak is visible at a ratio of 1, meaning only a small proportion of the BEVs charge their vehicle and depart when the BEV battery is fully charged. Further analysis of the variables connection time, idle time and charging time is given below, which reveal more insight in the temporal trends and characteristics of the distributions.

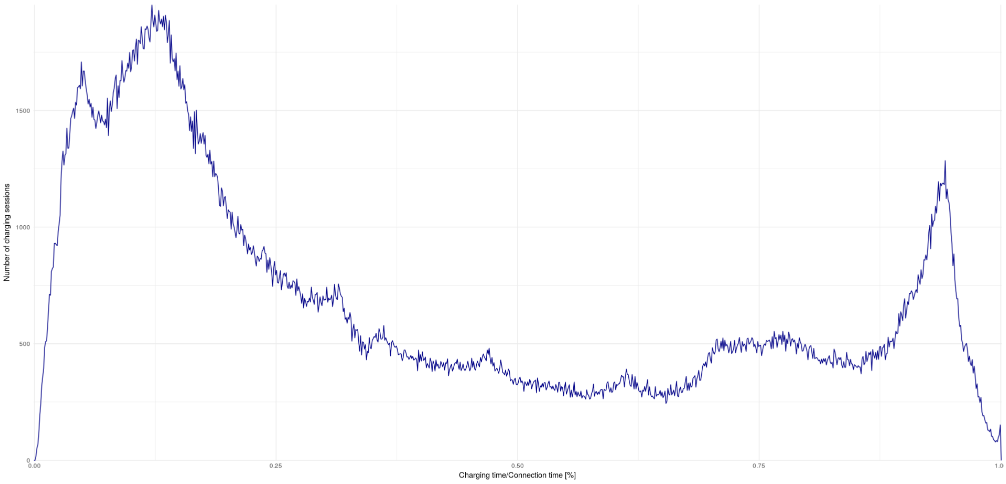


Figure 33: Frequency distribution of the ratio charging time/connection time

Connection Time

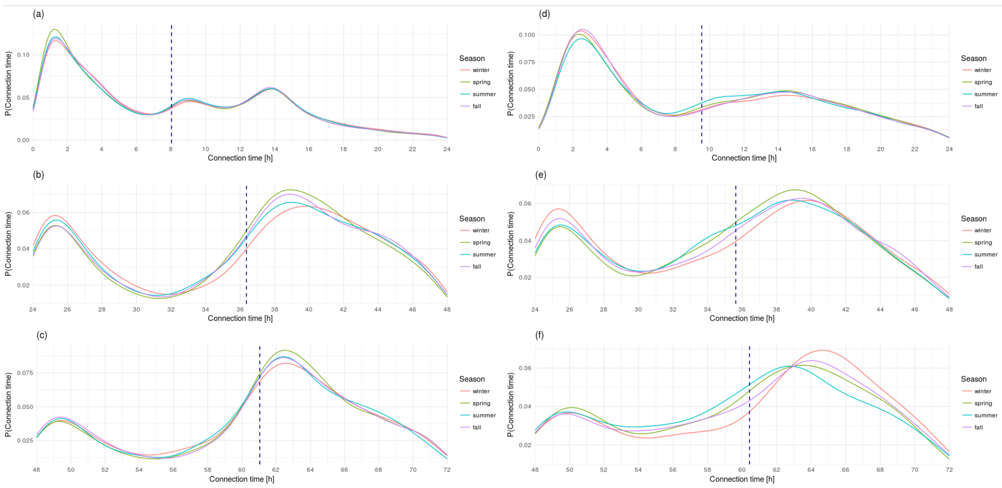


Figure 34: Probability-density plot of connection time duration by sub-clusters of weekend days and weekdays for respectively 24h (a) & (c), 2nd 24h cluster (b) & (d), 3rd 24h cluster (c) & (f)

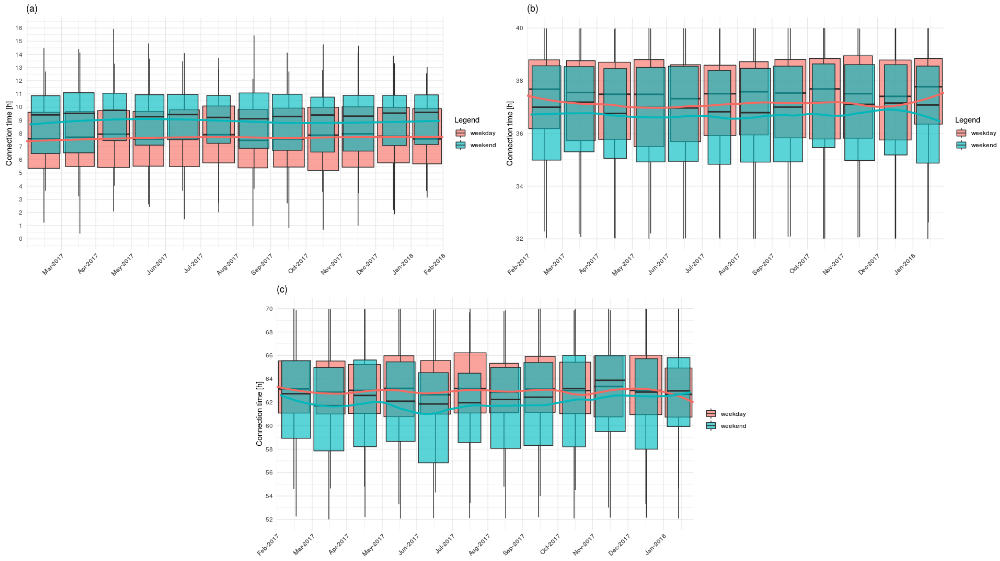


Figure 35: Boxplot and regression smoothing line of connection time duration by sub-clusters of weekend days and weekdays for 24h (a), 2nd 24h cluster (b), 3rd 24h cluster (c)

Idle time

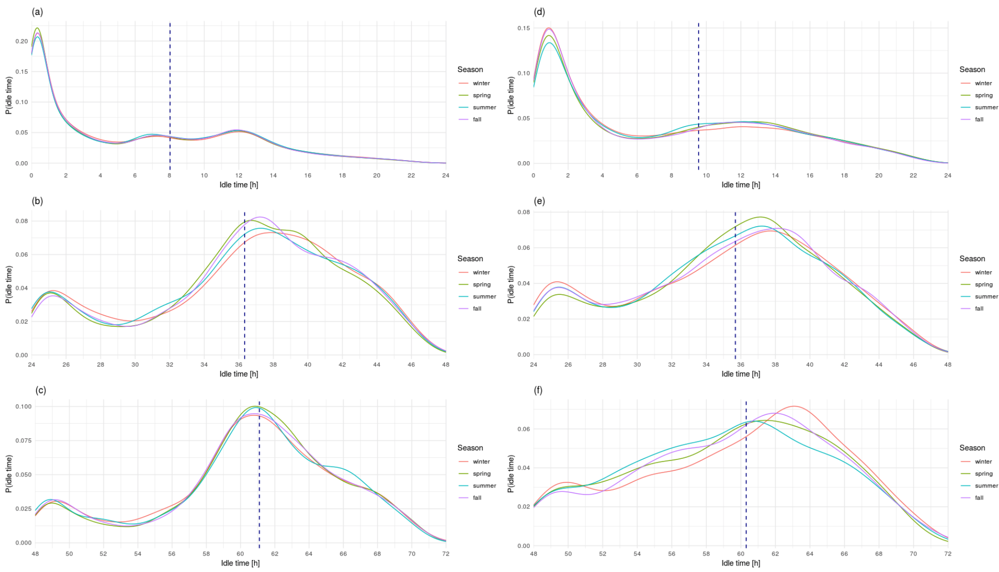


Figure 36: Probability-density plot of idle time duration by sub-clusters of 24h connection duration

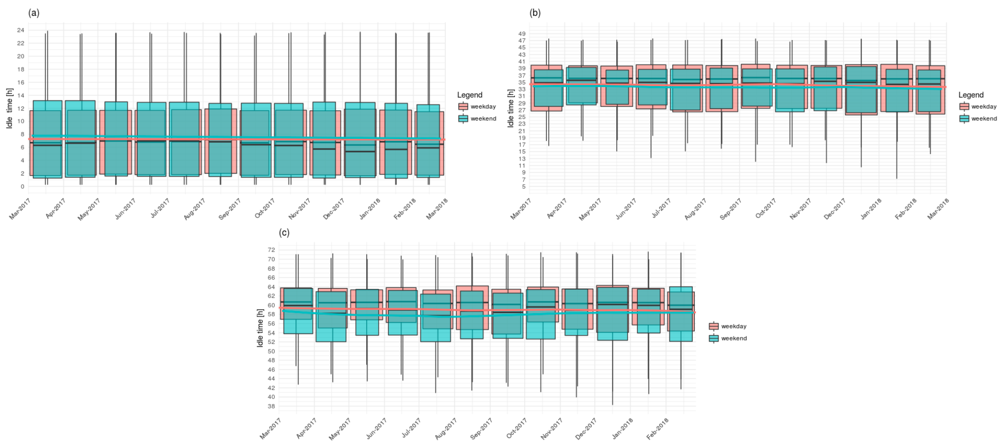


Figure 37: Boxplot and regression smoothing line of idle time duration by sub-clusters of weekend days and weekdays for 24h (a), 2nd 24h cluster (b), 3rd 24h cluster (c)

Charging Demand

Figure 38 is the probability-density function (PDF) of the relative- and cumulative occurrences for different capacities charged. The graph displays the density function of the univariate continuous charging demand variable (a) and is interpreted as a relative likelihood that this variable takes on any particular value on the given range. The cumulative-density function (CDF) depicts the probability that the charging demand variable takes a value less then or equal to p_i. The PDF (31) and CDF (32) are expressed as:

$$P[1 \leq P^i \leq 100] = \int_1^{100} f(p_i) \quad dp_i \tag{31}$$

$$F^i(p_i) = P[P^i \leq p_i] = \int_1^{100} f(p_i)\, dp_i \tag{32}$$

$$P(1 < P^i < 100), \quad \forall p_i \in P^i(p^i) \tag{33}$$

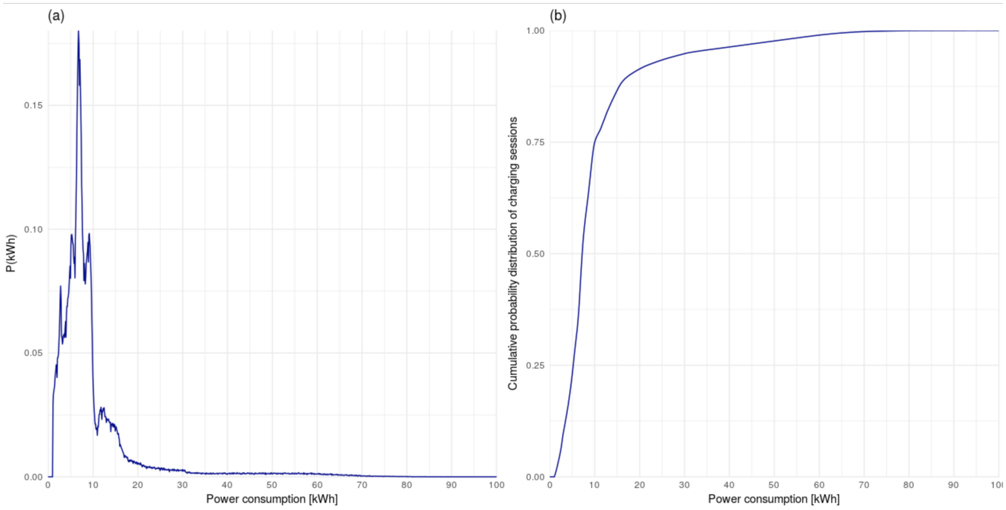


Figure 38: (a) Probability-density distribution of charging demand

C.1. Time- & Load flexibility

Time flexibility

Figure 39 displays the probability density distribution of charging sessions for the time flexibility. The plot on the right is a cumulative distribution of the time flexibility that represents the probability (or frequency of sessions), for which the load-flexibility variable takes a value less than or equal to the load-flexibility on the semi-closed interval $(0, 1006]$. Formally expressed as:

$$F_{T_{Flex}}(x) = P(T_{Flex} \leq x) = \int_{-\inf}^{1} f(T_{Flex}) \quad dx \tag{34}$$

Where

$$P(0 < T_{Flex} < 1, \quad \forall x \in F_{T_{Flex}}(x), \tag{35}$$

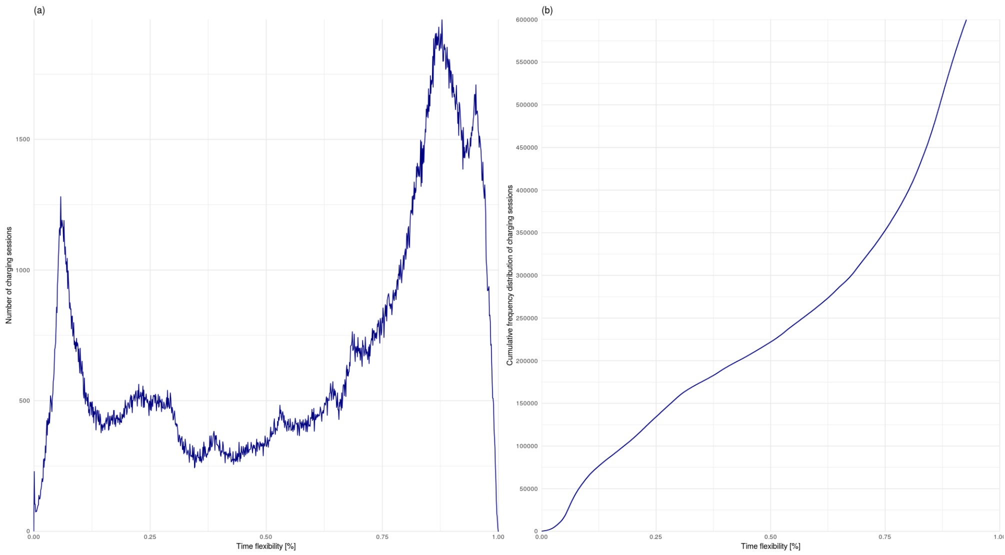


Figure 39: Frequency polygon time-flexibility fraction of the charging session distribution

Load flexibility

In the (probability-density) frequency distributions of the load-flexibility below, a positive skewness and a laptocurtic kurtosis characterise the shape indicating a long-tailed distribution with extreme outliers. To explain the dispersion these extremities cause, the Interquartile Range (IQR) characterises the spread in the data equal to the difference between the 75th and 25th percent quantiles of the median. Where the median is a measure of central tendency, and the IQR is the measure in spread of 50% of the data from the median, also plotted in figure 27. More formally addressed and computed with values of the data set (table 8), 50% of the sessions have a load-flexibility of: $IQR = Q_3 - Q_1$. The heavy kurtosis and skewness can be explained mainly by the fraction of the charging sessions that exhibit long (24h $<$) connection times. In other words, longer connection times are amongst other factors influenced by charging demand (initial battery capacity), however no session recorded charges longer than 22h which leaves every session connected longer than 22h with a increasing potential for load-flexibility.

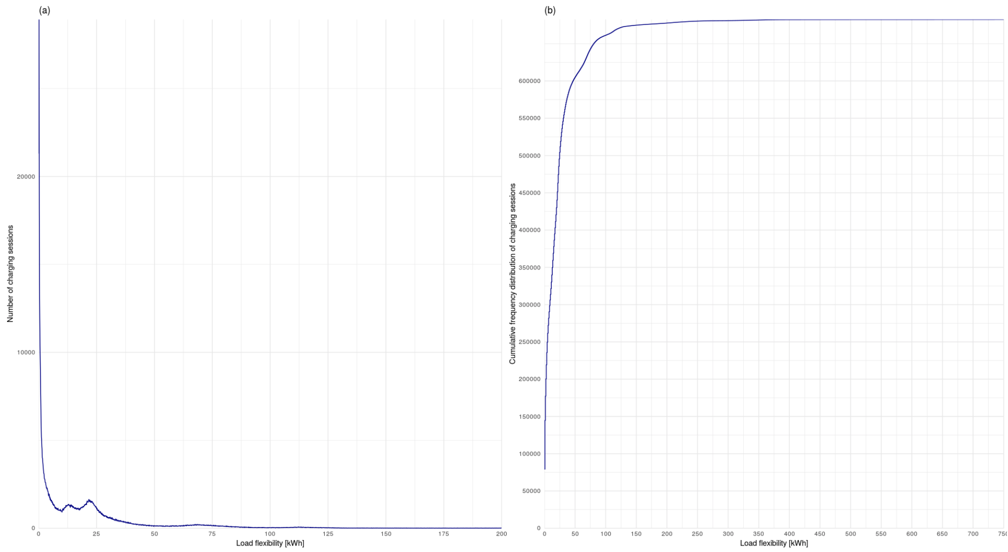


Figure 40: Frequency polygon load-flexibility of the charging session distribution

D. FEEDER POWER LOAD PROFILES

Electricity profiles for load on low-voltage feeders in Amsterdam are used to retrieve hourly profiles for residential buildings. These profiles represent the electricity consumption and generation of electrical appliances, cooking, lighting and PV solar cells of residential buildings. This local distribution grid also operates two working V2G charging points. In the figures 41 & 42 below, the feeder load profiles without V2G charging, the feeder with V2G charging and the V2G charging load are measures and depicted.

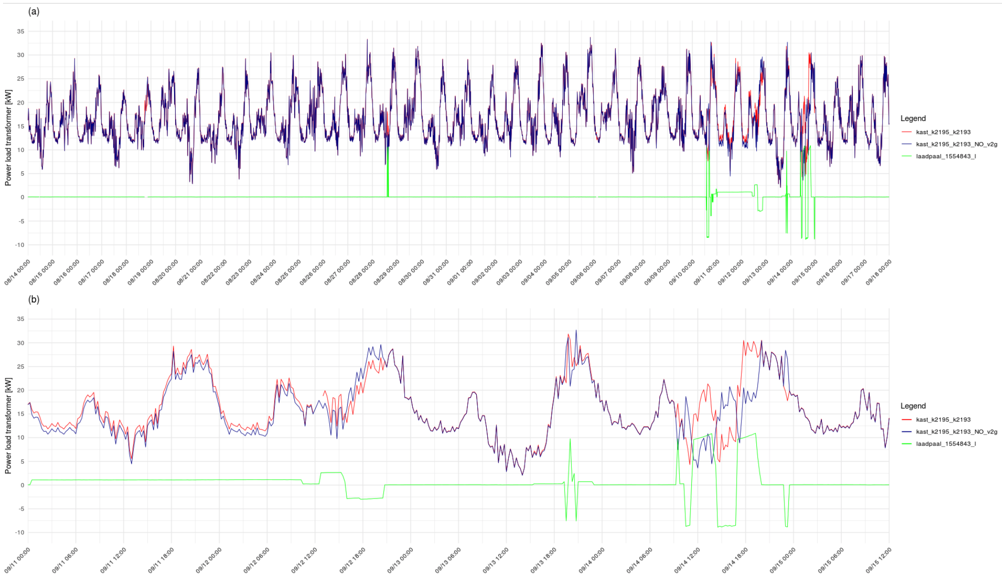


Figure 41: Total power load on feeder k2195-k2193 at Amsterdam Nieuw-West with two V2G charging point

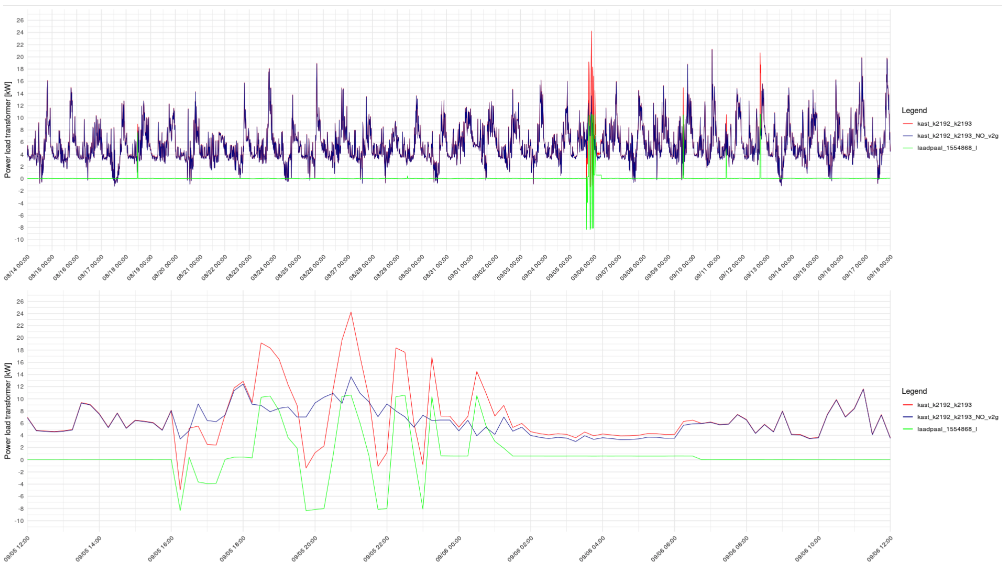


Figure 42: Total power load on feeder k2192-k2193 at Amsterdam Nieuw-West with two V2G charging point

E. Dutch electric vehicle market share & battery characteristics

Information used in this study about battery characteristics of PHEVs and BEVs top five and top ten models with largest market shares respectively, are listed below in the tables.

Table 19: Top five most sold PHEVs in the Netherlands and market share [61, 43, 78, 77]

Brand/Model	Number/Fraction	Battery capacity (kWh)	Battery type
Mitsubishi Outlander	24.992 / 25.5%	12	Li-ion
Volvo V60	15.554 / 15.9%	11.2	Li-ion
Volkswagen Golf	10.907 / 11.1%	8.7	Li-ion
Volkswagen Passat	7.994 / 8.2%	9.9	Li-ion
Audi A3	6.274 / 6.4%	8.8	Li-ion
Other	32.298 / 33%	10.7	Li-ion

Table 20: Top ten most sold BEVs in the Netherlands and market share [61, 49, 57, 7, 28, 48, 58, 53, 45, 46]

Brand/Model	Number/Fraction	Battery capacity (kWh)	Battery type
Tesla model S	8.824 / 33.9%	75	Li-ion
Nissan Leaf	2.842 / 10.9%	40	Li-ion
Renault ZEO	2.751 / 10.6%	22	Li-ion
BMW I3	2.196 / 8.4%	33.2	Li-ion
Volkswagen Golf	2.152 / 8.3%	35.8	Li-ion
Tesla model X	2.061 / 7.9%	100	Li-ion
Hyundai Ioniq	1.600 / 6.2%	28	Li-ion
Nissan E-NV200	816 / 3.1%	40	Li-ion
Renault Kangoo Z.E.	785 / 3.0%	33	Li-ion
Opel Ampera	595 / 2.3%	60	Li-ion

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