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Impact of Electric Vehicles Charging on the Distribution Network

A case study of Utrecht Science Park

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Abstract

Electric vehicles (EVs) have a high potential in reducing greenhouse gas emissions and are able to achieve other advantages such as a reduction in local air emissions and increasing energy security. As a result, EVs are rapidly increasing in popularity, electrifying the transportation sector. This poses a serious problem for the grid as existing distribution grids were mainly sized in the pre-EV era. Therefore, they were often not designed to operate under increasing loads due to the charging of EVs. In this thesis, a method is proposed to determine the load of future EV fleets. The study is empirical in nature and is based on analysing real transaction data of 42 EVs charging for over a year at Utrecht Science Park (USP), the considered case study. The transaction data allows for an examination of the potential impacts of future EV fleets. The impact of the future load of EV fleets on distribution transformers is evaluated. The results show that the studied transformers are able to accommodate EV penetration for the 2030 scenario. In 2050 however, 4 out of 7 studied transformers are overloaded. This is followed by an analysis on the mitigation of the determined impact. This analysis indicated the flexibility in EV demand, around 50% of the EV demand can be delayed for more than 8 hours. When optimal use is made of this flexibility, overloading of 3 out of 4 transformers could be mitigated.

Keywords: electric vehicles, charging power, grid impact, demand flexibility

Preface

"*The world is changed by your example, not by your opinion.*" - Paulo Coelho

The transition to a sustainable energy system is perhaps the biggest challenge of the 21st century. Let us all contribute and take individual action in a way that is suitable for us. With this master thesis and with my career I hope to focus not on fighting the old, but on building the new. This thesis is made as a completion of the master education in Energy Science, which is the last part of the study at Utrecht University, Copernicus Institute of Sustainable Development, Faculty of Geosciences.

Several persons have contributed academically, practically and with support to this master thesis. I am thankful for everyone who guided me throughout this period. I would firstly like to thank my main supervisor Ioannis Lampropoulos, co-supervisors Marte Gerritsma and Wouter Schram and second reader Tarek AlSkaif for their time, valuable input and support throughout the thesis period. Furthermore, I would like to thank Berto Jansen from Phase to Phase for providing me with the Vision software. Thanks to Jan Willem Palland from Stedin for providing me the electricity network configuration. Thanks to Frans Tak and Jolt Oostra for helping me with the data necessary that validates and completes this thesis. Finally, I would like to thank my family and friends for being helpful and supportive during my time studying Energy Science at Utrecht University.

Maria Ana (M.A.) van den Berg

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Nomenclature

Acronyms

BEV Battery Electric Vehicle

CS Charging station

DG Distributed Generation

DSO Distribution System Operator

EV Electric vehicle

$FCEV$ Fuel cell electric vehicle

HEV Hybrid Electric Vehicle

HU Hogeschool Utrecht

HV High Voltage

kVA kilo-Volt-Ampere

LDC Load duration curve

LV Low Voltage

$MaaS$ Mobility-as-a-Service

MV Medium Voltage

PF Power factor

$PHEV$ Plug-in Hybrid Electric Vehicle

RES Renewable energy resources

SSC Smart Solar Charging

TCO Total Cost of Ownership

UMC University Medical Centre

USP Utrecht Science Park

$V2G$ Vehicle-to-Grid

ZEV Zero-emission vehicle

EV ID An unique identity-key of an EV

Indices

j Index of EV in measured dataset

q Index of transaction in measured dataset

Symbols

$C_{parking}$	Parking area capacity	[-]
$C_{transf.}$	Transformer capacity	[MVA]
$N_{\text{EV,present-day}}$	Number of unique EVs charging in the present-day scenario	[-]
$N_{EV,cat,present-day}$	The unique amount of EVs per category	[-]
$N_{EV,dataset,present-day}$	Total amount of EVs counted in the transaction dataset	[-]
$N_{EVgroups}$	Number of EV groups	[-]
$p_{N_{EV,cat,present-day}}$	Share of EVs with a certain category	[%]
E_{req}	Energy required during transaction q	[kWh]
P	True power	[kW]
S	Apparent power	[kVA]
$\mathrm{t}_{\text{plug-in}}$	Plug-in time of transaction q	[-]
$\mathrm{t}_{\text{plug-out}}$	Plug-out time of transaction q	[-]

Chapter 1

Introduction

The CO_2 emissions from the transportation sector is one of the biggest contributors to global warming and consequently, climate change [2, 77]. As a way to deal with global warming and climate change, electric vehicles (EVs) are promoted worldwide. This is due to their potential to mitigate CO_2 emissions when the electrical energy used to charge the EV is of a renewable energy source. Apart from a reduction in global CO_2 production, EVs also contribute to a reduction in local emissions. The main contributor to the local emissions is road transportation [5]. For local air quality EVs offer clear benefits, mainly due to zero tailpipe emissions at street level of pollutants such as NO_x and particulate matter, reducing the local emissions [16, 57]. This is in particular important for densely populated urban areas. Other advantages of electric mobility, in addition to the reduction in CO_2 emissions, are lower traffic noise and a reduction in the dependence on fossil resources such as oil and gas [11]. Road transport in the Netherlands currently accounts for 32% of the national oil requirement [45]. Replacing internal combustion engine vehicles with EVs contributes to reducing the dependence on fossil resources and increase energy security. In addition, on a longer term, the battery of an EV can serve as a storage in which local electricity can be stored. The term used to describe this mechanism is Vehicle-to-Grid (V2G) [11]. This mechanism allows EVs to have a positive impact on the energy transition as it provides the ability for flexibility in the short-term electricity market [53]. In conclusion, EVs have a high potential in reducing greenhouse gas emissions, have a positive impact on local air quality, while increasing energy security by decreasing the dependency on fossil fuels imports. These factors contribute to increasing the sustainability of transport and mobility.

The Dutch Energy agreement, *Energieakkoord*, was composed in 2013, with the goal to provide a basis for the future Dutch energy and climate policies. In this Energy Agreement, the Dutch government has established the ambition to have all new passenger vehicles sold by 2035 be zero-emission [53]. By 2050 all passenger cars should be zero-emission [24], which equals 9.5 million EVs in 2050. Not only the national government, but also local governments have shown interest in electric mobility. An example is the municipality of Utrecht, which aims to be a climate neutral city in 2030 and achieve a 30% reduction in CO_2 emissions by stimulating electric mobility and aiming at 10,000 EVs in Utrecht by 2020 [72].

The combination of these policy initiatives and advancements in battery and EV technology will likely result in an extensive use of EVs in the future, electrifying the transportation sector. This growth is expected to be significant over the next few decades as indicated by several studies. A study by Movares expects an EV market share of 6.5-35% in 2030 and 19-65% in 2050 [42]. An international study by McKinsey expects a 2-5% share in 2020 and a 15-65% share in 2050 [43]. The International Energy Agency (IEA) expects a sales market share in Europe from EVs in 2030 of 23% [4].

1.1 Problem statement

EVs differ fundamentally from conventional vehicles in the way they refuel. EVs require the use of batteries with high energy density and with large electric load charging requirements. These batteries must be charged frequently, often daily, utilising the low-voltage (LV) distribution grid. An existing distribution grid is often built in a pre-EV era and is rated to deliver electricity depending on the number of customers and the historical electricity demand data [52]. Therefore, they were often not designed to take into account the increasing loads due to charging of EVs. As a result, distribution grid transformers that were sized before EV integration may become overloaded and not reliably support a large deployment of EVs. A transformers capacity is limited by the allowable temperature of the insulation material, which increases with the load [30]. A high operating temperature will result in the faster degradation of the board insulation, shortening the lifetime of the transformer [18]. The power transformer is one of the most expensive components in the distribution grid [67]. Overloading of the distribution transformers should therefore be kept to a minimum. As a continuation, several studies showed other impacts of parameters of the distribution networks system design and operation such as; high current demand [41], power flows [41], load unbalance [29], higher energy losses [37], voltage profile [10], harmonics [78] and peak load [74]. Additionally, EVs will have to share the load on the grid with the Distributed Generation (DG) like solar photovoltaics (PV) in low voltage distribution grids, causing impacts on the grid mentioned before [47, 75]. The combination of all these impacts might oblige to reinforce the grid at some locations. However, postponements of reinforcement may be achieved by using different EV charging methods.

1.2 Research aim

The Energy Agreement and Sustainable Fuels vision emphasise the ambition of the Dutch government to stimulate the uptake of EVs [53]. This should result in a passenger vehicle fleet which consists solely of EVs in 2050. However, it remains unclear how the charging infrastructure will develop to supply the charging demand from these vehicles. Therefore, this thesis aims to provide a view on the requirements of electricity demand of the future EV fleet and identify the impacts of this EV fleet on the distribution network. A scenario study is performed, to analyse the load on the distribution transformers and by studying the impact of EVs as their penetration levels increase. This study focuses on Dutch development in EV and it's ambitions and goals. The reason to focus on the Netherlands is firstly, because the Netherlands is one of the countries with the highest EV market share: 2.7% of new car sales was an EV in 2017, only exceeded by Norway which had a market share of 39.2% in 2017 [4]. Secondly, the Dutch government stated the ambition to have a fully EV passenger fleet in 2050 [24]. However, the selection for the focus on the Netherlands does not render the study useless for scientists in other countries, the methodology can be applied to other countries by changing the values of the indicators to represent the situation in that country.

1.3 Research gap

The academic field has proposed several intelligent or smart EV charging management methods to handle the potential problems described. Fan et al. [17] concluded that uncontrolled charging increases the peak load demand and recommended tariff based charging. Di Silvestre et al. [12] used an optimisation approach to devise efficient management strategies for EV parking lots. A study by Sehar et al. [58] showed the impacts of plug-in EVs on a retails buildings peak demand energy consumption and presented the ability of renewable energy resources (RES) and demand management options to reduce their impacts. They concluded that 38% of the EV load demand could be absorbed by demand management in combination with PV. [29] proposed coordinated charging strategies for plug-in EVs to facilitate a flexible charging process that may be delayed in time, ensuring that the users charging requirements does not suffer from the utlised flexibility. The general conclusion from these studies is that the existing distribution grid should be able to accommodate a substantial penetration level of EVs if the majority of the charging cycles are controlled in a way. Uncontrolled charging in addition to peaks of residential load will lead to component overloading and excessive voltage deviations [52]. The work in this thesis differs in its approach to the studies described above. Instead of minimising power losses and/or voltage deviations, the primary goal of the thesis is to determine the possible increase in load due to EVs charging, analyse it's impact on the loads experienced by existing distribution transformers and to identify when the grid transformers become overloaded. An additional goal is to evaluate the mitigation of the load. Other work that analysed the impact of EVs on the distribution grid are [6, 50, 74]. This thesis differs from these works on some aspects. While Ramanujam et al. [50] examines a similar case, their simulations are driven by synthetic estimates, rather than real-life empirical data, therefore being a less accurate characterisation of real-life conditions. This thesis has made use of a real EV transaction dataset which yields more realistic results. Clement-Nyns et al. [6] focuses on defining the aggregated load impact from EVs without considering to mitigate the impact. Verzijlbergh et al. [74] examines the distribution grid impacts using charging profiles based on real life driving data, as done in this thesis. However, the study is mainly applicable to the system level, rather than for individual network components, as achieved in this thesis. Other work likewise focused on the flexibility of EV demand and controlled EV charging [22, 60, 64]. This thesis is complementary to these works as these smart charging methods can be employed to reduce the overloading of distribution transformers.

1.4 Research questions

The research question is formulated in line with the stated research aim and literature gap:

To what extent does the integration of EVs present a problem for an existing electricity distribution network and can these problems be mitigated?

This question will be answered by means of the following sub-questions:

1. *What could future EV charging profiles look like?*
2. *What increase in power demand can be expected due to EVs charging?*
3. *How will EVs impact the load observed by distribution transformers?*
4. *How can flexibility in EV demand mitigate the impact?*

1.5 Research outline

This thesis contains ten chapters, of which the first is this introduction. Chapter 2 describes the theoretical background for this thesis. The theoretical background will look into the technical aspects of the Dutch power system, EVs and charging stations. Furthermore, the theoretical background will look into the relevant development of EVs and charging stations. Chapter 3 will look into the method used to create future EV charging profiles. This has been done by creating a Python model that simulates the electricity demand for an future EV fleet. Chapter 4 provides the results of the calculation of the future EV charging profiles. Chapter 5 describes the method used for calculating the grid impact. Chapter 6 provides the results of the grid impact calculation and the implication of grid impact. Chapter 7 describes the method for the mitigation of grid impact analysis. Chapter 8 provides the results for the mitigation of grid impact. Chapter 9 discusses the results obtained in the thesis and provides recommendations for further research. Chapter 10 will conclude the thesis.

1.6 Research steps

This thesis consists of several research steps. Figure 1.1 graphically displays these steps. In order to answer the research question, the thesis is divided into three parts: Part I: Creation of electric vehicle charging profiles, Part II: Grid Impact of electric vehicles and Part III: Mitigation of Grid Impact. Research question (RSQ) 1 and 2 are answered in Part I. RSQ 3 is answered in Part II and RSQ 4 is answered in Part III. The steps taken are elaborated on in the methodologies of the respective parts.

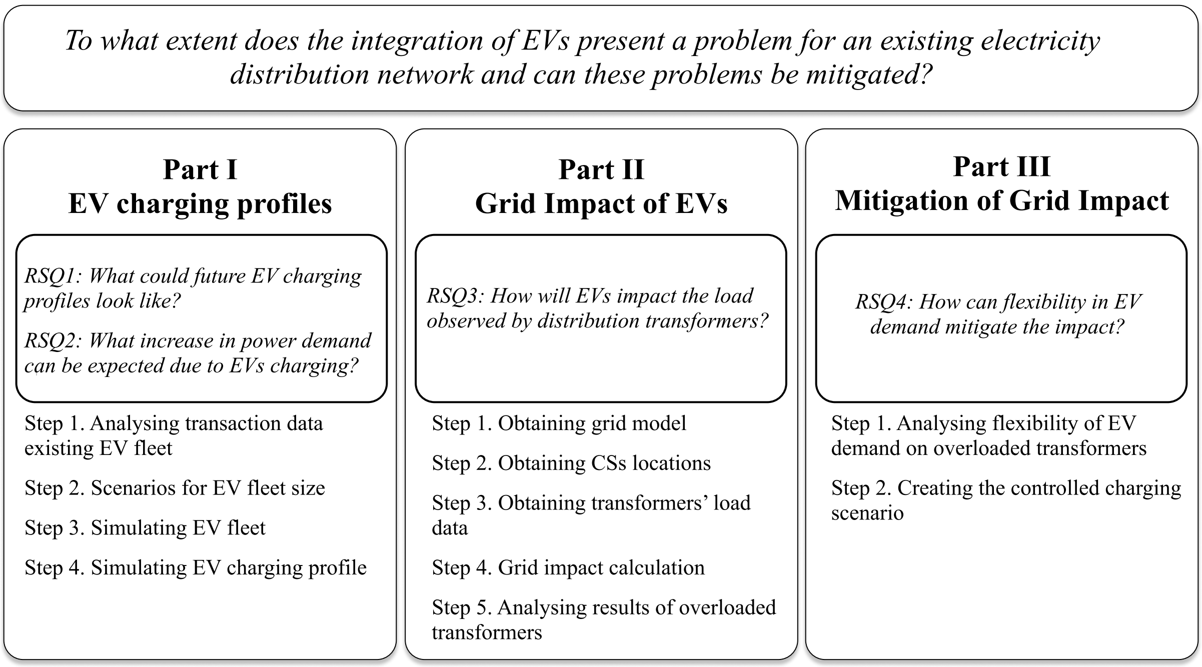


Figure 1.1: Research steps of this thesis.

Chapter 2

Theoretical background

2.1 The Dutch power system

In this section, the Dutch physical power system is addressed. The electrical power system consists of the transmission and distribution network as well as the energy generation and consumption [36]. The electric power system supplies, transfers and uses electric power. It is broadly divided into the generators that supply the power, the transmission system that carries the power from the generating entities to the load entities, and the distribution system that feeds the power to nearby homes and industries [32].

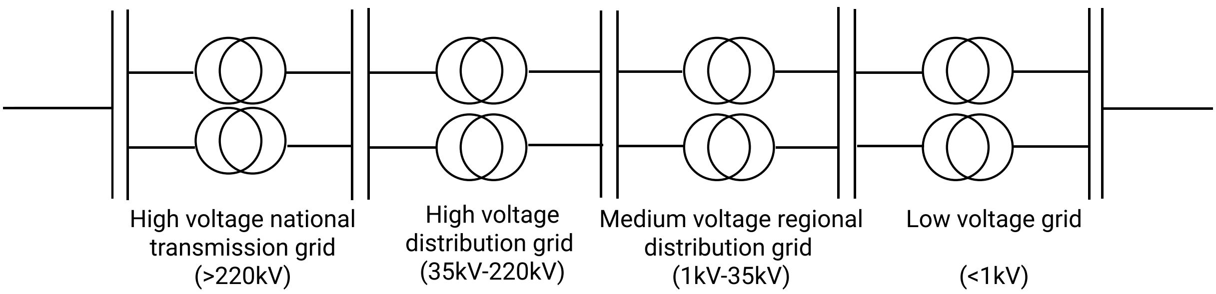


Figure 2.1: The Dutch power system, displaying the physical electric network. Based on [32].

In this thesis the focus is on the Dutch electricity network, which is used as a reference. Figure 2.1 provides an illustration of the power system distinguishing between the transmission, the sub-transmission, and the distribution systems. The transmission system in the Netherlands involves high voltage (HV) levels at 220 and 380 kV [36]. The voltage levels are reduced to the distribution level which operates typically at 10kV. The distribution system consists of both medium voltage (MV) and low voltage (LV) systems. Typically the power flow is an unidirectional flow, with power flowing from the distribution substations to the end-users. Recently with the introduction of distributed generation (DG), the bidirectional power flows have increased [36]. The HV to MV transformer is linked to either a transmission or a distribution grid. The HV network is left outside the thesis scope as literature found the impact of electric vehicles limited on a high voltage level [27, 31]. The two voltage levels at which the distribution network operates are explained in the following part.

2.1.1 Medium and low voltage networks

Medium voltage (MV) are either transmission or distribution networks and mostly consist of 10kV, 20kV or 30kV grid components. The MV network transmits electricity over longer distances from high voltage to medium voltage (HV/MV) transformers to MV distribution transformers. A MV distribution grid distributes electricity either from a high to MV transformer or from a MV (transmission) to MV (distribution) transformer. MV distribution grids have a voltage of 10kV and distribute either via a transformer station to low voltage networks or directly to (business) consumers [25]. Low voltage (LV) networks are designed to distribute the generated electricity to consumers. LV networks are mainly loaded by connections for small consumers and medium sized companies. However, larger electricity consumers can also be connected to the LV network. Large consumers have connections from 3x80A to 250A. LV networks have operate at a voltage level of 230/400V [25].

2.1.2 MV/LV transformers

The distribution network uses a series of transformers to step down the voltage and supply end-consumers with electricity at voltages of 230 V (in Europe and Asia) [35]. In the Netherlands, standard MV/LV transformer capacities vary from small (50, 100, 160) kilo-Volt-Ampere (kVA), to larger 250, 400, 640, 1000, 1600, 2000 and 2500 kVA. Note that transformer capacity is rated in kVA, which is the unit used for apparent power, i.e. the product of the root mean square (rms) of voltage and current in an AC power system. DSOs size distribution transformers based on their expected load and expected peak load [30]. A transformer is able to supply electricity that exceeds its rated capacity. However, the more power a transformer services, the more heat it generates [30]. In overloaded periods the transformer efficiency is reduced as the excess heat represents lost energy. Thus, limiting time periods in which the transformer is overloaded is important for reducing the negative impact on the transformer lifetime.

In this thesis, overloading means that the thermal loading is higher than the nominal thermal capability. The overload criterion used in [74] is 1.16 of their rated capacity. In [76], a transformer with a peak load between 0.9 and 1.25 is considered *highly utilised*, a peak load between 1.25 and 1.5 is *overloaded* and peak load exceeding 1.5 is considered *critically overloaded*.

A normal load is considered when the load is not higher than the nominal (electrical) capacity of the transformer [25]. DSOs include a natural load growth in addition to a base load for a period of 30 years [63]. The load at the end of the 30 years will be in the range of 'normal loading' the transformer.

Typically a seasonal variation in the load is experienced by a transformer, characterised by two peak demand periods - winter and summer, as illustrated in Figure 2.2. The winter peak occurs due to increased use of electric heating, while the summer load coincides with the increased use of electricity by cooling systems. Although the winter peak is slightly higher than the summer one, the summer peak has a greater impact on transformer efficiency and lifetimes. This is because high ambient temperature contributes to the effect of overloading by further heating up the insulation oil [21, 65]. With increased power demand from EVs charging, summers are likely to have a greater adverse impact on transformers than other summers.

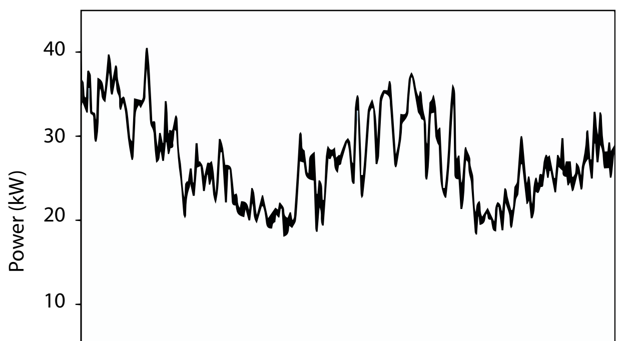


Figure 2.2: Illustration of the seasonal variation in the load profile of a typical MV/LV transformer. Data from [76], New England region of the United States.

2.2 Electric Vehicles and Charging Stations

This section describes shortly the types of electric vehicles available, the development of the Dutch EV fleet and the different types of charging stations (CS) .

2.2.1 Electric Vehicles

Electric cars, the most common type of EV, are becoming increasingly popular. Many car manufacturers now include electric cars in their product line up. There are three relevant types of electric vehicles: Hybrid Electric Vehicles (HEVs), Plug-in Hybrid EVs (PHEVs) and full EVs or Battery EVs (BEVs) [38]. Examples of BEVs include the Tesla Model S, Nissan Leaf and Chevy Bolt [14]. Examples of PHEVs are Chevy Volt and the Toyota Prius Prime [14]. PHEVs tend to have smaller batteries than BEVs since they are powered using a combination of gas-powered and electric motor and can fall back to the gas-powered motor. The larger battery sizes of BEVs imply a larger load, which results in a higher peak charging load and a longer charging time to fully charge the battery. Examples of popular BEVs and PHEVs with their different battery characteristics are shown in Table 2.1 and Table 2.2, respectively [14]. As shown in the tables 2.1 and 2.2, most PHEVs have a charge rate of maximum 3.7 kW. With the PHEV "Mitsubishi Outlander" being an exception, which allows a fast charge rate of 22 kW.

Table 2.1: Examples of popular BEVs with different battery characteristics [14].

BEV Model	Range (km)	Battery size (kWh)	Rate (kW AC)	Fast Charge Rate (kW DC)	Charge time (hours at 220V)
Renault Zoe R90	240	37	22	-	2h
Nissan leaf	230	38	6.6	50	7h
BWM i3 120Ah	235	37.9	11	50	4h15m
Tesla Model S Standard Range	400	75	16.5	120	5h30m
Volkswagen e-Golf	190	32	7.2	40	5h15m

Table 2.2: Examples of popular PHEVs with different battery characteristics [14].

PHEV Model	Range (km)	Battery size (kWh)	Rate (kW AC)	Fast Charge Rate (kW DC)	Charge time (hours at 220V)
Mitsubishi Outlander	37	13.8	3.7	22	3h30m
Volvo V60	50	11.2	3.7	-	5h
Volkswagen Golf GTE	35	8.7	3.7	-	2h15m
Vokswagen Passat GTE	35	9.9	3.7	-	2h40m
Audi A3 E-tron	50	8.8	3.7	-	2h20m

Dutch Electric Vehicles fleet

The number of EVs has increased rapidly in the Netherlands over the past years. Commissioned by the Dutch ministry of economic affairs, the Rijksdienst voor ondernemend Nederland (RVO) registers the development of EVs for personal transportation in The Netherlands. Table 4.5 presents the number registered EVs in The Netherlands on four dates in the years 2016 up to 2019 [54].

Table 2.3: Number of EV passenger cars registered in the Netherlands (EV feet) [54].

Type of vehicle	31-12-2016	31-12-2017	31-12-2018	31-01-2019
Passenger car BEV	13,105	21,115	44,984	47,381
Passenger car PHEV	98,903	98,217	97,702	97,659
Total	112,008	119,332	142,686	145,040

The same trend is shown in Figure 2.3, which represents the development of the number of passenger EVs in the Netherlands over the past years.

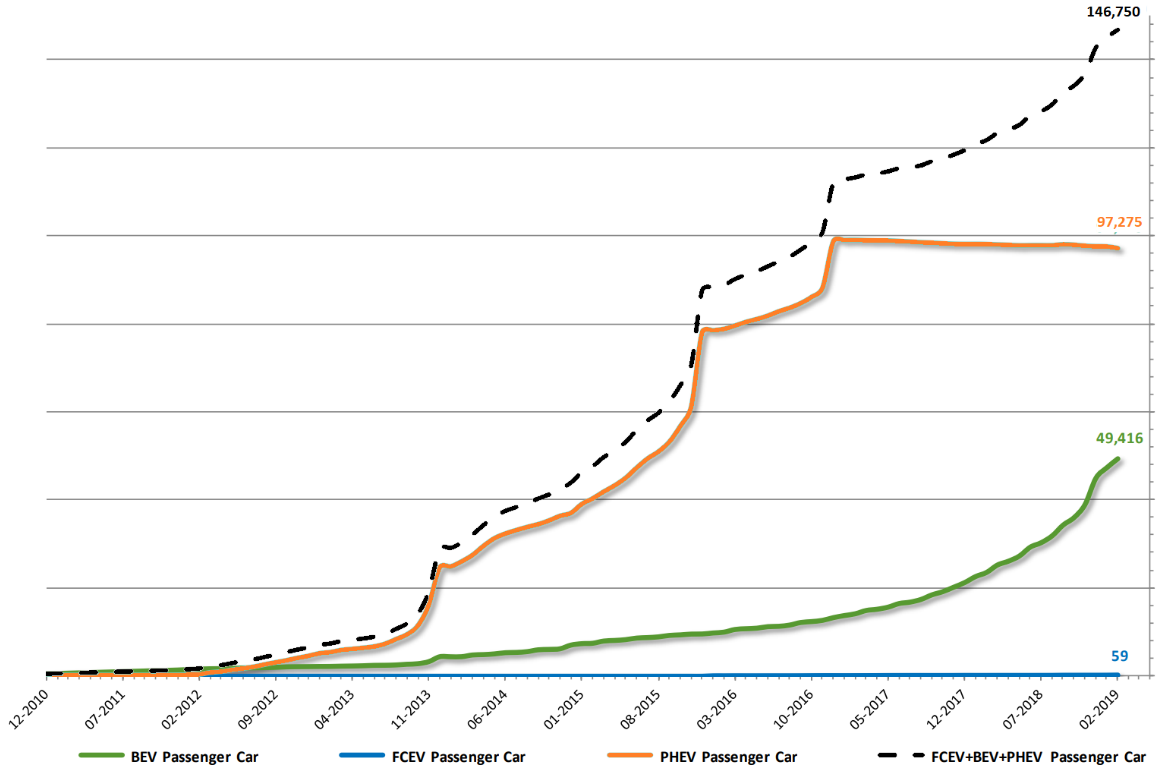


Figure 2.3: Development in the number of passenger EVs registered in the Netherlands (fleet) [54].

Scope definition electric vehicles and electric mobility

Literally the term electric mobility and electric vehicles cover several types of transport systems, from electric bikes to busses. In this thesis however, electric mobility and electric vehicles refer to electric cars and vans. Thus, electric scooters and bikes will not be taken into account when referred to electric vehicles (only when stated differently).

2.2.2 Charging Stations

The following section describes the types of CSs available and the development of CSs in the Netherlands.

Charging time depend on different factors such as the capacity of the vehicle battery and the power and settings of the CS. Charging time is expected to decrease rapidly in the coming years [55]. A regular CS allows for a transfer of electricity to an electric vehicle with a power less than or equal to 22 kW [3, 55] and makes use of the onboard charger. A high power "*fast*" CS allows for a transfer of electricity to an electric vehicle with a power of more than 22 kW [55]. A very common fast charger delivers 50 kW. The development of fast charging is going as the next generation of fast chargers was introduced in early 2018, delivering 175 kW and more (for heavy duty vehicles there are chargers which deliver 450 kW of power) [55].

Unsurprisingly, as a result of the increase in number of EVs the number of CSs has also been increasing. Table 2.4 shows the number of CSs in the Netherlands in the past years. The total amount of regular CSs installed at the end of January 2019 is 74,674. The amount of fast CSs at the end of January 2019 is 1,265. It is estimated that there are 100,000 private CSs in the Netherlands [53].

Table 2.4: Number of EV CSs installed in the Netherlands on four dates [54].

Number installed at	31-12-2016	31-12-2017	31-12-2018	31-01-2019
Public (24/7 publicly accessible)	11,768	15,288	20,228	20,538
Semi-public (limited publicly accessible)	14,320	17,587	15,666	16,799
Regular Public + Semi-public	26,088	32,875	35,894	37,337

Part I

Creation of Electric Vehicle Charging Profiles

Chapter 3

Charging Profiles Method

This chapter is adopted from [22].

This chapter describes the methods used to create power demand profiles of simulated EVs. To give a representation of real-life EV charging behaviour, this method makes use of a dataset including EV charge transactions. First the data analysis is described: section 3.1 describes the division of the EVs into different categories. Then, the method for the EV simulation is explained. In section 3.2 the method for the simulation of the EV fleet under different scenarios is given. Section 3.3 describes the simulation steps taken for the simulation of the EV charging profiles. All data analyses and simulations have been performed using Python 3.7 [49] on Spyder 3.3.3 [62].

For this method, for each EV transaction q the following data is required:
$t^q_{plug-in}$: the plug-in time for transaction q
$t^q_{plug-out}$: the plug-out time for transaction q
E^q_{req} $[kWh]$: the total charged energy during each transaction q
$EVID$: An unique anonymous identity for each EV j that occurs in the dataset.

3.1 EV categories

As discussed in Section 2.2.1, BEVs and PHEVs have different characteristics, and therefore, the charging behaviour differs. In addition, in the future the share of BEVs in the EV fleet is expected to increase [53]. Categorizing provides more insight into the charging behaviour of the EVs and is a basis on the simulation of future scenarios. The EVs are therefore categorized, as done in [22], resulting in four different categories. The categorization is based on the identity-key of the EV (EV ID). For each transaction q, the EV ID is known. Therefore, the number of unique EVs j in the dataset can be determined. The EVs IDs are split into BEVs and PHEVs.

Because the volume charged (E_{req} $[kWh]$) is known per transaction, the division is based on the maximum charged energy ($E_{\text{req,max}}$ $[kWh]$) that occurs during the transaction periods logged for the specific EV j. For the top 5 best sold PHEVs in the Netherlands, as show in Table 2.2, the maximum battery size is 13.8 kWh. Therefore, an EV is considered a PHEV if $E_{\text{req,max}} < 13.8$ kWh and a BEV if $E_{\text{req,max}} \geq 13.8$ kWh. This results in the occurring amount of BEVs and PHEVs in the logged dataset.

The mobility sector is changing, and often vehicles are shared among its users [46], [54]. This implies the need for a further division. Therefore, two other categories are determined, namely the "company EV" and "commuting EV". The **company EV** is an EV that is shared among the employees in the office environment. The **commuting EV** is an EV that is owned or leased privately by employees. The company EVs are expected to have a different charging behaviour from the commuting EVs as they presumably charge overnight at the investigated area and charge frequently. The commuting EVs presumably charge overnight at the home of the user and charge in the mornings at the investigated area when the employee arrives at work. An EV is considered an company EV when the maximum duration that it has been connected to a CS has been more than 24 hours ($H_{\text{DUR,max}} > 24\text{h}$) and it has started the charging process in the evening hours ($H_{\text{plug-in,max}} > 16{:}00$). The categorisation is illustrated in Figure 3.1.

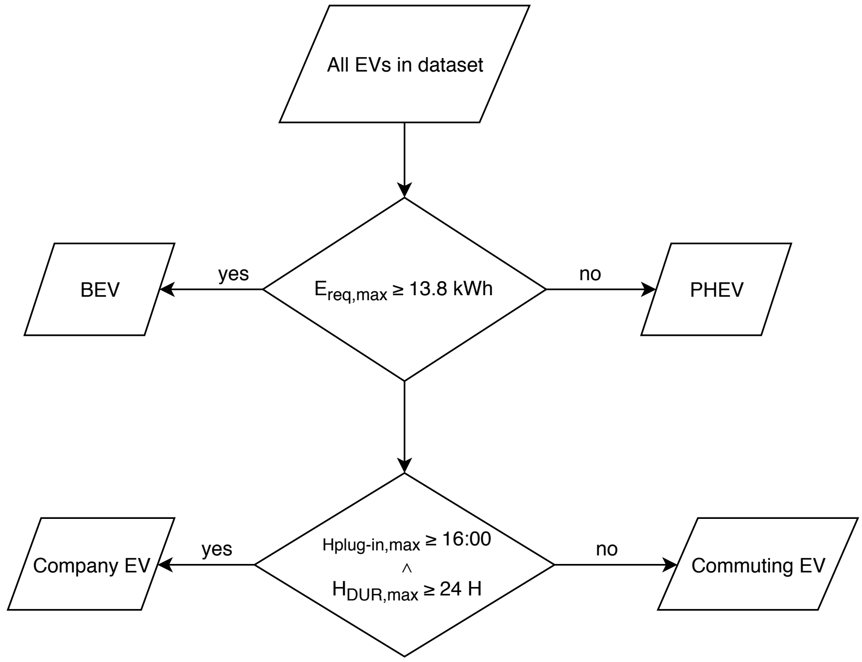


Figure 3.1: Categorization of EVs in the logged dataset. Based on [22].

3.2 Scenarios EV fleet size

In this section, the method for the size of the EV fleet is described for the scenarios studied. In this thesis the 'Present-day', '2030' and '2050' scenarios are studied. The EV fleet size of the measured CSs for the present-day has been determined in Section 3.1. To derive the number of unique EVs charging in the investigated area for the present-day scenario ($N_{\text{EV,present-day}}$), the obtained number of EVs ($N_{\text{EV,data}}$) is multiplied by the ratio of the total number of CSs ($N_{\text{CS,tot}}$) to the number of measured CSs ($N_{\text{CS,data}}$) using equation 3.1, as done in [22].

$$N_{\text{EV,present-day}} = N_{\text{EV,data}} * (N_{\text{CS,tot}} \div N_{\text{CS,data}}) \tag{3.1}$$

For the 2030 scenario, the current car fleet at the investigated area is considered to have an EV share of 50%. In the 2050 scenario the share is 100%.

3.3 Simulation of EV fleet

In this section, the method of the simulation of the EV fleet for the different scenarios is explained. The categories are considered as the share of BEV and PHEV is expected to change in the future and the charging behaviours for these four categories might differ.

For each EV (j) the simulation randomly picks a category based on the share of that category in the total EV fleet. The share of the category at 'Present-day' is obtained by dividing the unique amount of EVs per category ($N_{EV,cat,present-day}$) by the total amount of EVs counted in the transaction dataset ($N_{EV,dataset,present-day}$), as expressed by equation 3.2, obtained from [22]. This equation returns the share of the number of EVs per category ($p_{N_{EV,cat,present-day}}$).

$$p_{N_{EV,cat,present-day}} = \frac{N_{EV,cat,present-day}}{N_{EV,dataset,present-day}} \tag{3.2}$$

Furthermore, the probability that an EV j has a certain charge frequency (f_{daily} [EV^{-1} * day^{-1}]) is determined. The average daily charge frequency ($f_{\text{av,cat,daily}}$) is determined per category. The average is used in a normal distribution with a standard deviation σ of 25%. The distribution is simulated with Python's Scipy package, which simulates x amount of values of $f_{\text{cat,daily}}$ depending on the $f_{\text{av,cat,daily}}$ and the standard deviation. $f_{\text{cat,daily}}$ is counted ($N_{sm,cat,f_{daily}}$) and divided by the total number of values ($N_{sm,cat}$) as shown in equation 3.3.

$$p_{f_{daily}} = \frac{N_{sm,cat,f_{daily}}}{N_{sm,cat}} \tag{3.3}$$

The charging power, P_{Max}, depends on the EV category, with P_{Max} being 22 kW for BEVs and 3.7 kW for PHEVs. The charge frequency also depends on the category, and it gets randomly picked based on the distributions explained above. The EV fleet is simulated and returns a dataset for x amount of EVs, depending on the scenario, with their characteristics:

- EV number
- The EV category
- P_{Max} [kW] at which the EV charges
- f_{daily}, frequency at which the EV charges.

3.4 Simulation of EV charging profile

This section explains the method for the simulation of the EV charging profile. In the previous section, the EV fleet for the three scenarios was simulated. This returned a dataset for the amount of expected EVs in which relevant information for this step was obtained. The charging profile of an EV depends on the category of the EV, the power at which the EV charges and the frequency at which it needs to charge.

Histograms are created for each one of the four categories for the plug-in hour of the day ($H_{\text{plug-in}}$ [h]), the total charged energy (E_{req} [kWh]) and the connection time (T_{connect} [h]).

- Histogram plug-in hour ($H_{\text{plug-in}}$ [h])
  The histogram of the plug-in hour counts how many times a transaction started in hour k (for $\{0 \leq k \leq 23\}$).
- Histogram charged energy (E_{req} [kWh])
  The histogram for the charged energy counts the occurrence of a certain value for E_{req}.
- Histogram connection time (T_{connect} [h])
  The histogram for the connection time counts the times an EV is connected for a certain amount of hours. With T_{connect} being the amount of hours within $\text{t}_{\text{plug-in}}$ and $\text{t}_{\text{plug-out}}$ logged in the transaction dataset, see equation 3.4, obtained from [22].

$$\Delta T^{q}_{connect} = t^{q}_{plug-out} - t^{q}_{plug-in} \tag{3.4}$$

Based on the histograms, the probability a certain value occurs can be assigned. The probability that a simulated transaction q starts within a certain hour is chosen based on the number of transactions in each set with size $N_{\text{tr,data,cat,h}_{\text{plug-in}}=\text{k}}$ and is determined by using equation 3.5, from [22].

$$p_{\text{h}_{\text{plug-in}}} = \frac{N_{\text{tr,data,cat,h}_{\text{plug-in}}=\text{k}}}{N_{\text{tr,data,cat}}} \qquad for\{0 \leq k \leq 23\} \tag{3.5}$$

The probability an EV in a certain category is charged with a certain volume, E_{req}, during transaction q is determined using equation 3.6, from [22].

$$p_{E_{req}} = \frac{N_{tr,data,cat,E_{req}}}{N_{tr,data,cat}} \tag{3.6}$$

The probability an EV within a certain category has a certain connection time, T_{connect}, for transaction q is determined using equation 3.7, from [22].

$$p_{T_{connect}} = \frac{N_{tr,data,cat,T_{connect}}}{N_{tr,data,cat}} \tag{3.7}$$

The charging profile is simulated as follows: For each transaction, an EV number is assigned, depending on the charge frequency. As each EV has been assigned a category in representing the EV fleet, the volume the EV is charged with during transaction q is randomly picked from a list which contains the volumes and certain probabilities for that EV category. Per transaction $h^{q}_{plug-in}$ is assigned, based on the probability an EV of a certain category plugs-in at a certain hour. The exact simulated plug-in time, $t^{q}_{plug-in}$, is derived by assigning a number of minutes within $h^{q}_{plug-in}$. With the number of minutes randomly chosen. It is assumed that all EVs in the simulation charge uncontrolled at power rate P_{Max}, starting at $t^{q}_{plug-in}$ and ending when E^{q}_{req} of that specific transaction is reached. The duration the EV is connected to the CS, $T_{connect}$, is selected randomly based on the EV's category and the probability an EV is connected for x amount of hours. The dependency of E^{q}_{req} and $\Delta T^{q}_{connect}$ are respected by randomly choosing T_{connect} based on the simulated E_{req}. This means that a transaction with a large required energy, has a high probability of a longer connection time. The plug-out time, $t^{q}_{plug-out}$ is then determined by summing $t^{q}_{plug-in}$ with $T_{connect}$. The duration for which the EV is getting charged is determined by dividing the volume charged by the power at which it charges as expressed in equation 3.8. The time at which the EV has completed the charging process, $t^{q}_{end-charge}$, is then determined by summing $t^{q}_{plug-in}$ with $T^{q}_{DUR,charge}$.

$$T^{q}_{DUR,charge} = \frac{E^{q}_{req}}{P^{q}_{max}} \tag{3.8}$$

3.5 Case study description

In this thesis the distribution grid of Utrecht Science Park (USP) has been considered as a case study. This area is located on the east side of the city of Utrecht, the Netherlands. The investigated area is an area for education, research, entrepreneurship and healthcare. USP includes 108 companies, 2,500 studenthouses, 51,000 daily students and approximately 26,000 daily employees [70]. At the time of writing this thesis, there are 21 CSs installed at the 7 locations shown in Figure 3.2. This study looks into office charging only, residential charging is excluded.

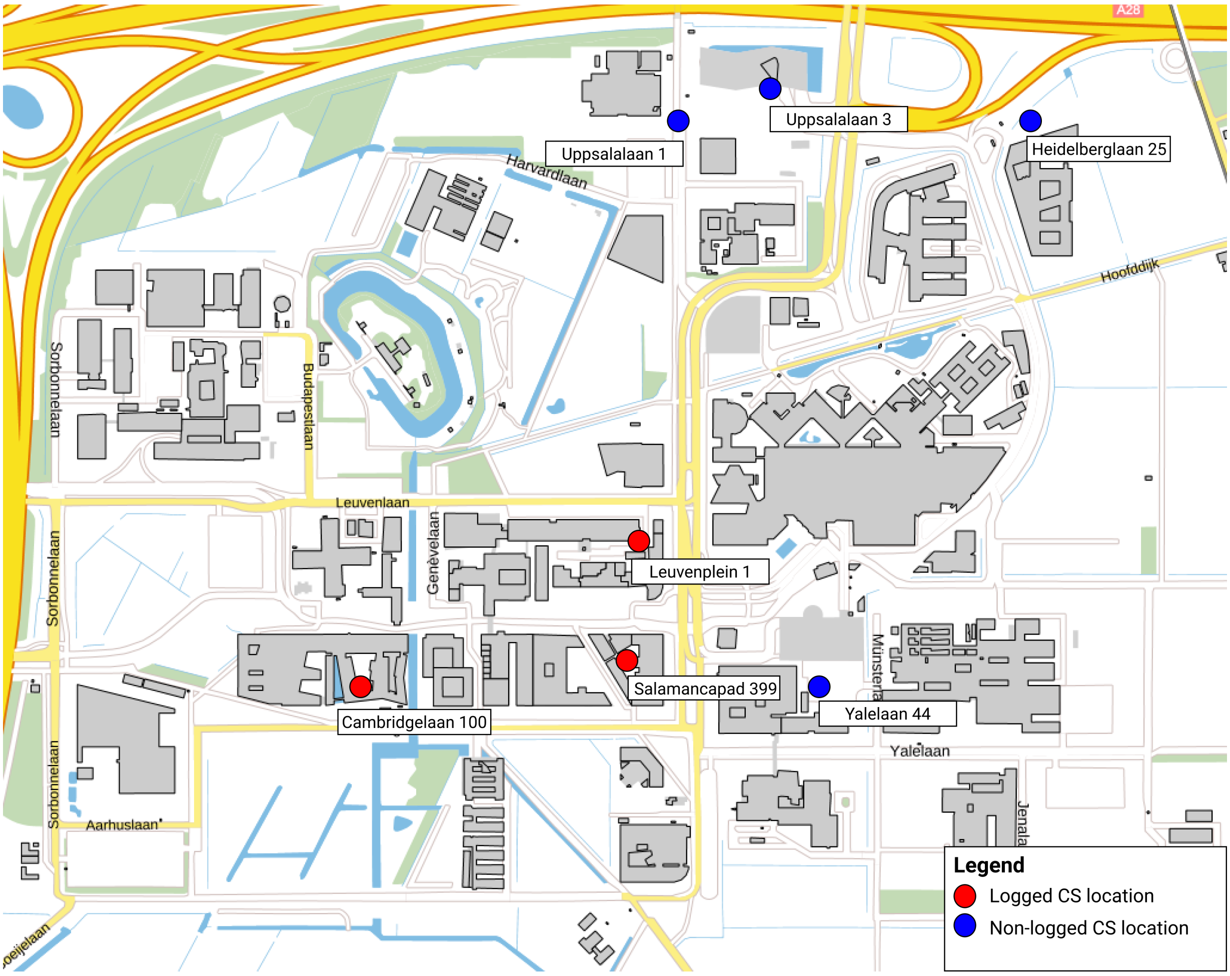


Figure 3.2: Locations of CSs at investigated area, including the locations of logged CSs.

Since this study seeks to understand the impact of electric vehicles, a transaction dataset from Last Mile Solutions is used [39]. The transaction dataset consists of the charge data of EVs at 4 logged CSs in 3 locations of the investigated area. Last Mile Solutions is the supplier of the CSs and keeps track of the transactions that occur at the CSs. The CSs were logged from 2nd of January 2017 up to and including 28th of February 2019. Each CS is equipped with two charging points, both equipped with a 3x32A connection on a 230V network, so P_{max} is 22 kW. The dataset includes detailed information per transaction.

For each transaction q, the following data is available:
$t^q_{plug-in}$: the plug-in time
$t^q_{plug-out}$: the plug-out time
E^q_{req} $[kWh]$: the total charged energy
$EV\ ID$: An identity-key of each unique charging EV

The locations of the logged CSs are displayed with a red dot in Figure 3.2. Leuvenplein 1 and Salamancapad 399 both have one CS, Cambridgelaan 100 has two. The two CSs at Cambridgelaan 100 are in use by the company EVs of Hogeschool Utrecht (HU). This is a project by Smart Solar Charging (SSC) where various parties are testing the possibilities of storing the generated solar energy in the batteries of the company EVs [59].

Data cleaning steps included removing transactions where no EV ID was logged. Furthermore, the dataset was filtered so that it covers a one-year period, the start date was 28th of February 2018 and the end date 28th of February 2019. This results in a dataset of 807 transactions. Specifications of the logged CSs are given in Table 3.1.

Table 3.1: Specifications of logged CSs.

	Station id	Station Address	Maximum charge rate $[kW]$	Type
1	1702548	Leuvenplein 1	22	Type 2 Mennekes
2	1702548	Leuvenplein 1	22	Type 2 Mennekes
3	1706508	Cambridgelaan 100	22	Type 2 Mennekes
4	1706508	Cambridgelaan 100	22	Type 2 Mennekes
5	1601034	Cambridgelaan 100	22	Type 2 Mennekes
6	1601034	Cambridgelaan 100	22	Type 2 Mennekes
7	1703856	Salamancapad 399	22	Type 2 Mennekes
8	1703856	Salamancapad 399	22	Type 2 Mennekes

Chapter 4

Charging Profiles Results

4.1 Results of measured EV dataset

In the transaction dataset the following vehicles were identified: 4 company BEV, 18 commuting BEV and 20 commuting PHEV. At the 4 measured CSs, no company PHEV was identified. The distribution of the EV categories in the dataset is shown in Figure 4.1. The key results determined from the measured dataset are shown in Table 4.1. As shown by the daily energy demand, company BEVs have a high impact on the aggregated electricity demand in comparison to the other EV categories. The company BEVs have the highest charge frequency, with an average charge frequency of 0.412 [EV^{-1} * day^{-1}]. The daily energy demand for commuting PHEVs and commuting BEVs are identical whereas the commuting BEVs have a higher charge frequency.

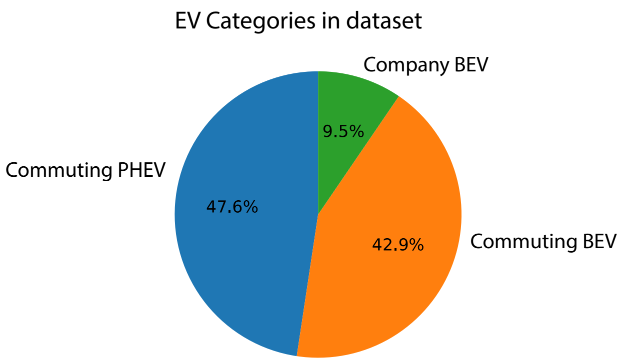


Figure 4.1: Distribution of EV categories determined in the measured transaction dataset.

Table 4.1: Key results of EVs charging at 4 EV CSs at Utrecht Science Park, measured in the period from 28th of February 2018 to 28th of February 2019.

Category	Number of EVs [#]	$f_{daily,av}$ [EV^{-1} * day^{-1}]	$E_{daily,av}$ [kWh * EV^{-1} * day^{-1}]
company BEV	4	0.412	4.874
commuting BEV	18	0.027	0.548
company PHEV	0	-	-
commuting PHEV	20	0.004	0.019
All EVs	42	0.053	0.708

The distribution of several parameters were analysed for the different identified categories, Figure 4.2 shows histograms of the four parameters analysed. These results are later used in the simulation of the EV fleet and the charging profile. The first row in the figure shows the plug-in hour EV category. It illustrates that company BEVs plug-in mostly around 10:00, commuting BEVs plug-in a bit earlier with its peak between 7:00 and 8:00. commuting PHEVs have a different charging behaviour and tend to plug-in in the afternoon. The second row of graphs show the distribution of the required energy for EVs in different categories. The distributions for company BEVs and commuting BEVs are quite similar. For the commuting PHEVs E_{req} is lower, with a maximum of 13.8 kWh, which was set as a constraint in Section 3.1. The third row in the figure shows the connection duration, $T_{connect}$. With company BEVs having the longest connection duration, followed by commuting BEVs. For commuting PHEVs, the connection duration is expectedly shorter with commuting PHEVs most often plugged in for a 0-4 hour period. Lastly, the 4th row of the figure shows the normal distribution of the charge frequency per EV category. The red line depicts the probability density. The normal distribution is obtained by a simulation for the mean of the charge frequency ($f_{\text{av,cat,daily}}$) with a standard deviation σ of 25%.

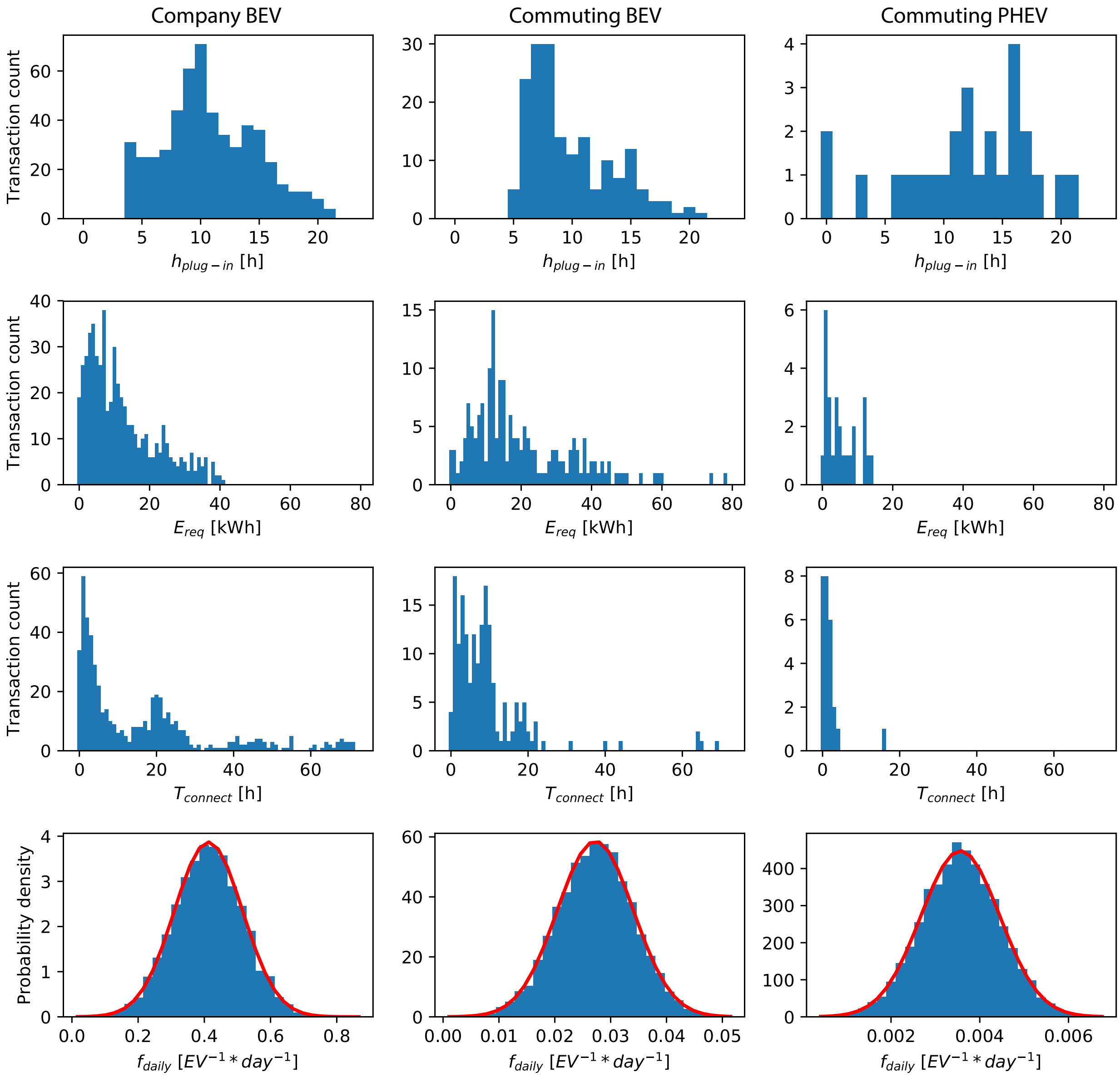


Figure 4.2: Histograms of transaction parameters and a normal distribution of the charge frequency per category, of transactions in the period of the logged year, 28th of February 2018 to 28th of February 2019.

The load over the 4 CSs was obtained and is displayed in Figure 4.3. The load profile shows peaks as high as 66 kW when there is coincidental charging.

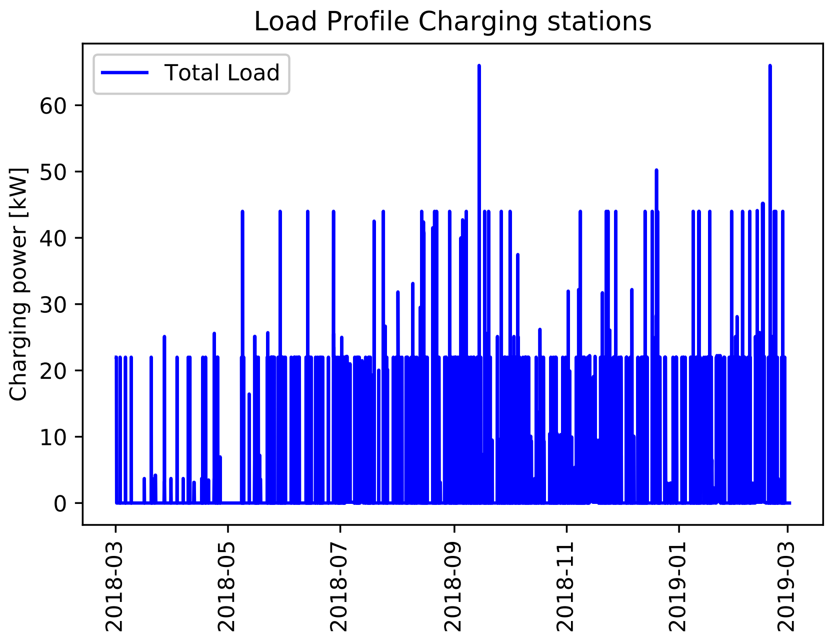


Figure 4.3: Load profile of measured CSs over the period of one year, from 28th of February 2018 to 28th of February 2019.

4.2 EV fleet size

Utrecht Science Park has been growing significantly, this is due to the concentration of education facilities, the growth of employment opportunities and the autonomous growth of students [26]. This section therefore looks at future scenarios, where an increase in number of EVs at the investigated area can be expected.

Every two years, in coordination between Utrecht University (UU), Hogeschool Utrecht (HU) and University Medical Centre (UMC), a large-scale mobility study is conducted. A result from this study is the modal split. The modal split (transport mode choice) of the employees (commuting) of these three organisations is shown in Table 4.2 [26].

Table 4.2: Modal split of employees commuting to UU, HU and UMC (2015) [26].

Organisation	Public transport	Bicycle	Passenger vehicle
UU	16%	58%	22%
HU	23%	35%	39%
UMC (winter-summer)	30-24%	40-50%	26%

As mentioned in Section 3.5, the daily visitors of USP are around 77,000 in 2019 (66% students and 34% employees). Evaluating the modal split and the amount of daily visitors this results in around 9,699 daily used passenger vehicles.

4.2.1 Scenario Present-day

In the transaction dataset, 4 CSs were measured. However, As mentioned in Section 3.5, there are 21 CSs currently installed at the investigated area. For the present-day, equation 3.1 is used, determining the actual amount of EVs charging at the 21 CSs. The identified vehicles for the present-day scenario are: 21 company BEV, 95 commuting BEV, 0 company PHEV and 105 commuting PHEV. Thus, in total 221 EVs are identified, 2.3% of the total vehicle fleet at the investigated area.

4.2.2 Future of mobility

The way people are transporting from A to B is changing, driven by a series of converging technological and social trends [23]. This section describes the results of a literature review that was performed regarding the future of mobility.

As urban density continues to grow, models such as sharing and mobility as a service (MaaS) provide an alternative way to move more people and goods in a way that is faster, cleaner, and less expensive than current options. Sharing solutions are expected to be a popular model of ownership in urban areas, in contrast to rural areas, where traditional model of ownership will continue to dominate [66]. This section looks at the expected number of shared vehicles and in particular shared EVs.

In the Netherlands, the number of shared vehicles is increasing [46, 54]. Figure 4.4 shows this increase of vehicle sharing in the Netherlands. The number of shared vehicles, and with that the share of EVs in the shared fleet, is shown in Table 4.3. Shared fleets that include EVs is increasing, with frequent announcements of new shared electric mobility services or the introduction of EVs within existing shared fleets.

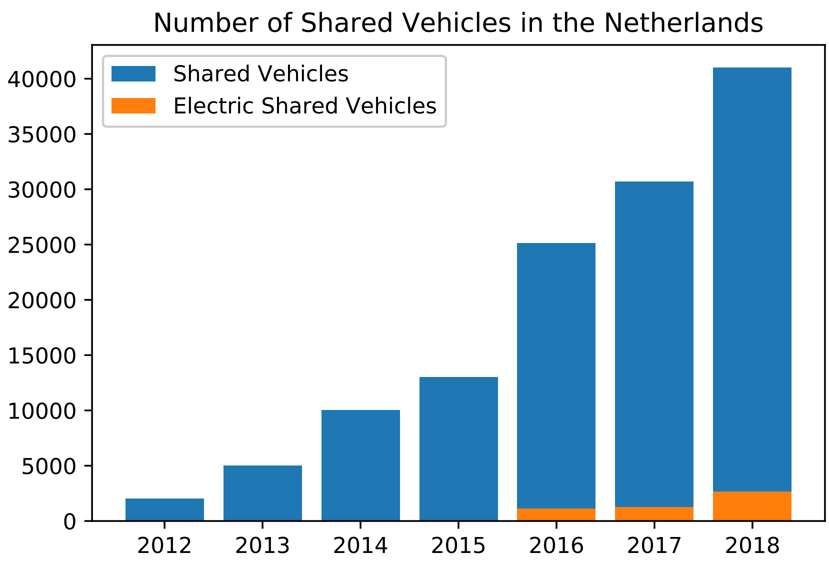


Figure 4.4: Number of shared vehicles in the Netherlands, between 2012 and 2018 obtained from [46, 54].

Table 4.3: Statistics Shared Vehicles in the Netherlands [54].

	2016	2017	2018
Shared vehicles (all fuels)	25,128	30,697	41,000
Shared EVs	1,131 (4.5%)	1,259 (4.1%)	2,665 (6.5%)

Vehicle sharing and autonomous driving offer the possibility to reduce the number of vehicles in the Dutch fleet up to 50% in 2050 [8]. Research of Fraunhofer ISI showed that in Germany in 2050, half of the vehicles in the Germand vehicle fleet could be replaced by shared vehicles [56]. The French environment and energy management agency (ADEME) came to a similar conclusion and found that each shared vehicle replaces on average 5 to 6 private vehicles, while freeing up at least 2 parking places [1]. It is expected that on the longer term, all shared vehicles will be EVs. This is caused by their high annual mileage, resulting in a much lower Total Cost of Ownership (TCO) for shared EVs than for conventional vehicles [8]. In addition to that, because shared vehicles are used relatively intensive and often in an urban environment, electrifying them therefore is logical [20].

Several studies were done regarding the expected share of shared vehicles on the total vehicle fleet. KPMG studied the passenger fleet for the UK and expects a share of shared vehicles of 6% and 17% for the years 2030 and 2040, respectively [33]. Another study by KPMG predicts that in the countries of the Triad (USA, Japan, Western Europe) 25% of the inhabitants of large cities in 2030 will use every day solutions for the optimization of routes within the city by using vehicle rentals and the use of other means of transport [34]. A 2016 study by Deloitte forecasted the total miles driven for the United States until 2040 and expects shared vehicles to account for 80% of the distance driven in 2040 [7]. A study at the University of Gdask, determined that generally 10% of vehicles sold in 2030 will be shared vehicles and in 2050 30%, mostly in urban areas [66]. Ecofys created a scenario study which studied the future of electric mobility in the Netherlands. The share of electric shared vehicles ranged from 1% to 7% of the total electric vehicle fleet in 2030 [8]. McKinsey studied the future of mobility towards 2030 and expects 10 out of 115 sold vehicles in 2030 to be a shared vehicle [44]. McKinsey's view on the total vehicle fleet is that new mobility services may result in a decline of private vehicle sales, but this decline is likely to be partially offset by increased sales in shared vehicles that need to be replaced more often due to higher utilisation and related wear and tear. They concluded that from 2030, vehicle unit sales will continue to grow, despite a shift towards shared mobility, but at a lower rate of 2% annually [44]. The studies mentioned above are summarised in Table 4.4.

Table 4.4: Summarised data found in literature for the share of shared vehicles on the vehicle fleet.

Data		Source
6% in 2030, 17% in 2040	Share of shared vehicles in UK passenger fleet.	[33]
25% in 2030	Share of inhabitants of large cities that use alternative modes of transport in the Triad.	[34]
80% in 2040	Share of total distance driven by shared vehicles in the United States.	[7]
1-7% in 2030	Share of shared EVs on the Dutch EV fleet.	[8]
10 out of 115 vehicles in 2030	Sales shared vehicles out of total sales vehicles.	[44]

Scenarios 2030 and 2050

The Dutch government has set goals and ambition for the Dutch passenger fleet. In 2030 all new passenger vehicles sold should be zero-emission [53]. In 2050, all passenger vehicles should be zero-emission [24]. Targets have also been set at European level. The use of conventionally-fuelled vehicles in urban areas should be reduced to 50% in 2030 and 100% reduced by 2050 [15]. As this thesis determines the impact of electric vehicles on the distribution network, it is assumed that in 2030 50% of the Dutch passenger fleet is driven by an electric motor, and in 2050 100%.

Comissioned by the Sociaal-Economische Raad (SER) the consortium of TNO/ECN/CE Delft determined the Dutch EV fleet in 2030 and 2050 for the Energy agreement of 2014 [11]. The result from this report is shown in Table 4.5. The results show that the share of PHEVs on the EV fleet is expected to increase until 2030 and then decrease in 2050 as more BEVs are introduced.

Table 4.5: Number and share of the Dutch EV passenger fleet in 2030 and 2050 [11].

Category	2030		2050	
BEV	595,000	29%	7,100,000	75%
PHEV	1,470,000	71%	2,360,000	25%
All EVs	2,065,000	100%	9,460,000	100%

Centraal Planbureau (CPB) and Planbureau voor de Leefomgeving (PBL) studied the development of the Dutch passenger vehicle fleet [9]. CPB and PBL are planning bureaus of the Dutch government. CPB is a Dutch government agency whose main task is to make economic forecasts and analyses. PBL is a Dutch government agency for making strategic policy analyses in the field of the environment, nature and space. In the study by CPB and PBL, two scenarios were created. In the low scenario, the growth is determined at 0.3% per year and in the high scenario the growth is determined at 0.9% a year. The growth of the Dutch vehicle fleet is assumed to be applicable for the investigated area. Therefore, in the low scenario 10,024 and 10,643 vehicles can be expected in 2030 and 2050, respectively. For the high scenario, this would mean 10,704 vehicles in 2030 and 12,804 vehicles in 2050. As in 2030 50% of the vehicle fleet is assumed to be an EV, 5,012 and 5,352 EVs were determined for the low and high scenarios, respectively. In 2050, the EV fleet would consist 10,643 and 12,804 EVs in the low and high scenarios, respectively. Due to high computation time it was decided that an average of these two scenarios would be taken into account. The averaged EV fleet at the investigated area would then be sized at 5,182 EVs in 2030 and 11,724 EVs in 2050.

For the 2030 scenarios, a share of 29% BEV and 71% PHEV on the EV fleet is considered, as in [11]. In all future scenarios, the company vehicle is considered a BEV [8, 20]. The share of company EVs is considered 7%, as determined in [8] for the Dutch EV fleet. Therefore for the 2030 scenarios, a share of 22% commuting BEV, 71% commuting PHEV and 7% company BEV on the EV fleet is considered.

Less data for the year 2050 is available. However, in order to comply with the Dutch ambition and European goals, all vehicles are assumed to be only driven by an electric motor. Therefore, all EVs should be either a company BEV or a commuting BEV. Data from [33] stated a 17% share of shared vehicles of the UK passenger fleet in 2040. Assuming this number is to be equal for the passenger fleet at the investigated area and considering the growth continues, this would mean a 28% share of company EVs on the EV fleet. The share of commuting BEVs would then be 72%.

4.2.3 Overview EV fleet Scenarios

An overview of the EV fleet determined in the previous sections for the present-day and future scenarios is represented in Table 4.6.

Table 4.6: Share and number of unique EVs charging at the investigated area per EV category and scenario.

Category	$N_{EV,Present-day}$	$N_{EV,2030}$	$N_{EV,2050}$
company BEV	21 (9.5%)	363 (7%)	3,283 (28%)
commuting BEV	95 (43%)	1,140 (22%)	8,441 (72%)
commuting PHEV	105 (47.5%)	3,679 (71%)	0
All EVs	221	5,182	11,724

4.3 Simulation of EV fleet

As described in the previous section, the EV fleet was simulated for the present-day, 2030 and 2050 scenarios. Figure 4.5 shows the results of this simulation. The number of EVs that were determined in the simulation are represented in Table 4.7. The EV fleet simulation resulted in a dataset with the number of simulated EVs and their charging specifications (P_{MAX}, f_{daily}, the EV category and an unique number per EV). The simulated EV fleet comes close to the theoretical EV fleet presented in Table 4.6.

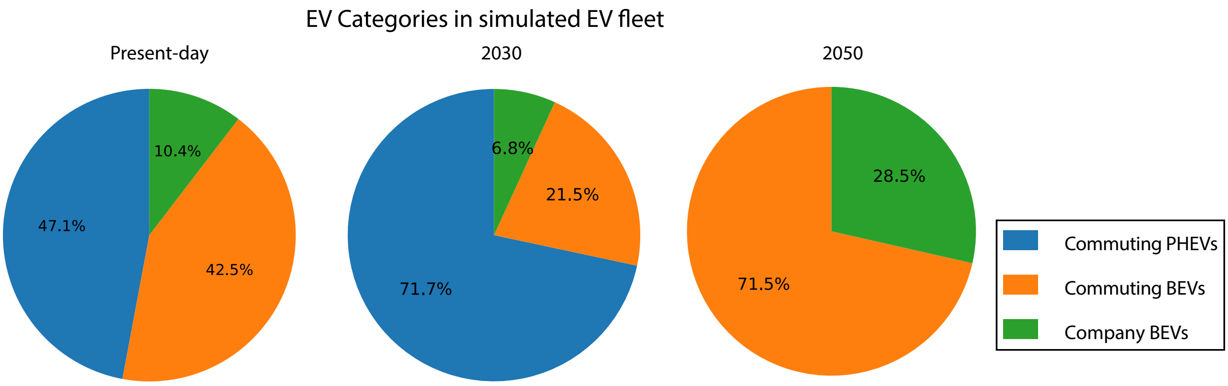


Figure 4.5: Distribution of EV categories determined in Present-day, 2030 and 2050 scenario.

Table 4.7: Results of the EV fleet simulation: number of unique EVs identified per scenario.

Category	$N_{EV,sim,Present-day}$	$N_{EV,sim,2030}$	$N_{EV,sim,2050}$
company BEV	25	354	3,347
commuting BEV	96	1,115	8,377
commuting PHEV	100	3,713	0
All EVs	221	5,182	11,724

4.4 Simulation of EV Charging Profile

In this section the results of the charging profile simulation of the EV fleet per scenario are described.

4.4.1 Scenario Present-day

The load profile of the 221 EVs charging at the investigated area is shown in Figure 4.6. The load profile shows the charging power ordered chronologically over the year. The peak charging power is 157.7 kW when there is coincident charging. The load duration curve (LDC) of the present-day scenario is shown in 4.7, which shows the charging power ordered in descending order of magnitude. The y-axis shows the charging power in kW, the x-axis shows the normalised duration. The normalised duration illustrates the load utilization rate (0% to 100% of the year). To give a representation of how the load varies during the period of a week, Figure 4.8 shows the charging power over the period of the first week after Christmas holidays, 7st of January 2019 to 13th of January 2019. The peak power during the week is 88 kW, the average charging power is 7.55 kW and the aggregated energy demand is 1,268 kWh. In the period of the simulated year, a maximum of 28 EVs are connected at once. In order to accommodate for the uncontrolled charging of the simulated number of EVs, 28 charging points should be available at the investigated area. As each CS is equipped with two charging points, 14 CSs should be available at the investigated area.

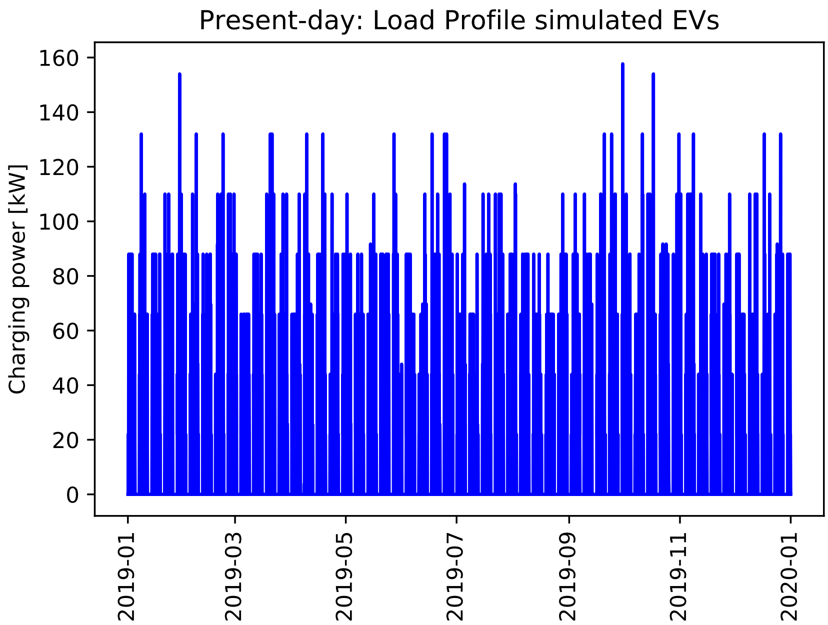


Figure 4.6: Load profile of simulated EVs charging over the period of the year 2019.

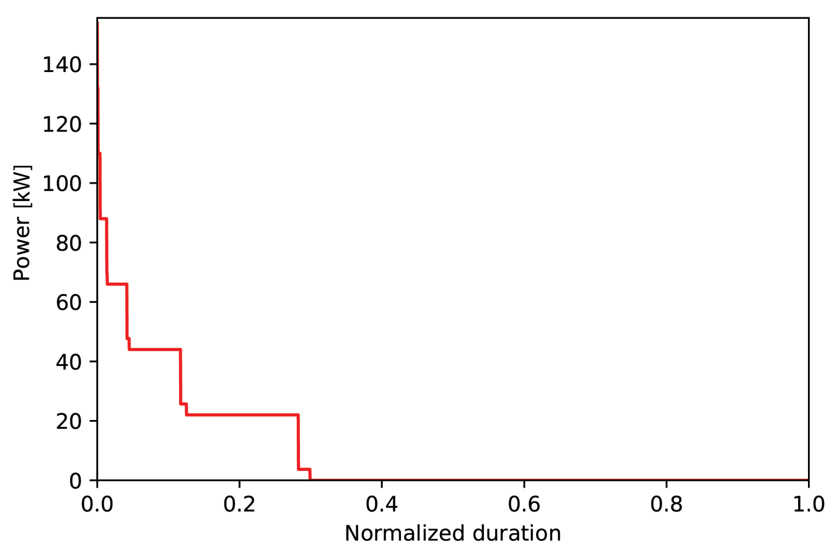


Figure 4.7: Load duration curve of simulated EVs charging over the period of the year 2019.

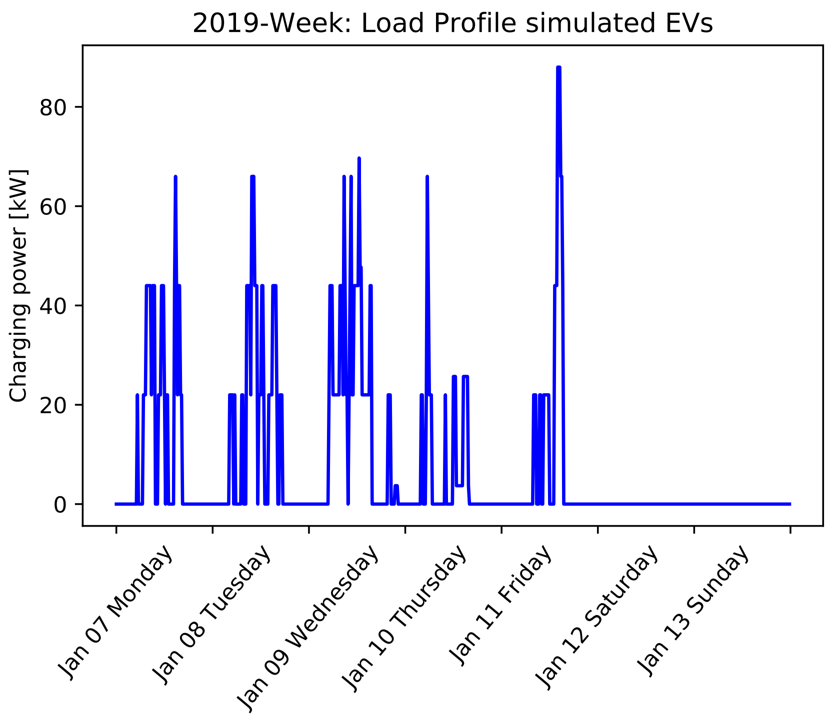


Figure 4.8: Load profile of simulated EVs charging over the period of one week in 2019.

4.4.2 Scenario 2030

The load profile of the 5,182 EVs charging at the investigated area in 2030 is shown in Figure 4.9. The load profile shows the charging power ordered chronologically over the year. The peak charging power is 993.7 kW and occurs on the 15th of October 2030. The average charging power over the year is 151.5 kW and the aggregated energy demand is 1,327,080 kWh. The LDC of the 2030 scenario is shown in Figure 4.10. Figure 4.11 shows the charging power over the period of one week, 7st of January 2030 to 13th of January 2030. The peak power during the week is 810.5 kW, the average charging power is 158.4 kW and the aggregated energy demand is 26,619 kWh. In the period of the simulated year, a maximum of 237 EVs are connected at once. In order to accommodate for the uncontrolled charging of the simulated number of EVs, 119 CSs should be available at the investigated area.

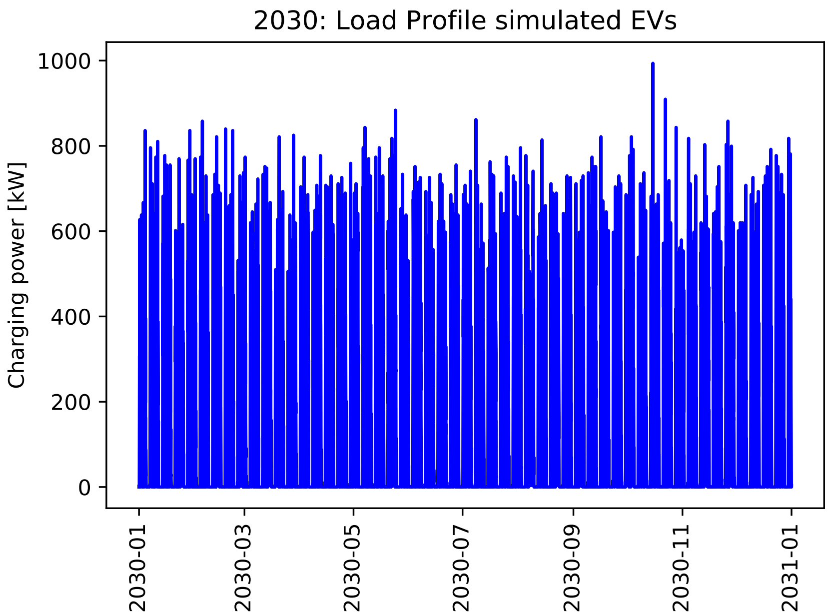


Figure 4.9: Load profile of simulated EVs charging over the period of the year 2030.

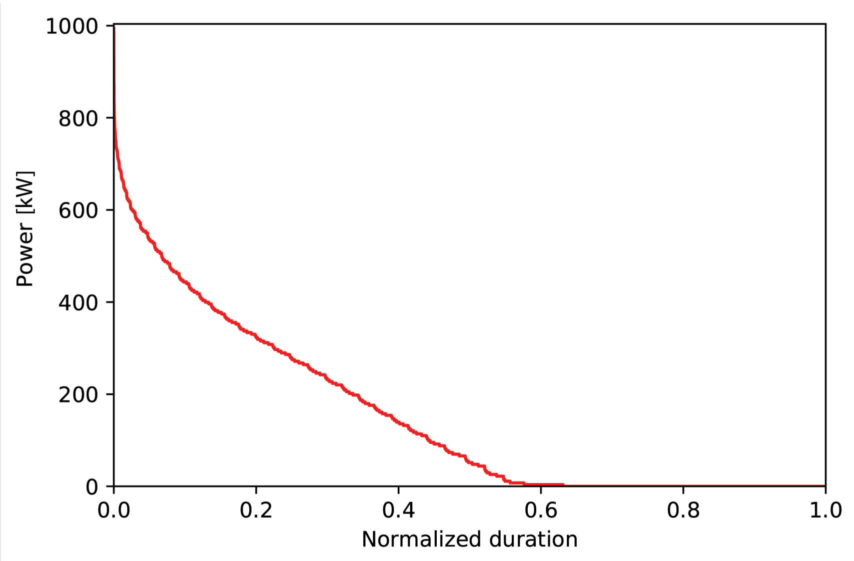


Figure 4.10: Load duration curve of simulated EVs charging over the period of the year 2030.

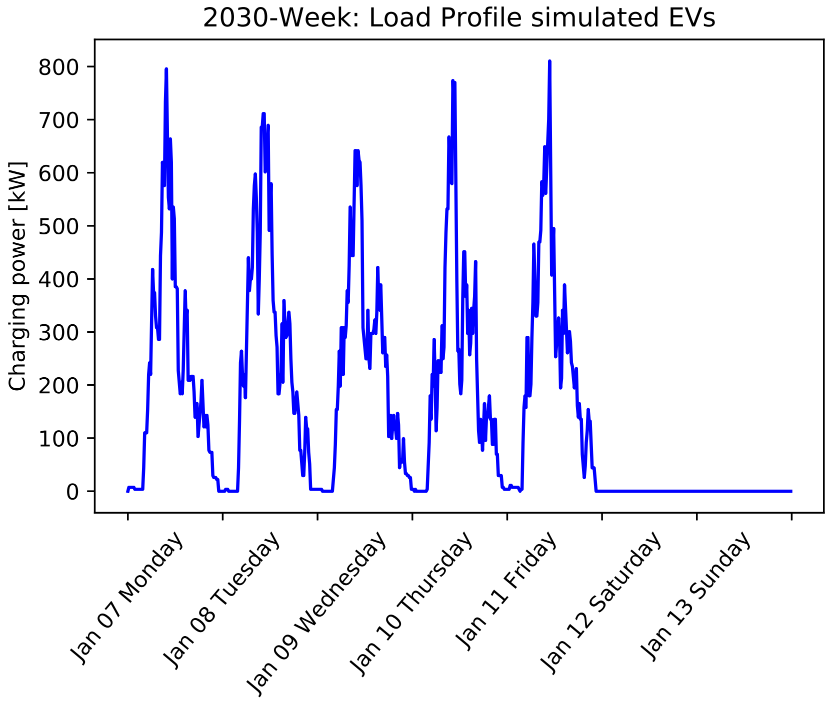


Figure 4.11: Load profile of simulated EVs charging over the period of one week in 2030.

4.4.3 Scenario 2050

The load profile of the 11,724 EVs charging at the investigated area in 2050 is shown in Figure 4.12. The load profile shows the charging power ordered chronologically over the year. The peak charging power is 6,094 kW and occurs on the 14th of September 2050. The average charging power over the year is 1,289 kW and the aggregated energy demand is 11,294,701 kWh. The LDC of the 2050 scenario is shown in Figure 4.13. Figure 4.14 shows the charging power over the period of one week, 10st of January 2050 to 16th of January 2050. The peak power during the week is 5,698 kW, the average charging power is 1,286.8 kW and the aggregated energy demand is 216,177 kWh. In the period of the simulated year, a maximum of 1713 EVs are connected at once. In order to accommodate for the uncontrolled charging of the simulated number of EVs, 857 CSs should be available at the investigated area.

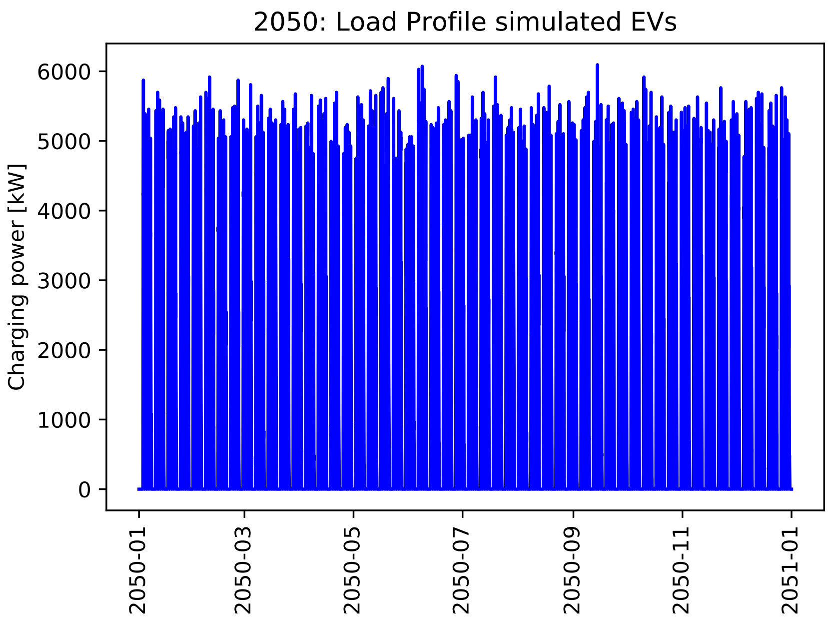


Figure 4.12: Load profile of simulated EVs charging over the period of the year 2050.

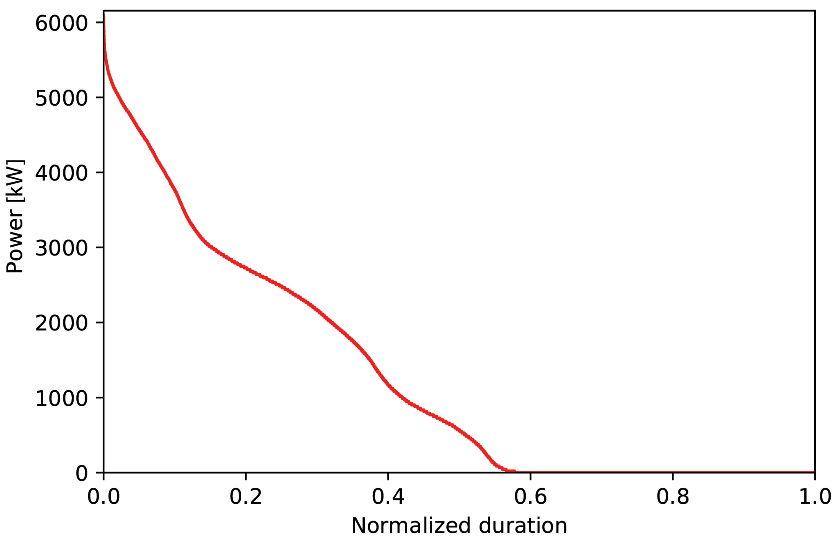


Figure 4.13: Load duration curve of simulated EVs charging over the period of the year 2050.

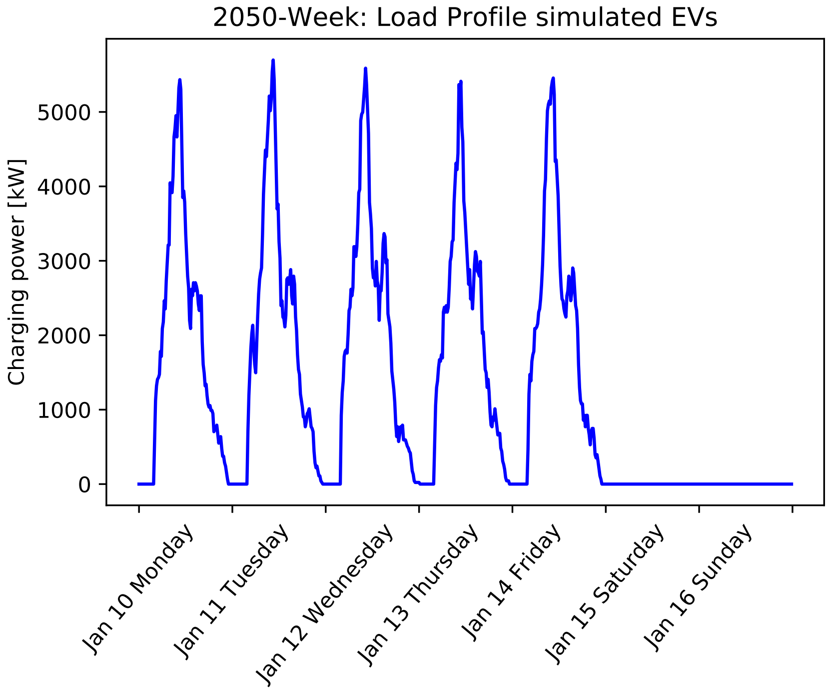


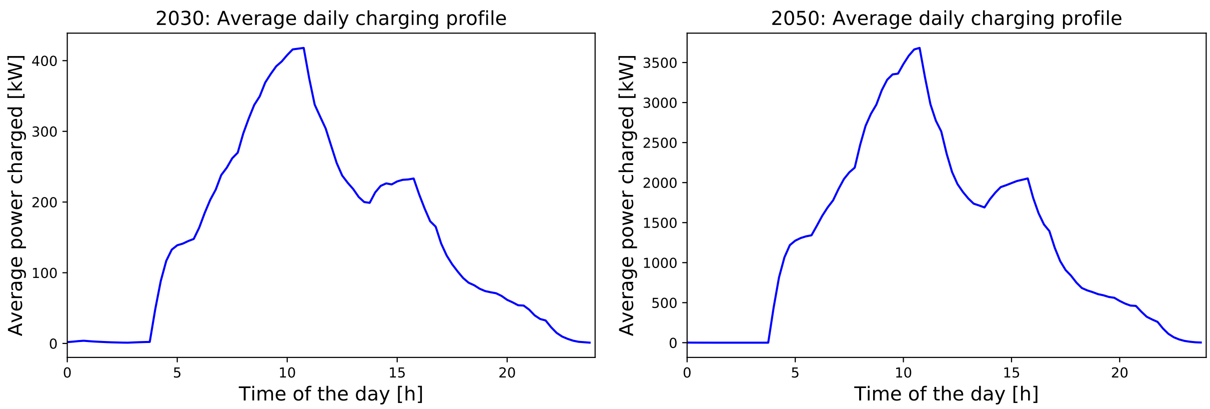
Figure 4.14: Load profile of simulated EVs charging over the period of one week in 2050.

4.4.4 Overview charging profile scenarios

Table 4.8 gives an overview of the results per year for the three scenarios. The daily average charging profiles for the 2030 and 2050 are represented in Figure 4.15.

Table 4.8: Overview of results from the load profile simulation per scenario.

	Present-day	2030	2050
Number of CSs [#]	14	119	857
Peak power [kW]	154	993.7	6,094
Average charging power [kW]	10.22	151.5	1,289
Aggregated energy demand [kWh]	89,514	1,327,080	11,294,701



(a) 2030 Scenario

(b) 2050 Scenario

Figure 4.15: Average daily charging profile for simulated EVs in the 2030 and 2050 scenario.

4.5 Sensitivity analysis

The development of the scenarios incorporates several assumptions. Therefore, a sensitivity analysis is performed to substantiate the assumptions made. One of these assumptions is that the use of shared vehicles will increase in the coming years. This assumption is based on literature review which forecasted the share of shared vehicles on the passenger fleet. Most of these studies consider the primary application of the shared vehicle to be used by residents. As this thesis looks at shared company EVs in an office environment a sensitivity analysis is performed on the share of this category within the total fleet. The developed simulation model assumes that the charging frequency of the simulated categories stays constant. However, one can imagine that the charging frequency will be much higher in the future, especially for the year 2050. This is due to the fact that in 2050 all vehicles at the investigated area are assumed to be an EV. Consequently, the employee with a commuting EV will charge more regularly at the office environment. Therefore, the sensitivity of this parameter, charge frequency $f_{daily,av}$, is tested. The sensitivity analysis is performed within the range from -50% to +50%. The inputs to the sensitivity analysis are presented in Appendix C. The result of the sensitivity analysis is displayed in Figure 4.16. The sensitivity analysis shows that $f_{daily,av}$ has a smaller impact on the observed peak power in the 2050 scenario than the share of company EV. With a decrease of $f_{daily,av}$ by 50%, the observed peak power decreases by 37%. With an increase of $f_{daily,av}$ by 50%, the observed peak power increases by 24%. The share of company EV has a higher impact on the peak power. With a decrease of $Share_{CompanyEV,2050}$ by 50%, the observed peak power decreases by 43%. With an increase of $Share_{CompanyEV,2050}$ by 50%, the observed peak power increases by 48%. This is possibly because the company EVs tend to plug-in around 10:00, see Figure 4.2, adding to the morning peak observed in Figure 4.15.

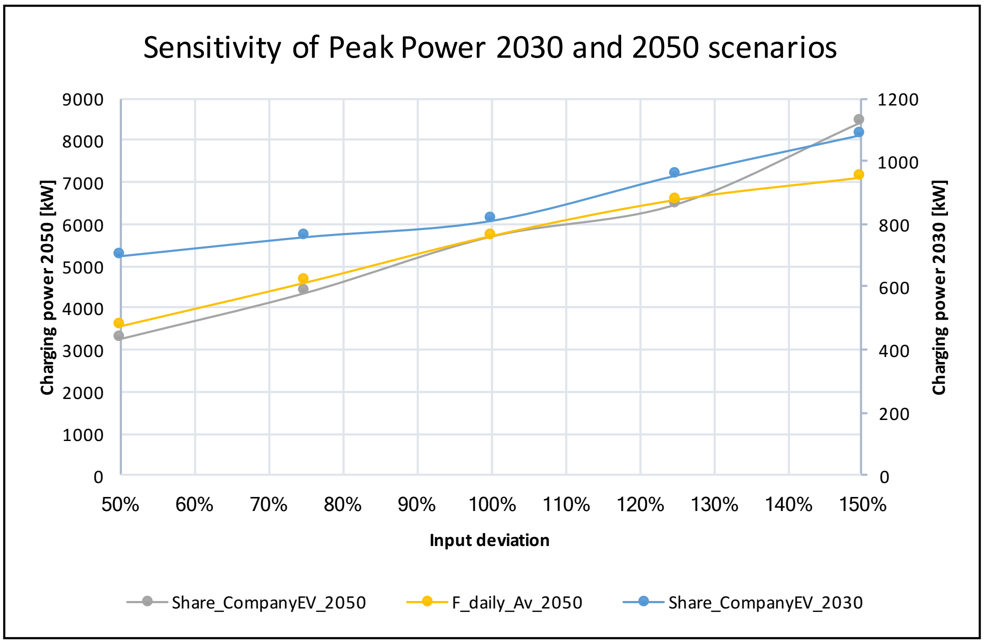


Figure 4.16: Sensitivity of two critical parameters on the peak power demand, 2030 and 2050 scenario.

Part II

Grid Impact of Electric Vehicles

Chapter 5

Grid impact calculation method

In this chapter a grid impact calculation will provide insight into the effect of electric vehicles charging on the grid. As this thesis looks at the case study of USP specifically, the calculation will look into local aspects of the grid and the loads connected to the grid. The calculation will be applied on an existing grid model with actual data of grid assets in a sub-grid in the municipality of Utrecht.

Note that the grid impact only looks at a medium voltage network. Low voltage grids are also expected to face impact from electric vehicles [13]. However, the data which was available and provided by the Distribution System Operator (DSO), Stedin, was the medium voltage grid. Therefore LV feeders are not part of the calculation and the calculation is done for the MV/LV transformers.

This section will describe the approach of the grid impact calculations. Firstly the software tool used will be described, followed by the explanation and definition of parameters used in the calculation. Next, the input data that is used in the software tool is described. For more information on the considered grid, one is referred to appendix B.

5.1 Software and grid model

In network planning, network operators often do several analyses, including load flow and short circuit analysis. A tool for these analyses is the software program 'Vision Network Analysis'. Vision is a software for the planning, design and management of electricity networks. Vision is suitable for large and small networks; it is used for transport, distribution and industrial networks [48]. This package is widely used for network planning in the Netherlands, and an important advantage is that the network, provided by the DSO Stedin, was already represented in the software program. The model of the the distribution grid is a 10 kV MV network. The model consits of two parts named 'UTR. SORBONNELAAN STAD' and 'UTR. SORBONNELAAN UITHOF'. This study focuses on 'UTR. SORBONNELAAN UITHOF', the grid model of USP. Appendix B includes an image of the nodes at the MV distribution network of the investigated area.

5.2 Preparation input data

This section describes the steps that were taken in order to prepare the input data used in the grid impact calculation. First, the grouping of simulated EV load profiles is explained. Secondly, the method for the determination of the locations for CSs is described.

5.2.1 EV Load profiles

In the chapter 4, the charging profile per simulated EV was obtained. To somewhat simplify the implementation of the load of many individual EVs onto the distribution grid of the investigated area, some sort of aggregation is needed. The charging profiles of the EV fleet is clustered into 20 groups, as done by [73], which makes it computationally feasible. This means that only 20 external load profiles are to be incorporated into Vision.

5.2.2 Location of charging stations

This section describes the method for the determination of the location of CSs at the investigated area. The location of the CS is essential as it determines on which nodes in the distribution grid the external load of the simulated EVs should be applied. The locations of the current and planned CS is obtained by interviewing university employees working at facility management and administrative services. In the next step, the available parking areas at the investigated area is studied. The available parking areas are a potential location for future CSs. These sources of data are combined and results in an overview of a number of CS that could be connected to certain nodes in the network.

As mentioned earlier, the following steps are taken for determining the location of future CS at the investigated area:

1. Locations of current and planned CSs are determined;
2. The parking areas and their capacities at the campus are defined;
3. Parking areas without sufficient parking capacity ($C_{parking}$) are excluded;
4. Finally, parking areas without a node in the network close by are excluded as the load data availability of the specific node in the network is taken into account.

5.2.3 Demand profiles of MV/LV transformers

As mentioned before, the load of a transformer is characterised by it's seasonal variation, with two peaks demand periods - winter and summer. Therefore, one week in each peak period is analysed. Note that since the rated capacity of a transformer is apparent power (S) [kVA] , in the analysis an average power factor (PF) is used to convert the apparent power to true power (P) [kW] . Equation 5.1 is used for the conversion.

$$P = S * PF \tag{5.1}$$

Here, $0 \leq PF \leq 1$ is the power factor. For the analysis, the average power factor of 0.9 and 0.95 is used for summer and winter, respectively, as done in [76].

5.3 Grid impact calculation

The grid impact is calculated in Vision by performing a load flow analysis. The demand profiles in the specified area are not logged by the DSO because of privacy reasons (*K. Diemers. E-mail correspondance, Jun 14, 2019; N. Brinkel. E-mail correspondance, Jun 3, 2019, Appendix A*). Therefore, because of lack of load data on many of the nodes in the network, the grid impact is only obtained for the transformers for which the external load of EVs is applied and for which the demand load data is made available. Because the network is a MV-network, and the CS are to be connected on the LV-network, the load is applied before the transformer, as displayed in Figure 5.1. The figure displays the way the loads are applied. "Load" relates to the load in case of no electric mobility. The load is obtained from the energy dashboard "Eview.nl" which includes energy consumption of many of the nodes of USP. In here, nodes represent the customers (aka "loads") in the electricity grid. Network operators always assume organic growth of electricity demand. Therefore the existing grid loads are assigned with a demand growth profile of 1.5% a year [63]. "LoadEV" refers to the load that is attributed to the EVs charging and has been determined in Part I. The load flow analysis is performed for the period of a week for each one of the developed scenarios.

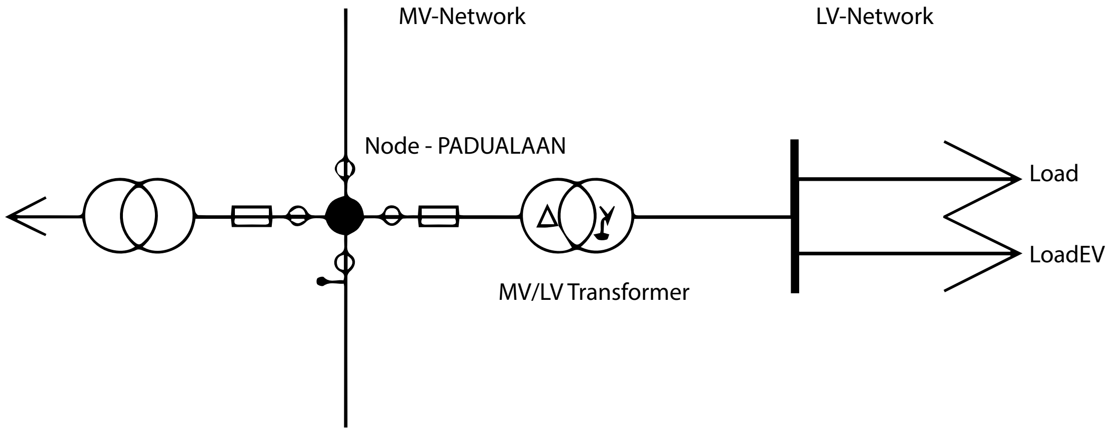


Figure 5.1: Example of applying the load of electric vehicles on a MV-network model.

The peak loadings of the transformers are studied. As a transformer allows to be overloaded for some time, the overload criterion considered is 1.25, and the critically overload criterion considered is 1.5, as considered in [76]. The number of hours over the week for which the transformer is overloaded ($H_{overload,week}$) is computed for the overloaded transformers, see equation 5.2. The next step is to determine the maximum "session duration" ($H_{overload,session}$) over which the transformer is continuously overloaded.

$$H_{overload,week} = H_{load,transf.} \geq 1.25 \tag{5.2}$$

Chapter 6

Grid impact calculation results

6.1 Input data

This section describes the input data that was used in the grid impact calculation. Firstly, the results of grouping the load profiles is described. Secondly, the results for the locations of CS is defined (e.g. the nodes in the network at which the external load of the CS is applied).

6.1.1 EV Load profiles

The load profiles of the simulated EVs are aggregated into 20 groups. The key results per scenario are displayed in Table 6.1.

Table 6.1: Key results of aggregating load profiles of simulated EVs.

	2030-scenario	2050-scenario
Number of EVs per group [#]	259	586
Average peak power demand [kW]	148.9	521.4
Aggregated energy demand [MWh]	1,315	11,271

6.1.2 Location of charging stations

This section describes the results for the determined locations for CSs and therefore where the external load of the simulated EVs is applied. Firstly, the locations of the planned CSs is described. Secondly, the location of future CSs is analysed by studying the available parking areas.

Interviews with project managers at the University's administration and facility department resulted in an overview of the planned CS that are to be installed (*J. Ponten. Personal communication, Feb 27, 2019; M. Scherrenburg. Personal communication, March 19, 2019, Appendix A*). Four CS are to be installed at each of the four locations, each with two charging points. Capacity of the CS is 22 kW at 400 V and the CS are able to charge and dis-charge (V2G) (*J. Ponten. Personal communication, Feb 27, 2019*). The parking areas for planned CSs are: Parking area Budapestlaan, Parking area Sorbonnelaan, Parking garage Cambridgelaan and Parking area Jenalaan.

Subsequently, the available parking areas at the investigated area is discussed. The available areas offer opportunities for the installation of new CSs. The available parking areas are represented in Figure 6.1.

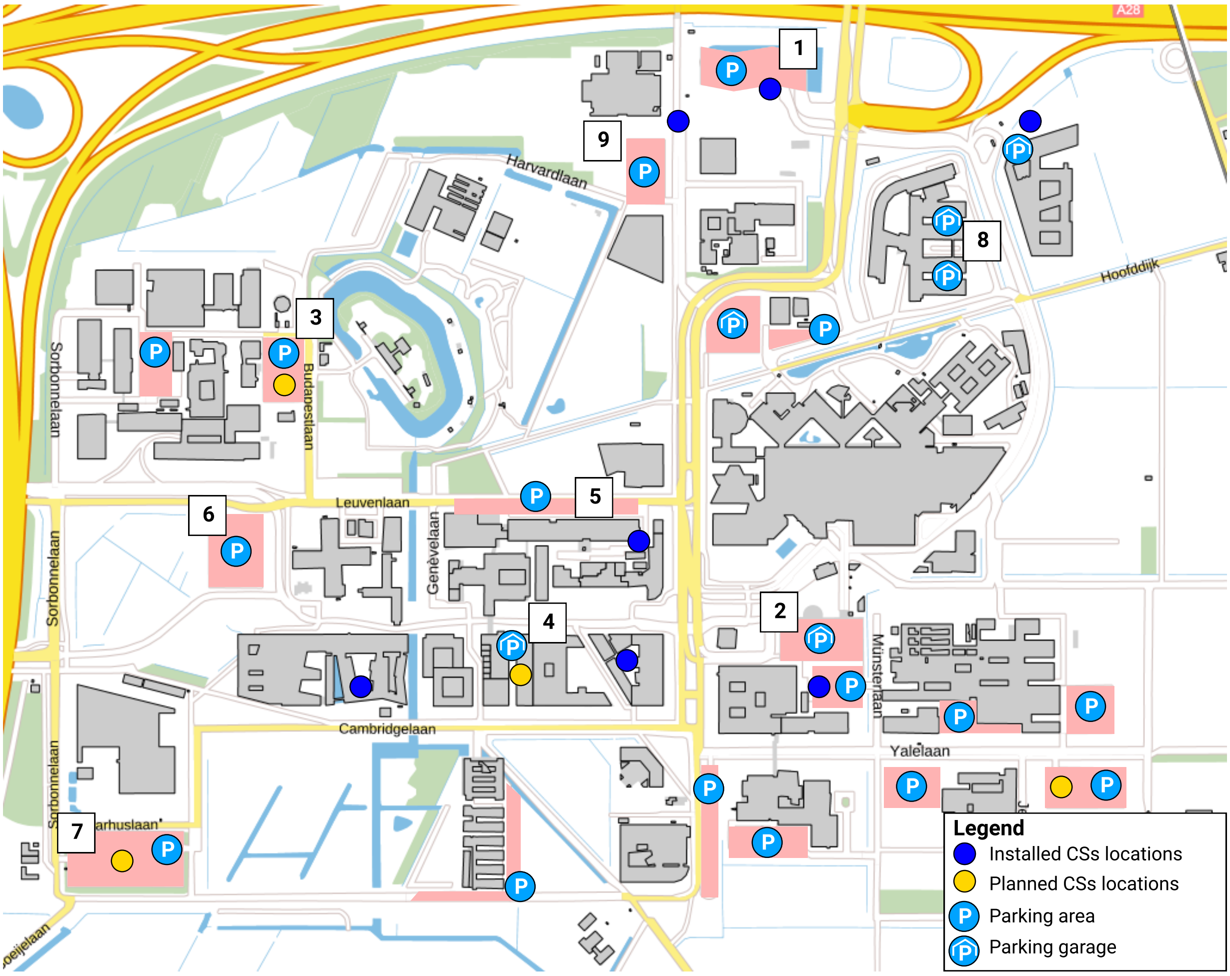


Figure 6.1: Representation of the available parking areas at the investigated area.

Main parking areas shown in Figure 6.1 are [68]:

1. P+R Utrecht Science Park (capacity 2,000).
2. Parking garage Zuid UMC Utrecht (capacity 1,727);
3. Parking area P9 Budapestlaan (capacity 135);
4. Parking garage P8 Cambridgelaan (capacity 504)
5. Parking area Leuvenlaan (capacity 113);
6. Parking area Padualaan (capacity 419);
7. Parking area Sorbonnelaan (capacity 613);
8. Parking area WKZ (capacity 271);
9. Parking area P10 Uppsalalaan (Sportcentre Olympos) (capacity 125).

The determined possible locations for CSs is displayed in Figure 6.2. Table 6.2 describes the main specifications of these locations including the parking area capacity ($C_{parking}$) the number of groups assigned to the node ($N_{EV groups}$), the number of CSs per scenario ($N_{CS,2030}$ & $N_{CS,2050}$) and the transformer capacities ($C_{transf.}$). Due to lack of data availability, the load of the University Medical Centre (UMC) and Wilhelmina Children's Hospital (WKZ) was not able to be determined. Therefore these parking areas were not considered in the grid impact calculation. Parking area Leuvenlaan was left out of the analysis as $C_{parking}$ was insufficient for the 2050-scenario.

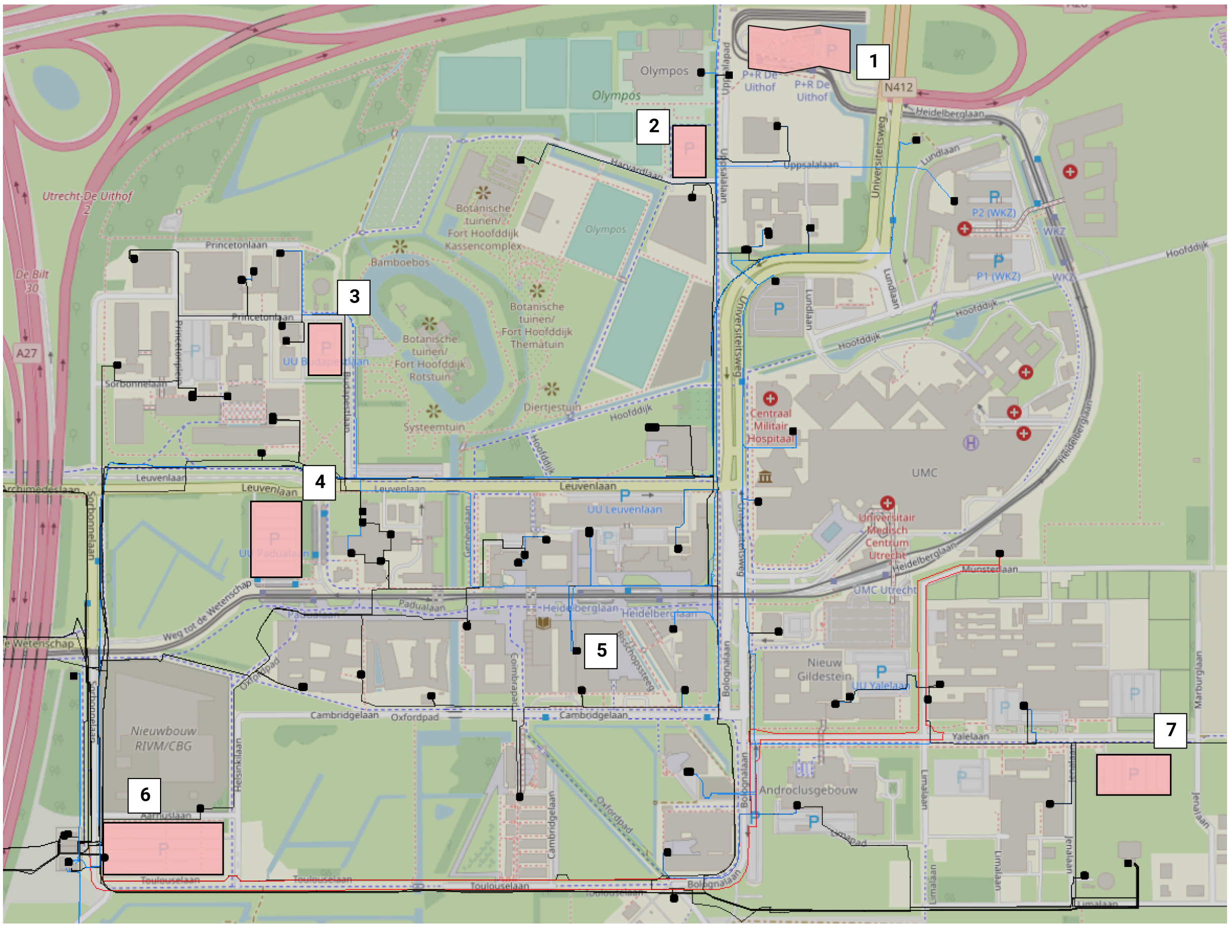


Figure 6.2: Representation of the determined parking areas for CS locations, the numbers represent the parking areas of which details are provided in Table 6.2.

Table 6.2: Key specifications of the CS locations.

	Parking name	$C_{parking}$	$N_{EV groups}$	$N_{CS,2030}$	$N_{CS,2050}$	$C_{transf.}$ $[MVA]$
1	P+R Utrecht Science Park	2000	8	57	379	0.4
2	Parking area P10 Uppsalalaan (Sportcentre Olympos)	125	1	11	62	0.63
3	Parking area P9 Budapestlaan	135	1	9	61	0.63
4	Parking area Padualaan	419	2	16	98	0.63
5	Parking garage P8 Cambridge-laan	504	3	26	132	1.25
6	Parking area Sorbonnelaan	613	3	24	136	0.63
7	Parking area P7 Jenalaan	236	2	16	111	0.63

6.2 Impact on the distribution transformers

This section describes the results from the load flow analysis performed for the transformers at which the external load of EVs charging was allocated. This section follows the structure of the numbered parking areas referred to in Table 6.2.

Figures 6.3 to 6.16 present the future load experienced by the analysed transformers. The figures include the demand load (e.g. baseload), the demand load represents the load excluding the load due to EVs charging but only the 1.5% load growth is taken into account. The total load includes the demand load and the load of the EVs charging. The figures are presented for the 2030 and 2050 scenarios, one week in winter and one week in summer as to cover the seasonal load variation experienced by the distribution transformers. The red line in the figures illustrates the rated transformer capacity, as show in Table 6.2.

Figure 6.3 and 6.4 represent the loads experienced by the transformer at P+R UPS in the 2030 and 2050 scenarios, respectively. Figure 6.5 and 6.6 represent the loads experienced by the transformer at P10 Uppsalalaan in the 2030 and 2050 scenarios, respectively. Figure 6.7 and 6.8 represent the loads experienced by the transformer at P9 Budapestlaan in the 2030 and 2050 scenarios, respectively. Figure 6.9 and 6.10 represent the loads experienced by the transformer at Padualaan in the 2030 and 2050 scenarios, respectively. Figure 6.11 and 6.12 represent the loads experienced by the transformer at P8 Cambridgelaan in the 2030 and 2050 scenarios, respectively. Figure 6.13 and 6.14 represent the loads experienced by the transformer at Sorbonnelaan in the 2030 and 2050 scenarios, respectively. Figure 6.15 and 6.16 represent the loads experienced by the transformer at P7 Jenalaan in the 2030 and 2050 scenarios, respectively.

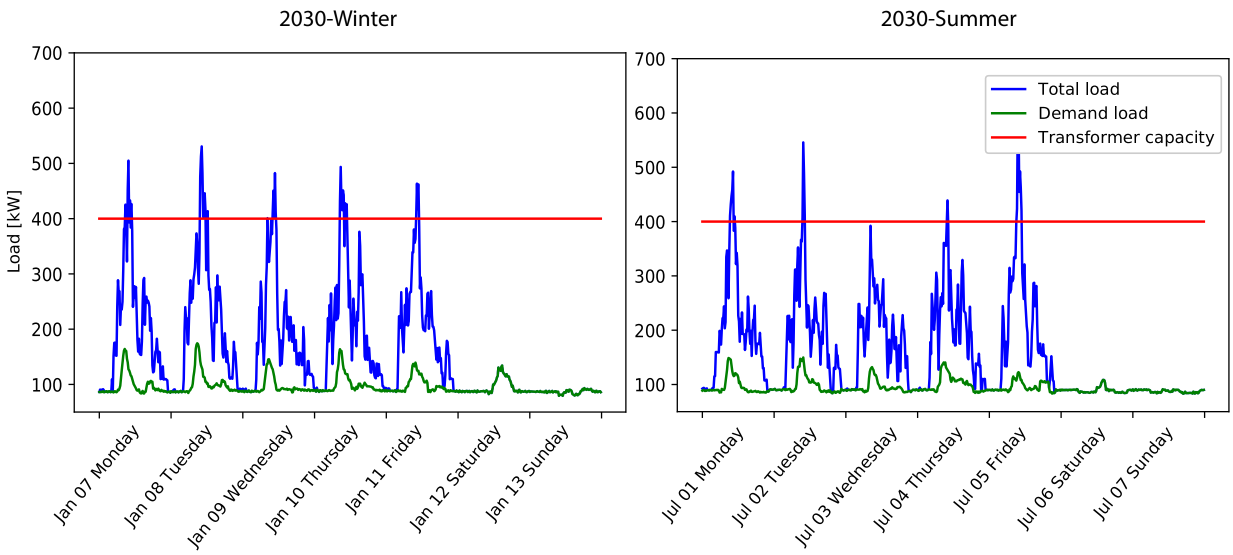


Figure 6.3: Scenario 2030: Loads on the Distribution Transformer at P+R Utrecht Science Park.

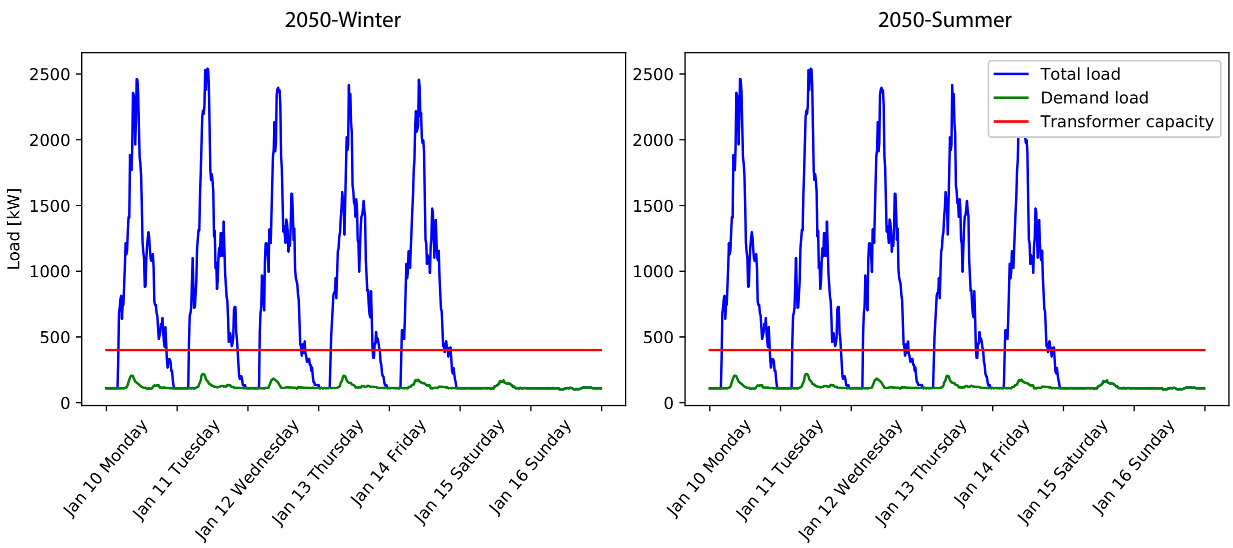


Figure 6.4: Scenario 2050: Loads on the Distribution Transformer at P+R Utrecht Science Park.

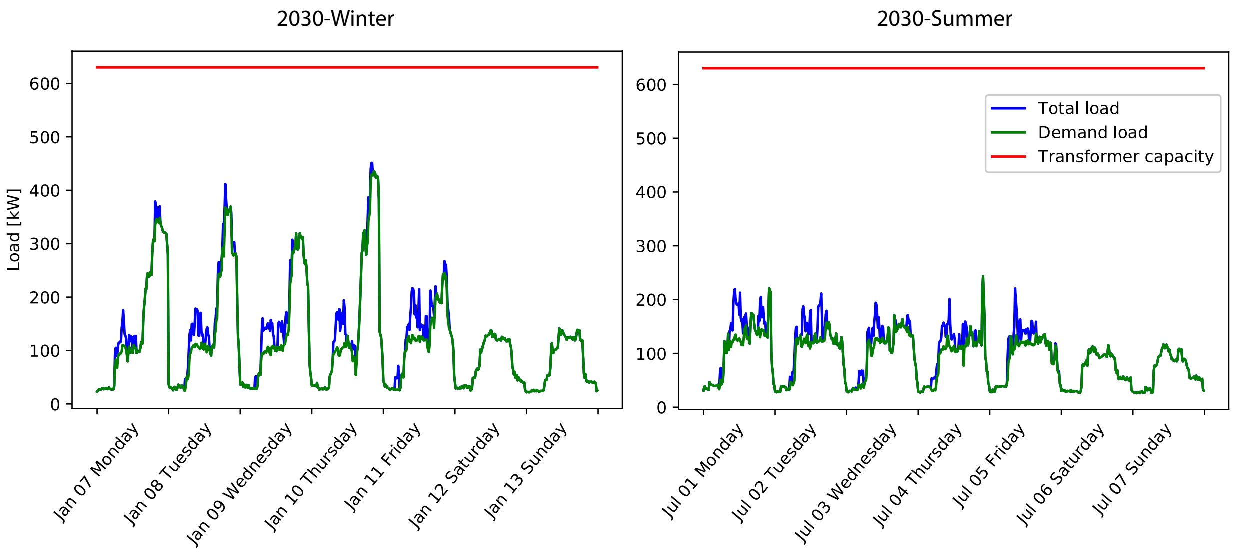


Figure 6.5: Scenario 2030: Loads on the Distribution Transformer at P10 Uppsalalaan.

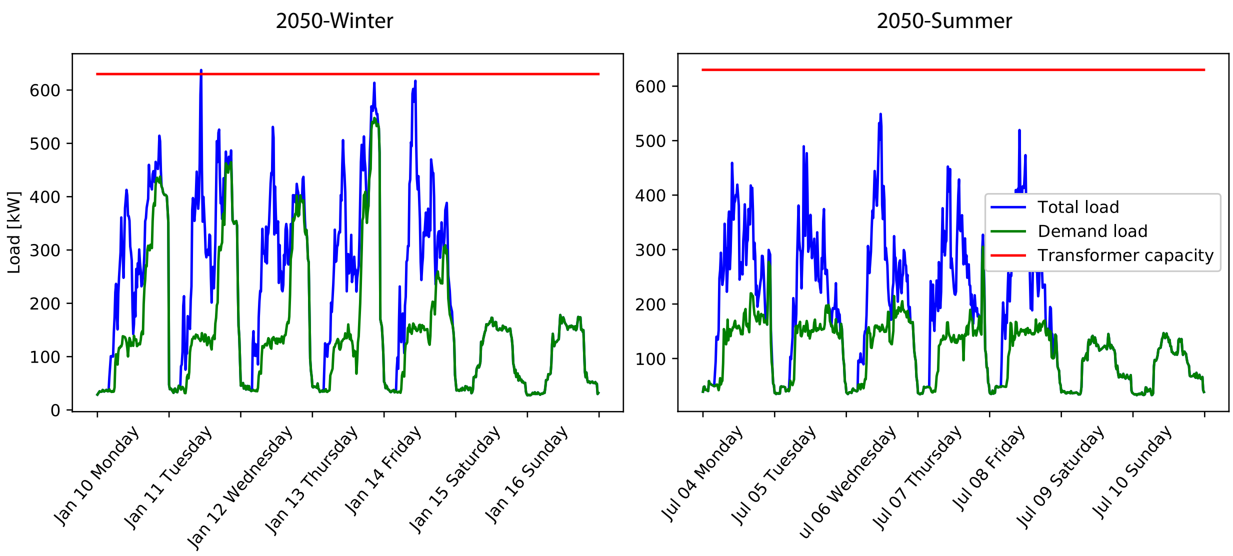


Figure 6.6: Scenario 2050: Loads on the Distribution Transformer at P10 Uppsalalaan.

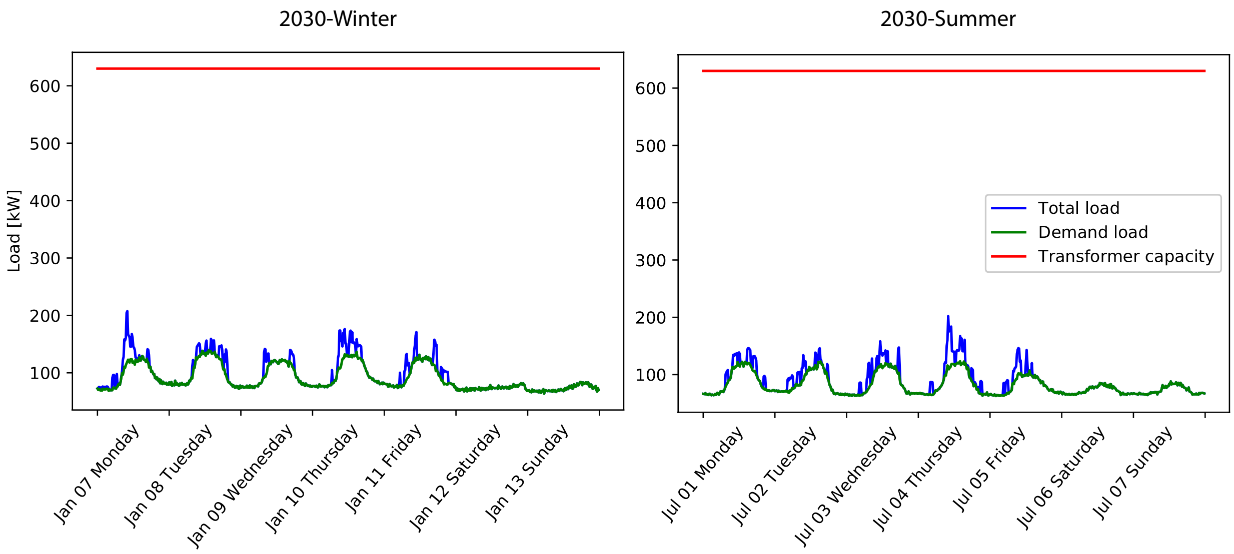


Figure 6.7: Scenario 2030: Loads on the Distribution Transformer at P9 Budapestlaan.

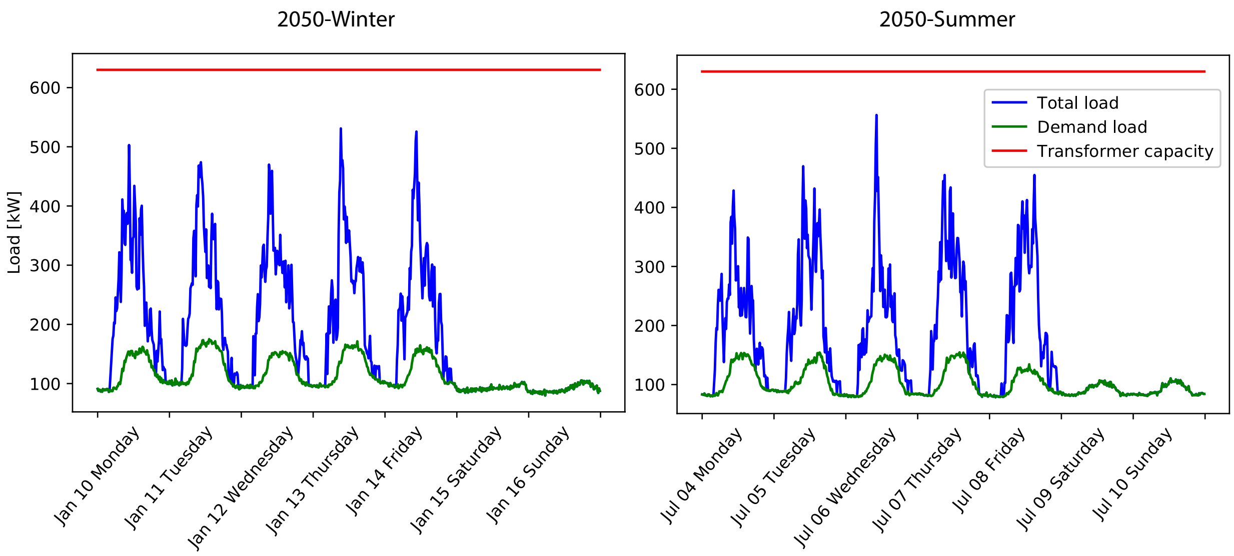


Figure 6.8: Scenario 2050: Loads on the Distribution Transformer at P9 Budapestlaan.

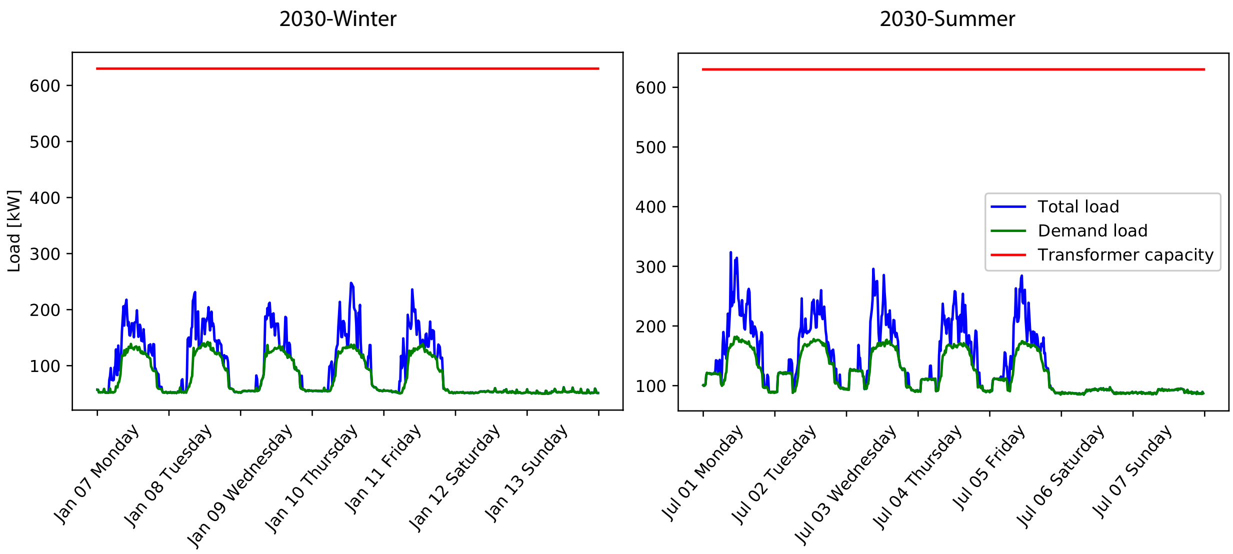


Figure 6.9: Scenario 2030: Loads on the Distribution Transformer at Padualaan.

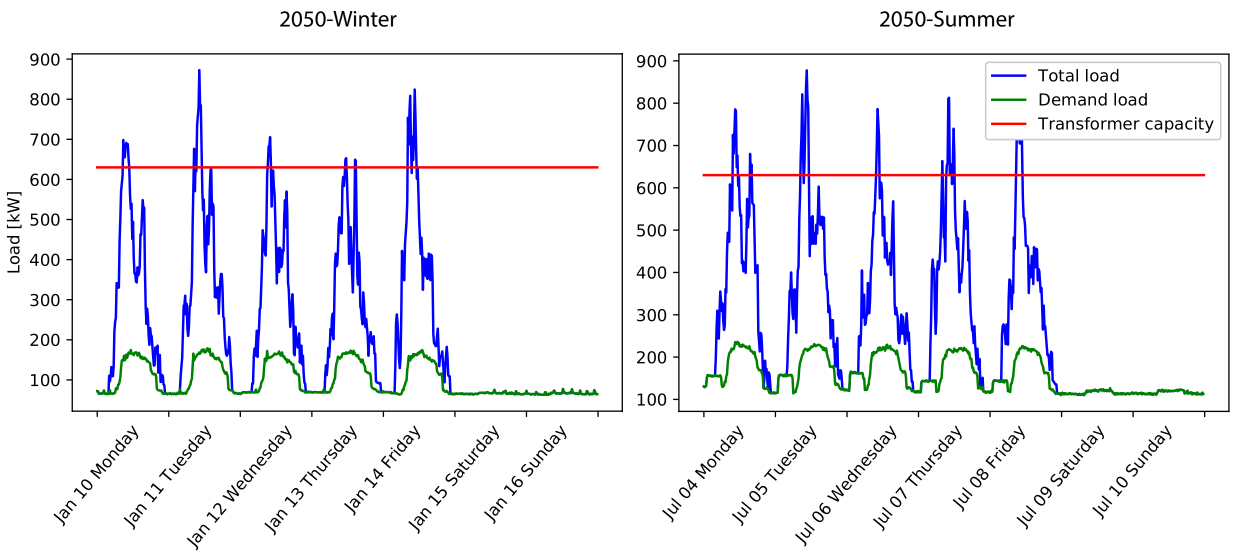


Figure 6.10: Scenario 2050: Loads on the Distribution Transformer at Padualaan.

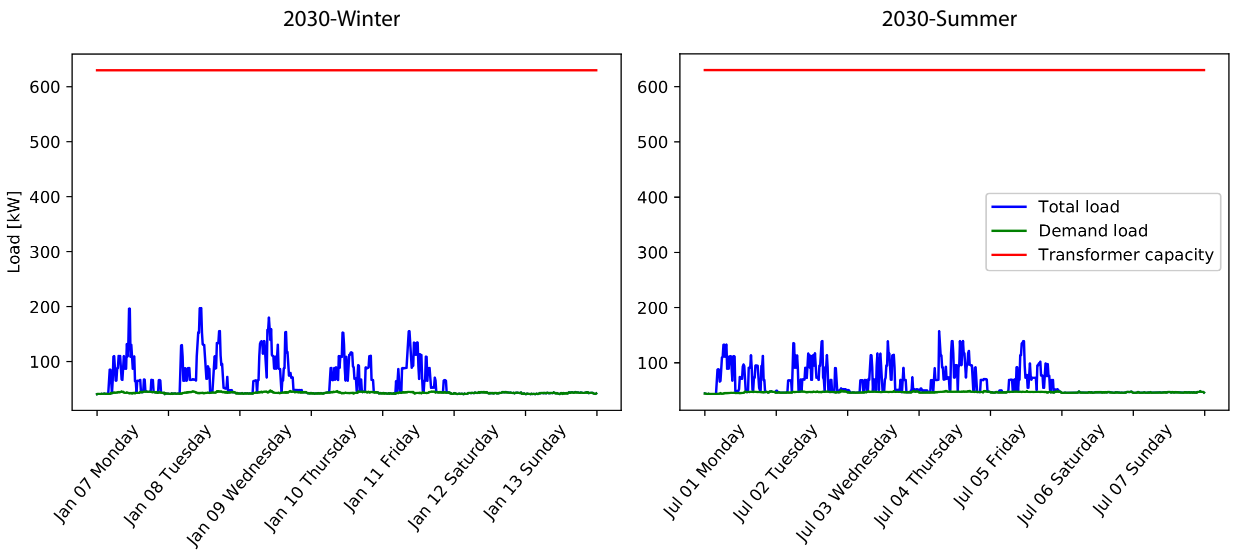


Figure 6.11: Scenario 2030: Loads on the Distribution Transformer at P8 Cambridgelaan.

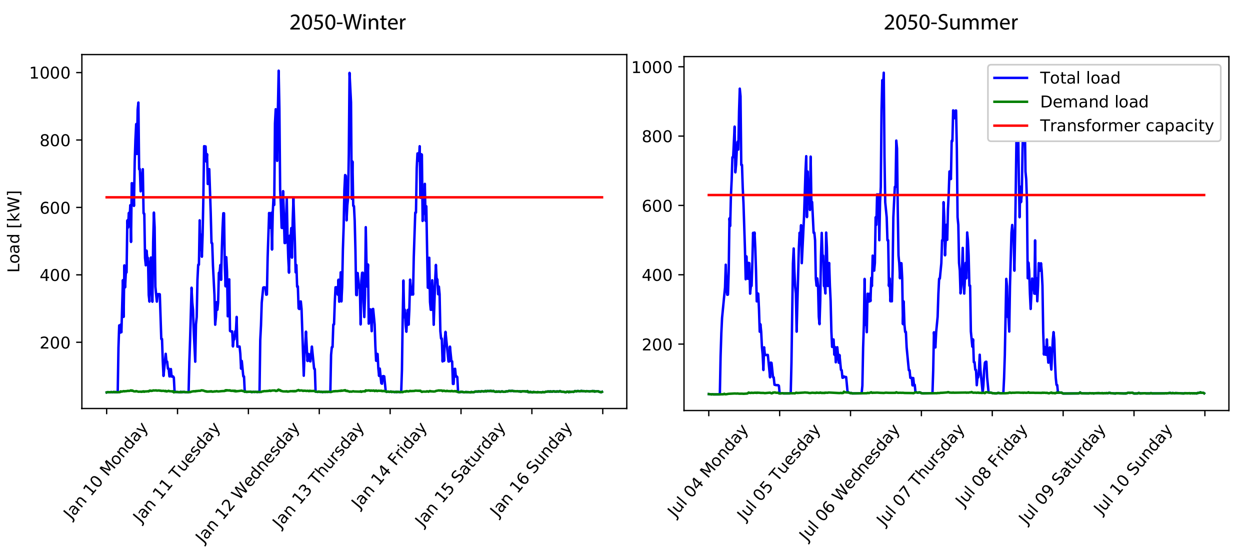


Figure 6.12: Scenario 2050: Loads on the Distribution Transformer at P8 Cambridgelaan.

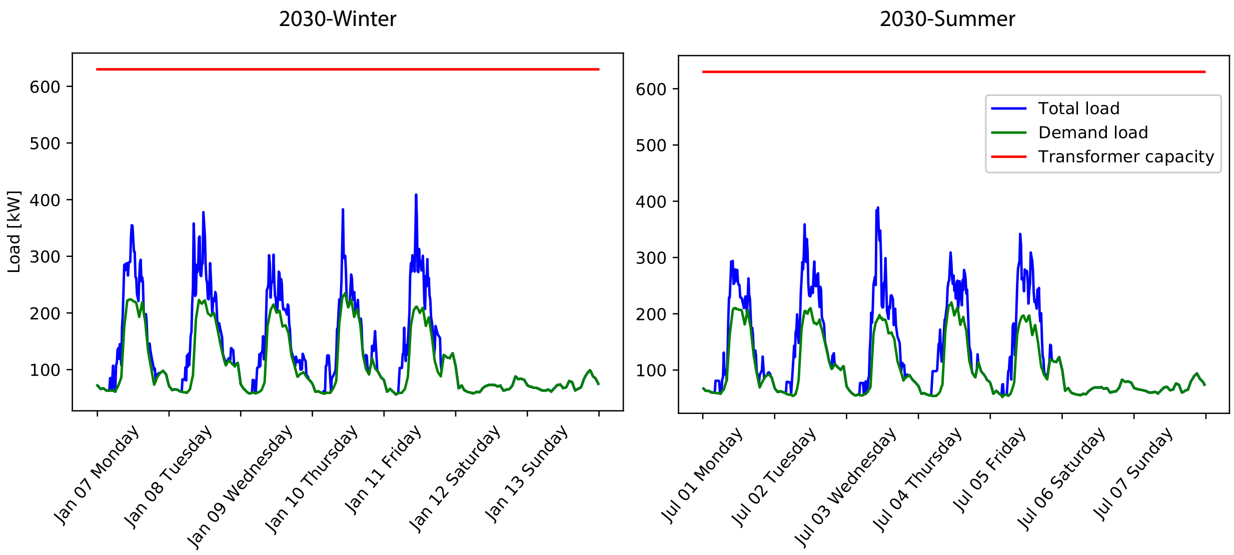


Figure 6.13: Scenario 2030: Loads on the Distribution Transformer at Sorbonnelaan.

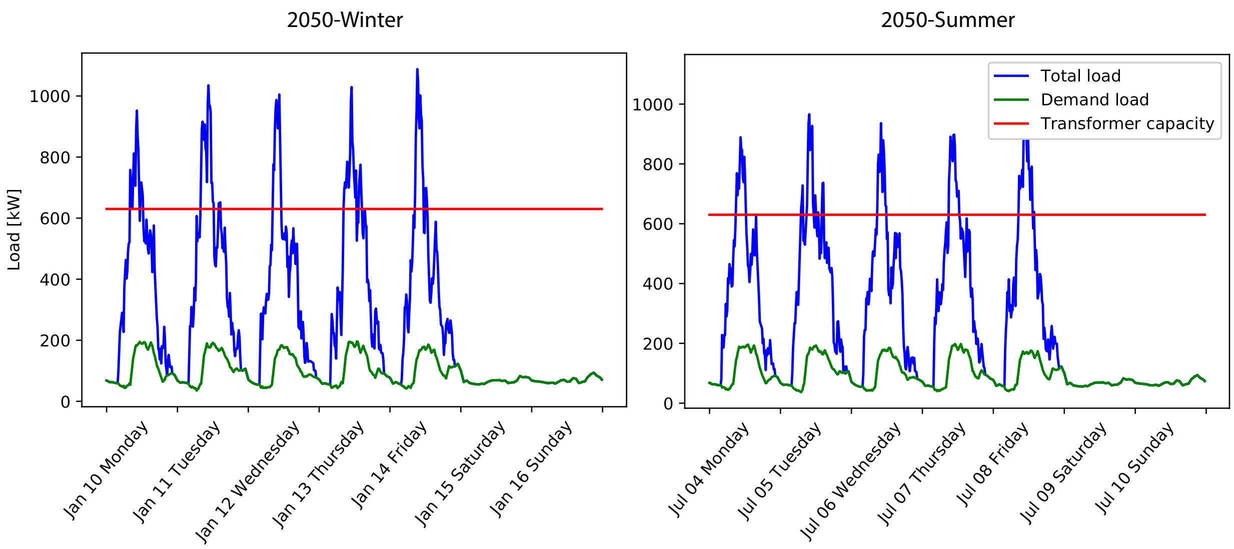


Figure 6.14: Scenario 2050: Loads on the Distribution Transformer at Sorbonnelaan.

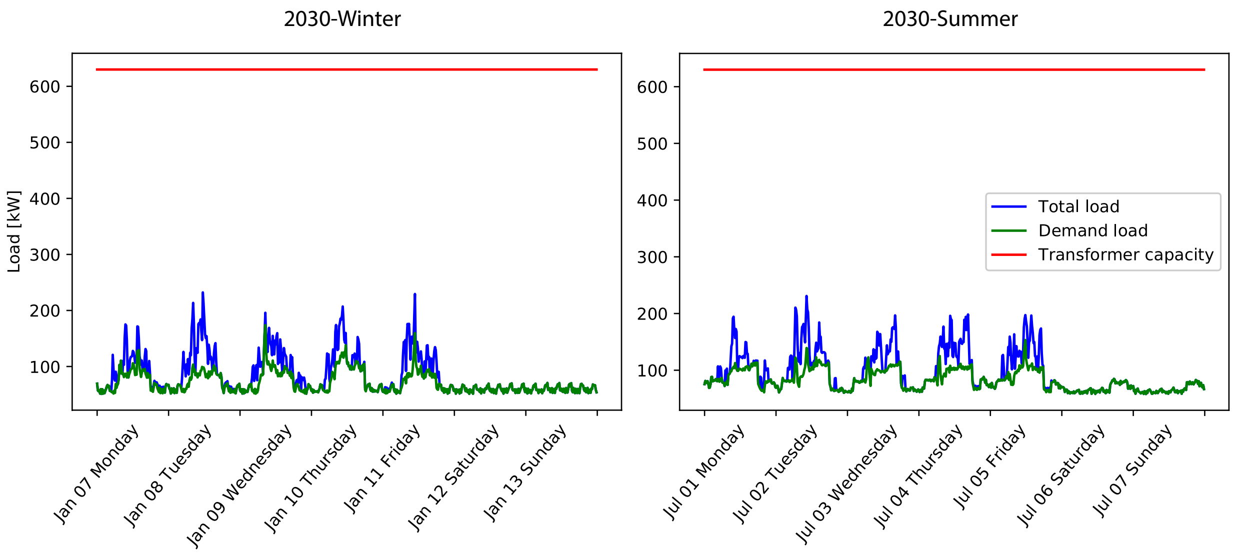


Figure 6.15: Scenario 2030: Loads on the Distribution Transformer at P7 Jenalaan.

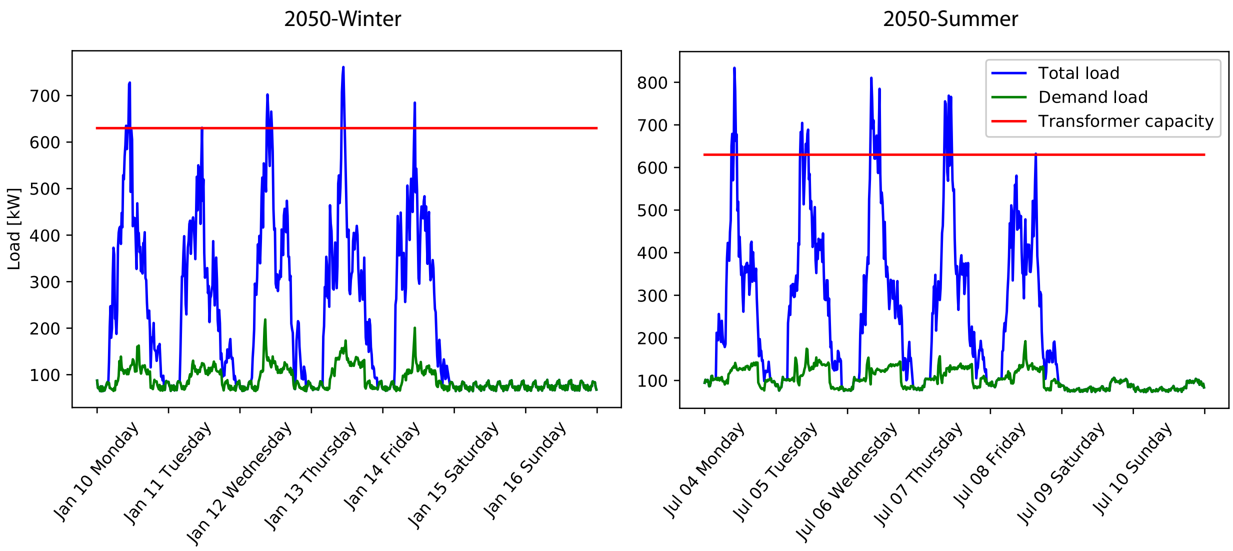


Figure 6.16: Scenario 2050: Loads on the Distribution Transformer at P7 Jenalaan.

6.3 Overview grid impact calculation results

Table 6.3 represents the expected MV/LV transformer peak loadings in 2030 and 2050, based on a week in winter and summer, together with the *Without EV*-scenario, which just includes the annual load growth of 1.5%. The overload criterion is 1.25, as considered in [30]. The overload criterion reflects the instantaneous peak value, which can be higher than the rated capacity. The transformer at P+R USP is overloaded in the 2030 scenario and critically overloaded in the 2050 scenario. The transformers at P7 Jenalaan and Padualaan are overloaded in the 2050 EV scenario. The transformer at Sorbonnelaan is critically overloaded in the 2050 scenario. None of the transformers are overloaded in the *Without EV*-scenario.

Table 6.3: Expected MV/LV transformer peak loadings.

	EV-scenarios		Without EV	
	2030	2050	2030	2050
P+R Utrecht Science Park	1.40	6.30	0.41	0.52
Parking area P10 Uppsalalaan (Sportcentre Olympos)	0.56	0.94	0.54	0.68
Parking area P9 Budapestlaan	0.33	0.86	0.21	0.27
Parking area Padualaan	0.45	1.39	0.26	0.33
Parking area P8 Cambridgelaan	0.15	0.80	0.04	0.05
Parking area Sorbonnelaan	0.64	1.75	0.36	0.31
Parking area P7 Jenalaan	0.31	1.27	0.33	0.33

As explained earlier, it is not "abnormal" for the load of a transformer to exceed the rated capacity for short periods, although sustained overloads for long periods are dangerous. Therefore, the duration of the overloads experienced by the overloaded transformers is analysed. The number of hours over the week for which the transformers serve a load exceeding 1.25 of their rated capacity is computed ($H_{overload,week}$). Also the maximum "session duration" ($H_{overload,session}$) over which the transformer is continuously overloaded is computed. An overview of the results is displayed in Table 6.4. These results show that even though the transformer at P+R USP is overloaded in the 2030 scenarios, this is only 15 minutes (0.3%) and 30 minutes (0.5%) in the winter and summer scenarios, respectively. This is considered to be insignificant. In the 2050 scenario this increases significantly to up to 76 hours in the summer week and with a $H_{overload,session}$ of 14.75 hours. Compared to this, the overload time of the other three transformers is quite less. However, these transformers still experience relatively long sessions of overload time: 4, 2.25 and 4.75 hours for the transformers at Padualaan, Sorbonnelaan and Jenalaan, respectively.

Table 6.4: Expected duration of overloads and the maximum session duration over which the transformer is overloaded. The table reads as follows: $H_{overload,week}$ (%) ; $H_{overload,session}$.

	2030-winter	2030-summer	2050-winter	2050-summer
P+R Utrecht Science Park	0.5h (0.3%) ; 0.25h	0.75h (0.5%) ; 0.5h	71.75h (42.7%) ; 14h	76h (45.2%) ; 14.75h
Parking area Padualaan	-	-	21h (12.5%) ; 4h	26.5h (15.8%) ; 4h
Parking area Sorbonnelaan	-	-	9.75h (5.8%) ; 2.25h	8.75h (5.2%) ; 2h
Parking area P7 Jenalaan	-	-	12.25h (7.3%) ; 2.5h	17h (10.1%) ; 4.75h

Part III

Mitigation of Grid Impact

Chapter 7

Mitigation of Grid Impact Method

In Part II the impact of uncontrolled EV charging on MV/LV transformers for 2030 and 2050 scenarios was investigated. It was determined that in the 2050 scenario some transformers are overloaded and critically overloaded. However, the mitigation methods described in this section might result in less overloading of those transformers.

7.1 Flexibility of EV demand

This section is based on a method described in [22], which describes the analysis of the time-dependent flexibility of EV demand. The results of this paper confirm the feasibility of congestion management using smart charging within flexibility constraints. The method is used in this thesis and provides an answer to the available flexibility of EV demand for overloaded MV/LV transformers. The charging profiles of the simulated future EV fleets, obtained in Part I, included the connection time, $\Delta T^{q}_{connect}$ and the charging time, $T^{q}_{DUR,charge}$. The available flexibility, ΔT^{q}_{flex} [h], during transaction q is obtained by the difference between $\Delta T^{q}_{connect}$ and $T^{q}_{DUR,charge}$, see equation 7.1. For each transaction q the delay is calculated, after which the EV demand is rebounded. Subsequently, the available flexibility of aggregated EV demand at each moment in time is calculated. This analysis is done for one day for each one of the overloaded transformers determined in Section 6.3.

$$\Delta T^{q}_{flex} = \Delta T^{q}_{connect} - T^{q}_{DUR,charge} \tag{7.1}$$

7.2 Controlled slow charging

Charging profiles were generated for the uncontrolled charging of a future EV fleet. With uncontrolled charging it was assumed that the EV is charged at P^{q}_{max} when the EV is plugged in. However, the charging power might be slowed down to an average charging power P^{q}_{av} [kW]. With P^{q}_{av} it is assumed that E^{q}_{req} for the transaction q is met when the EV is plugged-out. This charging method results in a different simulated charging power profile than the one obtained in Part I because the EV charges with a lower charge rate, P^{q}_{av}, over the connection time, $\Delta T^{q}_{connect}$. The P^{q}_{av} is a transaction-specific average constant charging power, determined by using equation 7.2. The before-mentioned simulation steps are carried out for each EV j. The simulation is performed for a week in 2030 and a week in 2050.

$$P^{q}_{av} = \frac{E^{q}_{req}}{\Delta T^{q}_{connect}} \tag{7.2}$$

Chapter 8

Mitigation of Grid Impact Results

8.1 Flexibility of EV demand

The time-dependent flexibility is determined for the expected overloaded transformers determined in Section 6.3. To make a clear representation, the flexibility is obtained for one day in the simulated period (10^{th} of January 2050). Figures 8.1a, 8.1b, 8.1c and 8.1d represent the charging power for the transformers at P+R USP, Padualaan, Sorbonnelaan and Jenalaan, respectively. The colours in these figures indicate the possible ΔT_{flex} [h] of the simulated EV demand at each time of the day. As mentioned earlier, ΔT_{flex} is defined as the number of hours over which the demand could be shifted within the connection duration of an EV, see Section 7.1. The figures indicate the opportunities to shift the EV demand over time i.e., 52% of the EV demand at Padualaan can be delayed for more than 8 hours and 9% of the demand for more than 24 hours. For Jenalaan, 56% and 15% of the EV demand can be delayed for more than 8 and 24 hours. For Sorbonnelaan this is 52% and 16%. For P+R USP this is 49% and 14%.

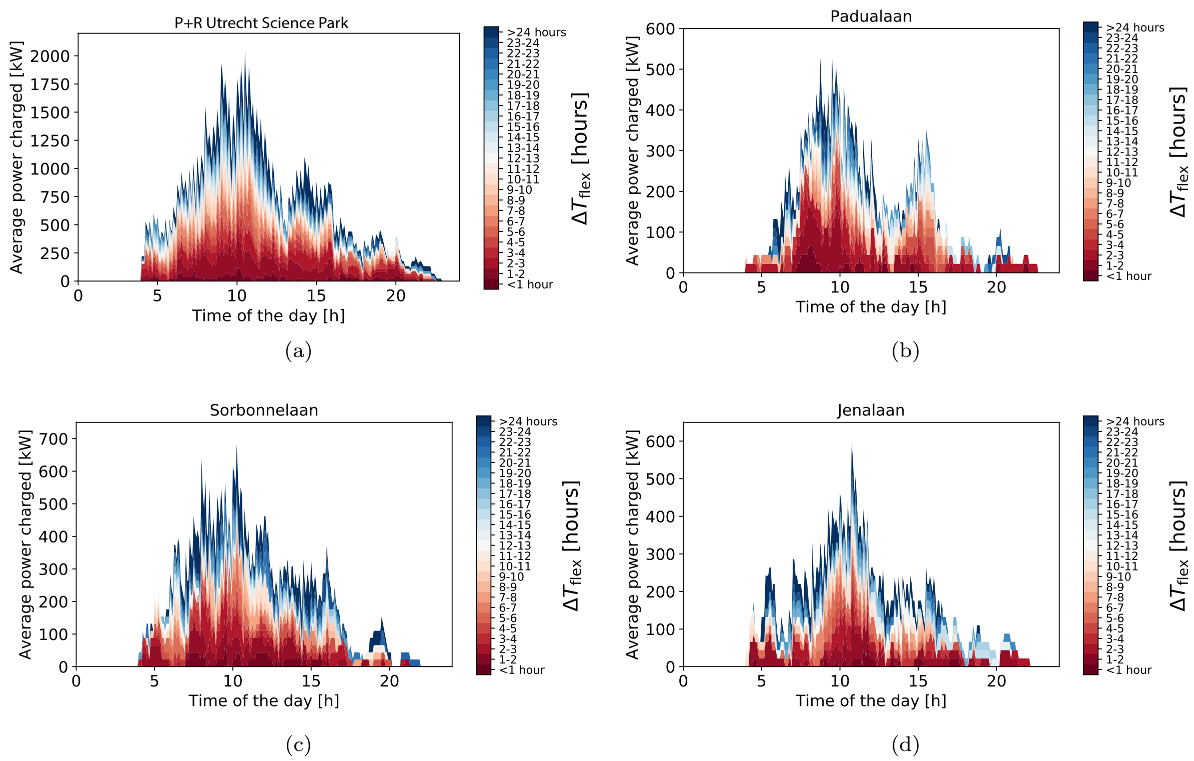
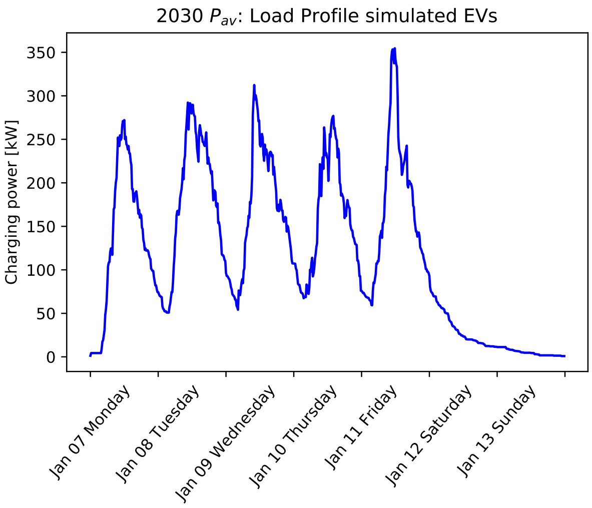


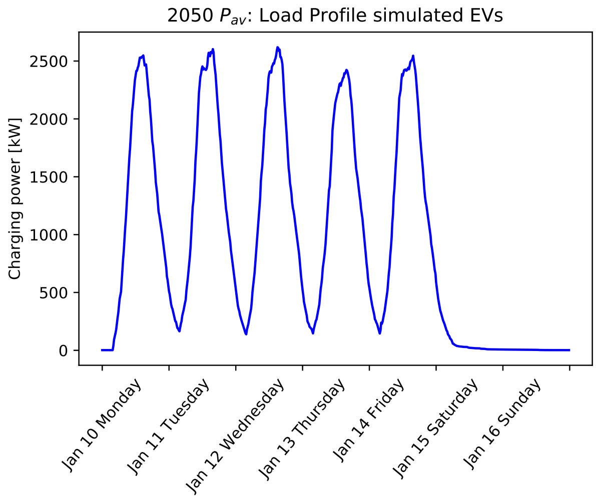
Figure 8.1: Available flexibility of aggregated EV demand at the overloaded transformers.

8.2 Controlled slow EV charging

The charging profiles were simulated for two weeks, one in winter in 2030 and one in winter in 2050. It was assumed the EV charges at an average charging power, P_{av}^{q}. Figure 8.2a and Figure 8.2b represent the load profiles of the simulated EVs charging with P_{av}^{q} in the 2030 and 2050 scenarios, respectively. It shows that because of the slow controlled charging, peaks can be reduced significantly. The peak in the 2030 scenario is reduced by 56.2%, from 811 kW to 355 kW. The peak in the 2050 scenario is reduced by 54.1%, from 5,698 kW to 2,620 kW.



(a) 2030 Scenario



(b) 2050 Scenario

Figure 8.2: Load profile of simulated EVs charging with P_{av}^{q} over the period of one week in 2030 and 2050.

This section looks further into the overloaded transformers in 2050 namely, the transformers at: P+R, Padualaan, Sorbonnelaan and Jenalaan. Figure 8.3, 8.4, 8.5 and 8.6 represent the loads on the distribution transformer at P+R, Padualaan, Sorbonnelaan and Jenalaan when controlled charging is applied, respectively. The figures show that the overloading at the transformers Padualaan, Sorbonnelaan and Jenalaan is mitigated with controlled charging. The transformer at P+R is however still overloaded. The transformer is overloaded for 74.5 hours of the week (44.3% of the time) and $H_{overload,session}$ is 15.25 hours continuously. The loads under controlled charging for the 2030 and 2050 scenarios for all other transformers can be found in Appendix D.

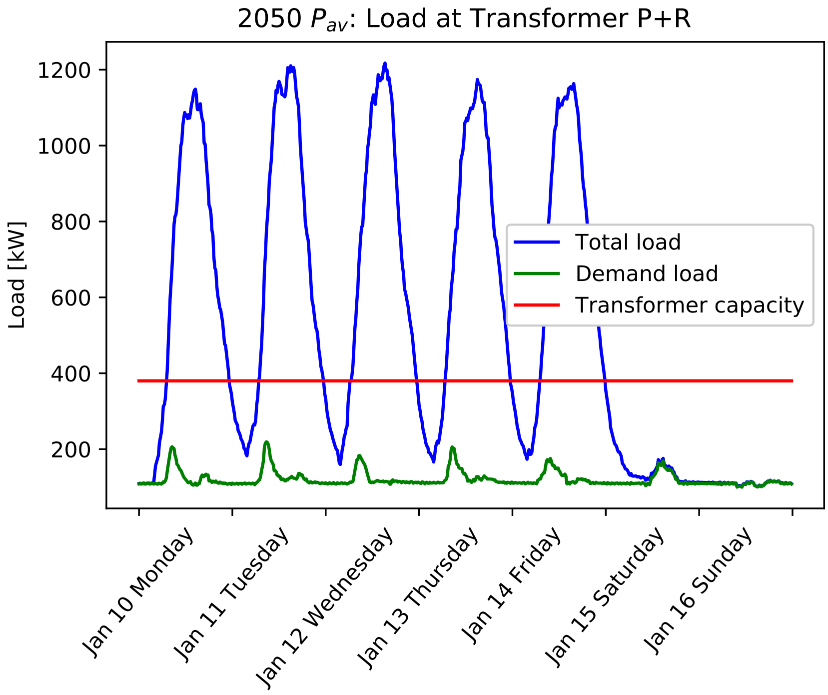


Figure 8.3: Scenario 2050 under controlled charging: Loads on the distribution transformer at P+R.

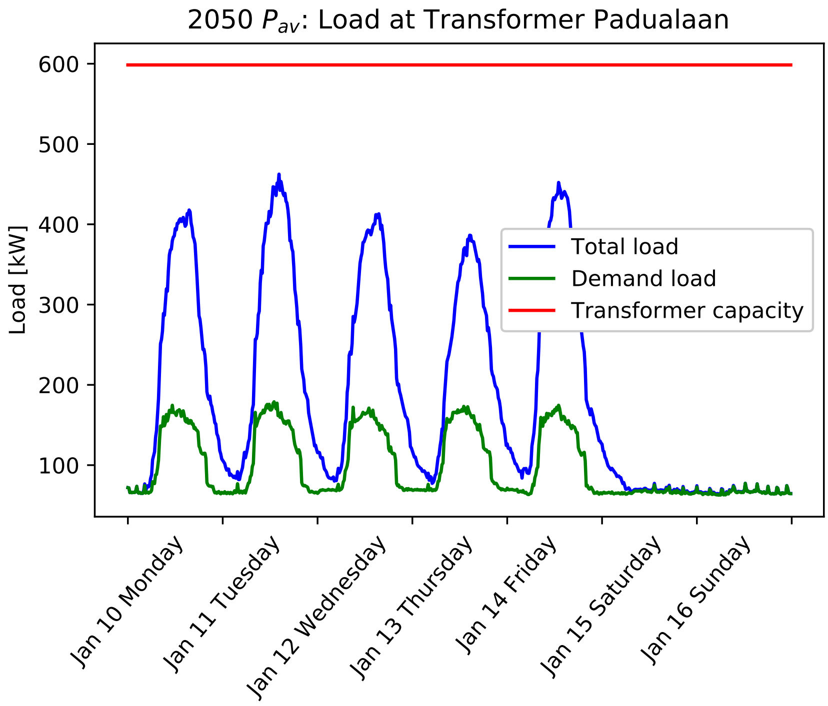


Figure 8.4: Scenario 2050 under controlled charging: Loads on the distribution transformer at Padualaan.

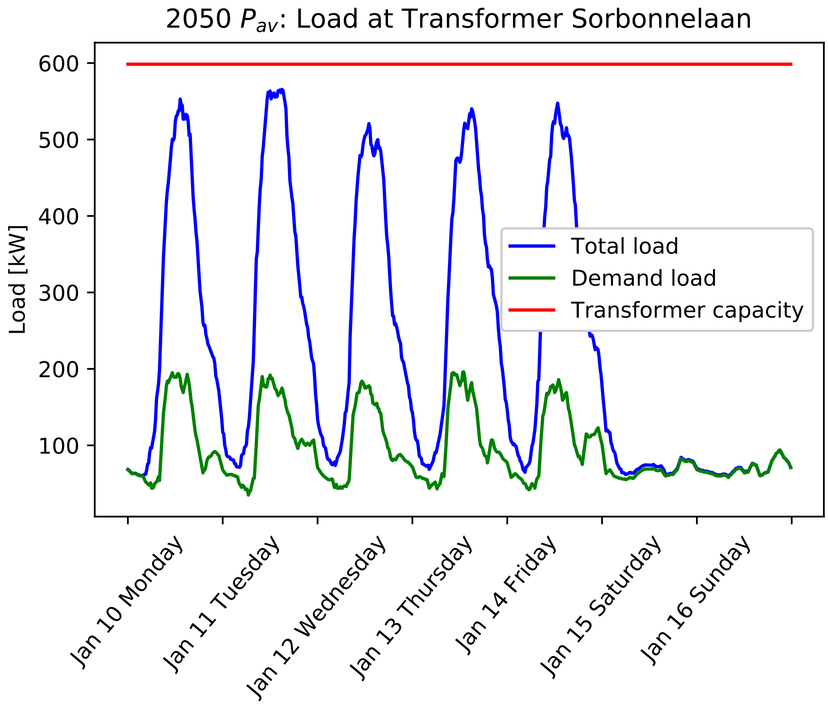


Figure 8.5: Scenario 2050 under controlled charging: Loads on the distribution transformer at Sorbonnelaan.

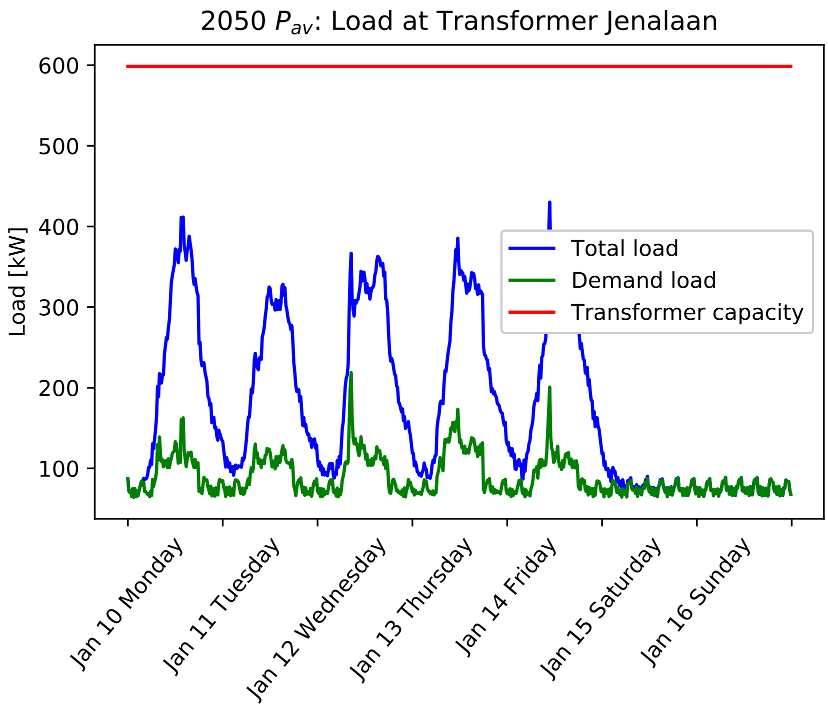


Figure 8.6: Scenario 2050 under controlled charging: Loads on the distribution transformer at Sorbonnelaan.

Chapter 9

Discussion

In this section, the methods and results described in this thesis are discussed. First of all, the development of the future EV fleet is uncertain. Several studies looked at the development of the future EV fleet in the Netherlands. For example, [11] determined the ratio for the number of BEV:PHEV at 29:71 in 2030. However, globally this ratio is the opposite than that of the Netherlands [28]. The study [11] might be based on the subsidy that was in place 5 years ago, the government invested in purchase subsidies and tax credits for PHEVs. However, in reality the vehicles were not as environmental favorable as expected and the incentive measures for PHEVs have been reduced since then. This should be taken into account when looking at these numbers. In addition, it is not clear if in 2030 and 2050 in reality 50% and 100% of the vehicles in the Netherlands will be an EV. The Dutch government has set goals based on the term *zero-emission* vehicles. This term would therefore also include fuel cell electric vehicles (FCEVs). However, the EV will most likely continue to dominate in the future ZEV fleet as the FCEV technology is not yet as developed as the EV technology, and it is presumed that the lowest cost technology will dominate [51]. In addition, the same article concluded that less energy reduction was obtained for a ZEV fleet if replaced by FCEVs than a ZEV fleet consisting of EVs, making it less attractive for policy makers to invest in this technology. For the vehicle fleet size it was assumed the modal split of employees commuting to the investigated area stays constant to 2030 and 2050. However, the modal split is likely going to change as Utrecht region is committed to facilitate the growth of USP by investing in public transport and bicycle accessibility [69].

To continue, vehicle sharing is likely to change the habits of its consumers [23]. Fully autonomous vehicles will drive this trend further. Most of these vehicles are expected to be electric [20]. Due to this trend, the EV driving range will increase and off-peak transport is likely to continue to occur during the night. This could mean that consequently, the net available flexibility in the EV demand might decrease, especially during daytime. The increased daily distances travelled per car will imply reduced parking time and therefore less flexibility in EV demand and less battery capacity for grid services and/or PV self-consumption. The implications for the EV demand flexibility, which may decrease in a future system based on shared and autonomous vehicles, is recommended to be studied in detail.

No additional PV profiles were included in the grid impact calculation. The grid impact calculation looked into the net demand load of the transformers, which was obtained through the University's energy dashboard, and included an annual demand growth of 1.5%. However, PV at the investigated area is likely to grow more than the 1.5% assumed as PV will play an important role in the future energy sector; it is expected to supply 25% to 30% of the energy demand in the Netherlands in 2050 [19]. This means that some transformers might experience less net demand due to PV power generation. Installing PV would supplement the EVs charging in the office environment. This is due to the fact that, in contrast to residential charging of EVs, EVs in the office environment charge during the day, with the charging peak at

10:00. Either, optimally placing the PV modules so that maximum generation is in the morning or smart charging of EVs would increase PV self-consumption. Results from this thesis show that the flexibility of the morning peak demand, could be shifted so that the EVs get charged during the PV peak generation a few hours later. This is in contrast to residential charging, where the evening EV demand shows to have the most flexibility [22]. This means that more flexibility would be necessary in the case of residential charging as to shift the evening peak until the next mid-day. For office charging the flexibility in EV demand for the morning peak could be less as the peak would only needed to be shifted by a few hours. This means that EV-based smart charging can be a crucial factor to scale up variable PV power generation. Gerritsma et al. [22] addressed the fact that for smart charging, the EV users would have to actively participate and willingly share information. This is still the case for office charging. However, the controlled charging of EVs in an office environment would be relatively easier compared to a residential case. In the office case, especially the commuting EVs are to some extent restricted to office hours, therefore its easier to control when the EV charges and when the charging process has to be finished (e.g. at the end of the work-day). In the residential case this is somewhat more unpredictable.

Lastly, the method for the creation of charging profiles is discussed. Prior work has also analysed the impact of EVs on the distribution grid [6, 50, 74]. However, as discussed in Section 1, this thesis differs from this work as this thesis has made use of a real EV transaction dataset which yields more realistic results compared to these studies. This thesis adopted a method by Gerritsma et al. [22] for the creation of charging profiles and to generate the flexibility of EV demand, but expands on this work by conducting an in-depth analysis of existing transformers and quantifies their different load profiles.

In the simulation for the creation of charging profiles weekend days were not taken into account. This is due to the fact that in the original transaction data, no transactions were found on the weekend days. This makes sense as the investigated area is in an office environment. Yet, if the city of Utrecht is to expand, possibly vehicles from outside of the office area will start to charge on weekend days. In addition, residential buildings rising in the area will likewise change the charging behaviour of the EV fleet. The EV demand in the weekend is more likely to be spread throughout the day as these vehicles are not restricted to office hours. Therefore a lower peak demand than on weekend days can be expected, making the analysis on weekdays in this thesis a nonetheless relevant case.

The number of EVs charging simultaneously is left unconstrained in the simulation. This means that the number of available CSs is driven by the EV demand and the connection duration. To determine the number of necessary CSs, the maximum number of EVs connected simultaneously was taken into account. However, this maximum number of EVs connected may occur once a year. Therefore in reality the number of CSs available can be smaller. In case of less available CSs in the area, lower charging peaks can be expected. However, with more available CSs, and therefore increasing EV connection periods, more flexibility in EV demand can be expected. Alternately the actual charging time of an EV could be used to determine the number of CSs required. It would be interesting to determine the maximum number of EVs charging simultaneously. The way EVs are charged in 2030 or 2050 may look differently from now. A mechanism could be put in place that automatically disconnects an EV when its fully charged and connects the following EV. This is however speculative and not in place as of yet. Therefore the number of CSs were determined by using the connection time.

As the original transaction data did not include the transaction specific charging power, for Part I a fixed charging power was set. The fixed charging power set was 3.7 kW for PHEVs and 22 kW for BEVs, based on the maximum charging power of these two EV categories [14]. This is not a rare assumption as a fixed charging power was set by several other studies such as [22, 40, 71, 74]. The charging power might actually be lower than the maximum charging power, but no comparison could be made with the original transaction data. This is due to the fact that in the EV transaction dataset used, no charging power was logged. If the original transaction data actually included transaction specific charging power, a more close to reality charging profile could be created. In case that EVs actually charge with a lower power, the EV peak power and the flexibility in EV demand would be overestimated. However, in the future the charging power of EVs is likely to be driven to higher power levels [61], and especially in the 2050 scenario this is very imaginable to happen. A recommendation for further research is to use the simulation model and vary the charging power when simulating the charging profiles and observe the peak power and flexibility. Section 8.2 showed what would happen if optimal use is made of the time dependent flexibility in EV demand. The peaks in EV demand were smoothed and reduced by 54-56% for the future scenarios. Overloading could be mitigated for 3 out of the 4 overloaded transformers. Due to limited time, other smart charging strategies were not included. Other smart charging strategies such as V2G, tariff-based charging and load shifting and their mitigation on grid impact are therefore recommended to be explored for this case study.

Chapter 10

Conclusion

This final chapter concludes the work described in this thesis by summing up its main results and insights. In the introduction of this thesis the following research question was formulated:

To what extent does the integration of EVs present a problem for an existing electricity distribution network and can these problems be mitigated?

To answer this question several steps were taken. First, in Chapter 4 scenarios were created for the size of the future EV fleet at the studied area that comply with the Dutch government's ambition and goals for the Dutch passenger fleet. Then in the same chapter the charging profiles of the simulated EV fleet were created. It was concluded that an EV fleet of 5,182 and 11,724 may result in a peak power demand of around 1 and 6 MW in 2030 and 2050, respectively. The average daily charging profile showed a peak at around 10:00 and a smaller one later in the afternoon, around 16:00. In order to accommodate the EV fleet charging, the number of CSs necessary at the investigated area are 120 in 2030 and 941 in 2050. In Chapter 6 the results of the previous chapters were combined by inputing the generated charging profiles into the software program used in this thesis and simulations were carried out to determine the impact of EV loads on the MV/LV transformers in two different future scenarios (2030 and 2050). The results from this chapter showed that overloading of the transformers is minimal in the 2030 scenario. Thus, as a transformer can serve a load exceeding its rated capacity for a short time, the transformers are expected to be able to accommodate the charging of the simulated EV fleet up to 2030. In the 2050 scenario, 4 out of 7 transformers become overloaded and if no mitigation strategy is put in place, these transformers are to be replaced with transformers of a higher rated capacity. None of the transformers are overloaded when no EV load is applied. In Chapter 8 the mitigation of the grid impact is elaborated on. It was also shown that part of the peak demand experienced at certain transformers can be delayed. This flexibility in EV demand is elaborated on by determining the charging profiles of the simulated EV fleet when controlled slow charging is applied. By applying slow charging, the charging peak can be reduced by 56.2% and 54.1% in 2030 and 2050, respectively. Overloading of 3 out of the 4 transformers can be mitigated. Critical overloading is still experienced by the transformer at P+R USP in 2050, this is due to the fact that the existing transformer has a small rated capacity (400 kVA) and that most EVs are expected to charge at this location because of its high parking capacity. The current small rated capacity gives the idea that the transformer was installed at the P+R without taking into account the increasing loads due to EV charging. When controlled slow charging is applied, the transformer experiences a peak demand of around 1.2 MW. In this case, the rated capacity should at least be around 1.2 MW, three times the current rated capacity. Further research into other mitigation strategies can provide a better view into the transformer capacity requirements for this specific location.

Chapter 11

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Appendix A

Overview interviews, meetings and other correspondence

Utrecht University

Brinkel, N. *Junior researcher.* Personal meeting. February 21, 2019.
Ponten, J. *Program manager Area Development.* Personal meeting. February 27, 2019.
Tak, F. *Energy coordinator.* Personal meeting. February 28, 2019.
Oostra, J. *Project manager.* Personal meeting. February 28, 2019.
Scherrenburg, M. *Program manager Sustainability.* Personal meeting. March 19, 2019.
Brinkel, N. *Junior researcher.* E-mail correspondance. June 3, 2019.

Other

Stedin:
Palland, J.W. *Specialist assetmanagement.* Personal meeting. April 15, 2019.

Phase to Phase:
Jansen, B. Personal meeting. May 16, 2019.

Gemeente Utrecht:
Soederhuizen, J. *Energy coordinator.* E-mail correspondance. May 28, 2019.

Eneco:
Diemers, K. *Clientadvisor SME.* E-mail correspondance. June 14, 2019.

Appendix B

MV Network at the investigated area

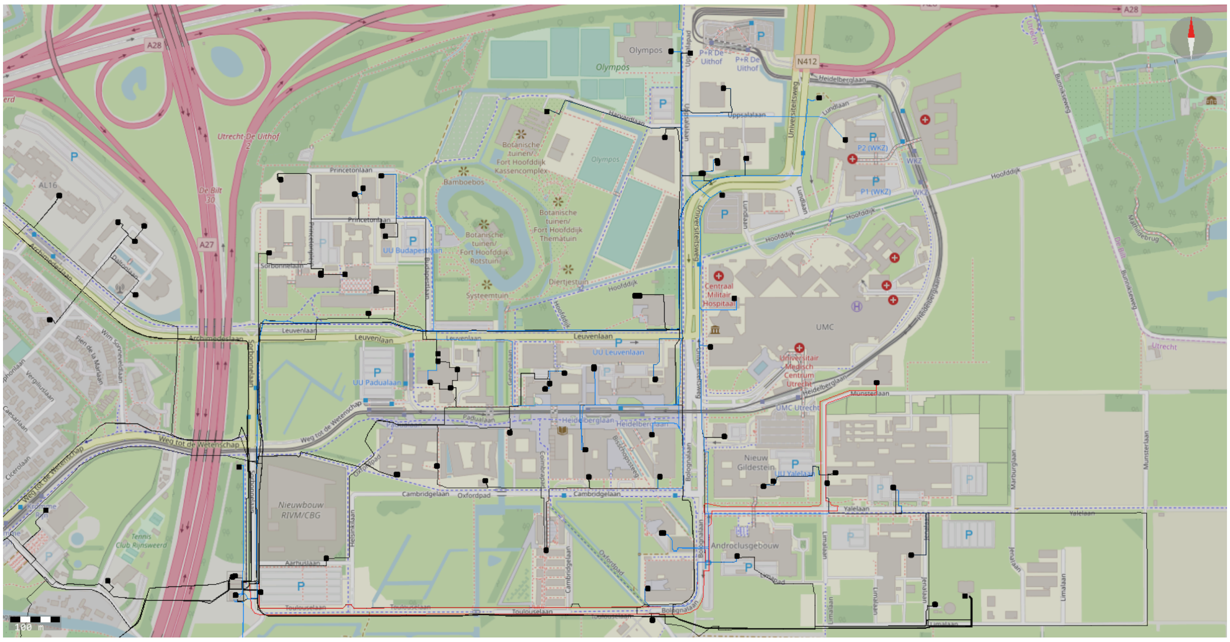

Figure B.1: Nodes in the MV distribution network of USP.

Appendix C

Input to sensitivity analysis Part I

Table C.1: Sensitivity analysis on the share of company EV in the 2030 EV fleet scenario.

Change	-50%	-25%	0%	+25%	+50%
company EV	3.5%	5.3%	7.0%	8.8%	10.5%
commuting BEV	23.8%	22.9%	22.0%	21.1%	20.3%
commuting PHEV	72.8%	71.9%	71.0%	70.1%	69.3%

Table C.2: Sensitivity analysis on the share of company EV in the 2050 EV fleet scenario.

Change	-50%	-25%	0%	+25%	+50%
company EV	14%	21%	28%	35%	42%
commuting BEV	86%	79%	72%	65%	58%

Table C.3: Sensitivity analysis on the charge frequency of EV categories.

Change	-50%	-25%	0%	+25%	+50%
company EV	0.206	0.309	0.412	0.515	0.618
commuting BEV	0.014	0.02	0.027	0.034	0.041
commuting PHEV	0.002	0.003	0.004	0.005	0.006

Appendix D

Loads on transformers under controlled charging

Scenario 2030

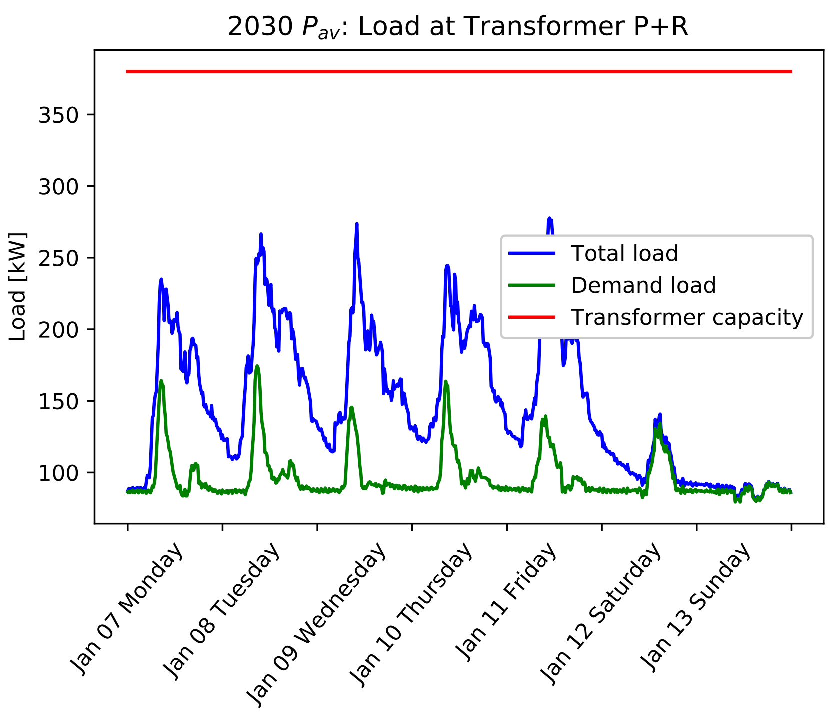

Figure D.1: Scenario 2030 under controlled charging: Loads on the distribution transformer at P+R.

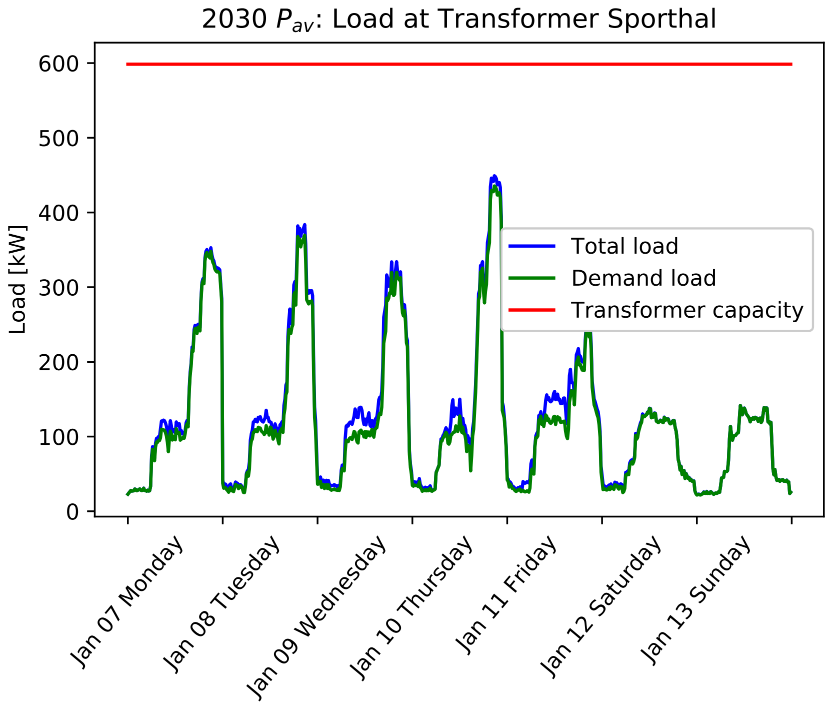

Figure D.2: Scenario 2030 under controlled charging: Loads on the distribution transformer at Olympos Sporthal.

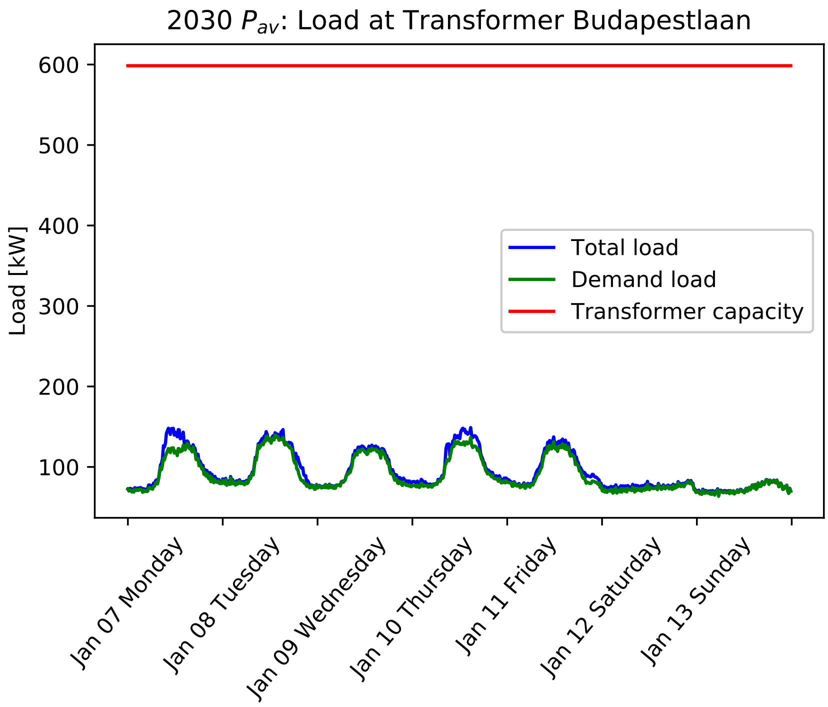

Figure D.3: Scenario 2030 under controlled charging: Loads on the distribution transformer at Budapestlaan.

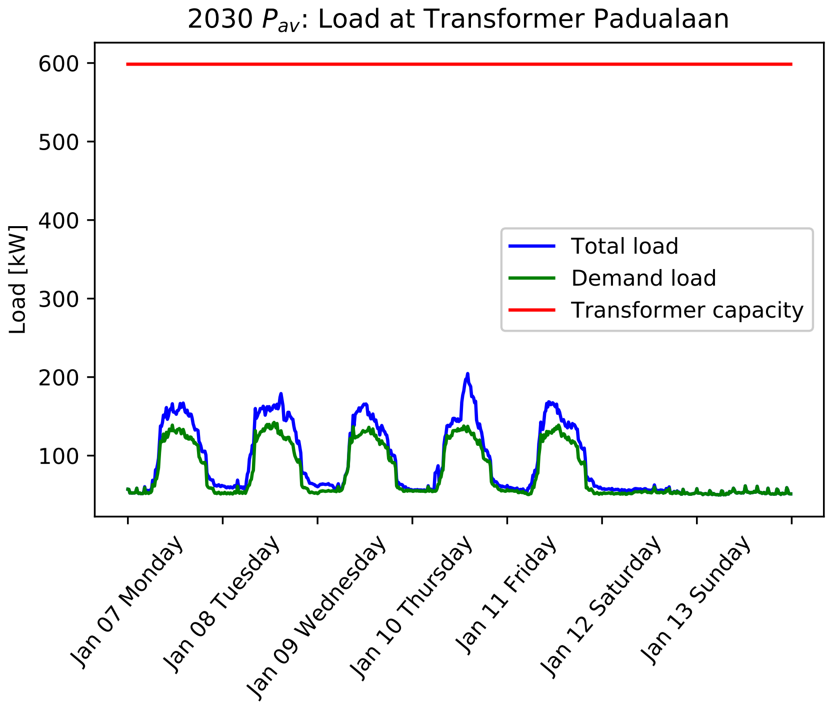

Figure D.4: Scenario 2030 under controlled charging: Loads on the distribution transformer at Padualaan.

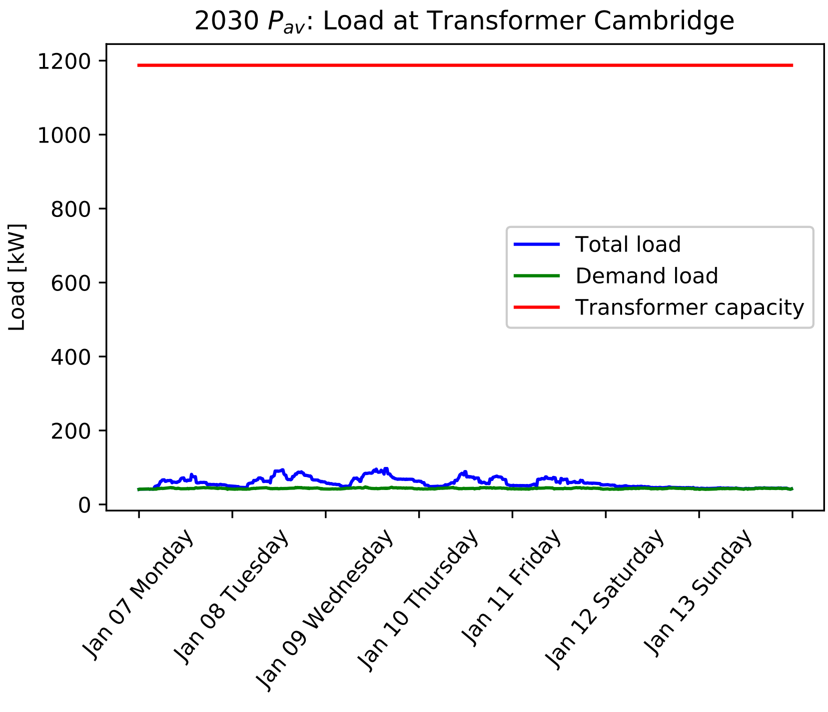

Figure D.5: Scenario 2030 under controlled charging: Loads on the distribution transformer at Cambridgelaan.

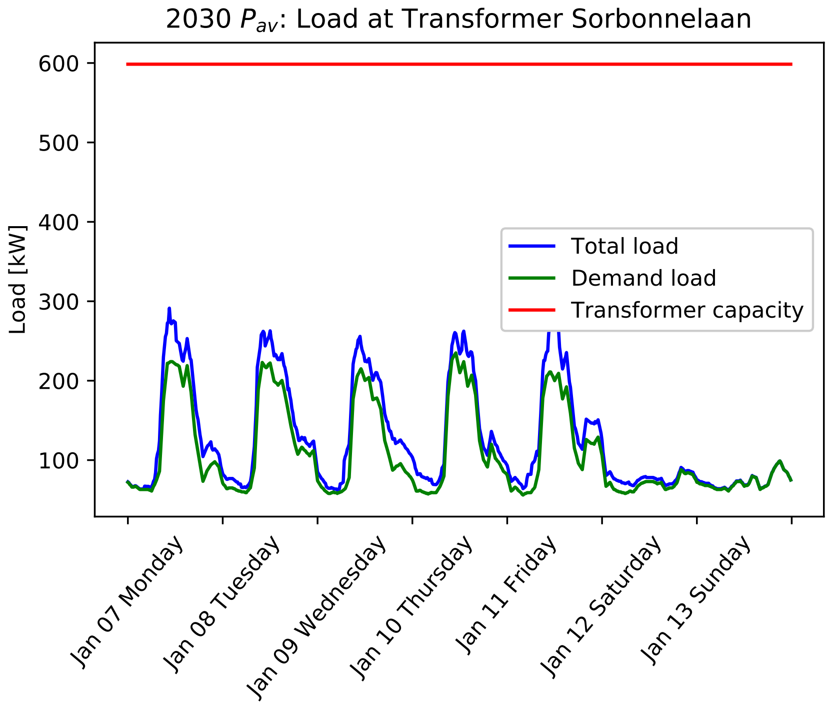

Figure D.6: Scenario 2030 under controlled charging: Loads on the distribution transformer at Sorbonnelaan.

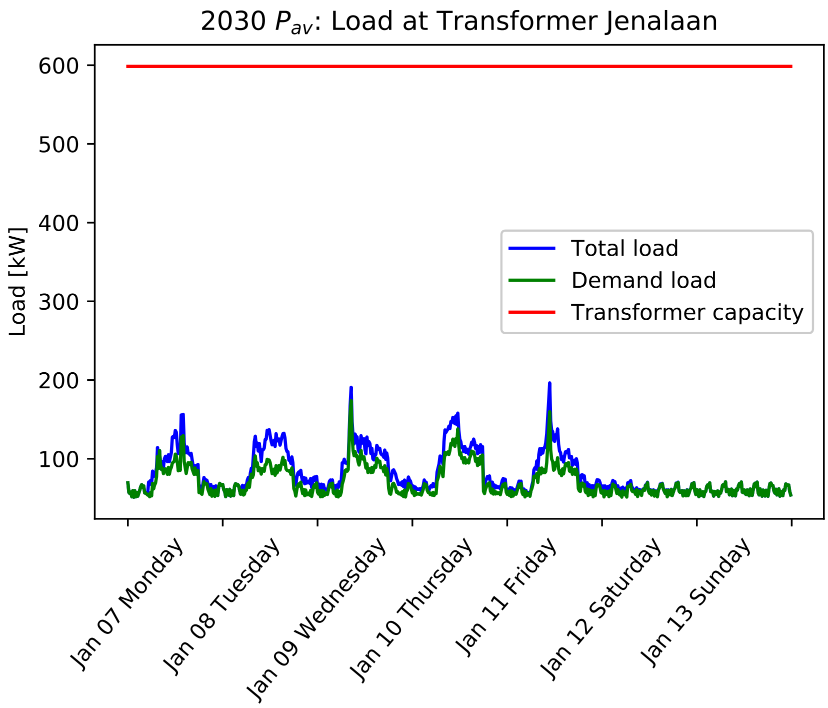

Figure D.7: Scenario 2030 under controlled charging: Loads on the distribution transformer at Jenalaan.

Scenario 2050

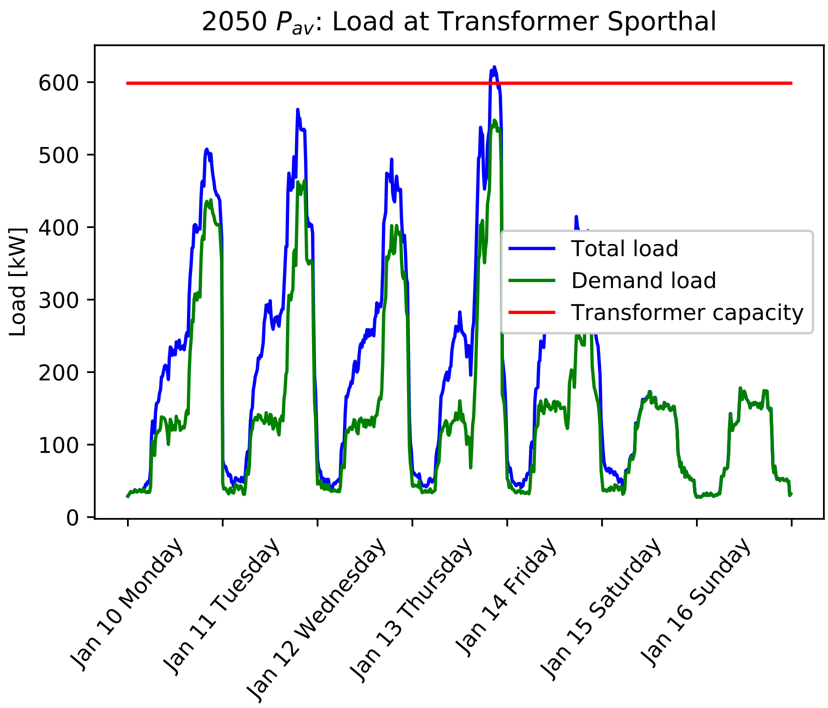

Figure D.8: Scenario 2050 under controlled charging: Loads on the distribution transformer at Olympos Sporthal.

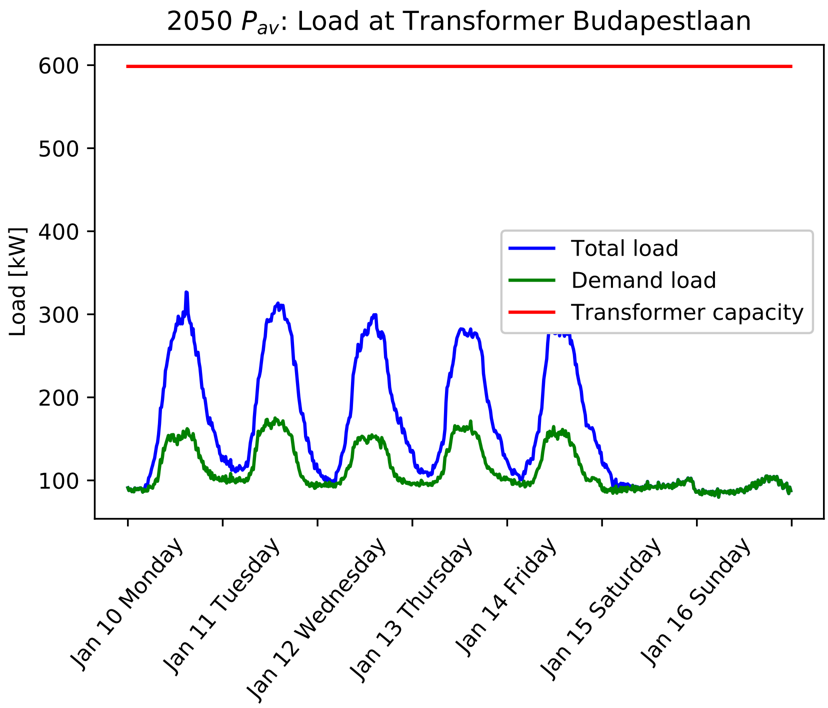

Figure D.9: Scenario 2050 under controlled charging: Loads on the distribution transformer at Budapestlaan.

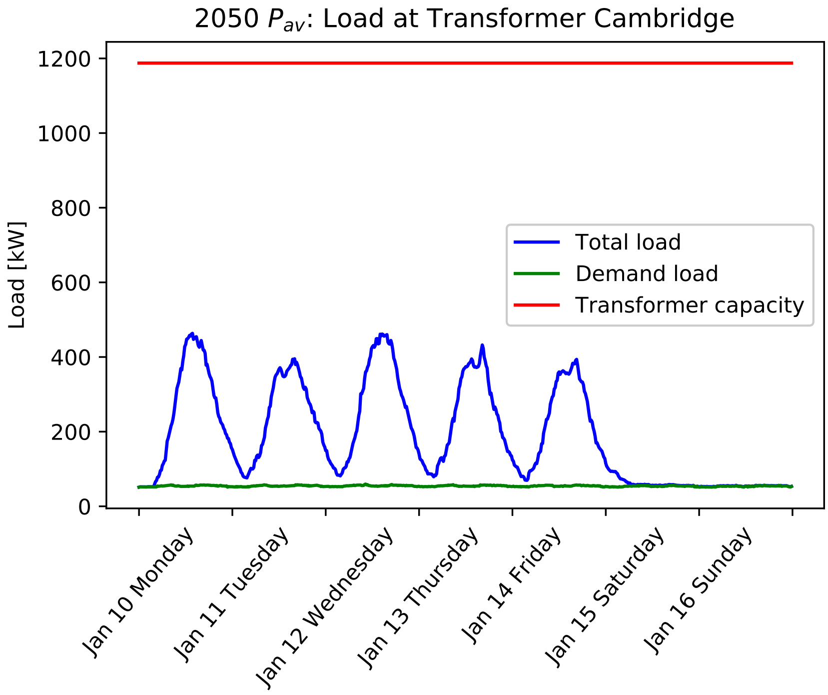

Figure D.10: Scenario 2050 under controlled charging: Loads on the distribution transformer at Cambridgelaan.