

Master thesis

Predicting the required public charging capacity for electric vehicles in Zwolle

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Zwolle

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Management Summary

In this research, we investigate how Zwolle can anticipate proactively on the expected growth of electric vehicle (EV) users in its municipality. Since Zwolle currently has no empirical data on EV charging, it does not have any reliable insights to anticipate on the required public charging infrastructure. As a solution, ElaadNL created a prognosis chart. In this prognosis chart, ElaadNL calculated the required number of public charging points (CPs) in each neighborhood in Zwolle, for three prognosis years: 2025, 2030 and 2035. However, since their underlying methods for calculating these numbers are not publicly available, Zwolle cannot validate these numbers.

To provide insights about the required number of public CPs in Zwolle, we developed a simulation model for Dutch municipalities, for two purposes. The first purpose is to determine the required number of CPs in a neighborhood and the peak number of public CPs charging simultaneously in a neighborhood. This is done with a simulation model, in which charging sessions are simulated for three categories of EV users in a neighborhood (i.e., residents without a home CP, visitors, and commuters).

The second purpose is to measure the number of required CPs in a neighborhood in three alternative scenarios. In the first scenario, the effect of placing a smaller or larger number of CPs on the peak CP shortages is measured. In the second and third scenario, the effect of a cap on the parked time and a cap on the idle time (parked time after charging is finished) on the required number of CPs is measured.

Methods

For each charging session in the developed simulation, several values were drawn from data. The time between two EV arrivals at a CP, the parked time at a CP, and the power demand during a charging session were drawn from empirical data distributions. The charging time was determined by dividing the drawn power demand over the mean charging power of a CP. This mean charging power of a CP was based on an assumption by Zwolle. The number of weekly charging sessions per EV were drawn from a normal distribution, with parameters estimated from literature. The number of expected EVs per neighborhood were taken over from the ElaadNL prognosis chart.

From the dataset generated by our simulation, the required number of CPs were determined by using a method that was proposed by the municipality of Utrecht. In this method, the mean number of occupied CPs during the busiest hour in a week (week peak hour) in a neighborhood is measured over 4 weeks of data. Utrecht defines the required number of CPs by the smallest value for which during the week peak hour on average 3 CPs remain unoccupied.

Results

Because there was no empirical data available on Zwolle, the required number of CPs from our simulation approach was compared with the prognosed number of CPs by ElaadNL. In this comparison we observed that our approach tends to predict a larger number of CPs than ElaadNL in neighborhoods with less EVs. On the contrary, in neighborhoods with a larger number of EVs, our approach tends to predict a smaller number of CPs than ElaadNL. Since our approach determines the required number of CPs based on the stochastic peak occupancy and smaller populations tend to be more volatile for stochastic peaks, these differences were expected. Using stochastic peaks as a basis to determine the required number of CPs can indicate a better reflection of real-world scenarios, compared to the method used by ElaadNL.

From the results, three conclusions were drawn. First, the effect of using excess capacity of private CPs at work locations for public charging on the required number of public CPs was estimated. This effect can decrease the total required number of CPs by about one fourth.

Second, in case of a shortage of CPs, the queued number of EVs increased exponentially. This exponential shortage becomes apparent during the peak hours when less than 95% of CPs are placed in a neighborhood. In case of excess CPs, the excesses CP capacity increased linearly. From this we conclude that Zwolle should avert capacity shortages over capacity excesses.

Third, a cap on the parked time or the idle time decreased the required number of CPs in a simulated neighborhood by up to 47% and 61% respectively. Of these two, a cap on the parked time is already used in regular parking, making it easiest to implement. However, a too short cap on the parking time led to the ending of sessions before the charging process had finished. This limited its potential for decreasing the required CPs in a neighborhood. In case of a cap on the idle time, this effect did not occur. However, for a maximum idle time a more advanced system is required to inform the EV user when the EV finished charging.

Recommendations

We have three recommendations for implementation. First, Zwolle should anticipate for at least 95% of the calculated required CPs for each neighborhood in the years 2025, 2030 and 2035, to prevent the shortages described in this thesis.

Second, Zwolle should look at the feasibility of implementing two legislative instruments that can decrease the required number of CPs, namely a cap on the idle time and the usage of excess capacity of private CPs at work locations by residents and visitors.

Third, Zwolle should stay alert for technological developments on the EV market. One way to anticipate on the effect of these developments on the required number of public CPs is by updating the probability distributions in our simulation model, when newer (more recent) data becomes available.

We have two recommendations for further research. First, this research proposed a method to determine the required number of CPs in a neighborhood. However, determining *where* in the neighborhood these CPs should be situated was beyond the scope of this research. This is a relevant problem for Zwolle on which further research is recommended.

Second, our method to determine the required number of CPs in a neighborhood also calculated the peak number of CPs charging. However, determining if this demand would be problematic for the current power grid required more research that was also beyond the scope of this research. This is a relevant problem on which further research is recommended after the previous recommended research is finished.

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List of Abbreviations

CI	C onfidence I nterval; the probability that a parameter will have a value between two values.
CP	C harging P oint; a single charging connection on which an EV can be charged.
EV	E lectric V ehicle; in this context an electric passenger car.
KPI	K ey P erformance I ndicator; measured characteristics that indicate the performance of a process or activity. In this context indicating the performance of grouped CPs.
LOS	L ength O f S tay; in this context indicating the total parking duration (including the charging process) of an EV.
SOC	S tate O f C harge; the power level of a battery, relative to the battery's maximum capacity.

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1. Introduction

In correspondence to the Paris climate agreement, the Dutch government aims to decrease the emissions of greenhouse gasses with 49% by 2030 and to 95-100% by 2035 (RIVM, 2021). To achieve this, the Dutch National Institute for Public Health and Environment (RIVM) regards the adoption of electric vehicles (EVs) as an important focus to transition to a more sustainable form of mobility. Since the use of EVs requires the availability of charging points (CPs) in neighborhoods, the transition from regular vehicles to EVs requires a revamp of the parking infrastructure in the Netherlands. Even though most municipalities have started the adoption of CPs in their neighborhoods, the current growth of new CPs is too slow for the growing demand. In almost 40% of the neighborhoods in the Netherlands, CP shortages occur during the occupancy peak hours (Enpuls, 2020).

The municipality of Zwolle recognizes the shortage of CPs but does not know how to anticipate proactively on the increasing CP demand. In this research, we investigate how Zwolle can anticipate on the growing adoption of EVs by citizens in the municipality.

This chapter discusses the objectives of the research and the outline of this thesis. Section 1.1 describes the context on the municipality of Zwolle with regards to EV charging and describes the motivations for this research in more detail. Section 1.2 identifies the problems that Zwolle faces when ensuring sufficient EV charging capacity and describes the problems regarded in this thesis. From this, the research goals are formulated in Section 1.3 that are used to formulate the research questions.

1.1 Context description

This section describes the relevant context on EV charging in Zwolle. Section 1.1.1 describes the most important characteristics of Zwolle and the current situation of the EV charging infrastructure in Zwolle. Section 1.1.2 introduces the research motivation.

1.1.1 EV charging in of Zwolle

The municipality of Zwolle is the capital of the province Overijssel, the Netherlands. With a total population of about 130,000 citizens (CBS, 2020), Zwolle is the 19th largest city in the Netherlands. Since the placing of the first public CP in 2011, Zwolle noted an increasing growth of the number of applications for new CPs since 2018.

In the current situation, the municipality of Zwolle has about 210 publicly available CPs for EVs available (Figure 1.1), of which 50 are situated in public parking garages and 160 in the residential areas (Arcgis, 2021).

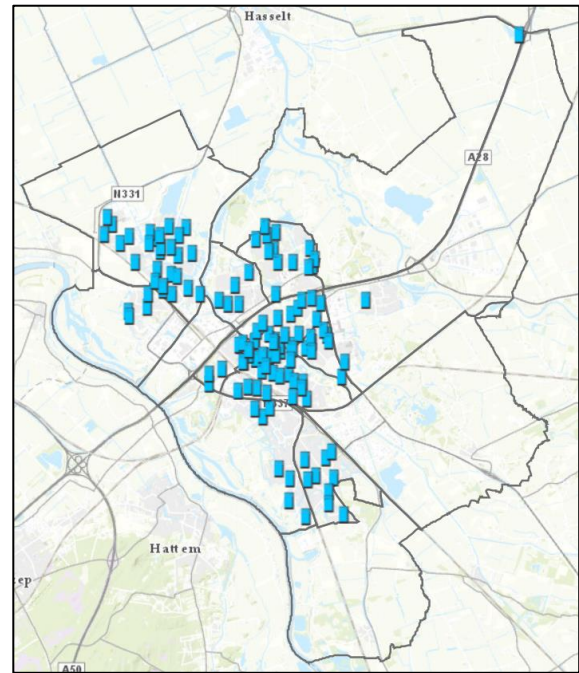


Figure 1.1: Publicly available CPs in Zwolle (Arcgis, 2021)

Zwolle currently does not anticipate proactively on new CPs and places its new CPs as a result of a filed application by a citizen (Zwolle, 2021). A citizen of Zwolle can freely apply for a new CP when they can prove buying or leasing an EV that cannot be charged at their own residence, or at a publicly available CP within a radius of 250 meters from their residence. After an application is approved, a location is selected and an objection procedure is started. If no residents object, the CP is placed at the selected location. In the current situation, in case of no objections, the procedural time from the first application to the placing of a CP as set by Zwolle should be 26 weeks.

In practice however, this procedural time often takes longer. In the media, several complaints can be found with regards to the currently existing procedure. In a response to a research by Stentor, a regional newspaper, tens of responders complained about the long procedure time before a new CP was realized (Stentor, 2020). The increased procedural time is partly caused by the objections of neighboring residents during the objection phase of the procedure. An important objection is that the adding of CP limits the number of available parking spots for regular cars, which are already perceived as scarcely available in some neighborhoods.

1.1.2 Research motivation

As a result of the Dutch climate goals, the number of EVs in the Netherlands is expected to grow at an increasing rate (RVO, 2020). Therefore, the municipality of Zwolle wants to anticipate on a strong increase of demand for public charging capacity by EVs in the near future. To do so, Zwolle wants to decrease the procedural time of the current application procedure for public CPs, whilst also anticipating on demand for public CPs proactively. Zwolle requires insights in the expected number of required public CPs. In the realization of new CPs, Zwolle acknowledges that it must take several factors into account. The two most important factors that are regarded by Zwolle, are the required capacity from already existing parking spots and the increased demand of power on the power grid. From a recent study, we expect the latter to be the most important bottleneck. This study indicated that parts of the low voltage grid may in its current state not be suitable to handle the increased demand for power for the charging of the expected number of EVs in the future (Hoogsteen, Molderink, Smit, Hurink, & Kootstra, 2017).

1.2 Problem identification

This section identifies the problems that Zwolle faces to proactively anticipate on the required number of public CPs in the future. To identify and describe the core problems, the problems and their mutual relations are structured in the problem cluster that is shown in Figure 1.2. The problem cluster starts with the discrepancy between the desired situation and the current situation, as perceived by the problem owner (Heerkens & Winden, 2012, pp. 22-23). In case of the municipality of Zwolle, we formulate this problem as “insufficient knowledge to fulfill the required charging capacity effectively”.

The main reason why Zwolle cannot plan effectively for the required charging capacity, is that Zwolle currently has no insights in where and when new CPs are required. Therefore, Zwolle cannot plan for future scenarios, without which Zwolle has no means to estimate if the power grid offers sufficient capacity in its current state to fulfill the future demand, or if improvements to the power grid are required. If the latter is the case, this should be anticipated such that alterations to the power grid can be made in time. Even though municipalities are not responsible for bottlenecks in (and alterations to) the power grid, these bottlenecks strongly influence the availability of CPs.

The difficulties of planning for new CPs are caused by two problems. The first problem is that Zwolle currently does not use any key performance indicators (KPIs) to measure the utilization of

CPs. Consequently, Zwolle cannot effectively determine when the capacity of a CP is fully utilized and therefore cannot decide when extra CPs in a neighborhood may be required. The second problem is that currently no numbers on the expected increase in EVs in Zwolle and their corresponding demand for charging capacity, are present. Hence, the installation of new CPs is not planned proactively, but is purely application driven. This means that the process of installing a new station is only initiated after a citizen applies for one.

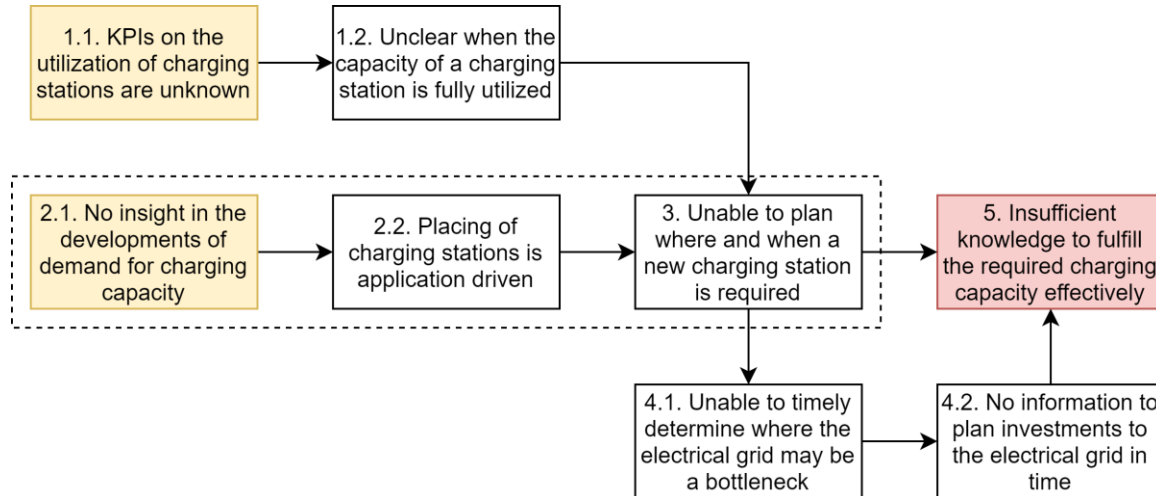


Figure 1.2: Problem cluster on the EV charging infrastructure in the municipality of Zwolle

Based on the problem analysis and the problem cluster in Figure 1.2, two core problems are identified (demarked in Figure 1.2 by yellow squares), namely:

- 1.) *The KPIs on the utilization of CPs are unknown to Zwolle (Problem 1.1).*
- 2.) *No insights in the future developments of the demand for charging capacity are available to Zwolle (Problem 2.1).*

The second core problem was recently addressed by the release of a national prognosis chart (ElaadNL, 2020) by ElaadNL. ElaadNL is a knowledge and innovation center, that is an authority in the field of smart charging in the Netherlands. The chart offers a prognosis for the number of residents with an EV and the required number of CPs for neighborhoods in the Netherlands in the years 2025, 2030 and 2035. The prognosis chart can offer a solution for the second core problem (Problem 2.1) and the two subsequent problems in the problem cluster (as depicted by the dotted square in Figure 1.2). However, the method of calculating the number of CPs in the prognosis chart are not publicly available. Therefore, Zwolle does not know how to estimate the required number of CPs (Problem 3) for the prognosed number of EVs (Problem 2.1).

As an alternative, we propose a simulation approach for calculating the required number of CPs. This model combines the EV quantities per neighborhood of the prognosis chart (Problem 2.1) and the KPI on the utilization of CPs (Problem 1.1). With this simulation approach, insights can be provided in the required number of CPs for a prognosed number of EV. By simulating the charging sessions of the prognosed number of EVs, the peak number of occupied CPs in a neighborhood can be estimated, for which the method is discussed in Section 2.2. By also calculating the peak number of EVs that charge simultaneously in our simulation, insights can be provided for the remaining problem, namely:

3.) *Zwolle is not able to timely determine where the power grid may be a bottleneck for new public CPs (Problem 4.1).*

1.3 Research design

This section describes the setup of the research. Section 1.3.1 formulates the research objectives. Section 1.3.2 formulates the research questions related to those research objectives. This section also serves as an outline for the thesis.

1.3.1 Research objectives

Two research objectives are identified from the problem identification in Section 1.2, namely:

1.) *To describe the context and the relevant KPIs required to predict the required number of CPs in a neighborhood.*

First, we require KPIs to measure when a CP is fully utilized to predict the required number of CPs in a neighborhood. This is done by describing a KPI that is used in other cities where the adaption of CPs is at a more advanced stage. The most frequently used KPI to measure the required number of CPs in a neighborhood was drawn up by the municipality of Utrecht. In this method, the number of required CPs are calculated based on the peak occupancy of existing CPs in a week. This method is explained in more detail in Section 2.2. Furthermore, we require insights in the expected growth of EVs in Zwolle. This information is obtained from the prognosis chart by ElaadNL and the corresponding documentation. The information on EV growth in this prognosis chart is discussed in more detail in Section 2.3.

2.) *To create a method for predicting the number of required public CPs in Zwolle proactively.*

Second, we want to develop an approach to predict the required number of CPs in a neighborhood. The main reason why Zwolle does not use the predictions by ElaadNL, is the lack of transparency in how ElaadNL determined the number of CPs in a neighborhood. The proposed approach must provide more insights to how we predict the number of CPs, compared to the prognosis chart by ElaadNL. The approach should also be able to provide insights in the peak capacity required from the power grid, in a neighborhood.

To develop an approach to predict the required number of CPs, the relevant literature is discussed in Chapter 3, that is used to develop a model in Chapter 4. This model must be able to simulate the charging sessions of a predicted number of EVs in a neighborhood. This is done by simulating their arrivals and lengths of stay (LOS) over a simulation time. The simulation model is used for two purposes in Chapter 5. First, to predict the required number of CPs from the simulated charging sessions, by using the KPI from the first research goal. Second, to show the effect of legislative instruments. This is done by experimenting with alternative numbers of CPs and caps on the length of stay, to predict their effect on the required number of CPs in a neighborhood.

1.3.2 Research questions

To meet the goals of Section 1.3.1, we require an answer to the following main question:

“How can we model the charging sessions that take place in a neighborhood, to predict the required number of public CPs in that neighborhood?”

To answer this question, several research questions are formulated and the approach on each research question is briefly addressed. Each of these research questions is covered in one chapter.

Chapter 2 discusses the context on EV charging that is relevant in this research. To do this, the context on the EV charging process is discussed. Furthermore, a KPI is discussed that is used by other municipalities to determine the required number of CPs in a neighborhood. Lastly, this chapter describes the EV growth in Zwolle, by using the ElaadNL prognosis chart. This chapter answers the following research questions:

- 1.) *What is the relevant context on EV charging?*
 - a. *What is the general context on EV charging?*
 - b. *How can we define the number of required public CPs?*
 - c. *What is the expected development of the EV charging demand in Zwolle?*

Chapter 3 describes the relevant literature to our research problem. It discusses the most important approaches used to model the arrivals and charging sessions of EVs at CPs by doing a systematic literature study. This chapter answers the following research questions:

- 2.) *What can we learn from the literature on modelling the occupancy of CPs over time?*
 - a. *Which modelling approaches are used on EV charging in literature?*
 - b. *Which modelling approach is best suited for our research problem?*

Chapter 4 describes our model of a public charging infrastructure in a neighborhood, by using the best fitting approach from the literature study of Chapter 3. This chapter discusses the characteristics and distributions that are necessary for our modelling approach and explains the assumptions made for the missing information. This chapter answers the following research questions:

- 3.) *How can we simulate for the required number of CPs in a neighborhood??*
 - a. *Which relevant distributions and characteristics can we extract from the available data?*
 - b. *How can we use the approaches from literature in our model?*
 - c. *Which assumptions need to be made as a substitute for missing information?*

Chapter 5 uses the model described in Chapter 4 for three purposes. First, to determine the required number of CPs in a neighborhood. Second, to look at the peak values of EVs that charge simultaneously, to indicate the required capacity from the power grid. Third, to experiment with the effect of legislative instruments on the required number of CPs in a neighborhood. This chapter answers the following research questions:

- 4.) *What conclusions can we draw from the results?*
 - a. *How does our simulation approach perform, compared to the predictions by ElaadNL?*
 - b. *How sensitive is our simulation approach to the assumptions in our model?*
 - c. *What is the effect of alternative scenarios on the performance of our simulated setup?*

Chapter 6 draws the most important conclusions, discusses our work and its limitations, and present our recommendations for future research.

2. Context analysis

This chapter concerns the relevant context for this thesis. Section 2.1 describes the general context on EV charging. Section 2.2 introduces a method proposed by the municipality of Utrecht to determine the required number of public CPs in a municipal area. This method is later used in Chapter 4, as the basis of the calculations for the required number of CPs in our simulation model. Section 2.3 introduces the prognosis charts by ElaadNL and discusses the expected EV growth in Zwolle. The outcomes from the prognosis chart are used in the experiments in Chapter 5. Section 2.4 concludes this chapter by answering the first set of research questions:

- 1.) *What is the relevant context on EV charging?*
 - a. *What is the general context on EV charging?*
 - b. *How can we define the number of required public CPs?*
 - c. *What is the expected development of the EV charging demand in Zwolle?*

2.1 Context on EV charging

This section provides a better view on the context on EV charging. Section 2.1.1 describes the charging process as it is regarded in this thesis. Section 2.1.2 discusses the different characteristics of EV users, which are necessary to understand when analyzing the data in Chapter 4. To do this, the EV users are described by three categories, namely “residents”, “guests and visitors” and “commuters” for which the different characteristics of each group are described. Section 2.1.3 describes the different types of chargers, by discussing the differences between public- and private CPs and their unique characteristics.

2.1.1 Description of the charging process

The charging process of a single EV can be described as the straightforward process of an arrival at a CP, a charging session, and a departure from a CP. In this research, we regard a neighborhood as an area in which many of these processes take place over a day. To make sure a charging process can take place when an EV arrives, a sufficient number of CPs should be available in a neighborhood. To describe the EV charging infrastructure in a neighborhood, we think of a neighborhood as a large parking area with N CPs evenly spread over that area. Before the start of a charging session, an EV arrives in a neighborhood, as is visualized in Figure 2.1. If the EV driver finds an unoccupied CP, the EV starts its charging session at that CP. If the EV driver cannot find

an unoccupied CP, the charging session is postponed until a parking spot becomes available. This is shown as “overflow” in Figure 2.1. When the charging session ends, the EV leaves the CP to either a regular parking spot or an alternative destination.

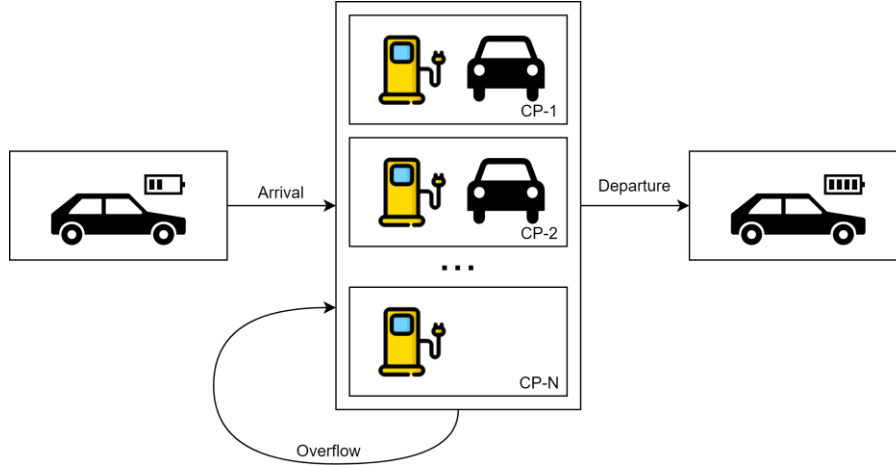


Figure 2.1: Graphical representation of the EV arrival and departure process in a neighborhood with N CPs

Two main factors are regarded that influence the required number of public CPs in a neighborhood. The first factor is the population size of EV users in the neighborhood that require a public CP, which is discussed in detail in Section 2.1.2.

The second factor is the length of stay (LOS) at a CP, which can be described by two parallel processes, namely the charging time and the parking time. The charging time is the time between the moment an EV is connected to a CP and the moment an EV stops charging. The parked time is the time between the EV arrival and EV departure. The difference between the charging time and parked time can be regarded as “idle time”, defined as the time in which an EV “blocks” a CP whilst not charging. The two parallel processes and the idle time are visualized in Figure 2.2.

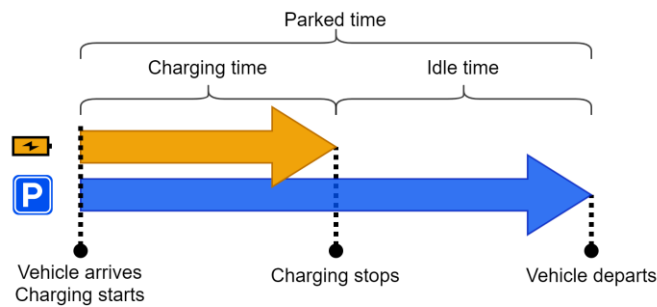


Figure 2.2: Graphical representation of the charging- and parked times, during a charging session

Both the mean charging time and the mean parked time can be influenced by the municipality, to influence the required number of CPs. The charging time can be influenced by the realized charging power of the CPs. The idle time can be influenced with a cap on the parked time. Chapter 5 experiments with the charging power and the use of a cap on the parked time, to determine their effect on the required number of CPs in a neighborhood.

2.1.2 Types of EV users

To understand the EV population in a neighborhood, EV users can be divided over subpopulations based on their charging behavior and needs. Three categories of EV users are identified based on literature, namely “residents”, “visitors” and “commuters”. In this section, these groups are described by their characteristics. These groups are used in our modelling approach in Chapter 4.

Residents

Residing EV users (residents) are citizens who own or lease an EV and use a CP near to their home. Residents should always use a private CP at home when their place of residence includes a private parking location, such as a driveway, carport or car shed. If this is not the case, a resident is dependent on a public CP. A public CP for residents must be reasonably close to their home. In literature, this distance varies between 100-250 meters. In case of Zwolle, the maximum distance of 250 meters is used (Zwolle, 2021).

Visitors

Visiting EV users, or visitors, are non-citizens who use a CP for a single or limited and infrequent use. Examples of visitors are houseguests, customers, or (day-) tourists. Visitors may charge at the private CPs at the private parking facilities of the visited party. If these are unavailable, a visitor is also designated to a public CP.

Commuters

Commuting EV users, or commuters, are generally non-citizens of the municipality who frequently use a CP in the area near or at their work location. Examples of commuters that drive EVs are mainly business workers, where the percentage of employees who drive an EV depends on the sector that they work in (NewMotion, 2021). Commuters can typically charge at a private CP at

the parking facilities at their office or working area. If these are unavailable, a commuter is designated to a public CP.

2.1.3 Types of CPs

Two different types of chargers can be distinguished, namely private- and public chargers. Technologically, these chargers are similar, but the difference between these chargers is the usage that they are intended for. This section explains the differences between public and private chargers, why we mainly focus on public chargers, and why we regard the privately owned work CPs as an opportunity.

Private chargers

Two types of privately owned chargers are discussed, namely CPs at home- and at work locations.

Home chargers

Home chargers are privately owned CPs by a citizen of the municipality. In principle, these CPs are not used by other citizens and serve no public purpose. However, owners of such chargers do not demand space of a public CP either. In the case of Zwolle, anyone with the spatial resources to charge an EV on their own property must provide for their own charging facility and cannot apply for a public CP. In this thesis, home CPs are regarded as unable to serve a public purpose. Home CPs and their required capacity from the power grid, are therefore left out of our simulation model, in Chapter 4.

Work chargers

Work chargers are privately owned CPs by a private or public organization, with the purpose to charge the EVs of their employees. The presence of such CPs at an office or workplace depends on the decision making of an individual organization and factors such as the availability of own parking facilities, job types, percentage of commuters employed and the average commuting distance (Refa, 2019). In principle, work CPs are privately owned and cannot be used by residents. However, the excess capacity after worktime and during weekends could be utilized by visitors or residents and may offer a strategic opportunity to the municipality in ensuring the public availability of CPs. We therefore incorporate these CPs in our simulation model, in Chapter 4.

Public chargers

Two types of public chargers are discussed, namely CPs on public chargers and CPs on charging clusters (freely translated from the Dutch term “laadpleinen”). In the remainder of this thesis, both are regarded as “Public CPs” used by residents without a private CP and by visitors and tourists.

Public chargers

Public chargers are typically owned by an operating company and can be found in the public domain. Typically, a regular public charging station has two CPs, located at two adjacent public parking spots. Public CPs are a public commodity, facilitated by the municipality for public use. Therefore, it usually does not matter if the user is a resident without a home CP, a commuter without a work CP, or a visitor. The parking spots that are adjacent to a charger are reserved for EVs, meaning regular cars risk a fine when parking at a location that is dedicated for EVs. This also means that an EV is only allowed to be positioned at such a parking spot for charging. In Zwolle, an EV should leave the CP when the EV battery is full, to utilize a CP as well as possible. However, this is not always complied with, resulting in the “idle time” described in Section 2.1. The costs for public charging consist of at least an electricity rate, but additional parking fees might apply. In Zwolle, only an electricity rate is charged (Allego, 2020).

Charging clusters

A charging cluster is a single charger station with more than two CPs, jointly connected to one connection on the power grid (NKL, 2019). When deciding between a CP and a charging cluster, two main tradeoffs must be considered. First, a charging cluster centralizes multiple CPs into a single parking lot, compared to multiple regular CPs that are placed at different parking locations over a larger area. This means that the average distance from a random home to the nearest CP will be larger compared to a decentralized alternative. However, a centralized option will have a higher expected availability compared to that of a regular charger, due to the concentration of a larger number of CPs at a single location. Second, with a charging cluster it is easier to moderate the available power capacity and distribute it more efficiently over the connected CPs, since all CPs in a cluster are jointly connected to the power grid. Moderating the available power capacity can lower the peak load on the power grid. However, this will also result in variable charging speeds, leading to a less predictable charging time compared to a regular CP.

2.2 Defining the required number of public CPs

Section 2.1.3 discussed the difference between public and private CPs. Since Zwolle is responsible for the availability of public CPs, this research focusses on this CP type. This section describes a method in which the peak occupancy rate of public CPs is measured as a KPI to determine the required number of public CPs in a neighborhood. This method was proposed by the municipality of Utrecht and is used by municipalities where the implementation of EV CPs is at a more advanced stage (M. Kok, personal communication, 2020).

Utrecht measures the utilization of CPs by the peak occupancy rate $R_{n,W}$ in a neighborhood n , during week number W . To calculate this, the mean occupancy rate during each week hour t is determined by dividing the total occupancy (the time an EV is connected to a CP $T_{o,n,t,w}$ (in minutes) and the total time a CP is defective $T_{d,n,t,w}$ (in minutes) over all CPs in the neighborhood) over the total potential charging time (number of CPs $C_{n,w}$ in the neighborhood multiplied by sixty minutes). Then, the average value for each hour over the last 4 weeks is taken to include (yet limit) the effect of incidental peaks. The maximum average value of all week hours is taken as the peak occupancy rate for a neighborhood. The peak occupancy rate $R_{n,W}$ for a neighborhood is calculated with Equation 2.1.

$$R_{n,W} = \max_{t \in \{1,2,\dots,168\}} \left(\sum_{w=W-3}^W \frac{\left(\frac{T_{o,n,t,w} + T_{d,n,t,w}}{C_{n,w} \cdot 60} \right)}{4} \right) \quad (2.1)$$

Where:

$R_{n,W}$ is the peak occupancy rate for neighborhood n , in week number W ,

$T_{o,n,t,w}$ is the total connected time (in minutes) over all CPs, in neighborhood n , on week hour t , in week number w ,

$T_{d,n,t,w}$ is the total downtime (in minutes) over all CPs, in neighborhood n , on week hour t , in week number w ,

$C_{n,w}$ is the number of CPs situated in neighborhood n , in week number w .

When the peak occupancy rate in a neighborhood surpasses a certain upper limit, Utrecht assumes a shortage in that neighborhood and new CPs should be added to bring the occupancy rate under that upper limit. Utrecht defined this upper limit for the peak occupancy rate in a neighborhood through two approaches. In the first approach, the upper limit $L_{n,W}$ is calculated by the peak occupancy rate $R_{n,W}$. The upper limit equals the number of CPs in a neighborhood that *should* be in the neighborhood to have on average at least 3 free CPs during the peak hour. In other words: the upper limit to the peak occupancy rate $L_{n,W}$ equals the peak occupancy rate $R_{n,W}$ for which the peak unoccupancy rate $(1 - R_{n,W})$, multiplied by the total number of CPs, is equal to or larger than 3. The upper limit value to the peak occupancy rate is calculated by Equation 2.2.

$$L_{n,W} = \max_{C_{n,w} \in \{Z^{\geq}\}} (R_{n,W} \mid (1 - R_{n,W}) \cdot C_{n,w} \geq 3) \quad (2.2)$$

Where:

$L_{n,W}$ is the upper limit to the peak occupancy rate for neighborhood n , in week number W ,

$C_{n,w}$ and $R_{n,W}$ are the same as for 2.1.

In the second approach, Utrecht has defined 7 intervals for the number of CPs in a neighborhood, as shown in Table 2.1. Utrecht has specified an upper limit to the peak occupancy rate for each interval. The intervals of CPs are chosen such that each number of CPs in an interval, multiplied by their shared peak unoccupancy rate, have a value close to 3 free CPs.

Table 2.1: Maximum allowed occupancy rate, for a number of charging points in a neighborhood, in Utrecht (Utrecht, 2020).

Number of charging points situated in the neighborhood (C_n)	Upper limit ($L_{n,w}$) to the peak occupancy rate ($R_{n,w}$)
<i>Up to 6 charging points</i>	50%
<i>7 - 10 charging points</i>	60%
<i>11 - 15 charging points</i>	70%
<i>16 - 20 charging points</i>	80%
<i>21 - 35 charging points</i>	85%
<i>36 - 60 charging points</i>	90%
<i>Over 60 charging points</i>	95%

In this second approach, each number of CPs in an interval share the same upper limit, whereas in the first approach, a new upper limit value is calculated when the number of CPs changed. When comparing the two approaches, the first is more precise but the second may be simpler in practice. In our simulation model in Chapter 4 and 5 we prefer precision and use the first approach.

As discussed, Utrecht determined that on peak hours, on average at least 3 CPs in a neighborhood must remain unoccupied. This value results from a subjective tradeoff by Utrecht between costs and peak occupancy. The peak occupancy rate of a CP decreases as the number of neighboring CPs increase. A decreased peak occupancy rate leads to an increased availability for EV drivers. However, an increased number of CPs leads to an increase of the fixed operating costs. Therefore, the “right” peak occupancy of a CP is subjective and a tradeoff between the fixed operating costs and the availability must be made by the municipality. This tradeoff is beyond the scope of this research. However, Chapter 5 looks at the effect of a deliberate peak shortage (or excess) of CPs in a neighborhood, on the number of EVs that must wait for a CP during the peak hour.

In conclusion: the required number public CPs in a neighborhood can be determined by the mean number of occupied CPs during the peak hour. If there are on average less than 3 CPs available during this peak hour, new CPs should be placed in that neighborhood until this criterion is met.

2.3 EV user development in Zwolle

Sections 2.1 and 2.2 discussed the context of EV charging and how to calculate the required number of CPs. This section provides insights in the expected population growth of EV users in Zwolle. This is done by describing the prognosis chart that was introduced in Chapter 1. This prognosis chart is developed by ElaadNL, a knowledge and innovation center that is specialized in the field of smart charging in the Netherlands. To help municipalities in preparing for the expected growth of EVs in their municipality, ElaadNL publishes an annually updated prognosis chart for the total required number of CPs in the years 2025, 2030 and 2035. This section discusses the most relevant outcomes from the prognosis chart for Zwolle, that was published in 2020.

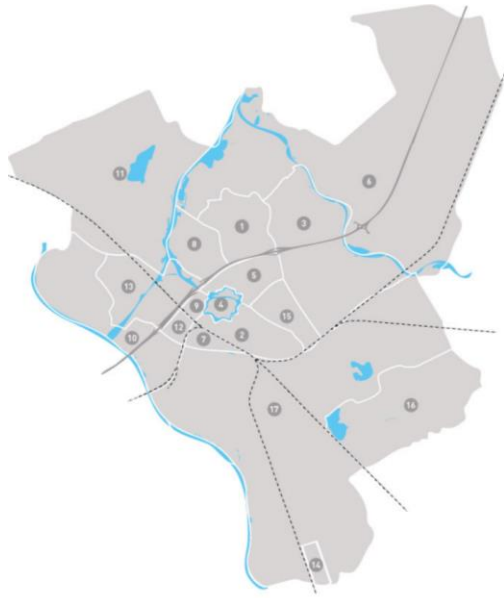


Figure 2.3: Seventeen residential areas in Zwolle (Zwolle, Wijken in Zwolle, 2020)

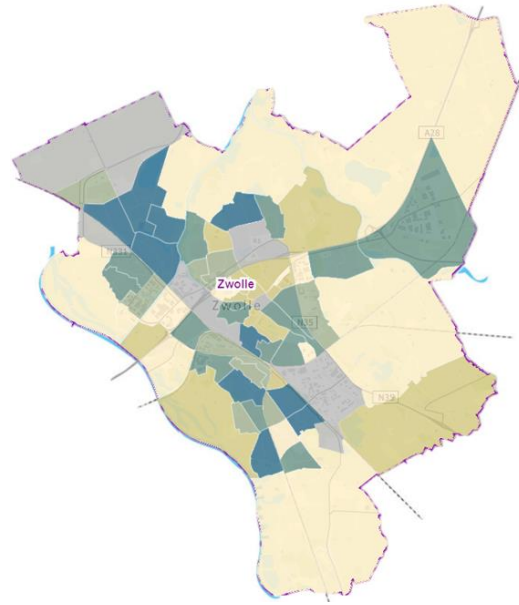


Figure 2.4: Visualization of EV intensity per neighborhood in the prognosis chart for Zwolle for 2025 (ElaadNL, 2020)

The municipality of Zwolle can be divided into a historical city center, surrounded by a total of sixteen other residential areas, as shown in Figure 2.3. Each residential area consists of several zip code neighborhoods. These neighborhoods are used as the basis of the prognosis chart of ElaadNL (ElaadNL, 2020). Figure 2.4 shows a picture of the municipality of Zwolle, as shown in the prognosis chart for 2025. In this figure, a color was assigned to each of the neighborhoods, corresponding to the total number of prognosed CPs that are required in the prognosed year. For each of these neighborhoods in each prognosed year, the number of EV users and the number of each different CP type are estimated.

The method to determine these numbers is not publicly available and therefore unknown to us. However, from an early publication on which the prognosis chart is based (Montfort, Visser, Poel, & Hoed, 2016), it can be concluded that these numbers are the result from a multiple regression-analysis on a number of variables. An overview of the variables used is not publicly available, but from Montfort, Visser, Poel & Hoed we know they include demographic characteristics, such as the average income and age distribution of a neighborhood and data obtained from private research, e.g., the analysis of aerial photos for the number of private driveways and public parking availability.

Since ElaadNL does not show how their prognosed values are calculated, or offer options for different scenarios of legislative instruments, Zwolle is missing too much context to use these prognosed CPs as a basis plan for the required CPs in their municipality. However, due to the reputation of ElaadNL, we assume these predictions to be sufficiently reliable to be used to validate our simulation approach in Chapter 5, despite us being unable to verify them.

Prognosed growth by ElaadNL

When regarding the findings from the prognosis chart for Zwolle, the total expected number of CPs will increase, as is visualized in Figure 2.5. Based on the calculations by ElaadNL, Zwolle requires a CP increase from almost 4,000 CPs up to the year 2025 to over 7,500 CPs in 2030 and almost 14,000 CPs in 2035. These numbers consist of private CPs at home (27-28%), public CPs (31-32%) and private CPs at work (40-41%), corresponding to the three CP types discussed in Section 2.1.3. The total overview of the prognosed numbers for Zwolle per neighborhood can be found in Appendix A (ElaadNL, 2019).

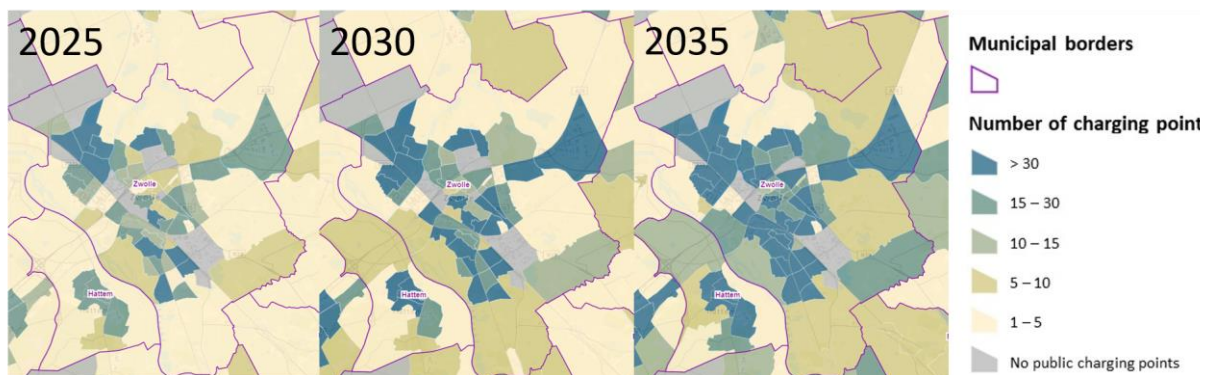


Figure 2.5: Visualization of the expected increase of required public CPs in Zwolle from 2025 to 2030 and 2035 (ElaadNL, 2020)

2.4 Conclusions

This chapter answered the first set of research questions, namely:

- 1.) *What is the relevant context on EV charging?*
 - a. *What is the general context on EV charging?*
 - b. *How can we define the number of required public CPs?*
 - c. *What is the expected development of the EV charging demand in Zwolle?*

To answer to sub question a, we looked at three things. First, a charging process of an EV can be described as two parallel processes, namely a charging time and a parked time. The difference between the two processes can be regarded as an idle parked time. In the parking process, two factors influence the number of required CPs in a neighborhood, namely the idle parked time (time an EV occupies a CP after charging has finished) and the charging power.

Second, charging sessions can be divided over three categories of EV users, namely residents, visitors, and commuters. These categories are helpful to account for the difference between EV owners, in their behavior of charging and their charging needs.

Third, Zwolle is not responsible for private CPs at home and cannot utilize these CPs for public use. However, the availability of public CPs is the responsibility of Zwolle. Therefore, we focus solely on the public CPs in this research. The private CPs at work locations are also included, to determine the effect of utilizing the excess capacity of these CPs on the required number of public CPs in a neighborhood.

To answer sub question b, we discussed the method of the municipality of Utrecht, which is used to calculate the required number of CPs from empirical charging data. In this method, the number of CPs in a neighborhood is chosen such that in the peak occupancy hour in a neighborhood, on average 3 CPs are still available.

To answer sub question c, we looked at the prognosis charts from ElaadNL for the municipality of Zwolle. We compared the expected number of CPs, required at the years 2025, 2030 and 2035, and saw that the total expected number of CPs are expected to increase from almost 4,000 points in 2025 to over 7,500 points in 2030 and almost 14,000 points in 2035. From these, 31-32% CPs are required in the public domain and therefore should be facilitated by the municipality of Zwolle.

3. Literature review

This chapter introduces the relevant literary context on modelling the occupancy of CPs over time. In this literature review, two different modelling methods in literature are discussed, that can be used to model the occupancy of CPs over time. These methods are mathematical modelling approaches and simulation modelling approaches. Section 3.1 describes two examples of mathematical modelling approaches, namely the Markov Chain model in Section 3.1.1 and the Queueing theory model in Section 3.1.2. Section 3.2 describes the simulation modelling approach. Section 3.3 concludes this chapter by answering the second set of research questions:

2.) *What can we learn from the literature on modelling the occupancy of CPs over time?*

- a. *Which modelling approaches on EV charging are used in literature?*
- b. *Which modelling approach is best suited for our research problem?*

3.1 Mathematical modelling approach

This section describes two mathematical modelling approaches that are used in literature. The Markov chain model and the Queueing model are discussed in Section 3.1.1 and 3.1.2 respectively.

3.1.1 Markov chain model

The first modelling approach for the occupancy of CPs in literature uses a continuous-time Markov chain. This approach is based on a method by which the parking lot capacity of a regular parking lot can be calculated (Caliskan, Barthels, Scheuermann, & Mauve, 2007). Kumar & Udaykumar describe that the charging process of an EV can be regarded as the sequence of an arrival, a processing time, and a departure. In their approach, they assume that arrivals and departures of EVs are mutually independent (Kumar & Udaykumar, 2015) (Kumar & Udaykumar, 2016). We must note that Kumar & Udaykumar do not divide the processing time into a charging time and an idle parked time, which is necessary to determine the peak number of CPs charging or to experiment with the effect of the idle time on the required number of CPs in a neighborhood.

From data on EV charging behavior, an average probability for an arrival and an average probability for a departure of a single EV can be derived. With these probabilities, Kumar & Udaykumar form a Markov chain-based model as depicted in Figure 3.1.

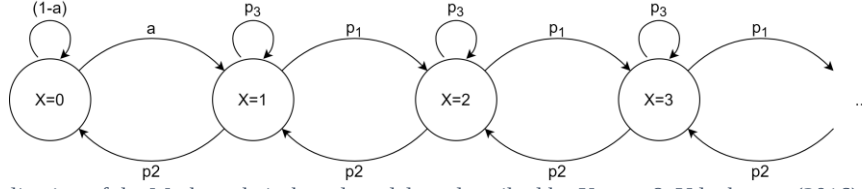


Figure 3.1: Visualization of the Markov chain-based model, as described by Kumar & Udaykumar (2016)

In this Markov chain the state X_n of the parking lot is equal to the number of EVs X that are charging at time n . In this method, n is the time slot that equals the time to transmit a single EV. The state changes depending on the occurring event in a timeslot: $X_{n+1} = X_n - 1$ if a departure takes place, $X_{n+1} = X_n + 1$ if an arrival takes place and $X_{n+1} = X_n$ if both an arrival and departure take place or if nothing happened, for $n \in \{0, 1, \dots, N - 1\}$. The transitions between two states are depicted by curved arrows in Figure 3.1. These transitions are dependent on probabilities a and b , where a is the probability of an EV arrival and b is the probability of an EV departure. The probabilities a and b are mutually independent and independent of state X_n . The probability $p_{i,j}$ is the probability to transition from state i to state j . This probability is dependent on probabilities a and b , as is shown in Equation 3.1.

$$p_{i,j} = \begin{cases} p_1 = a \cdot (1 - b), & j = i + 1, i = 1, 2, \dots; \\ p_2 = (1 - a) \cdot b, & j = i - 1, i = 1, 2, \dots; \\ p_3 = a \cdot b + (1 - a) \cdot (1 - b), & j = i, i = 1, 2, \dots; \\ a, & i = 0, j = 1; \\ 1 - a, & i = 0, j = 0; \\ 0, & \text{otherwise} \end{cases} \quad (3.1)$$

From these transition probabilities, the stationary distributions are derived by calculating the probability P_n that a certain state X_n occurs for each n , by Equation 3.2 and 3.3.

$$P_0 = \left(1 + \frac{a}{p_2} \cdot \frac{p_2}{p_2 - p_1} \right)^{-1} \quad (3.2)$$

$$P_n = \frac{a}{p_2} \cdot \left(\frac{p_1}{p_2} \right)^{n-1} \cdot P_0 \quad (3.3)$$

From the stationary distributions, Kumar & Udaykumar derive the expected (or, on average observed) number of EVs $E[X]$ on the parking lot by the steady state distribution of Equation 3.4.

$$E[X] = \sum_{n=0}^{\infty} n \cdot P_n \quad (3.4)$$

From the continuous-time Markov chain-based model presented Kumar & Udaykumar, we can derive a method to determine the right number of CPs, to meet a given availability rate (a certain percentage of time the demand can be fulfilled). In this method, the required number of CPs C , equals the smallest value N for which the sum of the stationary probabilities from P_0 to P_N equals (or is larger than) the lower limit of the availability rate A , as shown by Equation 3.5.

$$C = \min (N | \sum_{n=0}^N P_n \geq A) \quad (3.5)$$

Where:

C is the required number of CPs,

A is the lower limit value of the availability rate.

3.1.2 Queueing theory model

The second mathematical modelling approach found in literature was proposed by Bae & Kwasinski (2012). They use queueing theory to forecast the charging demand to determine the number of required CPs based on a desired occupancy rate. In this method, a M/M/s queueing model is used. The first M in M/M/s indicates that the arrivals of EVs at the charging location have a Poisson distribution with a mean arrival rate value of $z(y_i, t)$, at charging location y_i , at time t . The second M in M/M/s indicates that the charging times of the EVs are exponentially distributed and mutually independent. To determine the completed sessions in an interval, Bae & Kwasinski use the mean rate by which charging sessions are completed (charging completion rate). The charging completion rate per minute μ_0 is calculated by dividing the average charging power of a CP P_{av} (in kW) over the average recharged capacity of a vehicle soc_{av} (in kWh), as is shown in Equation 3.6. To make sure the completion rate is translated from hours to minutes, this fraction is multiplied by a proportional constant k_1 ($\frac{1}{60}$ to translate hours to minutes).

$$\mu_0(t) = k_1 \cdot \frac{P_{av}}{soc_{av}} \quad (3.6)$$

The s in M/M/s indicates the number of identical CPs that are located at the charging location. In case of s occupied CPs, the system follows a single first-in-first-out (FIFO) queueing rule. For the system, the occupancy rate ρ at time t is calculated by dividing the mean arrival rate ($z(y_i, t)$) over

the total discharge rate (number of CPs s multiplied by the charging completion rate $\mu_0(t)$), as is shown in Equation 3.7.

$$\rho = \frac{z(y_i, t)}{s \cdot \mu_0(t)} \quad (3.7)$$

The M/M/s system is stable if the occupancy rate of the total CP infrastructure in a neighborhood ρ is smaller than 1. Therefore, the required number of CPs to have a stable charging infrastructure at time t equals the smallest value s for which ρ is smaller than 1.

3.2 Simulation modeling approach

Both mathematical approaches have two shortcomings that make them not suitable for determining the required number of CPs by the method of Utrecht, as described in Section 2.2. First, these mathematical approaches calculate a steady state at a time t . In contrast, the method of Utrecht uses the occupancy peak, that is caused by the randomness of EV arrivals and the charging times. Second, both methods are not well suited to incorporate the continuously changing arrival and departure probabilities over the time.

As an alternative to mathematical approaches, most papers use a simulation method to assess the charging behavior. In this method, a series of EV charging sessions are simulated by drawing event data (e.g., arrival times, charging times and departure times) from empirical distributions. This section is structured by three topics. Section 3.2.1 describes the literature on the distribution of charging sessions over time. Section 3.2.2 describes the literature on the length of stay (LOS) at CPs. Section 3.2.3 describes the literature on the weekly returns.

3.2.1 Distributions of the start of charging sessions over time

One of the first simulation models on EV arrivals proposes a normal distribution for the arrival probability of an EV (Cao et al., 2012). In the data analysis of Cao et al., 90% of the charging sessions started between 13:00 and 23:00 hours, with a peak at 18:00 hours, as shown in Figure 3.2.

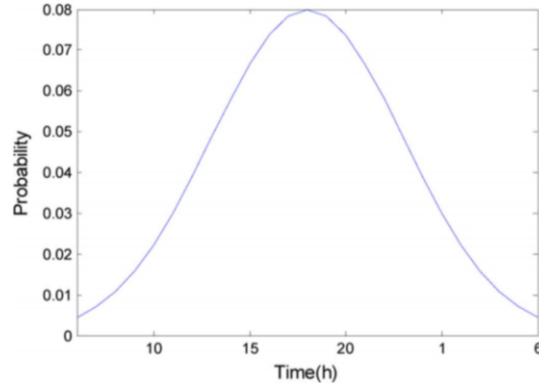


Figure 3.2: Distribution curve of the charging starting times of EV charging over the day, as proposed by Cao et al. (2012).

Li, Zhang & Wang (2018) state that the arrival intensity of EVs is indeed dependent on the time t , but that the arrivals at time t can be approximated by a Poisson process. Li et al. calculate the EV arrival probability $P(X = k)$ according to Equation 3.8 (Li, Zhang, & Wang, 2018). In this equation, $P(X = k)$ is the probability that k arrivals occur at time t and $\lambda(t)$ is the expected arrival intensity at time t .

$$P(X = k) = \frac{\lambda(t)^k}{k!} \cdot e^{-\lambda}, k = 0, 1, \dots, N \quad (3.8)$$

Predictors of demand load patterns

Arias, Bae & Sungwoo (2016) propose that event patterns have an influence on the intensities of traffic and therefore on the charging intensities over time. In a data analysis, Arias, Bae & Sungwoo assess the traffic volume of cars over the day, assuming a direct relation between the intensity of regular cars and the intensity of EVs. In their analysis, the data is divided over four day-types. The intensities are shown in Figure 3.3 a-d, for a; event days (festivals and conferences), b; regular weekdays, c; holidays, d; Sundays (Arias, Bae, & Sungwoo, 2016).

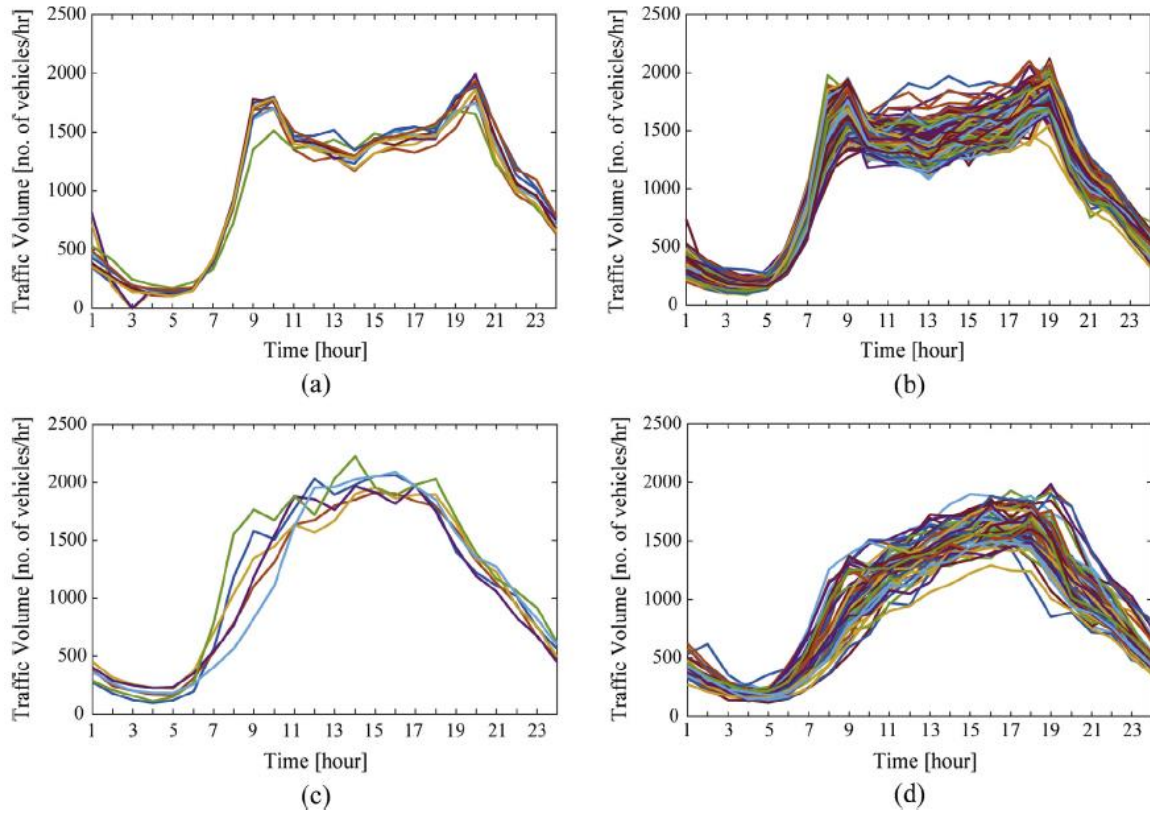


Figure 3.3: Four clusters of cars on different day-types, namely a; event days (festivals and conferences), b; regular weekdays, c; holidays, d; Sundays, on data from 1/1/2014-31/12/2014 by Arias & Bae (2016)

For day-type a, c, and d it is assumed that an EV is always charged at (or near) the home of the EV driver. For day-type b however, Arias, Bae & Sungwoo observe two distinct peaks (between 8:00 and 9:00 and at 19:00 hours). From the assumption that a charging session starts after traveling, Arias, Bae & Sungwoo conclude that on these days, 50% of the charging sessions must occur at a work location in the daytime and 50% of the charging sessions at (or near) the home in the evening.

Xing et al. (2019) show in an analysis of the load distribution of EV charging demand that not only the time and day-type, but also the different characteristics of urban areas affect the charging behavior of EV owners. For this analysis, the used data is divided over four areal categories and three day-type categories. The four areal categories are residential areas, commercial areas, industrial areas, and public service areas, which are shown in Figure 3.4 a-d, respectively. The number of charged vehicles in these four areal categories are 416, 328, 298 and 229, respectively. Each areal category shows the demand load pattern for the three day types, namely weekdays, weekend days and holidays.

From the analysis of the demand load patterns, three observations are made. First, residential areas have the lowest demand load, even though they have the highest number of charging EVs (Figure 3.4 a). This is because only low voltage charging facilities (3.5 kW) were available in these areas. Second, in industrial areas where EVs are mostly owned by commuters, a lower charging intensity on holidays is observed (Xing et al., 2019). Meanwhile the commercial areas and public service areas, where EVs are mostly for trips and entertainment, have a higher intensity on weekends and holidays than on weekdays. Third, the peaks of the charging intensity in residential areas are two hours later on holidays and weekend days, compared to workdays.

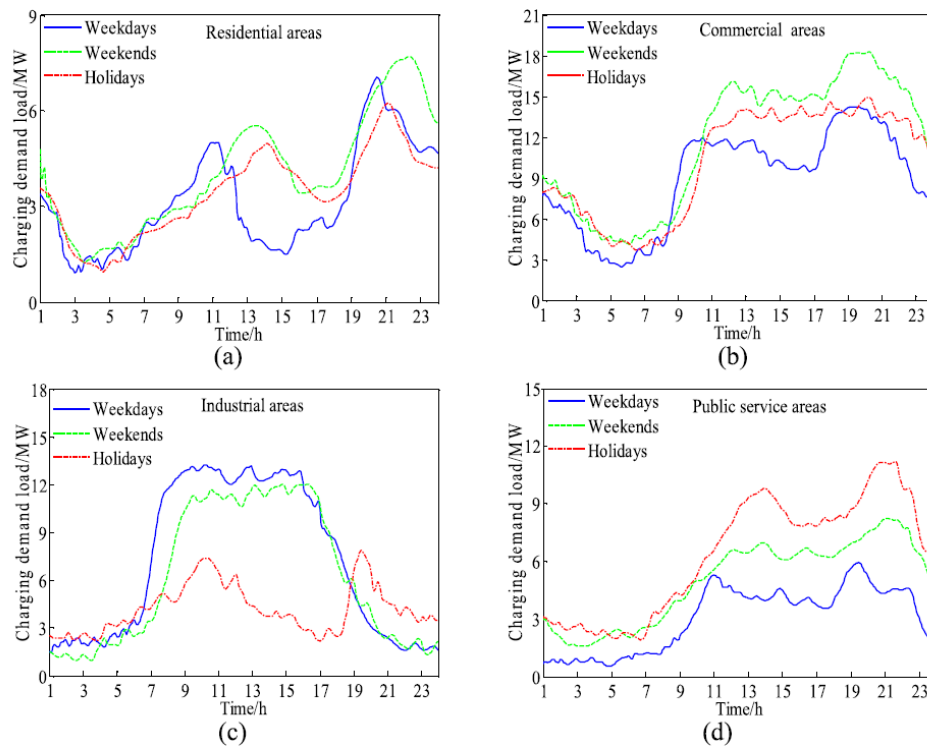


Figure 3.4: Distribution patterns of demand load of different data types in four functional areas by Xing et al (2019)

Charging intensities over the day

Most categorizations of EV charging behavior in literature are based on geographical characteristics. Shepero and Munkhammar (2018) present a different approach, where the EV charging sessions are divided over three distinct charging profiles that closely correspond to the profiles used in Chapter 2, namely “work”, “home” and “other”. By using these three categories, three distinct loading profiles can be identified, as is shown in Figure 3.5. In this figure, the arrival intensities over the day, for the three different groups are shown (Shepero & Munkhammar, 2018).

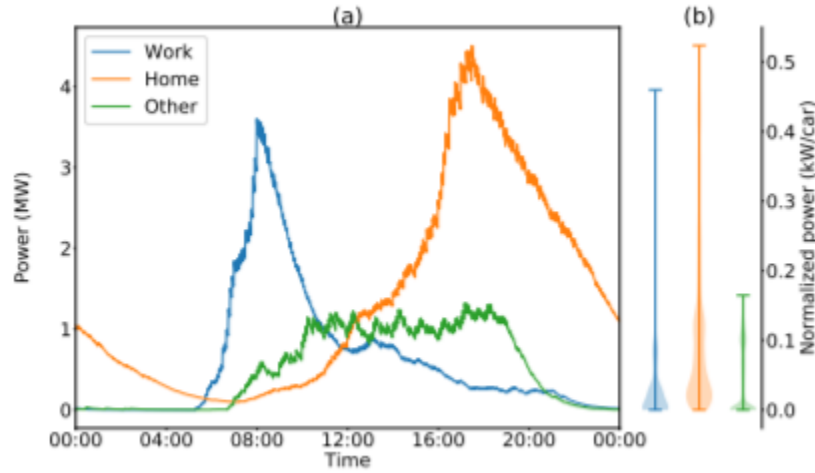


Figure 3.5: Load profiles for three categories on an average day, charged with 3.7 kW, by Shepero & Munkhammar (2018)

3.2.2 Determining the length of a charging session

Cao et al. (2012) introduced a method to determine the LOS by use of the charging time, where the charging time is calculated from the discharged battery capacity of a vehicle. Cao et al. assumed that the vehicle's initial state of charge (SOC) at arrival is commonly between 20% and 80%, with an average value of 50% and a standard deviation of 30%. However, multiple methods to determine the SOC of an EV have been proposed in literature. Li et al. (2018) state that the SOC can always be assumed to be lower than 80%. Xie et al. (2018), assume that the initial SOC is somewhere between 15%-30% and that SOC after charging is distributed evenly between 80%-90%. In their turn, Xing et al. (2019) state that the SOC at the end of charging follows a normal distribution with a mean of 85% and a standard deviation of 3%.

Drawing a SOC from a fitted distribution

In most cases however, when empirical data is available, the SOC is drawn from a fitted distribution. According to multiple studies (Cao et al., 2012) (Dong et al., 2016), this initial SOC has a Gaussian probability density function $f(s, \mu, \sigma)$, as shown in Equation 3.9. In this density function, s is the initial SOC, μ is the mean initial SOC and σ is the standard deviation of the initial SOC.

$$f(s, \mu, \sigma) = \frac{1}{\sqrt{2 \cdot \pi \cdot \sigma^2}} \cdot e^{-\frac{(s-\mu)^2}{2\sigma^2}} \quad (3.9)$$

Arias, Bae & Sungwoo (2016) observe that regular weekdays have two distinct peaks in the traffic intensity over a day, namely one at the work- and one at the home location. Based on this observation, they assume two charging periods. Therefore, they propose an alternative density function of the SOC of EVs on working days (Monday-Friday). The new density function for the SOC on these working days is shown in Equation 3.10. In this equation, p_w is the fraction of EVs that are charged at work during the daytime and p_h is the fraction of EVs that are charged at home during the evening. Furthermore, s is the initial SOC, μ_w and μ_h are the mean initial SOC at work and home respectively, and σ_w and σ_h are the standard deviations of the initial SOC at work and home, respectively (Arias, Bae, & Sungwoo, 2016).

$$F(s, \mu_w, \sigma_w, \mu_h, \sigma_h) = \frac{p_w}{\sqrt{2 \cdot \pi \cdot \sigma_w^2}} \cdot e^{-\frac{(s-\mu_w)^2}{2\sigma_w^2}} + \frac{p_h}{\sqrt{2 \cdot \pi \cdot \sigma_h^2}} \cdot e^{-\frac{(s-\mu_h)^2}{2\sigma_h^2}} \quad (3.10)$$

From a data-analysis study, Arias, Bae & Sungwoo assume that $p_w = 0.5$ and $p_h = 0.5$, meaning that on a weekday, half of EV drivers charge their EV at work and the other half at home.

Calculating a SOC based on vehicle characteristics and driving distance

As an alternative approach, the SOC of an EV can be calculated from the energy consumption of a vehicle by the distance traveled between two charging sessions. Fiori, Ahn & Rakhba (2016) present an approach for which a set of variables that influence the energy consumption of an EV are used to predict its SOC (Fiori, Ahn, & Rakha, 2016). A similar method was later developed by Xing et al. (2019), who developed a dynamic power consumption models on different grades of road qualities. Since these methods use more detail than required for Zwolle, an in-depth review of these models is beyond the scope of this research. A simpler method to predict the SOC from the driving behavior is used by Amini, Kargarian & Karabasoglu (2016), where the daily driven distance MD is drawn from the lognormal distribution shown in Equation 3.11. The parameters μ_M and σ_M in Equation 3.11 are calculated in Equation 3.12 from the mean μ_{MD} and standard deviation σ_{MD} of the daily driven distance as determined from empirical data. In Equation 3.12, RV_r is a standard normal random variable (Amani, Kargarian, & Karabasoglu, 2016).

$$MD = e^{\mu_m + \sigma_m \cdot RV_r} \quad (3.11)$$

$$\begin{cases} \mu_m = \ln \left(\frac{\mu_{md}^2}{\sqrt{\mu_{md}^2 + \sigma_{md}^2}} \right) \\ \sigma_m = \sqrt{\ln \left(1 + \frac{\sigma_{md}^2}{\mu_{md}^2} \right)} \end{cases} \quad (3.12)$$

From Equation 3.11, the expected EV energy demand $\hat{E}_d$ can be calculated by multiplying the daily driven distance MD by the average energy consumption per unit traveled E_m , as is shown in Equation 3.13.

$$\hat{E}_d = MD \cdot E_m \quad (3.13)$$

A drawback from this method is that it assumes a new charging session on each day, which is not in line with reality.

Translating the SOC to the charging time

From the initial SOC, the charging time can be calculated using a method proposed by Xie et al. (2018). This method is shown in Equation 3.14, where the charging time t_c is the charged capacity (the percentual difference of the SOC before and after charging ($SoC_f - SoC_i$), multiplied by the battery capacity Cap), over the realized charging power (charging efficiency rate η_c , multiplied by the charging power p_c) (Xie et al., 2018).

$$t_c = \frac{(SoC_f - SoC_i) \cdot Cap}{\eta_c \cdot p_c} \quad (3.14)$$

Relation between the EV arrival time and length of stay

The length of stay (LOS) cannot be assumed to be homogenously distributed over time (Sadeghianpourhamami et al., 2018). Sadeghianpourhamami et al. describe the relation between the arrival times and departure times over the day, as is shown in Figure 3.5. The charging sessions in this figure are grouped into three categories, based on the characteristics of those charging sessions.

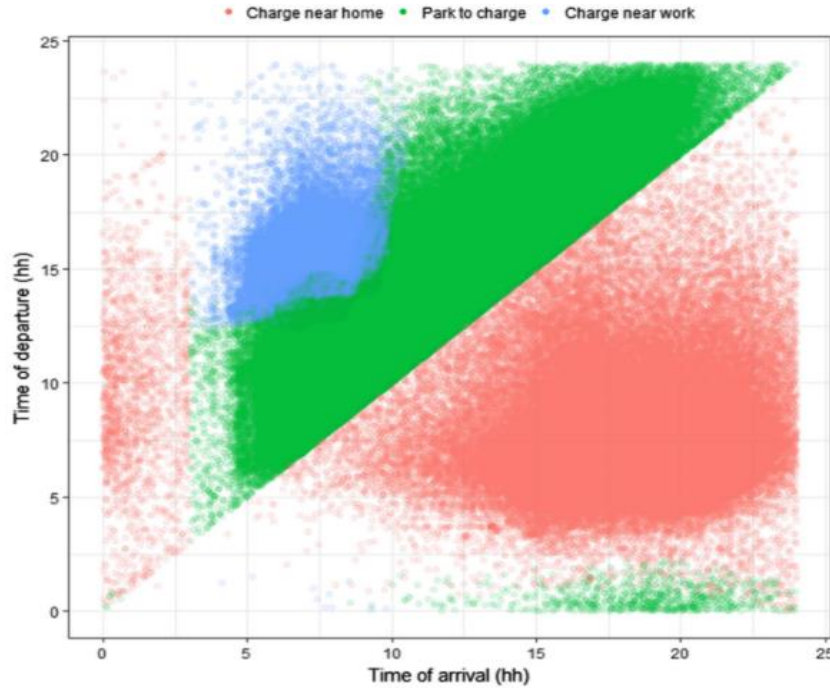


Figure 3.5: EV arrival and departure times per session by Sadeghianpourhamami et al. (2018)

The category “park to charge” (in green) is the largest group and covers 62.9% of the data. These sessions have an average LOS of 2 hours and 28 minutes, of which 48 minutes are idle time. The “park to charge” group has charging sessions with a LOS that is closest to the charging time. Sadeghianpourhamami et al. hypothesize that EVs in this group park purely for the purpose of charging. The sessions in this category are scattered throughout the day.

The category “charge near home” (in red) covers 9,3% of the data. In this category, charging sessions typically start in the afternoon and evening, stay connected over the nighttime and end the next morning between 4:00-12:00, regardless of the start time. Therefore, Sadeghianpourhamami et al. hypothesize that those sessions start on arrival at home, after work and stop before departing for work. Sessions in this category have an average LOS of 13 hours and 24 minutes, of which 10 hours are idle time and tend to end later during weekends compared to weekdays. The latter observation can be explained by a later leaving time in weekends.

The category “charge near work” (in blue) covers 27,8% of the data. In this category, most sessions typically start between 5:00-12:00 and end between 12:00 and 18:00, regardless of the start time. These sessions have an average LOS of 8 hours and 42 minutes, of which 5 hours and 30 minutes are idle time. Therefore, Sadeghianpourhamami et al. conclude that these are cars that are left to charge during work hours.

3.2.3 Weekly returns

Venegaz, Perez & Petit (2019) show the correlation between the battery capacity and the weekly number of charging sessions of an EV in Figure 3.6, which results from a data analysis of French mobility data. From this figure, two conclusions can be drawn. First, no more than 7 sessions per week take place for any of the battery types. Second, a larger battery capacity results in a smaller number of charging sessions (Venegas, Petit, & Perez, 2019).

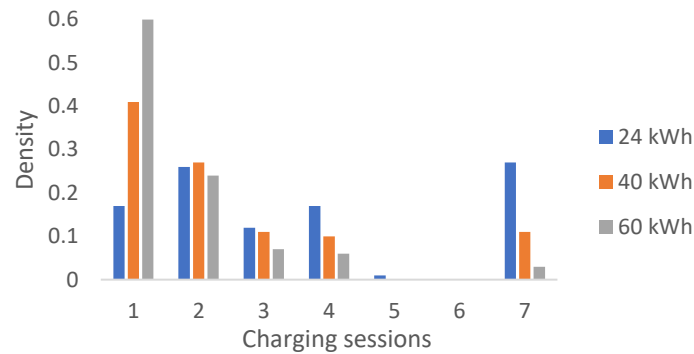


Figure 3.6: Distribution of the number of charging sessions per week of French EVs with a specific battery size by Venegas, Perez & Petit (2019)

Alternatively, Refa & Hubbers (2019) use a set of charging data to determine the charging frequency of Dutch EVs. In the analysis, the charging frequency of EV owners is defined by the average number of charging sessions per week (Refa & Hubbers, 2019). From the results shown in Figure 3.7, Refa & Hubbers conclude that an EV has on average 4 charging sessions per week, with a standard deviation of 2 charging sessions.

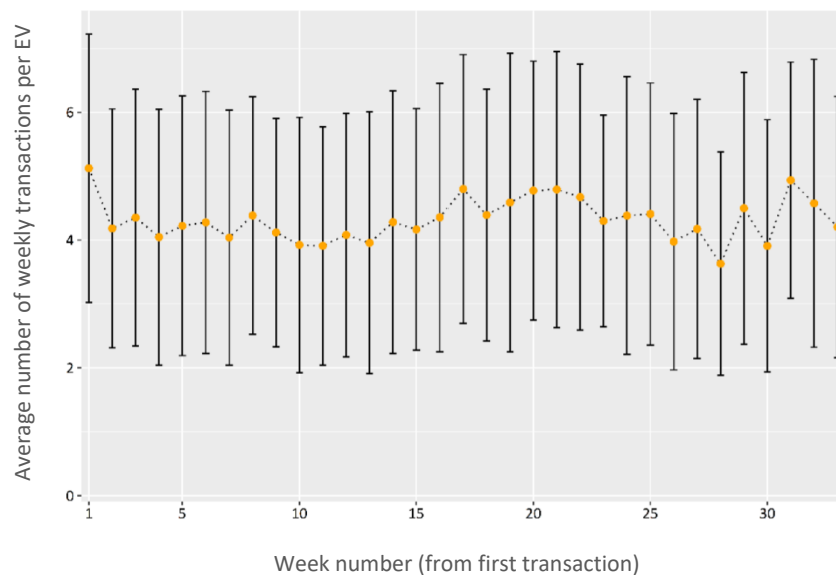


Figure 3.7: Distribution of charging frequencies of Dutch EVs by Refa & Hubbers (2019)

3.3 Conclusions

This chapter answered the second set of research questions, namely:

- 2.) *What can we learn from the literature on modelling the occupancy of CPs over time?*
 - a. *Which modelling approaches on EV charging are used in literature?*
 - b. *Which modelling approach is best suited for our research problem?*

To answer these questions, we described three methods to model EV charging from literature. The first two methods were mathematical modelling approaches used in the specific context of EV charging, namely Markov chains and queuing theory. The third method used is the simulation approach. To show how often the different approaches are used in literature, an overview of the papers that were discussed is shown in Table 3.1.

When analyzing the methods used in literature, both mathematical modelling options are not well suited to incorporate the continuously changing arrival and departure probabilities over time. Furthermore, both mathematical approaches calculated a steady state at a time t , whereas the method of Utrecht (as described in Section 2.2) uses the peak occupancy rate that is caused by the randomness of EV arrivals and the charging times. In contrast to the mathematical approaches, the three main processes regarded in Section 2.1.1 (arrival, charging time and LOS) can be modelled well with a simulation approach. Since we can apply the method of Utrecht on simulated data of these three processes, we consider simulation as the most appropriate modelling approach for our research.

Table 3.1: Overview of the most relevant papers used and their relation to the three approaches.

Mathematical modelling approach		Simulation modelling approach	Added relevance
Paper	Markov chain		
Amani, M., Kargarian, A., & Karabasoglu, O. (2016)		X	Daily driven distance used to calculate the SOC
Arias, M., Bae, & Sungwoo. (2016)		X	Relation between traffic behavior and charging behavior
Bae, S., & Kwansinksi, A. (2012)	X		Introducing Queuing to EV modelling
Caliskan, M. et al. (2007)		X	Introducing Markov chain
Cao, Y. et al. (2012)		X	Introducing Monte Carlo simulations to EV modelling
Dong, X. et al. (2016)		X	Initial SOC follows a Gaussian probability density function
Fiori, C., Ahn, K., & Rakha, H. (2016)		X	Vehicle characteristics used to improve the SOC predictions
Kumar, S., & Udaykumar, R. (2015)	X		Introducing Markov chain in EV modelling
Kumar, S., & Udaykumar, R. (2016)	X		Continuation on Markov chain in EV modelling
Li, W., Zhang, T., & Wang, R. (2018)		X	Arrivals are Poisson distributed, initial SOC is lower than 80%
Sadeghianpourhamami, N. et al. (2018)		X	Distribution for LOS is dependent on the EV arrival time
Shepero, M., & Munkhammar, J. (2018)		X	EV drivers can be deviated by their behavior into three distinct groups, namely Work, Home and Other.
Xie, R. et al. (2018)		X	Method to translate SOC to the charging time
Xing, Q. et al. (2019)		X	Region and day patterns influence arrival intensities, SOC at end of charging follows a N(0.85, 03)-distribution
Venegas, F., Petit, M., & Perez, Y. (2019)		X	Number of EV sessions per week decreases as the battery capacity increases. Indication of the number of sessions per EV per week

4. Simulation approach

This chapter describes our simulation approach on EV charging sessions in a neighborhood. Section 4.1 introduces our simulation approach. Section 4.2 discusses the required information for our simulation model and discusses the required data. Section 4.3 describes the process structure in our simulation approach. Section 4.4 describes the methods used for calculating the results in our simulation approach. Section 4.5 explains the alterations to our simulation approach for two experimental options. Section 4.6 concludes this chapter by answering the third set of research questions:

3.) *How can we simulate for the required number of CPs in a neighborhood?*

- a. *Which relevant distributions and characteristics can we extract from the available data?*
- b. *How can we use the approaches from literature in our model?*
- c. *Which assumptions need to be made as a substitute for missing information?*

4.1 Introducing the modelling approach

This section describes the objectives of our modelling approach and introduces how our simulation can model the charging infrastructure of Zwolle.

This simulation has three objectives. First and most importantly, to predict the required number of CPs and the peak number of CPs charging in a neighborhood for a prognosed year. In total three prognosed years are regarded, namely 2025, 2030 and 2035, in conformance with Section 2.3. The number of CPs in a neighborhood is predicted according to the method by Utrecht, as described in Section 2.2.

Second, to simulate the shortage when there are less CPs in a neighborhood than required. This shortage is measured by the peak queue length over the simulation duration in a neighborhood with a given number of CPs.

Third, to determine the effect of a decreased idle time on the required number of CPs in a neighborhood. Section 2.1.1 explained how a decrease of the average idle time decreases the required number of CPs in a neighborhood. Two measures are used to decrease the idle time, namely a cap on the parked time and a cap on the idle time. To determine the effect of these measures, the number of CPs are predicted in a scenario with one of the two measures applied and are compared with the predicted number of CPs without a decreased idle time.

Chapter 3 concluded that the EV charging process in a neighborhood can be modelled most adequately with a simulation model. For all three objectives formulated in this section, the same simulation approach is used. However, additional functions are used for the second and third objective, which are described in Section 4.5. Furthermore, a simulation run is performed for each of the three EV categories introduced in Section 2.1.2 (residents, visitors, and commuters). In each simulation run, charging sessions are simulated over a simulated timespan. Each charging session is simulated by the four events that were described in Section 2.1.1, namely an arrival at a CP, a charging duration, a parked duration, and a departure from a CP.

4.2 Used data in our modelling approach

This section introduces the data and information used in our simulation model in two steps. Section 4.2.1 covers the required information to determine the number of charging sessions in a simulation session. Section 4.2.2 covers the data on the different events during a simulation session.

4.2.1 Determining the number of charging sessions in a simulation session

To determine the number of charging sessions in a simulation session, three characteristics are used. The first is the timespan that is simulated, indicating the number of weeks of charging data that is generated. The second is the number of EVs in each of the three categories in the simulated neighborhood. The third is the average number of weekly sessions of a single EV in each category.

Simulated timespan

In conformance with the method of Utrecht, 4 weeks are used as the simulated timespan. As described in Section 2.2, the municipality of Utrecht defines its required number of CPs by the peak hour of EV charging in a week. To determine this peak hour, Utrecht calculates the average CP occupancy per week hour over 4 weeks of empirical data.

Number of EVs in a neighborhood

The number of EVs in each of the three categories of EV users per prognosed year by ElaadNL are used as the number of EVs in a simulated neighborhood. An overview of these numbers per neighborhood can be found in Appendix A.

Average number of weekly sessions of an EV in each category

The average number of charging sessions per week μ_i for an EV in a category i requires several assumptions, since there is no data available to us on these weekly returns. For the EV category “visitors”, we assume that their visit is an isolated event and therefore also require a single isolated charging session. From the literature study in Chapter 3, two details are known about the number of charging sessions per week for the EV category “resident” and “work”. First, Refa & Hubbers (2019) showed that an EV has on average 4 weekly charging sessions, with a standard deviation of 2 sessions. Second, Arias, Bae & Sungwoo (2016) discussed that half the sessions on workdays (Monday-Friday) can be assumed to take place on CPs near work and the other half on CPs near home. From these two assumptions, the mean number of charging sessions for residents and commuters in a neighborhood are defined by the following procedure: For a neighborhood, the population mean of the weekly sessions for EVs in a category is drawn from a normal distribution. Subsequently, the population mean of the weekly sessions is multiplied with the fraction of the sessions that take place in that neighborhood. The average number of weekly sessions per EV category are shown in Table 4.1.

Table 4.1: Estimated average number of weekly sessions per EV in a category i .

i	<i>Residents</i>	<i>Visitors</i>	<i>Commuters</i>
μ_i	$\frac{9}{14} \cdot N\left(4, \frac{2}{\sqrt{n_{residents}}}\right)$	1	$\frac{5}{14} \cdot N\left(4, \frac{2}{\sqrt{n_{commuters}}}\right)$

4.2.2 Required data on the simulated events

To simulate a charging session, data distributions are used on each event. Since no empirical data from Zwolle is available, data distributions from ElaadNL are used (ElaadNL, 2020). These data distributions are drawn from a large dataset of charging sessions between 2018-2020. The following distributions are used for each simulated event:

- Arrival at a CP: For the arrival at a CP, two probability distributions are used. First, the distributions of the total weekly sessions over weekdays. Second, the distribution of EV arrivals over the day.
- Charging duration: For the charging duration, a probability distribution on the charged energy (in kWh) in a charging session is used. The charging duration is determined by dividing the charged kWh over the mean realized charging power of a CP.

- Parked duration: For the parked duration, a probability distribution on the connected time to a CP is used.
- Departure from a CP: The departure time is determined by adding the parked duration to the arrival at a CP.

The remainder of this section describes each of the used distributions in more detail.

Arrivals per weekday

The first distribution set used for EV arrivals is the distributions of the total weekly sessions over weekdays. Figure 4.1 shows the boxplots for the fraction of the weekly arrivals per day, for the three EV categories. This figure shows that in these distributions, no commuter arrivals take place on weekend days. For the resident and visitor charging sessions, fewer sessions take place on weekend days compared to workdays.

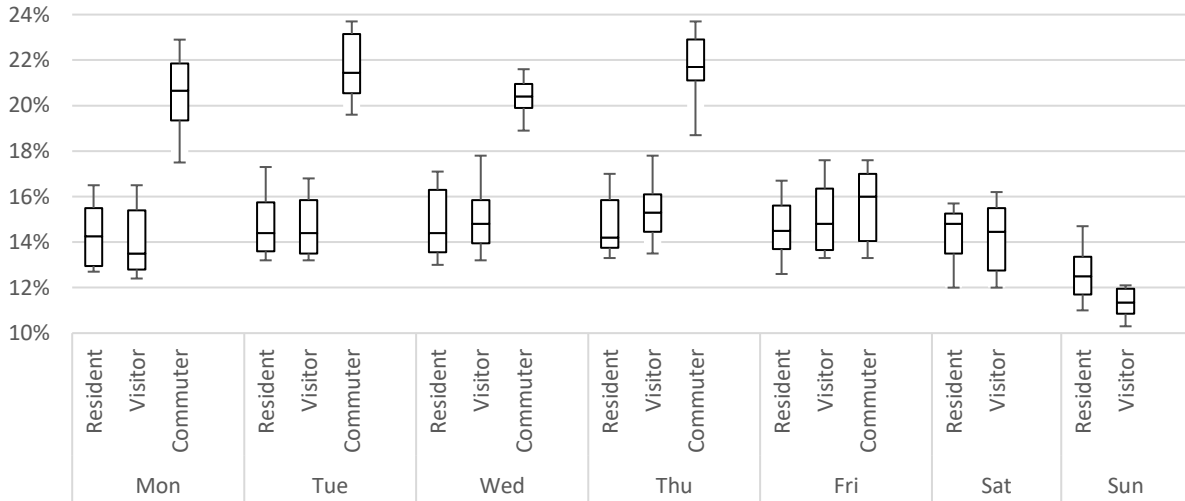


Figure 4.1: Distribution of charging sessions per day, per location type, as acquired from ElaadNL (2020)

Arrivals per 15 minutes over a day

The second and third distribution sets used for EV arrivals are the distributions of EV arrivals over the day, namely one for weekdays (Monday-Friday) and one for weekends (Saturday-Sunday). Figure 4.2a-b shows the arrival probabilities per 15 minutes of the three EV categories, on weekdays and weekends, respectively. For weekdays, we observe that resident sessions have their peak in the late afternoon and the beginning of the evening, whereas commuter sessions have their peak in the morning. Visitor EVs have their arrivals more evenly distributed over the daytime,

with two small peaks that correspond to those of resident- and commuter sessions. The weekday distributions observed in Figure 4.2a roughly correspond to the general distributions described in Section 3.2.1. For the weekends, a different distribution can be observed where resident and visitor charging sessions have their peak over the daytime and no commuter sessions take place.

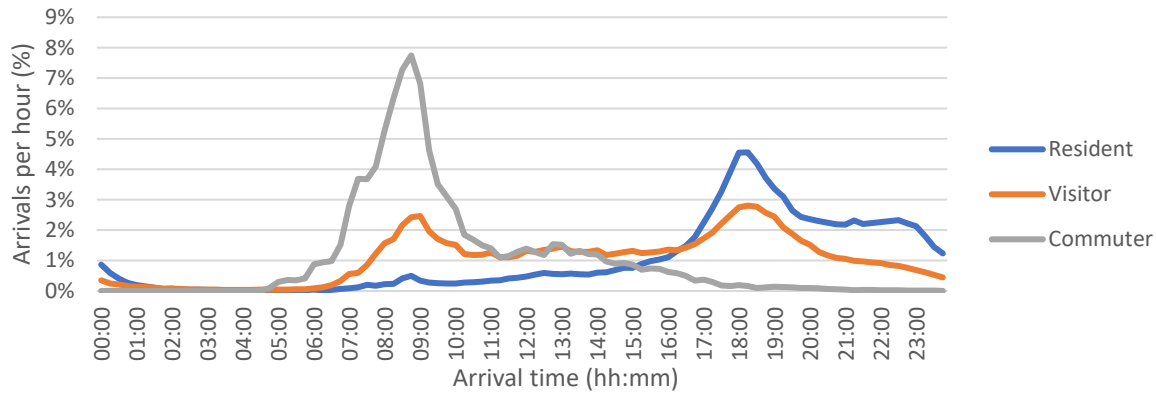


Figure 4.2a: Distribution of the start of charging sessions per EV type, over the day for weekdays, as acquired from ElaadNL (2020)

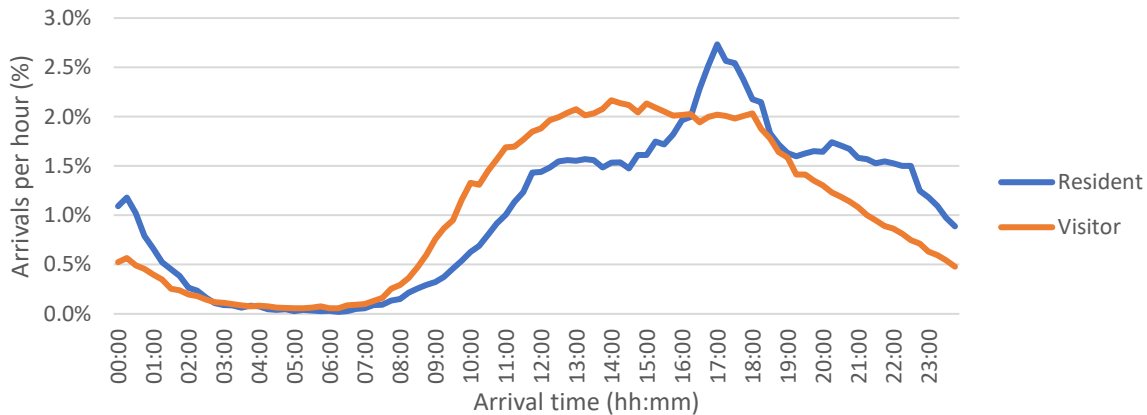


Figure 4.2b: Distribution of the start of charging sessions per EV type, over the day for weekend days, as acquired from ElaadNL (2020)

Energy demand per charging event

The distribution set used to describe the EV charging duration is the energy demand per charging event, from which the charging duration can be calculated. The cumulative distribution function (CDF) plot of the energy demand per charging session (in kWh) for each of the three EV categories are shown in Figure 4.3. The distribution of the energy demand of visitor- and commuter charging sessions appear to be distributed similarly, whereas the energy demand of resident charging sessions is much higher. The energy demand of charging sessions in the resident, visitor and commuter category are on average 24.1 kWh, 12.3 kWh and 12.7 kWh, respectively.

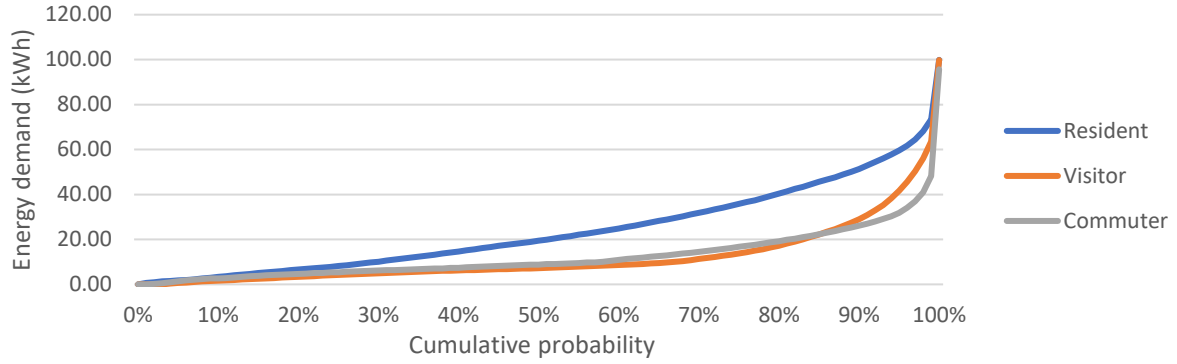


Figure 4.3: CDF for the energy demand of a charging session, as acquired from ElaadNL (2020)

Charging power of a CP

To determine the charging duration from the energy demand, the average charging power of a CP is required. For this simulation, the average charging power of a public CP is estimated by Zwolle at 11 kW/h (M. Corée, personal communication, 2021).

Connection times

The parked duration of an EV equals the length of the connection time and is determined for each category of EV users. The CDF plot of the connection durations for the three EV categories are shown in Figure 4.4. In this figure, we can observe that 90% of commuter charging sessions take less than 10 hours and that 30% of resident charging sessions take less than 10 hours. These two observations correspond to the assumptions made by Sadeghianpourhamami, Refa, Strobbe & Develder (2018) in Section 3.2.2, stating that resident charging sessions take the longest and typically go overnight, whereas commuter session durations typically correspond to generic working times. This is also confirmed by the average connection durations, which for the resident, visitor and commuter categories take on average 12.0 hours, 8.1 hours, and 6.6 hours, respectively.

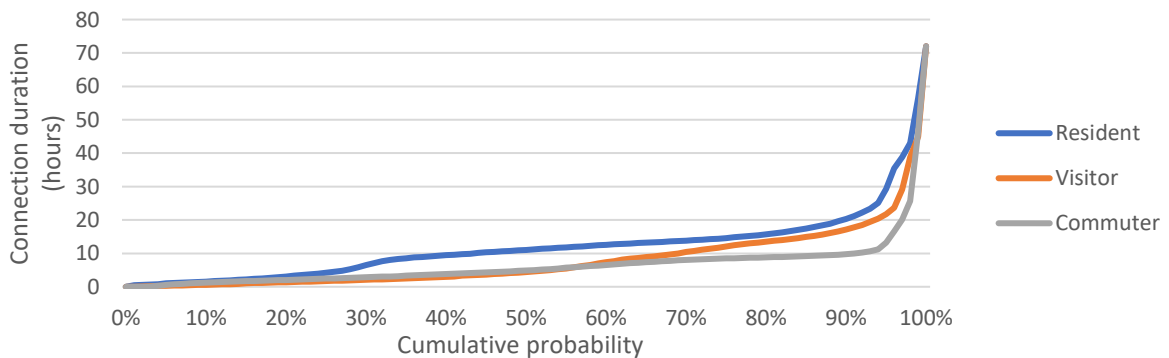


Figure 4.4: CDF for the connection duration of a charging session, as acquired from ElaadNL (2020)

4.3 Simulation structure

This section describes the main structure of our simulation approach. Our simulation approach always performs a separate iteration for each of the EV categories. Each of these three iterations follows the same simulation structure that is visualized in Figure 4.5.

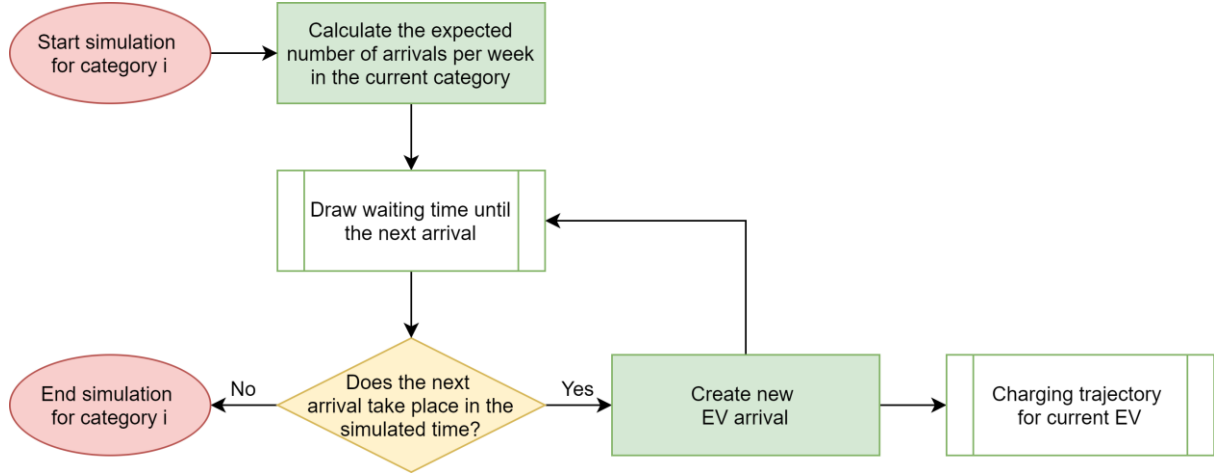


Figure 4.5: Visualization of the main simulation structure in our CP occupancy simulation approach

The first step for each simulation iteration is to calculate the expected number of the total arrivals per week for the current category. To calculate this value, the expected number of EVs $E[n_i]$ in the current category i is multiplied with the expected average charging sessions per EV per week in the current category μ_i , as shown in Equation 4.1.

$$E[s_i] = E[n_i] \cdot \mu_i \quad (4.1)$$

Where:

s_i is the number of weekly charging sessions in category i ,

n_i is the number of EVs in category i ,

μ_i is the mean number of weekly charging sessions per EV in category i .

When the expected number of sessions per week is determined, the simulation iteration of the current EV category starts. This is done by drawing a waiting time until an EV arrival is created, for which the method is described in Section 4.3.1. When an EV is created, it follows the charging trajectory that is described in Section 4.3.2 and a new waiting time is drawn before a new EV is created. This process continues until the simulated time has finished. Subsequently, the process is repeated for the next EV category. Once all categories are simulated, the simulation ends.

4.3.1 Method for determining the interarrival time

This section describes the structure of the procedure to determine the interarrival time. This method is visualized in the main simulation structure of Figure 4.5, by the box “Draw waiting time until the next arrival” and is called upon at the start of a simulation session and after each time an EV is generated. This method uses the data distributions on the arrivals per weekday (Figure 4.1) and the charging events over the day (Figures 4.2 and 4.3) discussed in Section 4.2.2. The structure of this method is visualized in Figure 4.6.

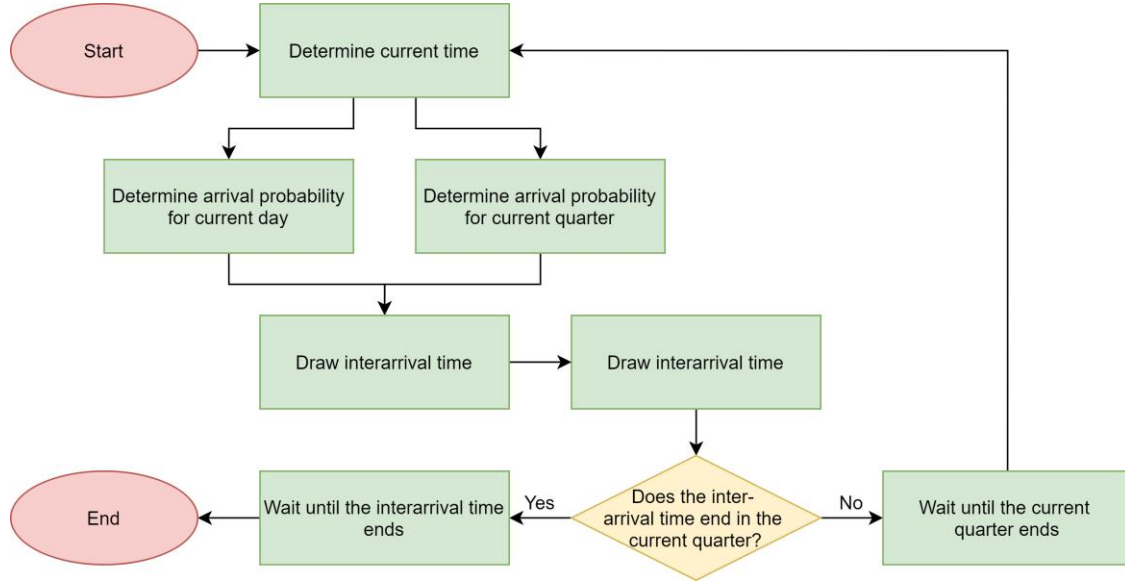


Figure 4.6: Visualization of the method for determining the interarrival time in our CP occupancy simulation approach.

When called upon, the method starts by determining the current time in the simulation. From this current time, the current day ({Monday, Tuesday, Wednesday, Thursday, Friday, Saturday, Sunday}) and the current day quarter ({0, 1, ..., 47}, corresponding to a 15-minute time interval {00:00-00:15, 00:15-00:30, ..., 23:45-00:00}) are determined. This current day and current day quarter serve as indices to draw from the data distributions described in Section 4.2.2. With these two values, the current arrival intensity $\lambda_{i,d,q}$ is calculated by multiplying the expected weekly sessions $E[s_i]$ (calculated by equation 4.1) with the mean fraction of sessions during the current weekday $p_{i,d}$ (drawn from the distribution in Figure 4.1) and the fraction of sessions during the current day quarter (drawn from the distribution in Figure 4.2), as shown in Equation 4.2.

$$\lambda_{i,d,q} = E[s_i] \cdot p_{i,d} \cdot p_{i,d,q} \quad (4.2)$$

Where:

$\lambda_{i,d,q}$ is the arrival intensity for category i , at day d , at quarter number q ,

$p_{i,d}$ is the average fraction of arrivals for category i , at day d ,

$p_{i,d,q}$ is the average fraction of arrivals for category i , at day d , at quarter number q ,

$E[s_i]$ is the same as in 4.1.

When the current arrival intensity is calculated, an interarrival time can be drawn. As described in Section 3.2.1, Li, Zhang & Wang (2018) showed that the arrivals of EVs can be approximated as a Poisson process, meaning that the interarrival time between two EV arrivals follows an exponential distribution. The interarrival time is therefore drawn from the probability density function shown in Equation 4.3, with the arrival intensity $\lambda_{i,d,q}$ calculated in the previous step.

$$f(x) = \lambda_{i,d,q} \cdot e^{-\lambda_{i,d,q} \cdot x}, x > 0 \quad (4.3)$$

After an interarrival time is drawn, it is checked if the interarrival time ends in the current quarter. If this is the case, the drawn interarrival time is the actual waiting time before a new EV is created. If this is not the case, we must assume that the arrival intensity and therefore the probability density function, changes in the next quarter. However, since the exponential distribution is a memoryless probability distribution, the distribution of the waiting time does not depend on the passed waiting time. Therefore, we can instead wait until the current quarter is over and when the current quarter has passed, ignore the remaining waiting time, return to the beginning of the procedure and draw a new interarrival time with the arrival intensity for that new quarter. This process is repeated, until an inter arrival time is drawn that ends in the current quarter. Once the interarrival time ends in that current quarter, the procedure finishes and either a new EV is generated or the current experiment ends.

4.3.2 Charging trajectory of a generated EV

This section describes the structure of the charging trajectory of an EV in our simulation. This trajectory is visualized in the main simulation structure of Figure 4.5, by the box “charging trajectory for current EV” and is called upon each time an EV is generated in the main simulation structure. This trajectory uses the data distributions on the energy demand and the connection times discussed in Section 4.2.2. The structure of this trajectory is visualized in Figure 4.7.

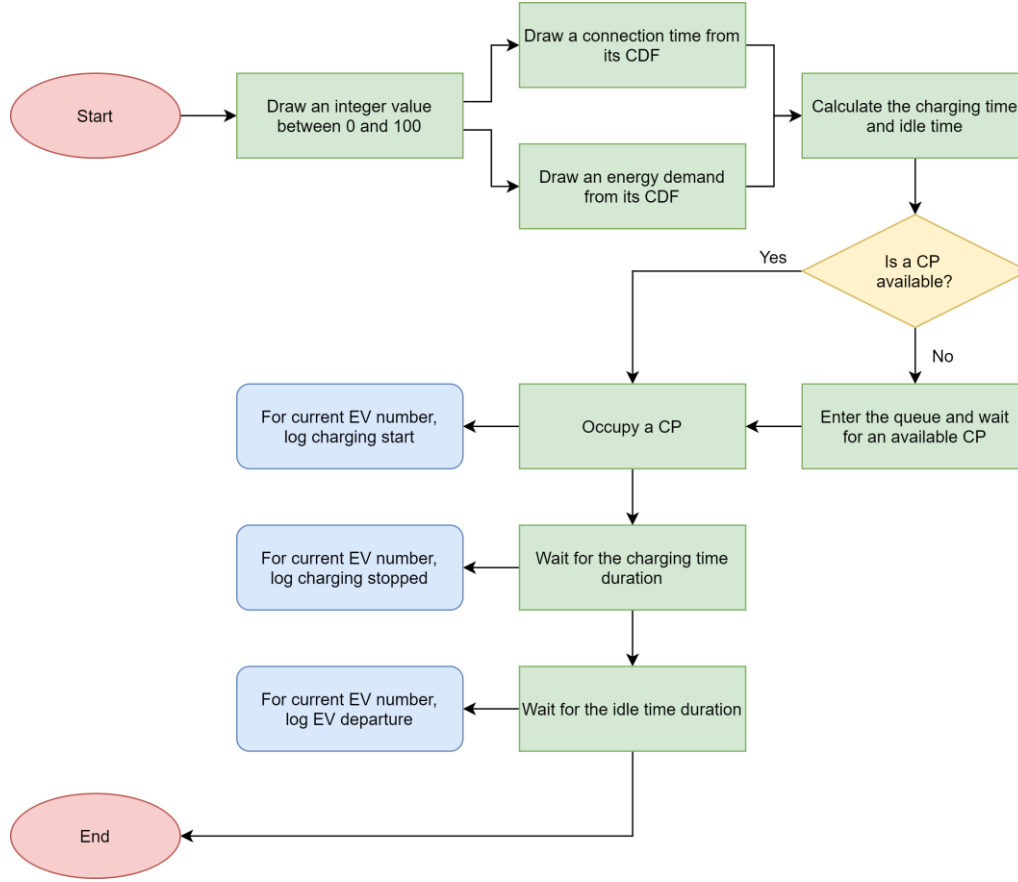


Figure 4.7: Visualization of the EV charging trajectory in our CP occupancy simulation approach.

At the start of this process, the connection time (from the distribution in Figure 4.4) and the energy demand (from the distribution in Figure 4.3) for an EV are drawn, in which we assume that this connection time is equal to the parked time.

From the drawn energy demand, the charging time is calculated. This is done by rewriting the method by Xie et al. (2018) in Section 3.2.2 into Equation 4.4. In this equation, the charging time of the n -th EV $t_{EV_n}^{\text{charging}}$ equals the drawn energy demand $d_{EV_n}^{\text{charging}}$ over the realized charging power (charging efficiency rate η_c multiplied by the charging power p_c)

$$t_{EV_n}^{\text{charging}} = \frac{d_{EV_n}^{\text{charging}}}{\eta_c \cdot p_c} \quad (4.4)$$

With the value for the connection time $t_{EV_n}^{\text{connected}}$ and the calculated value for the charging time $t_{EV_n}^{\text{charging}}$, the idle time $t_{EV_n}^{\text{idle}}$ is calculated by Equation 4.5, assuming the process in Section 2.1.1.

$$t_{EV_n}^{\text{idle}} = t_{EV_n}^{\text{connected}} - t_{EV_n}^{\text{charging}} \quad (4.5)$$

When drawing the value for the connection time and the energy demand for an EV, we must ensure that the calculated charging time, as determined from the drawn energy demand, does not exceed the connection time. However, we cannot simply redraw the connection time when the calculated charging time turns out to exceed the drawn connection time, since then the connection times in our simulation will no longer correspond to the empirical distributions. To make sure that the distributions in our model correspond to the empirical distributions from ElaadNL, whilst ensuring that the charging time does not exceed the connection time, we make the assumption that the distributions are strictly paired. This means that we assume that a value from the x -th percentile of one distribution, corresponds with a value from the x -th percentile of the other distribution. To incorporate this in our model, an integer value x is drawn from a uniform distribution between 0 and 100. This value x serves as an index value, for which the corresponding x -th percentile are selected from both the CDF of the connection time and the CDF of the energy demand.

After the charging time and idle time are initialized, it is checked if a CP is available. If this is the case, the current EV occupies that CP. If this is not the case, in reality the EV will come back after a short time to check if a CP has freed up. In our simulation, this is approximated by letting the EV enter a first-in-first-out (FIFO) queue. Once another EV finishes its charging session, the first EV in the queue immediately enters that CP. Therefore, there are never any free CPs in our model during peak hours with undercapacity. This is an optimal situation that is not likely to occur in the real world. In a real-world scenario, we expect a small ratio of unoccupied CPs during these peak hours. However, since we do not have the data to incorporate this effect in our simulation model, any inclusion of this in the simulation solely rely on assumptions, making the model more complex and not necessarily more reliable.

When an EV occupies a CP, the charging sessions starts and the charging-start time is logged. Immediately after, charging starts for the calculated charging time duration $t_{EV_n}^{charging}$. When the calculated charging time duration finishes, the charging-finished time is logged and the EV moves to an idle state, for the calculated idle time duration $t_{EV_n}^{idle}$. When the idle time duration finishes, the EV finishes its charging session, departs from the system and the departure time is logged.

4.4 Calculating the simulation results

This section describes how the results from our simulation approach are calculated and explains the chosen warmup period and the chosen number of replications for each experiment.

Required number of CPs

First the method for determining the required number of CPs and the corresponding peak number of CPs charging in a neighborhood are explained. To calculate the required number of public CPs in a neighborhood, the simulation model is used with infinite CPs such that each EV always has a CP available on arrival. Section 2.1 mentioned that public usage of the excess capacity from private CPs for commuters can decrease the required number of public CPs in a neighborhood. Therefore, the required CPs for this category are calculated as well. The required number of CPs is calculated as follows:

Section 4.3 three simulated event types (i.e., EV starts charging, EV stops charging, EV departs from CP). Each time one of these events occur, regardless of which EV triggers that event, two characteristics are logged for the current time in the simulated neighborhood:

- The number of CPs that are currently occupied by an EV in the simulated category. From this, the average number of occupied CPs per week hour is calculated for each category.
- The number of CPs that are currently actively charging an EV in the simulated category. From this, the average number of charging CPs per week hour is calculated for each category.

From the data on the number of CPs that are occupied over time, each average occupied number of CPs $\bar{C}_{i,n,t}$ is calculated for the three sets of categories $\hat{i}$, in current neighborhood n , during each week hour t . These three sets of categories $\hat{i}$ are as follows:

- 1.) The CP occupancy for public charging, calculated for the EV categories residents and visitors together.
- 2.) The CP occupancy for charging at work locations, calculated for only the EV category commuters.
- 3.) The CP occupancy for both public charging and charging at work locations, when excess charging capacity at work locations can be used for public charging, calculated for the EV categories residents, visitors, and commuter together.

Next, the required number of CPs $C_{i,n}$ is calculated according to the method of Utrecht. To do so, from each average number occupied of CPs $\bar{C}_{i,n,t}$ the peak value is selected. To this peak hour value, the average number of CPs that should remain unoccupied during the peak hour C^{rest} is added, as shown in Equation 4.6. In conformance with the method of Utrecht, C^{rest} is set to 3 CPs.

$$C_{i,n} = \max_{t \in \{1,2,\dots,168\}} \bar{C}_{i,n,t} + C^{rest} \quad (4.6)$$

Where:

$C_{i,n}$ is the number of CPs, required by EVs in the set of categories $\hat{i}$, in neighborhood n ,

$\bar{C}_{i,n,t}$ is the average number of CPs, occupied by EVs in the set of categories $\hat{i}$, in neighborhood n , at week hour t ,

C^{rest} is the average number of CPs that should remain unoccupied, at the peak hour.

From the data on the number of CPs that are actively charging over time, the mean number of charging CPs during the peak hour is determined. This is done by the same method used to calculate the required number of CPs in Equation 4.6. Only now the peak value is selected from the mean number of charging CPs per week hour, without adding a C^{rest} value. Translating this peak number of CPs charging to an actual power demand on the power grid and determining if this power demand exceeds the current power grid capacity is beyond the scope of this research.

Warmup period

Since our initial simulation always started with 0 CPs occupied, a warmup period is used before the data is logging such that the simulated neighborhood can reach a steady state and show a typical occupancy level from the start. To understand why a warmup period is required, the effect of having a warmup period on the number of occupied CPs by residents is shown in Figure 4.8. In this figure, two paired simulation sessions for the CP occupancy over time are shown, where simulation session 1 (Sim 1) has no warmup period and simulation session 2 (Sim 2) has a warmup period of 4 weeks. In Figure 4.8 we observe that after 3 days, there is no difference anymore between the number of CPs occupied with and without a warmup period. For the number of CPs charging, we no longer observe this difference after about half a day. From Figure 4.8 we conclude that a warmup period of 3 day is sufficient. For programming convenience however, instead a warmup period of 1 week is used.

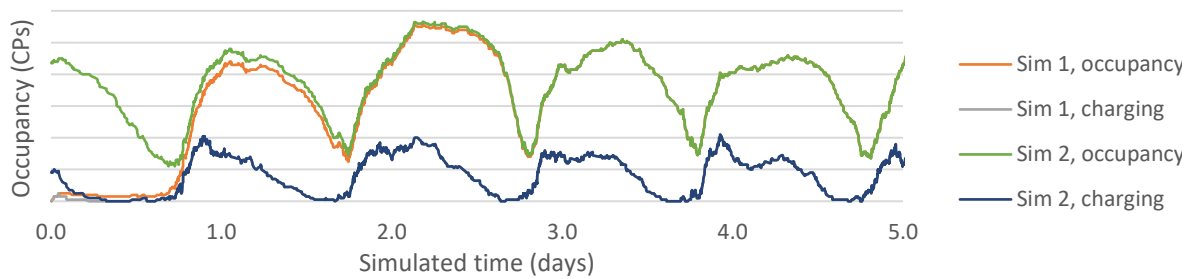


Figure 4.8: The effect of a warmup period, on the number of CPs occupied and charging over time.

Simulation replications

Since the results are prone for stochastic peaks, each simulation is replicated 1000 times, from which the average number of required CPs are calculated. This number of replications was chosen such that the 95% confidence interval (CI) for the mean number of required CPs has the same value for the upper and lower bound when rounded to whole numbers.

For each set of simulation results, a 95% CI of the spread of the simulated results was made. This 95% CI can be interpreted such that that 95% of the time, a simulation result is in this interval, as is visualized in Figure 4.9. In this figure, the 95%-CI is demarked by red lines, the blue dots are simulation results that are within this CI and the orange dots are outside this CI.

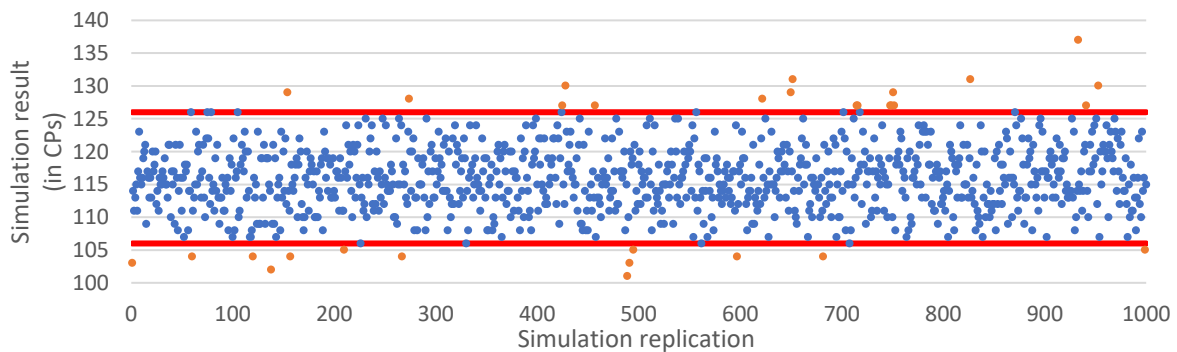


Figure 4.9: Example of a 95%-CI for the spread of the results of 1000 simulation replications

4.5 Experimental scenarios in the trajectory

Section 4.1 described three simulation objectives, of which the second and third objectives were formulated to experiment with the required number of CPs in a neighborhood. For these experiments, scenarios are used. First, to determine the effect of using a different number of CPs in a neighborhood, a scenario for a custom number of CPs in a neighborhood is used. Second, to determine the effect of a decreased idle time on the required number of CPs, two scenarios are used, namely a cap on the parked time and a cap on the idle time. For both caps, the effect on the required number of CPs is determined with the assumption that citizens fully comply with those caps. This section describes the simulation of the three scenarios in more detail.

Custom CPs Scenario

When simulating the effect of a custom number of CPs, an input number of CPs is used for each of the three categories of EV users (residents, visitors, and commuters) and queues are logged to indicate the shortages of those numbers of CPs. To test the performance of the input CP numbers a neighborhood, the peak shortage is determined for the same three sets of combined categories $\hat{i}$ as used in Section 4.4. The peak CP shortage $S_{i,n}$ in neighborhood n is determined by calculating the average CP shortage $\bar{S}_{i,n,t}$ per week hour t and selecting the peak number from these values, as shown in Equation 4.7.

$$S_{i,n} = \max_{t \in \{1,2,\dots,168\}} \bar{S}_{i,n,t} \quad (4.7)$$

Where:

$S_{i,n}$ is the shortage of CPs, required for the set of categories $\hat{i}$, in neighborhood n ,

$\bar{S}_{i,n,t}$ is the average number of EVs waiting for a CP, in the set of categories $\hat{i}$, in neighborhood n , in week hour t .

Capped parking time Scenario

When simulating a strict enforcement of a maximum to the parking time it is not always necessary or desirable to restrict parking times over the entire day (e.g., during nighttime). Therefore, a capped parking time is enforced over a part of the day. In case of a capped parking time, we cut off the parked time (as drawn from Figure 4.4) and the charging time (calculated as $t_{EV_n}^{charging}$ in Equation 4.4), when these pass the maximum cap during the enforced time. In this scenario, we assume that the enforcement of the capped parking duration is 100% complied with and no vehicles stay parked after this duration. To explain how this works, 6 possible situations in a neighborhood are visualized in Figure 4.10, with an enforced period from 8:00 to 20:00 hours and a maximum parking duration of 3 hours. These 6 charging sessions would normally have taken 6 hours.

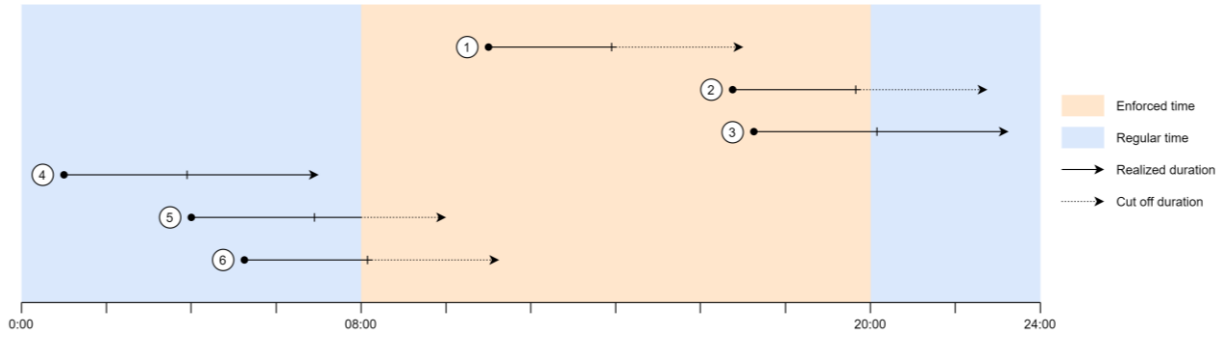


Figure 4.10: Visualization of six examples of sessions with a duration of 6 hours, with a maximum duration cap of 3 hours and an enforced time between 8:00 and 20:00 hours.

Session 1 starts during the enforced time and has both the normal duration and capped duration finish during the enforced time. In such a case, we cut off the duration at the capped time. Session 2 starts during the enforced time, has the normal duration finish outside the enforced time, but has the capped duration finished during the enforced time. In such a case, we cut off the duration at the capped time. Session 3 starts during the enforced time but has both the normal duration and capped duration finish outside the enforced time. In such a case, we do not cut off the duration early, letting the session complete the full charging duration. Session 4 starts outside the enforced time and has both the normal duration and capped duration finish outside the enforced time. In such a case, we do not cut off the duration early, letting the session complete the full charging duration. Session 5 starts outside the enforced time, has the normal duration finish outside the enforced time, but has the capped duration finished during the enforced time. In such a case, we cut off the duration at the start of the enforced time. Session 6 starts outside the enforced time but

has both the normal duration and capped duration finish during the enforced time. In such a case, we cut off the duration at the capped time.

The required number of CPs in a neighborhood with a capped session time is determined by the same method used for the required number of CPs in a regular neighborhood as explained Section 4.4. In case a cap on the parked time is used, it is possible that the LOS is cut off before the charging time has finished. This means that an EV must leave before charging has finished. Since we deem this undesirable, the number of sessions that were cut off during the charging time is logged as an additional output.

Capped idle time scenario

The third scenario simulates the results from a strict enforcement of a maximum idle time duration. This can be the result of tracking the time between the moment charging has finished and the EV is disconnected from a CP, penalizing people after a certain idle time duration. In case this scenario is simulated, the idle time duration is cut off when it passes the capped idle time limit. This is done similarly to the capped parking time scenario, for which we again assume that the enforcement of the capped idle time is 100% complied with and no vehicles stay parked after the capped idle time has passed.

4.6 Conclusions

This chapter answered the third set of research questions, namely:

3.) *How can we simulate for the required number of CPs in a neighborhood?*

- a. *Which relevant distributions and characteristics can we extract from the available data?*
- b. *How can we use the approaches from literature in our model?*
- c. *Which assumptions need to be made as a substitute for missing information?*

To answer sub question a, five publicly available distribution sets from ElaadNL were used. Three were used for determining the arrival intensity, namely one on the fraction of sessions over the days in a week, one on the intensity per 15 minutes over workdays, and one on the intensity per 15 minutes over weekend days. Two were used for determining the charging events, namely one on the charging time and one on the parked time during a session.

To answer sub question b, several approaches were used from the literature study from Chapter 3, either as a direct or indirect implementation. Examples of these direct implementations are the Poisson arrivals, as described by Li, Zhang & Wang (2018), a method to calculate the charging time from a specific energy demand, as described by Xie et al. (2018), and the three categories to work with (residents, visitors, commuters), as described by several papers. Examples of indirect implementations are the relation between the different arrival intensities over time and the typical lengths of charging sessions for each of the categories, as described by several papers.

To answer sub question c, three assumptions were made. The first is the assumption of the average number of weekly charging sessions per EV, for which we used the insights from the papers by Arias, Bae & Sungwoo (2016), Venegaz, Perez & Petit (2018) and Refa & Hubbers (2019). From these sources, we assumed the values shown in Table 4.1. The second assumption is a simplification, namely that of the queuing structure. We assume that, when all CPs are occupied, EVs enter a FIFO queue, in which the EV remains until a CP becomes available. Therefore, all CPs are always occupied when EVs are queued. In practice, we expect that some CPs remain unoccupied during these peak hours. However, since we do not have any data on this, we cannot incorporate this effect into our model. The third assumption is that the proposed caps on the LOS can be enforced 100% successfully, having no vehicles stay at a CP after the time cap. In practice, this would not be the case, but no empirical data is available on this.

5. Analysis of results

This chapter presents and analyzes the results from our simulation approach. Section 5.1 presents the prognosed number of CPs that result from our simulation approach and compares these results with the prognosed number of CPs by ElaadNL. Section 5.2 describes a sensitivity analysis performed on two assumptions, namely the mean number of weekly charging sessions per EV category and the realized mean charging power of the CPs. Section 5.3 describes the effect of three scenarios. First the effect of using a different number of required CPs in a neighborhood than calculated in Section 5.1, on the peak shortage of CP capacity. Second and third, the effect of using an enforced cap for the parked time and the idle time on the required number of CPs. Section 5.4 concludes this chapter by answering the fourth set of research questions:

4.) *What conclusions can we draw from the results?*

- a. *How does our simulation approach perform, compared to the predictions by ElaadNL?*
- b. *How sensitive is our simulation approach to the assumptions in our model?*
- c. *What is the effect of alternative scenarios on the performance of our simulated setup?*

5.1 Simulation performance and results

This section elaborates on the first simulation objective formulated in Section 4.1, by describing the results from our simulation model. To do this, the numbers of the three categories EV users in residential areas are used, as prognosed by ElaadNL. Section 5.1.1 discusses the results from our simulation approach in general. Section 5.1.2 describes our simulation results in detail for the neighborhood Berkum and compares those with the prognosed numbers of CPs by ElaadNL.

5.1.1 Simulation results

This section briefly address two generic observations from our results, before discussing the results in more detail. The full overview of the prognosed numbers by ElaadNL and our own simulation results can be found in Appendix A.

First, in the neighborhoods that have a number of predicted EVs below 10, our simulation model strongly overpredicts the number of required CPs. This is caused by the method used, since a low number of EVs is more prone for stochastic peaks. Additionally, our approach determines the required number of CPs such that there are on average at least 3 free CPs during the peak hour, regardless of the number of CPs that are situated in that area.

Second, strange irregularities occur in the prognosed number of public CPs per neighborhood by ElaadNL. For instance, the southern city center has a low number of prognosed residents and visitors, but a high number of prognosed CPs for these categories in the prognosis chart by ElaadNL. When comparing our results with those of ElaadNL, large deviations occur for this type of neighborhoods. These differences cannot be explained by the information currently available.

5.1.2 Simulation results for Berkum

To look at our results in more detail, the remainder of this chapter is based on the numbers for the neighborhood Berkum. Berkum is used since this is a neighborhood with the most average number of EV users in each category, compared to the other neighborhoods in Zwolle in Appendix A. Table 5.1 shows the predicted number of CPs for each category of EV users in each of the 3 prognosed years.

Table 5.1: Prognosed number of CPs in Berkum, Zwolle, in the prognosis chart of ElaadNL (2020)

	<i>Residents using public CPs</i>	<i>Weekly visitors using public CPs</i>	<i>Commuters using private CPs</i>
2025	105	28	182
2030	197	52	356
2035	344	115	654

The remainder of this section describes the results in two parts. The first part discusses the required number of CPs that are presented in Table 5.2. The second part discusses the peak number of active CPs, as observed in our simulated data, to indicate the expected load on the power grid. These results are shown in Table 5.3.

Demand for public CPs in Berkum

For the three groups of EV categories described in Section 4.4, the prognosed number of CPs by ElaadNL, the average required number of CPs in our results, and the intervals of the required number of CPs in our results are shown in Table 5.2. When regarding these results, we make two observations.

Table 5.2: Required number of CPs in the prognosis chart of ElaadNL (2020) and in three results of our simulation model, in Berkum, Zwolle.

<i>Year</i>	<i>Category</i>	<i>ElaadNL</i>	<i>Mean result</i>	<i>Interval of results</i>
2025	Residents and visitors	33	38	[33, 43]
	Commuters	36	36	[31, 40]
	Residents, visitors, and commuters	-	52	[46, 58]
2030	Residents and visitors	62	67	[60, 74]
	Commuters	71	67	[61, 74]
	Residents, visitors, and commuters	-	96	[88, 105]
2035	Residents, visitors	137	116	[106, 126]
	Commuters	130	122	[113, 131]
	Residents, visitors, and commuters	-	172	[161, 183]

First, when comparing “residents and visitors” and to a lesser degree the “commuters”, we observe an interesting trend. For the 2025 scenario we predict a larger number of CPs (approximately 12%) and for the 2035 scenario we predict a smaller number of CPs (approximately -14%) than ElaadNL. To explain these differences, we should look at the main difference between our modelling approach and the approach by ElaadNL, as discussed in Section 2.3. In our approach, the number of CPs is determined by the peak CP occupancy in a stochastic simulation approach, whereas ElaadNL uses a deterministic regression approach, that uses a multitude of linear functions. This means that in our approach, lower quantities are more volatile for accidental peaks than larger quantities, especially compared to the results from linear regression. In our approach, this volatility for stochasticity gets lower as the population size increases. Therefore, both in the real world and in our simulation model, we expect a relatively larger number of required CPs per EV in neighborhoods with a smaller number of EVs compared to neighborhoods with a larger number of EVs. In contrast, using linear regression could result in an underprediction of the number of required CPs in neighborhoods with a smaller number of EV users and an overprediction in neighborhoods with a larger number of EV users. Since the method by ElaadNL is not publicly available we cannot validate this explanation. However, Section 2.3 described an early publication of the method by ElaadNL in which a multiple regression analysis was used. Since EV charging is a stochastic process, the methodological differences may indicate a more realistic “real world” prognosis from our simulation approach, compared to a multiple regression analysis by ElaadNL.

Second, when the excess capacity of private CPs at work locations can be used as public CPs, we observe this reduces the required number of public CPs by a fourth in each of the simulated years compared to simply adding the private CPs at work locations to the public CPs. To better understand the peak hour of occupied CPs, we look at the stacked bar chart for the average occupancy per week hour for the three categories of EV users in Figure 5.1. This figure shows that the peaks of the workplace CP occupancy correspond to the troughs of the public CP occupancy.

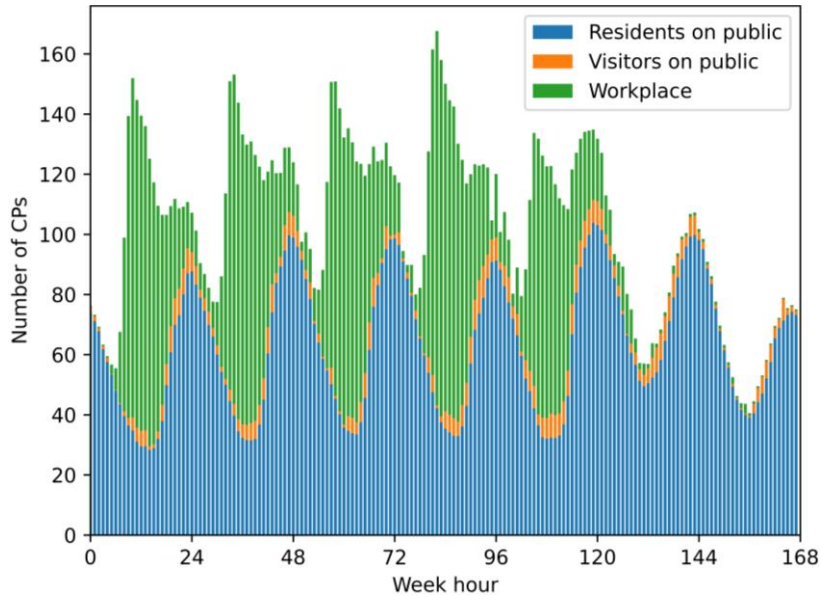


Figure 5.1: Average number of occupied CPs per week hour, over 4 weeks of data, for the scenario of 2035 in Berkum, Zwolle

Peak hour demand of the power grid

The average peak hour demand of the power grid is shown in Table 5.3. These results cannot be compared to ElaadNL data, since ElaadNL does not have any prognoses related to the power grid. When comparing these values to their corresponding peak number of occupied CPs in Table 5.2, we observe that during each peak hour about one third of the occupied CPs are actually charging.

Table 5.3: Peak number of CPs charging simultaneously in three results of our simulation model, in Berkum, Zwolle.

Year	Category	Mean result	Interval of results	# CPs charging over # CPs occupied
2025	Residents and visitors	13	[10, 15]	33.6%
	Residents, visitors, and commuters	16	[14, 19]	31.3%
2030	Residents and visitors	23	[19, 26]	33.7%
	Residents, visitors, and commuters	30	[27, 34]	31.5%
2035	Residents and visitors	39	[34, 43]	33.3%
	Residents, visitors, and commuters	55	[50, 59]	31.7%

Translating the peak numbers of CPs in Table 5.2 to an actual power demand on the power grid and determining if this power demand exceeds the current power grid capacity is beyond the scope of this research.

5.2 Sensitivity analysis on the assumptions

Two values for our simulation had to be assumed, since no data was available on these values. The first of the two estimated values are the average number of weekly sessions per EV, for which the assumed values were determined from the literature explained in Section 4.2.1. The second is the realized charging power, for which an estimation by Zwolle was used. This section describes a sensitivity to measure the effect of errors in the assumed values, on the required number of CPs in a neighborhood presented in Section 5.1.

To flatten outliers in the analysis results due to stochasticity while keeping the simulation time at feasible levels, each experiment in the sensitivity analysis is performed 100 times. The sensitivity analysis uses the average values of those 100 simulation sessions.

The remainder of this section discusses the sensitivity analysis for public charging (only regarding the EV categories residents and visitors) in two parts. The first part describes the effect of the charging power and the number of weekly sessions, on the peak number of occupied CPs. The second part describes the same effect on the peak number of CPs charging.

Sensitivity of the peak CP occupancy

To understand the effect of the charging power per CP and the weekly sessions per EV on the peak CP occupancy, its sensitivity analysis is visualized in Figure 5.2. From this figure, we make two observations. First, we observe that changes in the charging power do not affect the number of occupied CPs. This is caused by how we calculate the length of stay at a CP, for which the time is drawn from an empirical distribution, as discussed in Section 4.3. Therefore, the charging power is most of the time not a factor when determining the occupancy and uncertainties in the charging power therefore do not affect the peak number of occupied CPs in our model.

Second, we observe that changes in the number of sessions per EV affect the peak CP value by the same percentage. This is in line with our expectations, since all the session arrivals are distributed by the same probabilities over time. From this, we expect that percentual difference of the total sessions affect the number of arrivals in a timeslot by the same percentage. Since the length of stay

is not affected by the number of weekly sessions, the occupancy of CPs is only affected by the number of arrivals. From this, we reason that the percentual difference of the total sessions affect the peak occupancy by the same percentage.

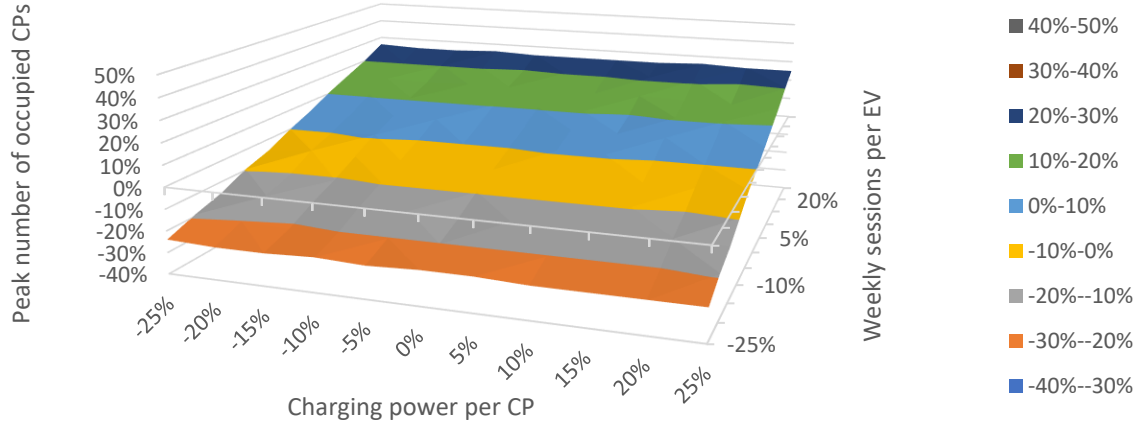


Figure 5.2: The effect of the number of sessions and the estimated charging power on the peak number of CPs occupied.

To help interpreting Figure 5.2, an arbitrary example is given: when the mean charging power increases by 10% (either by misprediction or technological developments) and the mean number of weekly sessions of an EV decreases by 10%, the peak number of occupied CPs decreases by 10%. An overview of all individual values in this figure are shown in Appendix B.

Sensitivity of the peak number of CPs charging

To understand the effect of the charging power per CP and the weekly sessions per EV on the peak number of CPs charging, its sensitivity analysis is visualized in Figure 5.3. From this figure we make three observations. First, we observe that changes in power directly affect the number of charging CPs. This is expected, since the charged time is calculated by dividing the power charged during a charging session (as drawn from data) over the realized charging power of a CP, as explained in Section 4.3.

Second, the percentual change in the number of sessions per EV affect the peak number of CPs charging negatively by the same percentage, as shown in Table 5.4. Of the two factors in Figure 5.3, the charging power has a smaller influence on the peak number of charging CPs than the number of weekly sessions. The influence of the charging power decreases further as the charging power decreases, as shown in Table 5.4. We can explain this with the arrival peak of public EVs that we saw in the data analysis of Section 4.2.2. We reason that a longer charging time leads to EVs with an earlier arrival time still charging during the peak hour. However, since the arrival rate

decreases as we move further from the peak, the number of extra EVs that are still charging during the peak hour due to an increased charging duration also decreases. This results in a smaller increase of the peak number of CPs charging for an increased charging power.

Third, the effect of the two factors on the peak number of CPs charging influence each other. The effect of both factors together can be determined from the multiplication of the effects of the individual factors that are shown in Table 5.4.

Table 5.4: Individual effects of the number of sessions and the estimated charging power, on the peak number of CPs charging

Effect of factor		25%	20%	15%	10%	5%	0%	-5%	-10%	-15%	-20%	-25%
Effect on peak	Weekly sessions	-25%	-20%	-15%	-10%	-5%	0%	5%	10%	15%	20%	25%
# CPs charging by	Charging power	23%	18%	13%	9%	4%	0%	-3%	-7%	-10%	-13%	-16%

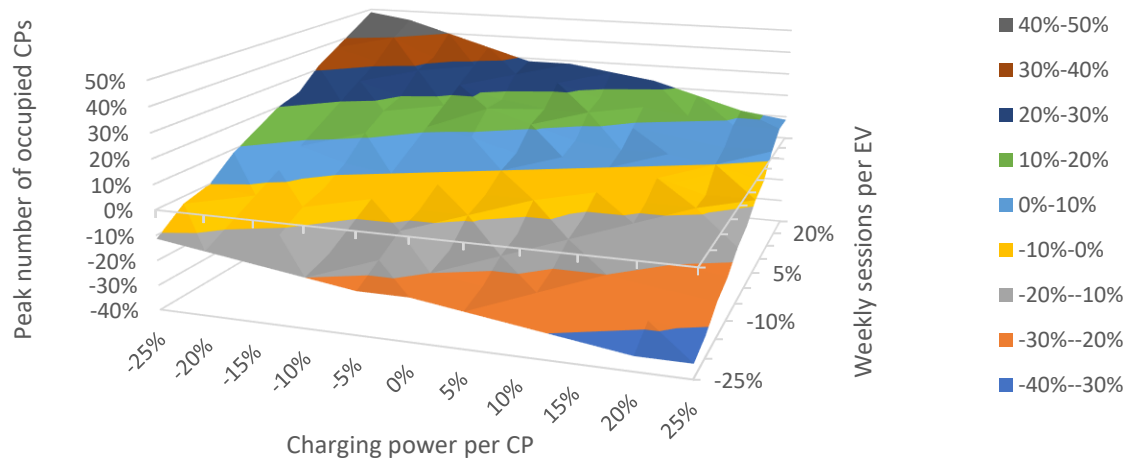


Figure 5.3: The effect of the number of sessions and the estimated charging power on the peak number of CPs charging.

To help interpreting Figure 5.3, an arbitrary example is given: when the mean charging power increases by 10% (either by misprediction or technological developments) and the mean number of weekly sessions of an EV decreases by 10%, the peak number of occupied CPs decreases by 14%. An overview of all individual values in this figure are shown in Appendix B.

5.3 Results of alternative scenarios

This section elaborates on the second and third simulation objectives formulated in Section 4.1, by describing the effect of three scenarios that were introduced in Section 4.1. Section 5.3.1 describes the effect on the peak shortage when deviating from the required number of CPs, as calculated in Section 5.1. Section 5.3.2 describes the effect on the required number of CPs when enforcing a cap on the parked time and the idle time, for which the method is explained in Section 4.5.

5.3.1 Finite resources

This section discusses the effect of deviating from the calculated required number of public CPs on the peak shortage of CPs. This is done for Berkum, using the expected numbers of public EVs (only regarding the EV categories residents and visitors) for the year 2035 and the corresponding calculated number of 116 required CPs. The results are shown in Figure 5.4, where the CP shortages and the realized number of CPs are shown relative to the required number of 116 CPs.

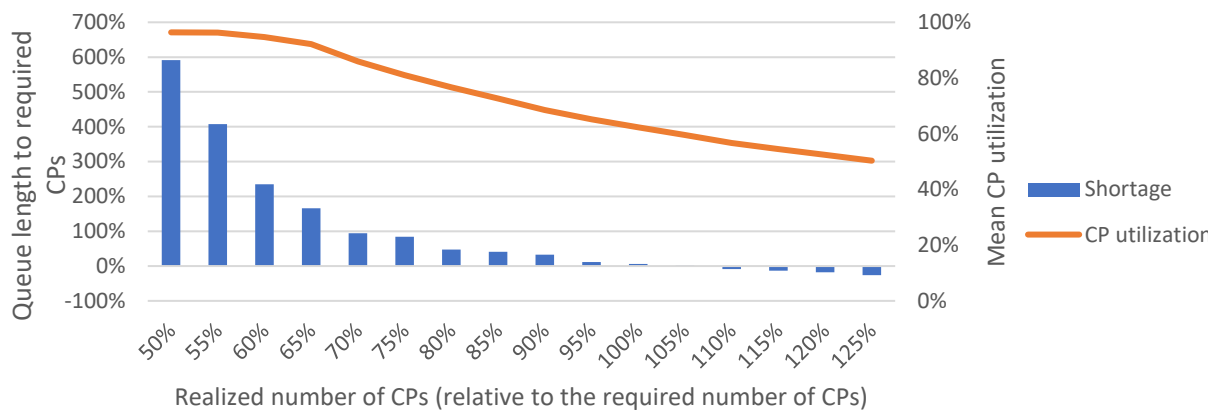


Figure 5.4a: Peak CP shortage for a realized number of CPs (relative to the required number of CPs) and the mean CP utilization

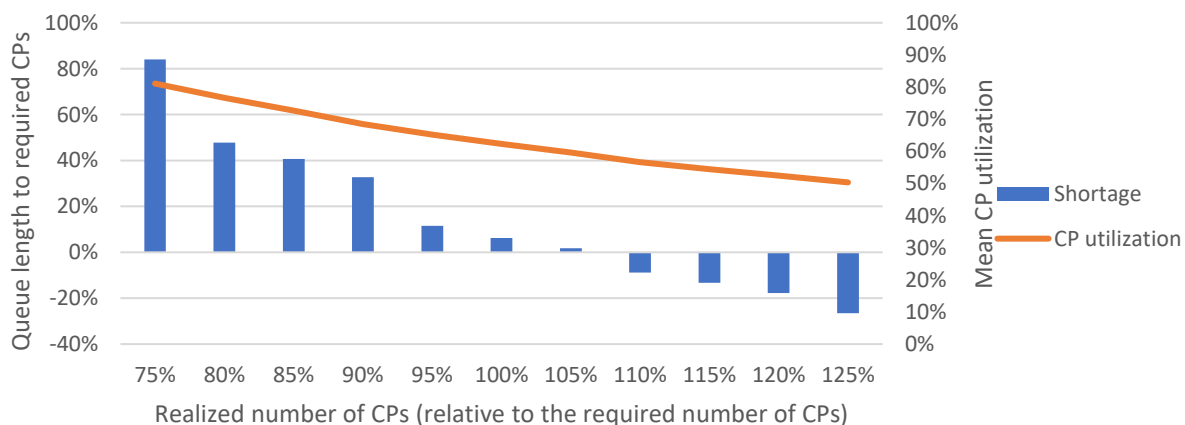


Figure 5.4b: Peak CP shortage for a realized number of CPs (relative to the required number of CPs) and the mean CP utilization

From Figure 5.4 we make three observations. First, in Figure 5.4a we observe that the shortage increases exponentially as the number of CPs decreases. Beforehand, we might have expected that the shortage would increase linearly by the same number as the total number of CPs is decreased. However, when an EV arrives and cannot occupy a CP, that EV must wait for the duration of the shortest remaining LOS. When a second EV arrives, that EV must wait for the duration of the second shortest remaining LOS, etc. This waiting time increases the initial LOS of the waiting EV. This results in a bottleneck effect in the system, where the arrival rate of EVs is larger than the departure rate and the departure rate depends on the number of CPs. When the realized number of CPs are below 95%, the bottleneck results in exponentially growing peak queue lengths. When this bottleneck duration becomes too long and a queue length does not structurally reset (by having no waiting EVs somewhere over the span of a day), the system becomes unstable, resulting in ever increasing queue lengths that equal the entire EV population size of a neighborhood.

Second, in Figure 5.4b we observe a shortage when taking 100% of the calculated number of CPs. However, since we calculate the number of required CPs based on the mean peak occupancy, small shortages may still occur that get amplified by the effect that we discussed in the previous observation. When we look at the average occupancy per hour that we saw earlier in Figure 5.1, we can confirm that these shortages are incidental. In case we want to decrease these shortages further, we can pick a higher value for the number of CPs that should remain unoccupied during peak hour (depicted by C^{rest} in Equation 4.9 of Section 4.4) at the cost of a lower utilization level.

Third, Figure 5.4 shows that for the results with stable shortages (with a realized number of CPs that is 95% or larger), the utilization decreases linearly with an increased number of realized CPs. Over the interval of Figure 5.4b, the utilization decreases on average by 3%, as the total number of CPs is increased by 5%.

From these three points we conclude that even though small shortages in the peak hour do not disrupt the availability of CPs too much, deliberate shortages should be limited as much as possible, since the negative effect of larger CP shortages is much greater than the negative effect of CP excesses.

5.3.2 Capped connection times

This section describes the effect of a decreased idle time on the required CPs in Berkum. Two options were introduced in Section 4.1 and 4.4 to decrease the idle time. These are a maximum allowed parked time duration and a maximum allowed idle time duration. Both are simulated with an enforced time between 08:00 and 22:00 hours, meaning that EVs with sessions that end during nighttime (22:00-08:00) should be removed from the CP before 8:00, as explained in Section 4.5.

Capped parked times

The first option to decrease the idle time, namely the maximum allowed parked time duration at a CP, is the most traditional and therefore easier to enforce. When enforcing a cap on the parked time, we want to shorten the LOS as much as possible. However, when the allowed LOS is too short, we start cutting of the charging time, making EVs leave before charging has finished. To show this effect, we also plot the total number of charging sessions that were stopped early over the simulated time of 4 weeks. The effect of a capped parked time on the peak hour occupancy is visualized in Figure 5.5. This figure shows the parked time cap relative to the observed mean parked duration in our simulation results, namely 12 hours.

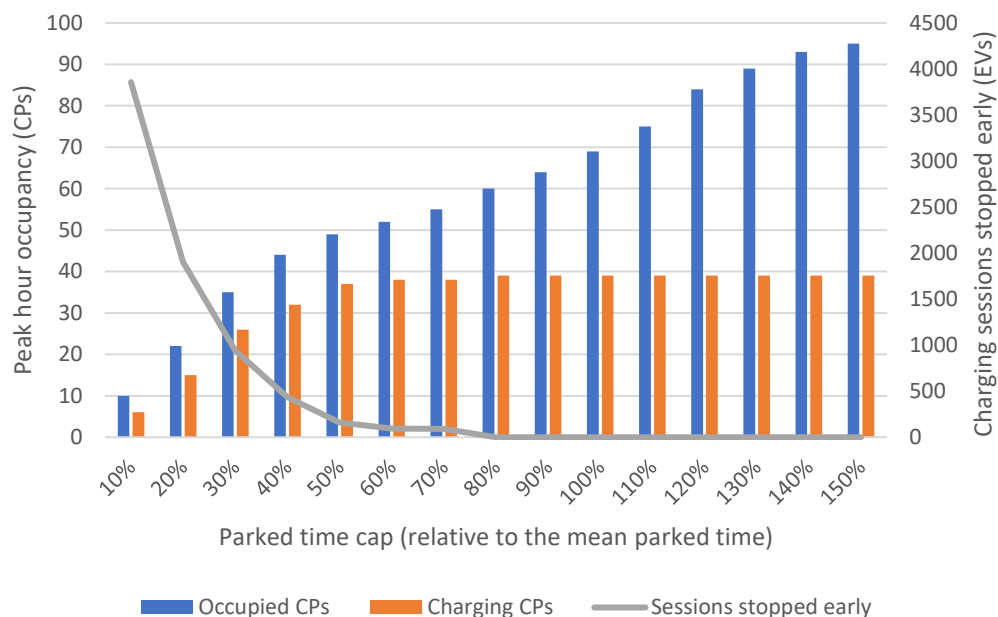


Figure 5.5: Required number of CPs and the number of charging sessions stopped early when using a cap on the parked time (relative to the mean parked time)

When regarding the results, we observe that enforcing a cap on the parked time has a significant influence on the total number of CPs required. However, we also observe that an enforced cap that is lower than 80% of the mean parked time results in early stopped charging sessions and a decreased mean number of CPs charging. Since this is a negative effect, we conclude that we should not enforce a cap on the parked time that is lower than 80% of the current mean parked time. This means that we should not handle a cap that is lower than 9.6 hours, at which level the required number of CPs is decreased from 113 to 60 (decreasing 47%).

Capped idle times

The second option to decrease the idle time, namely a maximum allowed idle time duration, requires more advanced technology. This option requires the EV owner to know when the EV has stopped charging and a method to specifically track the idle time. However, since both technologies are currently available on the market, we can realistically look at the effect on the required number of CPs when enforcing a cap on the connection time. The effect of a capped idle time on the peak hour occupancy is visualized in Figure 5.6. This figure shows the idle time cap relative to the observed mean idle time in our simulation results, namely 10 hours.

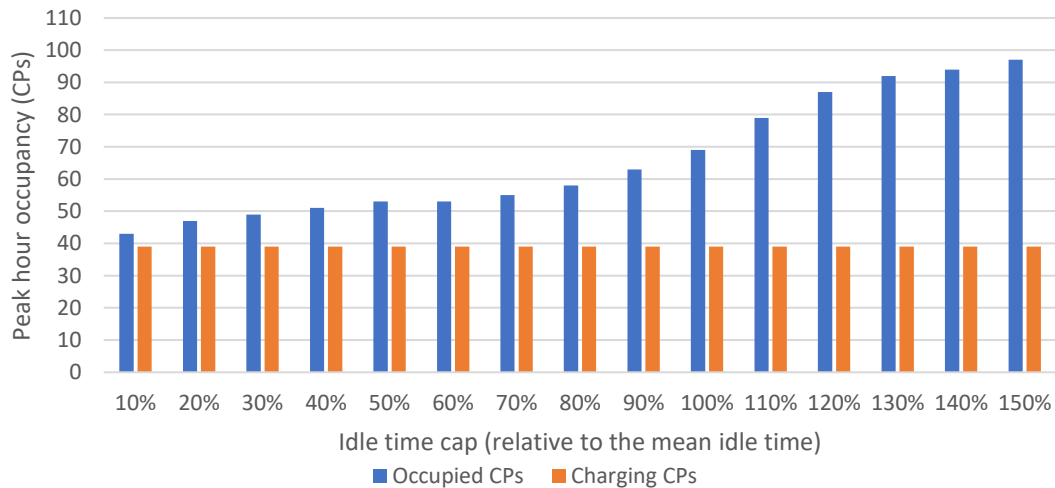


Figure 5.6: Required number of CPs when using a cap on the idle time (relative to the mean idle time).

When regarding the results, we observe that enforcing a cap on the idle time has a significant influence on the total number of CPs required, without having the negative effects of the lower cap durations that we saw with the capped parked times. For a capped idle time however, it is less transparent for the EV user to know when the cap is reached compared to a cap on the parked time, since the total cap is now dependent on the at forehand unknown charging time.

5.4 Conclusions

This chapter answered our fourth set of research questions, namely:

4.) *What conclusions can we draw from the results?*

- a. *How does our simulation approach perform, compared to the predictions by ElaadNL?*
- b. *How sensitive is our simulation approach to the assumptions in our model?*
- c. *What is the effect of alternative scenarios on the performance of our simulated setup?*

To answer sub question a, we concluded that the number of required CPs that we calculate are close to those calculated by ElaadNL. In our results for Berkum, we predicted more CPs in 2025 and fewer CPs in 2035 compared to the predictions by ElaadNL. We explained this by the different methods that were used. When the excess capacity of private CPs at work locations can be used as public CPs, we concluded that the required number of public CPs can be reduced by a fourth.

To answer sub question b, we concluded from the sensitivity analysis on the realized charging power per CP and the number of weekly charging sessions per EV that only the latter influenced our results on the required number of CPs. This number of required number of CPs was affected by the same percentage as the prediction error of the weekly charging sessions per EV. The peak number of CPs charging was affected by both assumed factors, making it more volatile to errors.

To answer sub question c, we tested the effect of three scenarios. The first scenario tested the effect of deliberate shortages to the number of required CPs. We conclude that these shortages should be limited, since the peak EV queue length increases exponentially to the CP shortage in a neighborhood when less than 95% of the required number of public CPs are realized. Second and third, we tested a cap on either the parked time or on the idle time between 08:00 and 22:00 hours. A cap on the idle time works most effectively, since it cannot break off a charging session before the battery is full, which can happen for a cap on the parked time. When disregarding the cap values that affect the charging time, a parked time cap can decrease the required CPs by up to 47% at a cap of 9.6 hours. An idle time cap can go as far as 0 hours, decreasing the required CPs by up to 61%.

6. Conclusions and recommendations

This chapter concludes this thesis in three parts. Section 6.1 summarizes the most important conclusions of our research, by answering our research question. Section 6.2 discusses the strengths and limitations of our research. Section 6.3 describes our final recommendations for further research and for implementations.

6.1 Conclusions

This thesis supported Zwolle in anticipating proactively on the required charging capacity for the expected EV growth in its municipality. This was done by proposing and developing a simulation approach as our answer to our main research question in Chapter 1:

“How can we model the charging sessions that take place in a neighborhood, to predict the required number of public CPs in that neighborhood?”

A simulation model generated the charging sessions of three categories of EV users in a neighborhood (residents, visitors, and commuters), by using publicly available data distributions. Three sets of distributions were used to simulate the arrival intensities over time (fractions of sessions over the seven weekdays, arrival probabilities for Mondays-Fridays, and arrival probabilities for Saturdays-Sundays) and two sets of distributions were used to determine the LOS of EVs (power charged and connected times). A method developed by the municipality of Utrecht was used in this simulation model to calculate the required number of CPs in a neighborhood. This value was determined by the average occupancy rate of CPs during the peak hour.

The simulation approach was used for three objectives. As first objective, our simulation model was used to predict the required number of public CPs in each neighborhood and the peak number of public CPs charging for three prognosed years (2025, 2030 and 2035), that are shown in Appendix A. In our results we saw that about one third of the peak number of occupied public CPs are actually charging during this peak hour. When the excess charging capacity of private CPs at work locations was utilized as public charging capacity, the required number of public CPs was reduced by a fourth. When comparing our results for neighborhoods in Zwolle with the prognosed numbers by ElaadNL, we observed that our results predict a lower EV/CP ratio for the 2025 prognosis and a higher EV/CP ratio for the 2035 prognosis. These differences were explained by the different methods used to determine the required number of CPs.

As second objective, the simulation model was used to predict the shortage when a neighborhood has fewer CPs than required. We concluded that these shortages should be limited, since the peak EV queue length increased exponentially to the CP shortage in a neighborhood, when less than 95% of the required number of public CPs were realized.

As third objective, the simulation model was used to predict the effect of a decreased idle time on the required number of CPs in a neighborhood. To decrease the idle time, two measures were simulated. The first was a cap on the parked time and the second was a cap on the idle time directly. When comparing the two, the cap on the parked time is easier to implement than a cap on the idle time and can reduce the required number of CPs in a neighborhood by up to 47% before charging durations start getting cut off. A cap on the idle time is less transparent for the user but does not share the issue of cutting off charging durations, potentially reducing of the required number of CPs in a neighborhood by up to 61%.

6.2 Discussion

In this research, a recurring problem was the availability of data. Even though data distributions were used that were drawn from large populations, several assumptions had to be made that could not be substantiated with data. This section addresses the four most important assumptions and simplifications made in this research.

First, no data was available to us on the number of sessions per EV per week, or the realized charging power of a CP. For both, different studies were used to make assumptions on these values. However, these assumptions could not be validated.

Second, the charging time and idle time are drawn paired in our model, to ensure that the charging sessions in our data follow the underlying data distributions. This meant that EVs that charged the most power, also stayed the longest and therefore had the largest idle times. In practice, this is not necessarily the case and for an individual EV session not a realistic representation of reality. However, since the populations for which the model was used are sufficiently large, this simplification does not affect the outcomes of our model significantly.

Third, several articles in literature described a relation between the arrival time and the LOS of an EV. Since only one distribution for the power charged and one on the connected times for the entire day were available, this effect could not be implemented in our simulation model.

Fourth, the prognosed numbers of CPs in the future were estimated by data distributions that were drawn from the currently available empirical data, disregarding future (technological) developments that may have an influence on this process. In reality we expect future developments that will have an influence on the current data distributions, such as changes to batteries (e.g., battery capacity, battery charging speed), charging behavior (e.g., shifting charging location, changes in charged quantities) or innovations in alternative fuel substitutes (e.g., hydrogen, biofuels). Since we cannot estimate the future effects of these innovations, these effects were disregarded in this research.

Despite of these assumptions, we are confident about our results. We saw that our results are close to those of ElaadNL, for the neighborhoods with at least 20 prognosed EV users. However, compared to the predictions of ElaadNL, we tend to predict an increasingly lower number of EVs per CP for lower quantities of EVs (<200) and a larger number of EVs per CP for larger quantities of EVs in a neighborhood (>300). These observed deviations can be explained by comparing our approach with the theory behind the approach by ElaadNL, who in an early publication on their model used a multiple regression-analysis on a number of variables. However, since the currently used approach by ElaadNL is not publicly available, their results cannot be explained in detail. In contrast, our approach is fully transparent and our solutions can be visualized with graphs and be experimented on. Therefore, we are confident in the relevance of the outcomes of our simulation approach.

6.3 Recommendations

Two recommendations are made for improvements to the model presented in this thesis, which we already introduced in the discussion:

First, we recommend implementing a relation between the arrival time and the LOS. This is the most important recommendation for improving our simulation approach, by which the generated data can become more realistic.

Second, we recommend improving the method used for drawing the charging time and the idle time. This does not necessarily improve the model on the scale that it is currently used for but makes individual simulated charging sessions more realistic when the model should be used for other purposes.

Furthermore, three recommendations are made for implementations:

First, we recommend using the calculated CP values as a realistic indication for the CP quantities that are required in 2025, 2030 and 2035. However, since the data is based on historic data, Zwolle needs to stay alert for technological developments that may affect the charging behavior of EVs. One way to do this, is to repeat the experiments when the underlying data distributions can be updated with more recent data.

Second, we recommend looking into the results for each neighborhood in detail, to value the simulation results for each neighborhood differently. For the neighborhoods with larger expected numbers of EV users, the outcomes in our model can be used as a good predictor for the required quantity of CPs. For these neighborhoods we recommend placing at least 95% of the prognosed CPs proactively, to limit the critical shortages as much as possible. For the remainder of the required CPs and for the CPs in neighborhoods with smaller expected numbers of EVs, the outcomes should be regarded as an indication for which candidate locations should be anticipated, but for which the CPs can be placed reactively.

Third, we recommend utilizing the excess charging capacity of private CPs at work locations for public charging and implementing either a parked time cap or an idle time cap, since we demonstrated that these measures lower the required number of CPs significantly.

Lastly, two recommendations are made for further research:

First, in this thesis we proposed a method to determine the required number of CPs in a neighborhood. However, determining *where* in that neighborhood these CPs should be realized was beyond the scope of this research. This is a relevant problem for Zwolle on which we recommend further research.

Second, in this thesis we determined the peak number of CPs charging simultaneously in a neighborhood as an indicator for the demand from the power grid. However, determining the actual power demand from the power grid and determining whether this demand requires alterations to the current power grid required a lot more work and were therefore also beyond the scope of this research. Determining the load on the grid heavily depends on the positioning of the required CPs in a neighborhood. This makes it a relevant problem for Zwolle, on which we recommend further research after the previous recommended research is finished.

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Appendices

Appendix A: Prognoses and simulation results per neighborhood

Table A1: Prognosis and results for 2025

CBS-buurtnaam	Prognosed EVs			ElaadNL		Simulation			Difference		Peak charging	
	residents	visitors	commuters	residents+visitors	commuters	residents+visitors	commuters	all	residents+visitors	commuters	residents+visitors	all
Binnenstad-Zuid	55.1	15.1	971.2	18.1	192.7	22	181	186	21.5%	-6.1%	7	74
Binnenstad-Noord	13.5	16.8	136.1	19.9	27.0	9	30	31	-54.8%	11.1%	3	12
Noordereiland	22.1	7.6	202.6	9.2	40.2	11	43	44	19.6%	7.0%	4	17
Het Noorden	16.0	2.5	202.6	6.8	40.2	9	42	43	32.4%	4.5%	3	17
Schildersbuurt	6.9	3.4	20.2	3.9	4.0	6	8	9	53.8%	100.0%	2	3
Bollebieste	23.6	8.4	101.3	10.0	20.1	12	23	25	20.0%	14.4%	4	9
Dieze-Centrum	14.7	6.7	81.1	8.1	16.1	9	20	20	11.1%	24.2%	3	8
Bagijneweide	22.5	0.0	101.3	9.0	20.1	11	23	25	22.2%	14.4%	4	9
Hogenkamp	45.2	5.9	141.6	14.8	28.1	19	31	36	28.4%	10.3%	6	13
Indischebuurt	13.1	9.2	0.0	11.1	0.0	9	3	9	-18.9%	-	3	3
Meppelerstraatweg-Zuid	4.8	1.7	0.0	2.2	0.0	5	3	5	127.3%	-	1	1
Bedrijventerrein Floresstraat	15.9	7.6	60.5	8.8	12.0	9	16	17	2.3%	33.3%	3	6
Wipstrik-Noord	89.3	25.2	121.5	29.8	24.1	33	27	39	10.7%	12.0%	11	12
Wipstrik-Zuid	65.5	15.1	0.0	17.8	0.0	25	3	25	40.4%	-	9	9
Stationsbuurt	37.2	0.0	1092.7	12.0	216.8	17	205	208	41.7%	-5.4%	5	84
Oud-Assendorp	77.2	28.6	0.0	34.0	0.0	30	3	30	-11.8%	-	10	10
Nieuw-Assendorp	57.5	21.0	0.0	25.4	0.0	24	3	24	-5.5%	-	8	8
Wezenlanden	14.2	6.7	101.3	7.9	20.1	9	23	24	13.9%	14.4%	3	9
Pierik	53.3	14.3	20.2	17.4	4.0	22	8	23	26.4%	100.0%	7	7
Bedrijventerrein Marslanden-Noord	1.6	0.0	81.1	0.1	16.1	4	20	20	3900.0%	24.2%	1	8
Hanzeland	44.0	11.8	424.9	14.4	84.3	19	82	86	31.9%	-2.7%	6	34
Kamperpoort	21.6	0.0	506.0	9.0	100.4	11	97	99	22.2%	-3.4%	4	40
Veerallee	56.3	16.8	181.9	20.2	36.1	23	38	44	13.9%	5.3%	8	15
Bedrijventerrein Voorst-A	5.6	0.0	202.6	3.0	40.2	6	42	42	100.0%	4.5%	1	17
Bedrijventerrein Voorst-B	1.6	0.0	202.6	0.1	40.2	4	43	43	3900.0%	7.0%	1	17
Spoolde	3.3	5.0	0.0	6.0	0.0	5	3	5	-16.7%	-	1	1
Oud-Westenholte	62.4	17.6	15.1	25.4	3.0	24	7	25	-5.5%	133.3%	8	8
Westenholte-Stins	104.9	24.4	0.0	28.6	0.0	38	3	38	32.9%	-	13	13
Vreugderijk	1.0	0.0	0.0	0.3	0.0	4	3	4	1233.3%	-	1	1
Bedrijventerrein Voorst-C	39.9	10.9	323.6	13.1	64.2	18	64	67	37.4%	-0.3%	6	26
Bedrijventerrein Voorst-D	3.0	1.7	121.5	1.8	24.1	5	27	28	177.8%	12.0%	1	11
Frankhuis	227.9	0.0	20.2	39.5	4.0	74	8	75	87.3%	100.0%	25	25
Mastenbroek	0.0	0.0	0.0	0.0	0.0	3	3	3	-	-	0	0
Schoonhorst	135.3	35.3	40.3	41.9	8.0	48	12	49	14.6%	50.0%	16	16
Werkeren	150.2	36.1	40.3	42.9	8.0	53	12	53	23.5%	50.0%	18	18
Milligen	269.4	58.8	60.5	70.3	12.0	91	16	91	29.4%	33.3%	31	31
Tippe bij de Ijssel	0.0	0.0	0.0	0.0	0.0	3	3	3	-	-	0	0
Breecamp	56.0	12.6	0.0	15.2	0.0	22	3	22	44.7%	-	8	8
Breezicht	0.0	0.0	0.0	0.0	0.0	3	3	3	-	-	0	0
Stadsbroek	0.3	0.0	0.0	0.1	0.0	3	3	3	2900.0%	-	0	0
Holtenbroek IV	39.7	10.9	202.6	13.3	40.2	18	42	46	35.3%	4.5%	6	18
Holtenbroek I	44.9	12.6	40.3	14.7	8.0	19	12	20	29.3%	50.0%	6	6
Holtenbroek II	34.2	14.3	0.0	17.1	0.0	16	3	16	-6.4%	-	5	5
Holtenbroek III	30.2	9.2	0.0	10.6	0.0	14	3	14	32.1%	-	5	5
Aalanden-Zuid	35.9	0.0	60.5	15.0	12.0	16	16	20	6.7%	33.3%	5	6
Aalanden-Midden	68.1	0.0	60.5	22.0	12.0	26	16	27	18.2%	33.3%	9	9
Aalanden-Noord	143.8	32.8	40.3	39.4	8.0	50	12	50	26.9%	50.0%	17	17
Aalanden-Oost	110.6	25.2	0.0	30.1	0.0	40	3	40	32.9%	-	14	14
Brinkhoek	3.1	5.9	0.0	7.0	0.0	5	3	5	-28.6%	-	1	1
Langenholte	2.7	0.8	0.0	1.2	0.0	5	3	5	316.7%	-	1	1

Haerst	2.1	2.5	20.2	2.8	4.0	4	8	8	42.9%	100.0%	1	2
Berkum	105.1	27.7	181.9	33.1	36.1	38	38	52	14.8%	5.3%	13	16
Bedrijventerrein de Vrolijkheid	12.8	0.8	161.8	1.2	32.1	8	35	35	566.7%	9.0%	3	14
Veldhoek	3.1	2.5	20.2	2.6	4.0	5	8	8	92.3%	100.0%	1	3
Kantorenterein-Oosterenk	26.5	9.2	951.0	11.2	188.7	13	178	179	16.1%	-5.7%	4	73
Bedrijventerrein Hessenpoort	76.1	21.8	202.6	26.1	40.2	29	42	51	11.1%	4.5%	10	17
Tolhuislanden	2.7	0.8	0.0	1.2	0.0	5	3	5	316.7%	-	1	1
Herfte	6.1	1.7	0.0	2.1	0.0	6	3	6	185.7%	-	1	1
Bedrijventerrein Marslanden-Zuid	0.0	0.0	0.0	0.0	0.0	3	3	3	-	-	0	0
Wijthmen	12.2	5.0	20.2	6.2	4.0	8	8	9	29.0%	100.0%	2	3
Oud Schelle	28.7	11.8	0.0	14.4	0.0	14	3	14	-2.8%	-	5	5
Schellerhoek	48.7	13.4	161.8	16.0	32.1	20	35	40	25.0%	9.0%	7	14
Schellerbroek	51.6	14.3	20.2	17.0	4.0	21	8	21	23.5%	100.0%	7	7
Schellerlanden	99.2	27.7	60.5	33.4	12.0	36	16	37	7.8%	33.3%	12	12
Oldenelerlanden-Oost	83.5	19.3	0.0	22.7	0.0	32	3	32	41.0%	-	11	11
Oldenelerlanden-West	50.1	11.8	0.0	13.7	0.0	21	3	21	53.3%	-	7	7
Oldenelerbroek	104.3	28.6	10.1	34.2	2.0	37	6	38	8.2%	200.0%	12	12
Schelle-Zuid en Oldeneel	1.5	5.0	0.0	5.8	0.0	4	3	4	-31.0%	-	1	1
Katerveer-Engelse Werk	9.0	4.2	121.5	5.4	24.1	7	28	28	29.6%	16.2%	2	11
Oud Ittersum	33.5	10.1	60.5	12.3	12.0	16	16	19	30.1%	33.3%	5	6
Ittersumerlanden	81.9	0.8	101.3	26.8	20.1	30	24	34	11.9%	19.4%	10	11
Ittersumerbroek	105.0	24.4	0.0	28.6	0.0	38	3	38	32.9%	-	13	13
Geren	12.6	5.0	0.0	5.8	0.0	9	3	9	55.2%	-	3	3
Gerenlanden	122.2	31.9	20.2	38.0	4.0	43	8	43	13.2%	100.0%	14	14
Gerenbroek	140.6	37.0	20.2	44.0	4.0	50	8	51	13.6%	100.0%	17	17
Oude Mars	0.0	0.0	0.0	0.0	0.0	3	3	3	-	-	0	0
Windesheim	8.2	2.5	0.0	2.9	0.0	7	3	7	141.4%	-	2	2
Harculo en Hoogzutmen	3.0	3.4	20.2	3.7	4.0	5	8	8	35.1%	100.0%	1	2

Table A2: Prognosis and results for 2030

CBS-buurtnaam	Prognosed EVs			ElaadNL		Simulation			Difference		Peak charging	
	Residents	visitors	commuters	residents+visitors	commuters	residents+visitors	commuters	all	residents+visitors	commuters	residents+visitors	all
Binnenstad-Zuid	110.5	30.2	1900.1	36.2	377.0	40	351	364	10.5%	-6.9%	13	145
Binnenstad-Noord	27.0	39.5	136.1	47.2	27.0	15	30	33	-68.2%	11.1%	5	12
Noordereiland	44.3	11.8	395.6	14.4	78.5	19	77	81	31.9%	-1.9%	6	32
Het Noorden	32.1	8.4	395.6	13.6	78.5	15	78	81	10.3%	-0.6%	5	31
Schildersbuurt	13.9	6.7	39.8	7.8	7.9	9	12	13	15.4%	51.9%	3	4
Bollebieste	47.5	13.4	198.1	15.7	39.3	20	42	47	27.4%	6.9%	7	17
Dieze-Centrum	29.4	10.1	158.3	12.3	31.4	14	34	36	13.8%	8.3%	5	13
Bagijneweide	45.2	0.0	115.9	24.0	23.0	19	26	31	-20.8%	13.0%	6	10
Hogenkamp	90.6	18.5	277.2	29.8	55.0	33	56	67	10.7%	1.8%	11	23
Indischebuurt	26.3	14.3	0.0	16.6	0.0	13	3	13	-21.7%	-	4	4
Meppelerstraatweg-Zuid	9.6	3.4	0.0	4.4	0.0	7	3	7	59.1%	-	2	2
Bedrijventerrein Floresstraat	31.8	10.9	118.9	13.3	23.6	15	27	30	12.8%	14.4%	5	11
Wipstrik-Noord	179.1	42.0	237.4	50.2	47.1	62	49	73	23.5%	4.0%	21	22
Wipstrik-Zuid	131.4	28.6	0.0	33.6	0.0	46	3	46	36.9%	-	16	16
Stationsbuurt	74.6	5.0	2137.5	24.9	424.1	28	390	398	12.4%	-8.0%	10	161
Oud-Assendorp	154.7	53.8	0.0	63.6	0.0	55	3	55	-13.5%	-	18	18
Nieuw-Assendorp	115.1	40.3	0.0	47.6	0.0	41	3	41	-13.9%	-	14	14
Wezenlanden	28.4	10.1	198.1	11.9	39.3	13	41	44	9.2%	4.3%	4	17
Pierik	107.0	29.4	39.8	35.0	7.9	39	12	39	11.4%	51.9%	13	13
Bedrijventerrein Marslanden-Noord	3.3	0.0	158.3	0.3	31.4	5	34	34	1566.7%	8.3%	1	14
Hanzeland	88.3	24.4	831.1	29.0	164.9	32	156	166	10.3%	-5.4%	11	65
Kamperpoort	43.3	0.0	989.9	14.0	196.4	18	185	189	28.6%	-5.8%	6	76
Veerallee	112.9	27.7	356.3	33.4	70.7	40	71	85	19.8%	0.4%	13	30
Bedrijventerrein Voorst-A	11.3	0.0	395.6	6.0	78.5	8	78	78	33.3%	-0.6%	2	32
Bedrijventerrein Voorst-B	3.3	0.0	395.6	0.3	78.5	4	78	78	1233.3%	-0.6%	1	32
Spoolde	6.8	7.6	0.0	9.3	0.0	6	3	6	-35.5%	-	2	2
Oud-Westenholte	125.1	32.8	15.1	43.2	3.0	45	7	45	4.2%	133.3%	15	15
Westenholte-Stins	210.5	39.5	0.0	47.1	0.0	71	3	71	50.7%	-	24	24
Vreugderijk	2.0	0.8	0.0	0.7	0.0	4	3	4	471.4%	-	1	1
Bedrijventerrein Voorst-C	80.9	21.8	633.5	26.4	125.7	30	120	129	13.6%	-4.5%	10	50
Bedrijventerrein Voorst-D	6.9	3.4	237.4	3.9	47.1	6	49	49	53.8%	4.0%	2	20
Frankhuis	457.0	134.4	39.8	159.7	7.9	153	12	153	-4.2%	51.9%	50	50
Mastenbroek	0.0	0.0	0.0	0.0	0.0	3	3	3	-	-	0	0
Schoonhorst	271.3	59.6	79.1	70.7	15.7	90	19	91	27.3%	21.0%	31	31
Werkeren	301.2	79.8	79.1	95.1	15.7	99	19	100	4.1%	21.0%	33	33
Milligen	540.3	156.2	118.9	186.2	23.6	179	27	180	-3.9%	14.4%	59	59
Tippe bij de IJssel	0.0	0.0	0.0	0.0	0.0	3	3	3	-	-	0	0
Breecamp	112.3	24.4	0.0	28.7	0.0	41	3	41	42.9%	-	14	14
Breezicht	0.0	0.0	0.0	0.0	0.0	3	3	3	-	-	0	0
Stadsbroek	0.6	0.0	0.0	0.2	0.0	4	3	4	1900.0%	-	1	1
Holtenbroek IV	79.7	22.7	395.6	26.8	78.5	30	78	88	11.9%	-0.6%	10	32
Holtenbroek I	89.9	24.4	79.1	29.4	15.7	33	19	35	12.2%	21.0%	11	11
Holtenbroek II	68.4	22.7	0.0	26.7	0.0	26	3	26	-2.6%	-	9	9
Holtenbroek III	60.6	13.4	0.0	16.4	0.0	24	3	24	46.3%	-	8	8
Aalanden-Zuid	71.5	0.0	118.9	23.0	23.6	27	27	36	17.4%	14.4%	9	11
Aalanden-Midden	135.5	0.0	118.9	42.0	23.6	47	27	49	11.9%	14.4%	16	16
Aalanden-Noord	286.0	66.4	75.6	78.9	15.0	95	19	96	20.4%	26.7%	32	32
Aalanden-Oost	221.8	42.0	0.0	49.7	0.0	74	3	74	48.9%	-	25	25
Brinkhoek	6.4	10.9	0.0	13.0	0.0	6	3	6	-53.8%	-	2	2
Langenholte	5.4	1.7	0.0	1.9	0.0	5	3	5	163.2%	-	1	1
Haerst	4.2	3.4	39.8	4.2	7.9	5	12	12	19.0%	51.9%	1	4
Berkum	196.6	52.1	356.3	62.0	70.7	68	70	96	9.7%	-1.0%	23	30
Bedrijventerrein de Vrolijkheid	23.9	1.7	316.5	1.7	62.8	12	64	65	605.9%	1.9%	4	26
Veldhoek	5.7	4.2	39.8	4.7	7.9	6	12	12	27.7%	51.9%	2	4
Kantorenterrein-Oosterenk	53.2	15.1	1860.8	17.6	369.2	22	342	347	25.0%	-7.4%	7	140

Bedrijventerrein Hessenpoort	175.7	40.3	395.6	48.2	78.5	60	77	100	24.5%	-1.9%	20	33
Tolhuislanden	5.4	1.7	0.0	1.9	0.0	6	3	6	215.8%	-	1	1
Herfte	12.2	2.5	0.0	3.3	0.0	8	3	8	142.4%	-	2	2
Bedrijventerrein Marslanden-Zuid	0.0	0.0	0.0	0.0	0.0	3	3	3	-	-	0	0
Wijthmen	24.5	10.1	39.8	12.3	7.9	12	12	14	-2.4%	51.9%	4	5
Oud Schelle	57.5	20.2	0.0	23.8	0.0	23	3	23	-3.4%	-	8	8
Schellerhoek	97.6	26.9	316.5	32.1	62.8	36	64	76	12.1%	1.9%	12	26
Schellerbroek	103.4	28.6	39.8	34.1	7.9	38	12	38	11.4%	51.9%	13	13
Schellerlanden	199.0	46.2	118.9	55.3	23.6	68	27	70	23.0%	14.4%	23	23
Oldenelerlanden-Oost	164.8	31.1	0.0	36.9	0.0	57	3	57	54.5%	-	19	19
Oldenelerlanden-West	98.9	21.0	0.0	25.2	0.0	35	3	35	38.9%	-	12	12
Oldenelerbroek	205.6	48.7	10.1	57.7	2.0	69	6	69	19.6%	200.0%	23	23
Schelle-Zuid en Oldeneel	3.0	6.7	0.0	8.4	0.0	5	3	5	-40.5%	-	1	1
Katerveer-Engelse Werk	18.0	9.2	237.4	11.0	47.1	10	48	49	-9.1%	1.9%	3	19
Oud Ittersum	67.2	25.2	70.6	29.9	14.0	26	18	28	-13.0%	28.6%	9	9
Ittersumerlanden	164.4	15.1	198.1	44.3	39.3	56	41	63	26.4%	4.3%	19	19
Ittersumerbroek	210.6	39.5	0.0	47.2	0.0	71	3	71	50.4%	-	24	24
Geren	25.4	7.6	0.0	8.9	0.0	13	3	13	46.1%	-	4	4
Gerenlanden	245.2	53.8	39.8	64.1	7.9	81	12	82	26.4%	51.9%	27	27
Gerenbroek	282.0	62.2	39.8	74.1	7.9	94	12	94	26.9%	51.9%	32	32
Oude Mars	0.0	0.0	0.0	0.0	0.0	3	3	3	-	-	0	0
Windesheim	16.6	4.2	0.0	4.6	0.0	10	3	10	117.4%	-	3	3
Harculo en Hoogzutmen	5.8	5.0	39.8	5.7	7.9	6	12	13	5.3%	51.9%	2	4

Table A3: Prognosis and results for 2035

CBS-buurtnaam	Prognosed EVs			ElaadNL		Simulation			Difference		Peak charging	
	residents	visitors	commuters	residents+visitors	commuters	residents+visitors	commuters	all	residents+visitors	commuters	residents+visitors	all
Binnenstad-Zuid	207.9	47.0	3486.2	56.1	691.7	71	638	664	26.6%	-7.8%	24	263
Binnenstad-Noord	50.8	67.2	136.1	80.3	27.0	25	29	37	-68.9%	7.4%	8	12
Noordereiland	83.2	22.7	726.3	27.2	144.1	31	137	147	14.0%	-4.9%	11	56
Het Noorden	60.4	13.4	726.3	19.8	144.1	24	137	144	21.2%	-4.9%	8	57
Schildersbuurt	26.1	9.2	72.6	11.0	14.4	13	18	20	18.2%	25.0%	4	7
Bollebieste	89.2	24.4	363.4	29.4	72.1	33	72	83	12.2%	-0.1%	11	30
Dieze-Centrum	55.3	15.1	290.3	18.1	57.6	23	58	64	27.1%	0.7%	7	24
Bagijneweide	84.9	23.5	115.9	54.6	23.0	31	27	38	-43.2%	17.4%	11	12
Hogekamp	170.4	31.9	508.5	46.0	100.9	58	98	120	26.1%	-2.9%	19	42
Indischebuurt	49.3	20.2	0.0	24.0	0.0	21	3	21	-12.5%	-	7	7
Meppelerstraatweg-Zuid	18.0	5.0	0.0	6.2	0.0	10	3	10	61.3%	-	3	3
Bedrijventerrein Floresstraat	59.8	16.8	217.7	19.6	43.2	24	45	51	22.4%	4.2%	8	18
Wipstrik-Noord	336.8	105.0	436.0	124.8	86.5	113	85	133	-9.5%	-1.7%	37	40
Wipstrik-Zuid	247.2	44.5	0.0	53.0	0.0	82	3	82	54.7%	-	28	28
Stationsbuurt	140.0	16.8	3921.6	38.6	778.1	49	716	735	26.9%	-8.0%	16	293
Oud-Assendorp	290.9	84.0	0.0	99.9	0.0	97	3	97	-2.9%	-	32	32
Nieuw-Assendorp	216.5	63.0	0.0	74.8	0.0	74	3	74	-1.1%	-	25	25
Wezenlanden	53.5	14.3	363.4	17.4	72.1	22	71	76	26.4%	-1.5%	7	29
Pierik	201.2	45.4	72.6	54.1	14.4	68	18	69	25.7%	25.0%	23	23
Bedrijventerrein Marslanden-Noord	6.3	0.8	290.3	0.6	57.6	6	59	59	900.0%	2.4%	1	24
Hanzeland	166.0	37.8	1525.1	45.0	302.6	57	283	304	26.7%	-6.5%	19	117
Kamperpoort	81.3	0.0	1815.9	27.0	360.3	30	336	344	11.1%	-6.7%	10	138
Veerallee	212.5	70.6	423.4	83.7	84.0	73	82	111	-12.8%	-2.4%	24	36
Bedrijventerrein Voorst-A	21.2	0.0	726.3	9.0	144.1	11	138	139	22.2%	-4.2%	3	57
Bedrijventerrein Voorst-B	6.2	0.8	726.3	0.6	144.1	6	137	137	900.0%	-4.9%	1	56
Spoolde	12.8	14.3	0.0	17.3	0.0	8	3	8	-53.8%	-	3	3
Oud-Westenholte	235.1	73.1	15.1	90.8	3.0	80	7	80	-11.9%	133.3%	27	27
Westenholte-Stins	395.7	82.3	0.0	98.0	0.0	129	3	129	31.6%	-	43	43
Vreugderijk	3.7	0.8	0.0	1.0	0.0	5	3	5	400.0%	-	1	1
Bedrijventerrein Voorst-C	153.0	34.4	1162.2	41.1	230.6	52	216	235	26.5%	-6.3%	18	89
Bedrijventerrein Voorst-D	13.9	6.7	436.0	7.8	86.5	9	85	86	15.4%	-1.7%	3	35
Frankhuis	859.1	252.0	72.6	300.2	14.4	280	18	281	-6.7%	25.0%	92	92
Mastenbroek	0.0	0.0	0.0	0.0	0.0	3	3	3	-	-	0	0
Schoonhorst	510.1	147.0	145.2	175.3	28.8	167	32	170	-4.7%	11.1%	55	56
Werkeren	566.2	171.4	145.2	204.2	28.8	187	31	189	-8.4%	7.6%	62	62
Milligen	1015.6	294.0	217.7	350.1	43.2	331	45	335	-5.5%	4.2%	109	110
Tippe bij de IJssel	0.0	0.0	0.0	0.0	0.0	3	3	3	-	-	0	0
Breecamp	211.2	37.8	0.0	45.2	0.0	70	3	70	54.9%	-	24	24
Breezicht	0.0	0.0	0.0	0.0	0.0	3	3	3	-	-	0	0
Stadsbroek	1.1	0.8	0.0	0.6	0.0	4	3	4	566.7%	-	1	1
Holtenbroek IV	149.9	35.3	726.3	41.6	144.1	53	137	155	27.4%	-4.9%	17	57
Holtenbroek I	169.1	38.6	145.2	45.6	28.8	57	32	61	25.0%	11.1%	19	20
Holtenbroek II	128.7	39.5	0.0	46.9	0.0	46	3	46	-1.9%	-	15	15
Holtenbroek III	113.9	24.4	0.0	29.0	0.0	41	3	41	41.4%	-	13	13
Aalanden-Zuid	133.3	0.0	217.7	41.0	43.2	45	45	61	9.8%	4.2%	15	19
Aalanden-Midden	252.9	19.3	217.7	65.8	43.2	82	45	88	24.6%	4.2%	28	28
Aalanden-Noord	533.5	162.1	75.6	192.8	15.0	178	19	179	-7.7%	26.7%	58	59
Aalanden-Oost	416.9	86.5	0.0	103.2	0.0	136	3	136	31.8%	-	45	45
Brinkhoek	12.0	16.8	0.0	20.3	0.0	9	3	9	-55.7%	-	3	3
Langenholte	10.1	2.5	0.0	2.8	0.0	7	3	7	150.0%	-	2	2
Haerst	7.7	6.7	72.6	7.8	14.4	6	18	19	-23.1%	25.0%	2	7
Berkum	344.2	115.1	653.7	137.0	129.7	116	124	173	-15.3%	-4.4%	39	54
Bedrijventerrein de Vrolijkheid	41.7	1.7	581.1	2.2	115.3	18	111	115	718.2%	-3.7%	6	46
Veldhoek	10.0	5.0	72.6	6.4	14.4	7	18	19	9.4%	25.0%	2	7
Kantorenterrein-Oosterenk	100.1	27.7	3413.6	33.0	677.3	36	622	633	9.1%	-8.2%	12	256
Bedrijventerrein Hessenpoort	350.5	79.8	726.3	95.4	144.1	115	138	184	20.5%	-4.2%	39	60

Tolhuislanden	10.0	2.5	0.0	2.7	0.0	7	3	7	159.3%	-	2	2
Herfte	22.9	5.0	0.0	5.9	0.0	12	3	12	103.4%	-	4	4
Bedrijventerrein Marslanden-Zuid	0.0	0.0	0.0	0.0	0.0	3	3	3	-	-	0	0
Wijthmen	46.0	16.0	72.6	19.1	14.4	20	18	24	4.7%	25.0%	7	8
Oud Schelle	108.1	37.8	0.0	44.7	0.0	40	3	40	-10.5%	-	13	13
Schellerhoek	183.3	42.0	581.1	49.7	115.3	62	111	135	24.7%	-3.7%	21	47
Schellerbroek	194.3	44.5	72.6	52.9	14.4	65	18	66	22.9%	25.0%	22	22
Schellerlanden	374.1	110.0	217.7	131.3	43.2	125	45	129	-4.8%	4.2%	41	42
Oldenelerlanden-Oost	304.8	57.1	0.0	68.4	0.0	100	3	100	46.2%	-	34	34
Oldenelerlanden-West	183.0	32.8	0.0	39.2	0.0	62	3	62	58.2%	-	21	21
Oldenelerbroek	380.5	119.3	10.1	141.8	2.0	128	6	128	-9.7%	200.0%	43	43
Schelle-Zuid en Oldeneel	5.5	10.1	0.0	12.2	0.0	6	3	6	-50.8%	-	2	2
Katerveer-Engelse Werk	34.0	14.3	436.0	17.0	86.5	16	85	87	-5.9%	-1.7%	5	35
Oud Ittersum	126.2	42.8	70.6	51.3	14.0	45	18	46	-12.3%	28.6%	15	15
Ittersumerlanden	308.9	47.9	363.4	83.4	72.1	101	72	115	21.1%	-0.1%	34	35
Ittersumerbroek	395.8	82.3	0.0	98.0	0.0	129	3	129	31.6%	-	43	43
Geren	47.9	10.9	0.0	13.0	0.0	20	3	20	53.8%	-	7	7
Gerenlanden	460.9	133.6	72.6	159.2	14.4	153	18	154	-3.9%	25.0%	51	51
Gerenbroek	530.3	154.6	72.6	184.1	14.4	174	18	175	-5.5%	25.0%	58	58
Oude Mars	0.0	0.0	0.0	0.0	0.0	3	3	3	-	-	0	0
Windesheim	31.2	6.7	0.0	8.0	0.0	15	3	15	87.5%	-	5	5
Harculo en Hoogzutmen	11.0	8.4	72.6	10.1	14.4	8	18	19	-20.8%	25.0%	2	7

Appendix B: Sensitivity analysis of Section 5.2 in tables

Table B1: The effect of the number of sessions and the estimated charging power, on the peak number of CPs occupied.

		Charging power per CP										
		-25%	-20%	-15%	-10%	-5%	0%	5%	10%	15%	20%	25%
Weekly sessions per EV	-25%	-24%	-25%	-25%	-24%	-25%	-24%	-24%	-25%	-25%	-25%	-25%
	-20%	-19%	-20%	-21%	-20%	-20%	-20%	-20%	-20%	-20%	-20%	-19%
	-15%	-15%	-14%	-15%	-14%	-14%	-15%	-14%	-14%	-14%	-14%	-15%
	-10%	-10%	-11%	-11%	-10%	-10%	-10%	-10%	-10%	-10%	-11%	-10%
	-5%	-6%	-4%	-5%	-5%	-5%	-5%	-5%	-5%	-5%	-5%	-4%
	0%	0%	0%	1%	0%	0%	0%	1%	1%	0%	0%	0%
	5%	5%	5%	6%	6%	5%	5%	6%	6%	6%	5%	5%
	10%	11%	11%	11%	11%	11%	11%	11%	10%	11%	11%	10%
	15%	15%	15%	14%	15%	15%	15%	15%	15%	14%	14%	14%
	20%	20%	20%	20%	20%	19%	20%	20%	21%	21%	19%	20%
	25%	26%	25%	25%	26%	25%	25%	25%	25%	26%	25%	25%

Table B2: The effect of the number of sessions and the estimated charging power, on the peak number of CPs charging.

		Charging power per CP										
		-25%	-20%	-15%	-10%	-5%	0%	5%	10%	15%	20%	25%
Weekly sessions per EV	25%	49%	46%	40%	34%	29%	29%	26%	23%	17%	11%	9%
	20%	43%	40%	31%	29%	26%	23%	17%	14%	11%	9%	9%
	15%	37%	31%	29%	23%	17%	14%	14%	9%	6%	3%	3%
	10%	31%	26%	20%	17%	17%	11%	6%	3%	3%	0%	-6%
	5%	23%	20%	17%	11%	9%	3%	3%	0%	-3%	-9%	-9%
	0%	20%	14%	11%	6%	3%	0%	-3%	-6%	-9%	-9%	-14%
	-5%	14%	9%	3%	0%	-3%	-6%	-6%	-11%	-11%	-14%	-17%
	-10%	9%	3%	-3%	-6%	-9%	-9%	-14%	-14%	-17%	-20%	-23%
	-15%	0%	-3%	-6%	-11%	-11%	-17%	-17%	-20%	-20%	-23%	-26%
	-20%	-3%	-9%	-11%	-17%	-17%	-20%	-23%	-23%	-26%	-29%	-31%
	-25%	-11%	-14%	-17%	-20%	-23%	-23%	-26%	-29%	-31%	-34%	-34%

Appendix C: Extensive results for Berkum, Zwolle

Table C1: Required CPs when using a cap on the LOS

LOS cap to the average LOS	LOS cap (Hours)	CPs required				Peak charging				# Charging sessions ended early
		Residents+ Visitors		Residents+ Visitors+ Commuters		Residents+ Visitors		Residents+ Visitors+ Commuters		
10%	1.2	10	-91.15%	26	-57.87%	6	-84.62%	21	-65.00%	3857
20%	2.4	22	-80.53%	60	-51.12%	15	-61.54%	45	-25.00%	1901
30%	3.6	35	-69.03%	85	-43.82%	26	-33.33%	56	-6.67%	941
40%	4.8	44	-61.06%	97	-38.76%	32	-17.95%	58	-3.33%	435
50%	6	49	-56.64%	103	-35.96%	37	-5.13%	58	-3.33%	162
60%	7.2	52	-53.98%	105	-34.27%	38	-2.56%	58	-3.33%	94
70%	8.4	55	-51.33%	115	-32.58%	38	-2.56%	58	-3.33%	92
80%	9.6	60	-46.90%	130	-29.78%	39	0.00%	60	0.00%	0
90%	10.8	64	-43.36%	133	-27.53%	39	0.00%	60	0.00%	0
100%	12	69	-38.94%	135	-24.72%	39	0.00%	60	0.00%	0
110%	13.2	75	-33.63%	138	-21.35%	39	0.00%	60	0.00%	0
120%	14.4	84	-25.66%	142	-16.29%	39	0.00%	60	0.00%	0
130%	15.6	89	-21.24%	146	-13.48%	39	0.00%	60	0.00%	0
140%	16.8	93	-17.70%	148	-11.24%	39	0.00%	60	0.00%	0
150%	18	95	-15.93%	150	-10.11%	39	0.00%	60	0.00%	0

Table C2: Required CPs when using a cap on the idle time

idle time cap to the average idle time	LOS cap (hours)	CPs required				Peak charging			
		Residents+ Visitors		Residents+ Visitors+ Commuters		Residents+ Visitors		Residents+ Visitors+ Commuters	
10.00%	1	43	-61.95%	65	-39.33%	39	0.00%	60	0.00%
20.00%	2	47	-58.41%	75	-37.08%	39	0.00%	60	0.00%
30.00%	3	49	-56.64%	91	-35.96%	39	0.00%	60	0.00%
40.00%	4	51	-54.87%	98	-34.83%	39	0.00%	60	0.00%
50.00%	5	53	-53.10%	103	-33.71%	39	0.00%	60	0.00%
60.00%	6	53	-53.10%	107	-33.71%	39	0.00%	60	0.00%
70.00%	7	55	-51.33%	122	-32.58%	39	0.00%	60	0.00%
80.00%	8	58	-48.67%	132	-30.90%	39	0.00%	60	0.00%
90.00%	9	63	-44.25%	133	-28.09%	39	0.00%	60	0.00%
100.00%	10	69	-38.94%	136	-24.72%	39	0.00%	60	0.00%
110.00%	11	79	-30.09%	140	-19.10%	39	0.00%	60	0.00%
120.00%	12	87	-23.01%	146	-14.61%	39	0.00%	60	0.00%
130.00%	13	92	-18.58%	148	-11.80%	39	0.00%	60	0.00%
140.00%	14	94	-16.81%	150	-10.67%	39	0.00%	60	0.00%
150.00%	15	97	-14.16%	153	-8.99%	39	0.00%	60	0.00%

Table C3: Effect of deviating from the calculated required CPs

	CPs		Peak shortage				Utilization	
Realized CPs to the calculated required	Residents+ Visitors	Residents+ Visitors+ Commuters	Residents+ Visitors		Residents+ Visitors+ Commuters		Residents+ Visitors	Residents+ Visitors+ Commuters
50%	56.5	93	668	591%	1102	592%	96%	98%
55%	62.15	102.3	461	408%	756	406%	96%	97%
60%	67.8	111.6	265	235%	468	252%	95%	93%
65%	73.45	120.9	187	165%	345	185%	92%	89%
70%	79.1	130.2	106	94%	213	115%	86%	83%
75%	85	139.5	95	84%	159	85%	81%	77%
80%	90	148.8	54	48%	96	52%	77%	73%
85%	96	158.1	46	41%	74	40%	73%	69%
90%	102	167.4	37	33%	53	28%	69%	65%
95%	107	176.7	13	12%	23	12%	65%	62%
100%	113	186	7	6%	10	5%	62%	59%
105%	119	195.3	2	2%	-3	-2%	60%	56%
110%	124	204.6	-10	-9%	-15	-8%	57%	54%
115%	130	213.9	-15	-13%	-26	-14%	54%	52%
120%	136	223.2	-20	-18%	-36	-19%	52%	49%
125%	141	232.5	-30	-27%	-46	-25%	50%	48%