GIMA Geographical Information Management and Applications

Simulating Electric Vehicle driving and charging behaviour using an agent-based approach

MSc Thesis

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Preface and acknowledgements

Before you lies the thesis "Simulating Electric Vehicle driving and charging behaviour using an agent-based approach", in which I developed and demonstrated a simulation model that allows for exploration of spatial behaviour of electric motorists. This has been written as part of the graduation of the master programme Geographical Information Management & Applications and was conducted in the period September 2019 until May 2020. The subject of this thesis emerged from my interest in sustainable mobility and my ambition to find solutions for urban problems. There is an increasing need to understand the processes behind electric mobility and I found that simulation models could allow for the exploration of electric mobility. This combination gave me the opportunity to develop myself in a domain which was relatively unknown for me and the opportunity to learn a new programming language.

I would like to thank my supervisor Arend Ligtenberg for his guidance and support during this process. From the start, he shared my enthusiasm and helped me with discovering the possibilities of agent-based modelling. Thank you for helping me when I struggled with the programming and for all the feedback which led to the completion of this thesis. As well, I would like to thank the GAMA community, especially Srirama and Youcef, for reviewing my model when I got stuck.

I am pleased that I got the opportunity to work together with fellow students at the GIS lab. During the many well-deserved coffee breaks we debated each others problems and we kept each other motivated. Spacial thanks to the fellow students who used similar research methods, reviewing each others works was very valuable. Also many thanks to my friends for their support and especially Johanna, Lieke, Linde, Eva and Tijn for reviewing parts of my report.

Finally, I would like to thank my parents and brother for their support, specifically my dad. Thank you for helping me out with the data analysis in Excel and explaining me the possibilities of power queries with the greatest patience.

Summary

Electric Vehicles (EVs) are an opportunity for governments to reduce the greenhouse gas emissions and to improve air quality. There is an increasing need to understand the processes behind EV development and use. For this study, a behavioural model is developed to explore the behaviour of electric motorists in relation to CP placement. A literature research on factors influencing EV driver behaviour is conducted to explore which parameters could be included in the EV driving and charging behaviour model. As a simulation is an abstract representation of the reality, simplifications of these parameters have been made, and the parameter conceptualisation is based on multiple assumptions. The appropriate method for developing this simulation model is agent-based modelling, which allows for modelling the individual behaviour of EV drivers. The model as developed includes the main simulation process of EV drivers leaving home and moving to their destination. When it is needed, the EV driver will search for a charging point nearby. The model further includes behavioural concepts found in literature: charge point hogging, range anxiety, disappointment when a charging point is occupied and the level of satisfaction of the agents. The conceptual model is implemented in GAMA using spatial datasets of the case study area in Amsterdam.

The model verification and validation process is conducted to test the model on its plausibility. It is verified that the model behaves as it was designed and the final model is bug-free. A limited validation of the model is successfully conducted to test if the model represents the real-world. Due to lack of validation data, this is done by visual observation and comparing outputs to input variables. During the sensitivity analysis it was found that the share of EV ownership and the range anxiety have a notable impact on the model. These parameters could be further researched in order to improve the model. Additional data on these parameters will be needed to fully calibrate the model. Additionally, the usefulness of the model is tested by using two scenarios based on policies and technologies. This showed that the simulation model has clear potential for testing real-life scenarios and it can be used as a tool for policy makers. The ABM developed in this research proved itself as an adequate simulation model but it should be noted that the model is sensitive for parameters which are based on assumptions. There are many opportunities for further model improvement. When more extensive datasets are retrieved for validation and calibration, the quality of the model will increase.

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Chapter 1

Introduction

1.1 Context

The atmospheric concentration greenhouse gas levels have increased considerably over the past century, causing an increasing global surface temperature and climate change. Over 2017, the greenhouse gas emissions were about 55% higher than in 1990 and 40% higher than in 2000 (Olivier & Peters, 2018). As the European Environment Agency (EEA) states, the transport sector accounts for around a quarter of all the greenhouse gas emissions in Europe and passenger cars are contributing almost 45% to the sector's greenhouse gas emissions (EEA, 2015). The annual energy consumption of transport in the EEA member countries grew by 34% between 1990 and 2016, in contradiction to other sectors in which the consumption decreased. Electric vehicles (EVs) are, with their low carbon footprint, considered to be the key component of the future European mobility system and are thereby having the potential to decrease the greenhouse gas emissions. This will lead to a reduction of the impact of climate change and an improvement of the air quality (EEA, 2018).

In the Netherlands, the energy consumption by the transport section decreased with 11% between 2011 and 2014. Between 2014 and 2016 these levels remained nearly constant. The decrease of 11% is due to stagnating volumes of traffic and an increasing number of less-consuming vehicles. After 2014, the economic growth caused rising volumes of traffic. This increase in energy consumption was compensated by the more fuel-efficient vehicles (Schoots, Hekkenberg, & Hammingh, 2017). The Dutch government has set the goal to decrease the Dutch greenhouse gas emissions in 2030 by 49% compared to 1990, which led to a national climate agreement to achieve this objective (PBL, 2019a). This agreement is being negotiated by five different sectors, of which the mobility sector is one of them. The agreement aims for the stimulation of electric transport and strives for a 100% emission-free new sales of passenger vehicles in 2030. A number of 1.8 million EV charging points need to be realized to fit the future EV charging needs (PBL, 2019b).

All over the Netherlands, municipalities attempt to support the transition to sustainable mobility. Moving towards complete electric mobility is not likely to occur all by itself, and the process can be quite unpredictable and complex. According to van der Steen, van Schelven, Kotter, van Twist, and van Deventer (2015), buying an EV is a risky and expensive choice for consumers and brings considerable uncertainty caused by the limited battery range and charging points. As van den Hoed, Helmus, de Vries, and Bardok (2013) argue, the municipality of Amsterdam is one of the global leaders in the stimulation of EV driving. The poor air quality in the city is the major incentive for the municipality to have an active role in facilitating electric mobility. Amsterdam is performing this role by developing a proper EV charging infrastructure and establishing subsidies and incentive systems. Besides that, the municipality launched different awareness campaigns (van den Hoed et al., 2013). In April 2019, the municipal council of Amsterdam presented the 'Action Plan on Clean Air' in which the council aims for a longer life expectancy for inhabitants of the city by improving the air quality. The city of Amsterdam will be emission-free in the near future, by banning all the petrol vehicles by 2030. This will be a gradual process in which the municipality takes action to help its inhabitants with the transition by providing subsidies and tax-reliefs (Gemeente Amsterdam, 2019).

1.2 Problem Statement

Between December 2016 and August 2019, the number of public EV Charging Points (CPs) in the Netherlands has increased from 11,768 to 24,078. At this moment, in the city of Amsterdam, there are 4,180 public EV charging points (RVO, 2019a). It is expected that an additional 23,000 public charging points will be needed in the city by 2025 to meet the demand of EV drivers. Following the prognosis, this demand will keep increasing in the near future. In 2018 the amount of EVs in the Netherlands increased with 15%, in Amsterdam the increase is even greater (Gemeente Amsterdam, 2019).

According to Helmus (2018) there are two roll-out strategies for enabling a public charging infrastructure; demand-driven and strategic. In the demand-driven approach, the placing of the CPs is based upon requests by EV drivers near their homes. With the second roll-out strategy, the local governments decide the locations of CPs based on proximity of public facilities or on strategic locations where the use of a CP is expected. The municipality of Amsterdam wants to proceed with the demand-driven strategy, but furthermore wants to intensify an anticipating and strategic deployment of a CP infrastructure (Gemeente Amsterdam, 2019). This strategy asks for insights in the charging and driving behaviour of EV owners, which can help to predict the future spatial demand of CPs.

There is an increasing need to understand the processes behind the EV development and use (EEA, 2018). For this study, a simulation model will be developed to understand the behaviour of electric motorists in relation to CP placement. This will be done by developing an Agent Based Model (ABM), for simulating the behaviour and individual decision-making of the EV drivers. Bonabeau (2002) gives the following definition of a ABM:

> In agent-based modelling (ABM), a system is modelled as a collection of autonomous decision-making entities called agents. Each agent individually assesses its situation and makes decisions on the basis of a set of rules. Agents may execute various behaviours appropriate for the system they represent.

Management of flows is one of the areas of application for ABMs and traffic is an obvious application of this area (Bonabeau, 2002). In recent years, new application areas have been opened by combining ABM with geographical information systems (GIS), giving the models a location component. In this way, real-world cities and urban environments with their spatial and temporal patterns can be modelled (Macal, 2016). Agent-based modelling seems to be the appropriate method for modelling complex systems such as (EV) driving and charging behaviour. ABM allows for the modelling of individual behaviour of the agents and therefore gives insights of the spatial-temporal behaviours of electric motorists and their behaviour regarding to the locations of CPs.

1.3 Research relevance

Many simulations have been implemented to explore behaviour of road users, however there is a lack of models which focus on EV charging and driving behaviour within an urban environment. This ABM will be a behavioural model; the agents will adjust their behaviour according to the availability of CPs. This means that, the behaviour of the agents can be influenced by the municipality's roll-out of an extensive CP infrastructure. The scientific relevance of this research can be found in this type of EV behaviour modelling, these principles of modelling have not been used before in EV behaviour models. The ABM will be based on behaviour of EV drivers and how they react on their environment. It takes into account how motorist react to the presence or absence of CPs and how this will influence the mobility behaviour, for example; what happens to their behaviour when a CP is occupied and what is their willingness to search for other CPs. Therefore, this research aims to model the EV drivers in a more behavioural way than other models in the field of driver behaviour.

Besides the scientific significance of this thesis, this research could also be a contribution to policy making in the field of mobility within the municipality of Amsterdam. As described before, Amsterdam wants to stimulate the use of electric transport by intensifying a strategic deployment of a CP infrastructure. Insights in the charging and driving behaviour of EV drivers could help to predict the future spatial demand of CPs. Additionally, with a smart distribution of CPs throughout the city, the mobility behaviour of EV drivers can be affected. This change in mobility behaviour can be used to engage in the current problems of Amsterdam, concerning the overcrowded city. The municipality of Amsterdam wants to shift car parking in the city from the streets to designated parking spaces and garages (Gemeente Amsterdam, 2019). A smart distribution of CPs by the municipality could lower the high parking pressure in the city. Furthermore, when there will be less parking spaces on the streets, public space will become visually more attractive. A healthy balance between keeping EV drivers satisfied and excluding cars from the city will be needed.

1.4 Research objectives and questions

Based on the problem statement described in the previous section, the objectives of this study are formulated. The main aim of this thesis is the following: "*to develop and demonstrate a behavioural based agent-based model that allows to explore the spatial behaviour and dynamics of electric motorists in relation to CP placement in the city of Amsterdam.*" The spatial behaviour refers to the physical movement of the motorists in space, based on their choices. This results in certain dynamics, with all the agents interacting with the environment. The outcomes of this model will provide insights in charging and driving behaviour of EV owners, to prove insight where CPs can be installed in order to meet the needs of EV drivers. This will be of emerging relevance as the municipality plans to ban all petrol vehicles in the city by 2030 (Gemeente Amsterdam, 2019). On the other hand, the model can give insights in the effects the CP placement has on the driving and parking behaviour of EV drivers. This behaviour includes the behaviour of the driver when a CP is occupied, the willingness to search for other CPs, the willingness to walk from the CP to the destination and the satisfaction of the EV motorists. These insights will provide more understanding in the process behind EV use.

The following research questions are formulated in order to reach the main objective of this research.

1. What are important factors that affect EV driver behaviour and which modelling method is suitable for developing a simulation of EV driver behaviour?

2. How can behavioural aspects influencing EV driving and charging be conceptualized in a framework suitable for modelling?

3. How can this framework be implemented in an agent-based model?

4. How plausible and useful are the resulting patterns of the proposed behavioural agent-based model?

1.5 Research approach

For this research, an ABM simulating EV driving and charging behaviour will be developed. Amsterdam will be the case study for the implementation of this model, this case study and its area will be further explained in the methodology section. The research process can be appropriated along four main research steps, which are each related to the specific research question as presented in section 1.4. Figure 1.1 shows these steps and methods which this research will follow. The connection back from the analysis step to the model implementation step shows the iterative element, as the outcomes of the analysis will be used in the designing of the model to redefine model processes and parameters.

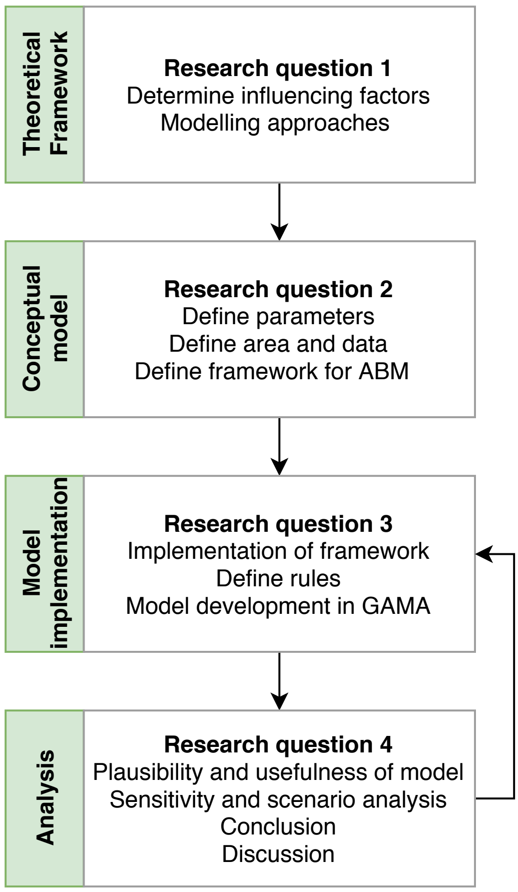


Figure 1.1: Research approach

1.6 Research feasibility

Due to limitations in time and resources, this thesis remains within a certain scope. First of all, this thesis will only cover battery electric vehicles (BEVs), in which the electricity is stored in a battery inside the vehicle and must be regularly charged. Another type of EV is the fuel cell electric vehicle (FCEV), which is completely powered by electricity. These vehicles use experimental fuel cell techniques which allow for using compressed hydrogen and oxygen from the air for charging (EEA, 2016). The main advantage of this type of EV is the faster refuelling, with similar refuelling times as conventional vehicles. These technologies are in an early stage of development. However, when these innovations will be more developed, the urgency of CPs will disappear. Some other developments outside the scope of this research are the improvements of the EV batteries. It might be possible to easily fast-charge those batteries in the near future which also will reduce the need for CPs.

Additionally, this research will not be able to represent an actual real-life situation as there is no data available of future EV drivers. The numbers used by the model will be based on recent mobility data and EV development predictions following recent trends. It is not certain that these expectations will be realized. This is also challenging when it comes to validating the model, as the model predicts future scenarios, the model cannot be validated by real-life data. Furthermore, this research will not be able to consider all aspects of EV driving and charging behaviour. Due to time limitations, choices have to be made in which aspects to include.

1.7 Reading guide

The structure of this thesis is mainly based on the research questions as proposed in Section 1.4. Chapter 2 comprises the theoretical background on EV driver behaviour as well as an overview of agent-based modelling and previous research on EV behavioural models. The methodology chapter (Chapter 3) presents the conceptual model of the proposed ABM and the methods and materials for implementation. The validation and verification for testing the plausibility of the model is described in Chapter 4. The usability of the model is tested in Chapter 5 by analysing the reaction of the model to two scenarios. Chapter 6 ends this thesis with summarising the main findings and discussing the limitations of this research.

Chapter 2

Theoretical framework

This theoretical framework consists of three parts; the chapter will start with theories about the behaviour of EV drivers in section 2.1. This comprises an understanding about vehicle related factors influencing EV behaviour, driver related factors, the charging infrastructure and charging behaviour. Section 2.2 consists of a review of different modelling approaches. This section starts with an outline of microscopic and macroscopic models and the ABM principles. Section 2.3 will discuss previous studies in EV driving behaviour modelling.

2.1 An understanding of EV driving behaviour

This section investigates possible parameters which might have a major impact on EV driving and charging behaviour.

2.1.1 Vehicle related factors

According to Franke and Krems (2013), the type of EV is of importance when defining the characteristics of EV driving and charging behaviour. This subsection describes those EV types and aims to point out how these types affect travel and driver choices. First of all, it is needed to define the type of EV used in this thesis. To create a better understanding of the different types of EVs, the European Environment Agency described five main types of EVs (EEA, 2016). These types exist besides conventional vehicles which are powered by fossil fuels. The five main EV types are the following;

- Battery electric vehicles (BEVs) are powered by electricity solely. The electricity is stored in a battery inside the vehicle and must be regularly charged.

- Hybrid electric vehicles (HEVs) are powered by both a conventional engine using fossil fuels and by an electric motor. The battery is charged during the driving of the vehicle.

- Plug-in hybrid electric vehicles (PHEVs) are very similar to HEVs, but the battery can be charged from the power grid. The conventional engine with a combustion motor supports the electric motor when the battery levels are low.

- Range-extended electric vehicles (REEVs) are powered by an electric motor with a plug-in battery. The vehicles also have a combustion motor used to supplement the battery charging.

- Fuel cell electric vehicles (FCEVs) are completely powered by electricity. The vehicles use experimental fuel cell techniques which allow for using compressed hydrogen and oxygen from the air for charging.

This thesis will focus on BEVs, so the term EV in this research refers to these full-electric battery vehicles. Within this type of EV, vehicles can have different characteristics regarding driving range, battery capacity, battery technology and energy consumption (Olivella-Rosell, Villafafila-Robles, Sumper, & Bergas-Jané, 2015). Franke and Krems (2013) state that the features and characteristics of an EV influence the charging behaviour of the motorists. The battery capacity is of importance as a bigger capacity requires longer charging times but also requires a lower charging frequency. EV batteries can have different technical characteristics which determine how much electricity the battery can store and how fast this energy can be released to power the EV.

According to the EEA (2016), the most important measures of EV batteries are the energy density and power density. Energy density is defined as "the amount of energy that can be stored in the battery per mass of the battery and is measured in watt- hours per kilogram (Wh/kg) or kilo joules per kilogram (kJ/kg)" and "Power density is the amount of power that the battery can deliver per mass safely without damaging the battery and is expressed as W/m which indicates the efficiency of a battery pack" (Azadfar, Sreeram, & Harries, 2015).

An often used measurement for the remaining capacity of a battery is the State of Charge (SoC);

$$SoC = \frac{remaining\ capacity}{rated\ capacity} \tag{2.1}$$

This parameter can be influenced by different conditions like temperature and the current load of EV batteries (Azadfar et al., 2015). The battery size influences the behaviour of EV drivers in a way that a larger battery requires longer charging times and a larger amount of energy to charge. On the other hand, a larger battery also causes a lower recharging frequency which influences the mobility patterns of EV drivers.

The range of an EV, which is the range the EV can drive on a charged battery, is related to this battery size. However, these two factors are not completely identical. This is due to the fact that another factor which influences the vehicle range is the weight of the EV. The range is of influence of the EV driving behaviour as a bigger vehicle range causes les range anxiety and longer EV trips (Eggers & Eggers, 2011).

2.1.2 Driver related factors

First of all, an overview can be obtained of the Dutch EV drivers. Hoekstra and Refa (2017) described the characteristics of Dutch EV drivers on the hand of a survey with 286 respondents. They found that an EV driver in the Netherlands is likely to be a middle aged man with a high income and a high level of education. The respondents mostly acquired an EV because of the tax incentives and because they like to adapt new technologies. Dutch EV drivers see themselves as eco-friendly and are open to sustainable technologies like renewable energy. The EV drivers would recommend EV driving to others and are happy with the driving experience. Moreover, the motorists tend to be unsatisfied with the ranges of their vehicles. These problems become less once the range is more than 350 kilometres.

Besides the characteristics of the EV drivers themselves, this sections provides an outline of the behavioural traits of EV drivers. Azadfar et al. (2015) argue that the driving behaviours and patterns of EV drivers are likely to differ from those who drive a conventional combustion vehicle. The behaviour of the EV motorist is primarily determined by their need to recharge the vehicle. Olivella-Rosell et al. (2015) argue that a strong relationship exists between the EV energy consumption and urban mobility. The mobility pattern of EV drivers has to be adapted to the capabilities of the EV.

Mobility patterns

The mobility patterns of EV drivers are determined by their daily driving profiles. The behaviour of an individual driver, can be seen as the result of multiple choices. Vincenzo (2014) distinguished two types of choices; long-term decisions such as home and work locations and vehicle ownership and shorter-term decisions such as "...trip frequency, timing, destination, mode and path"(Vincenzo, 2014). For developing a behavioural model, long-term decisions are out of the scope. Figure 2.1 shows at the left a schematic overview of the short term decisions at four levels; travel, strategic, tactical and operational.

The upper 'travel' layer includes the choice to make a trip (trip production), the destination choice (trip distribution) and the choice of the mode, for this research that will be the EV. The strategic layer includes the departure time and the route choice. This last choice requires information about the transport network and its actual traffic information. The 'tactical' and 'operational' layers refers to the choices during the trip like the driving speed, lane choices and the controls of the vehicles. Vincenzo (2014) argues that the use of EV affects these choices because of two factors: the range of EVs (range anxiety) and the recharging times of EVs.

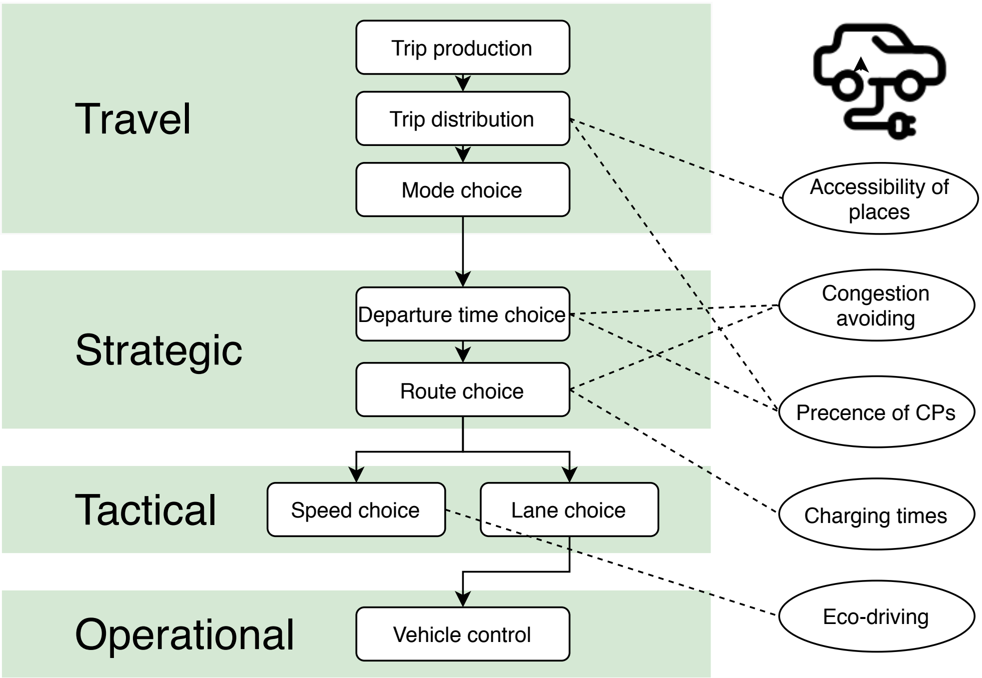


Figure 2.1: Travel choices and how EV driving affects them, adapted from Vincenzo (2014)

Figure 2.1 shows on the right how these factors influence the driving decisions. For example, places further away may not be accessible because of the EV range. Destination choices can also be affected by the availability of CPs. Furthermore, departure times can be influenced by the charging time (waiting till the EV is fully recharged) and by the avoiding of congestion; destinations can be unreachable during a specific time of day. In order to increase the range of the vehicle, the driver can reduce his or her speed (eco-driving).

Range anxiety

The so-called 'range anxiety' has been described by many researchers as one of the main obstacles for the success of EVs (Franke & Krems, 2013; Nilsson, 2011; Eggers & Eggers, 2011; Guo, Yang, & Lu, 2018). This refers to the fear of EV drivers to strand with a discharged battery. This range is exposed to all kinds of external factors, like driving style, weather conditions and the age of the battery. Typically, EV drivers tend to have more range anxiety compared to conventional fuel vehicle drivers (Yuan et al., 2018). This uncertainty causes concerns for drivers and influences their behaviour. Eggers and Eggers (2011) also pointed out these concerns regarding range anxiety. In their research, a model is developed which predicts the consumer EV adoption. This model shows that the adoption of EVs would strongly increase when the battery range is increased. The appearance of range anxiety also causes EV drivers to charge more often and longer than needed. This range anxiety could be reduced when consumers effectively plan their daily journeys or when more CPs are deployed so the drivers are more assured in finding a new CP (Franke & Krems, 2013). There are multiple methods proposed for expressing the range anxiety of an EV driver. Yuan et al. (2018) state that there is a gap between the distance of a trip and the remaining SoC of the vehicle which can dispose the range anxiety of the driver. Franke and Krems (2013) refer to this gap as the so-called 'safety buffer', which turned out to be around a buffer of 20% of the total distance of the trip.

Willingness to walk

Another dimension to take into consideration are the walking distances between CPs and the destinations of the EV drivers. These distances are likely to influence the charging behaviour of EV drivers. The aim of an ideal CP infrastructure is to place CPs close by places likely to be destinations, such as public institutions or supermarkets, in order for EV drivers to be able to park and charge within walkable distance to their destinations (Pagany, Marquardt, & Zink, 2019). Acceptable walking distances are expected to differ between different type of EV drivers and their aims. Pagany et al. (2019) defined these acceptable walking distances according to the destination type and driver age group (see Table 2.1). Walking distances for users aged above 65 years are assumed to be shorter than for younger groups, this is due to mobility reasons.

Table 2.1: Acceptable walking distances between CP and destinations depending on users and destination types, reprinted from Pagany et al. (2019)

	Maximum Walking Distance (in Meters) for User group:			
Destination type	**18-29 years**	**30-44 years**	**45-64 years**	**65+ years**
Living	300	300	300	150
Working	500	500	500	500
Shopping	100	100	100	100
Recreation	500	500	500	250

Brandstätter, Kahr, and Leitner (2017) made the following assumption about the walking distance between the CP and the drivers' destination: "Customers are willing to walk from their origin to a charging station and from a charging station to their destination, as long as the associated walking distance (time) does not exceed a given threshold" (p. 21). This acceptable walking distance can be referred to as "willingness to walk". In the research "Electric Mobility: Charged to Maturity" (RVO.nl, Accenture, Greenflux, Antea Group, Natuur & Milieu, 2015), a survey with 200 responses of EV drivers was performed. They asked the respondents what distance they are willing to walk from CP to the destination. They found there is no lack of willingness to walk; many EV drivers would walk up to 15 minutes from the charging point to their destination.

2.1.3 Charging infrastructure

The charging infrastructure for EVs and the locations of CPs are likely to influence the EV driving patterns (Azadfar et al., 2015). Having enough charging possibilities will cause a faster adoption of EV technologies.

Charging point characteristics

There are different ways to charge an EV, like plug-in charging, battery swapping or wireless charging. This thesis will use plug-in charging as leading charging type, as this is used by the majority of current EVs in Europe. With plug-in charging, the EV is connected to a CP using a cable and a plug. Charging can take place with different speeds. In general, EVs are charged using normal home-located CPs with a low amount of electric current. This causes the EV to charge slowly, taking around a full night to fully recharge the vehicle (EEA, 2016). Faster CPs require more advanced techniques and a specialised power infrastructure. In Europe, nowadays the most public CPs in cities offer only normal-speed charging (EAFO, 2016). The European Environment Agency (2016) distinguished four modes of charging technologies for EVs. These modes are illustrated in Figure 2.2. Each of the modes represents the supplied power level (expressed in kW), the estimated time in hours and the use of the mode. For charging an EV, the AC current provided by the power grid needs to be transformed to the battery of the EV which can only store DC current. This conversion can be done by an on-board AC/DC converter or by a converter integrated into the CP. Fast-charging stations (mode 4) have built-in converters so the CP is converting AC from the grid to DC for the EV itself.

The charging time of electric vehicles can be roughly calculated by a simplified formula;

$$Charging\,time\,(in\,Hours) = \frac{vehicle\,capacity\,(kWh)}{CP\,current\,(kW)} \tag{2.2}$$

However, in real life, the duration of charging sessions is influenced by many factors (Mies & Helmus, 2018). Some of these factors are; the number of EVs being connected, battery degradation and peak hours of the power grid.

Three different types of CP locations can be distinguished; private CPs, semi-public CPs and public CPs. These types differ in degree of accessibility for drivers. Private CPs are mostly found in domestic area; in homes and businesses. This requires the EV owner to have a private driveway or garage. In cities, where vehicles are mostly parked on public car parks, private CPs are not very common. Semi-public charging points are placed on a private area, but can be used by others. This access can be restricted to the customers and clients of for example commercial shopping centres or leisure facilities. The owner of the semi-public CP can choose whether the user needs to pay or not. Public CPs are mostly placed along parking spaces or in car parks. These CPs can be provided by local municipalities, mostly in cooperation with a

	Power	Time	Use
Mode 1	2.3 kW	8 - 10 hours	*Slow charging, using common households sockets. In domestic or office building.*
Mode 2	3.3 - 7.4 kW	3 - 8 hours	*Slow or semi-fast charging, with special charging cable.*
Mode 3	10 - 22 kW	1 - 3 hours	*Slow, semi-fast or fast charging, using a special plug socket. Common seen in public locations.*
Mode 4	50 - 120 kW	10 - 30 minutes	*Delivers DC current with a AC/DC converter. Much more expensive.*

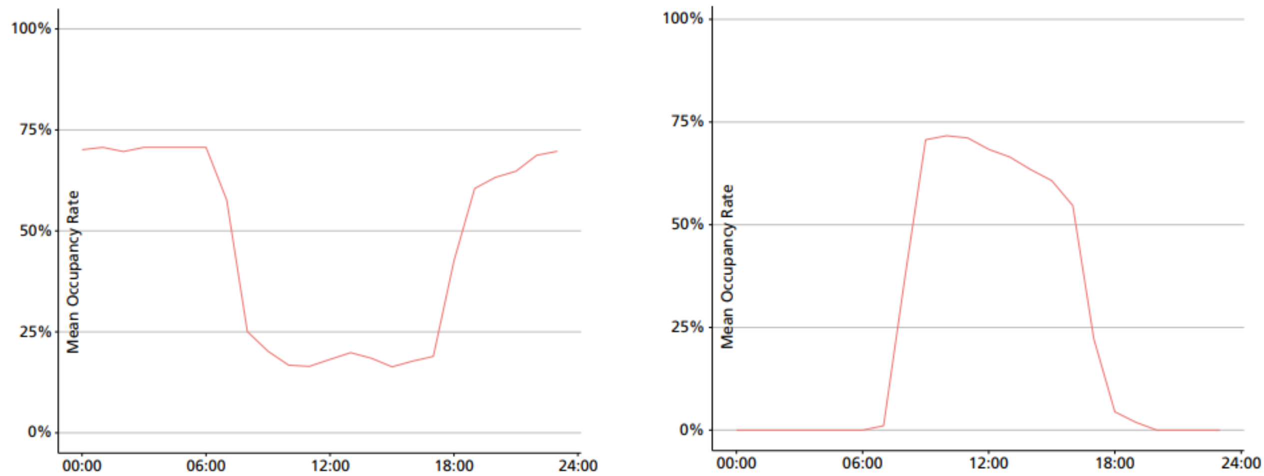
Figure 2.2: Charging modes and times to provide 100 km of EV driving adapted from EEA (2016)

commercial facilitator (EEA, 2016). Naturally, an EV driver wants to rely on the presence of an available CP close by their destination. However, the commercial facilitators are dependent on a high occupancy rate of CPs because of their economic aim. A balance between those two desires can be hard to find (Gnann et al., 2018).

Occupancy rates

According to Wolbertus, van den Hoed, and Maase (2016), stakeholders of CPs, such as operators and grid operators, found that CP occupancy rates are often either too low or too high. This occupancy rate differs between CPs and also differs in time of day and week. Even yearly patterns in the occupancy rate can be observed, such as summer holidays. In the beginning of 2016, the average occupancy rate in Amsterdam was 40%, which is quite high compared to other Dutch cities (RVO, 2019b). This high rate is due to the fact that EV drivers in Amsterdam often are not in possession of their own driveway. Their overnight charging sessions will take place at public CPs, which leads to a higher amount of connected hours (Wolbertus et al., 2016). During the day, charge data of Amsterdam shows a similar pattern of that of other cities in the Netherlands. During the night this occupancy ratio is about 48%, which is significantly higher than the ratio during the day (31%).

Van den Hoed et al. (2019) described occupancy rates per hour of CPs based on charging data. Figure 2.3 shows two different occupancy rate profiles, based on actual charging data of these CPs in March 2018. This shows that CPs can differ notably in their daily charging profiles. The profile showed in Figure 2.3a is that of a CP in a neighbourhood with EV owners who charge their vehicles at night. Figure 2.3b shows the profile of a CP placed at an office, with vehicles charging during office hours. The average occupancy rates for both CPs are quite the same, around 50%. However, due to their locations (residential versus office neighbourhood) both charging profiles are completely different.



(a) Night charger profile

(b) Office charger profile

Figure 2.3: Hourly occupancy rates for two different example CP profiles, van den Hoed et al. (2019)

2.1.4 EV charging behaviour

The charging behaviour of EV drivers can be determined by the frequency of EV charging, the charging time of day and the charging duration. Franke and Krems (2013) examined the charging behaviour of EV users based on a 6-month field study with data from 79 EV users. They found that on average EV drivers charge their vehicle three times a week and normally have an excess amount of energy left before recharging. The variable user-battery interaction style (UBIS) is used for conceptualizing the charging behaviour of EV drivers. This variable relates to the level of dealing with the limited energy resources by actively monitoring the battery levels. Users with a lower UBIS tend to charge more often than necessary to avoid uncomfortable situations, EV recharging is included in their daily routine. EV drivers with a high UBIS score decide their charging frequency and duration based on information of the battery levels. This results in a more energy-efficient charging behaviour.

Some previous research into EV charging patterns is conducted. Robinson, Blythe, Bell, Hübner, and Hill (2013) analysed 31,765 EV trips in England and created recharging behaviour profiles. Private users of EVs primarily charged their vehicles at home CPs in the evening. Organisation users were recharged upon arrival at home or when making multiple trips, at public CPs. Smith, Shahidinejad, Blair, and Bibeau (2011) constructed a daily driving profile of EV drivers, based on receiving GPS data from 76 vehicles in Canada. They found that the mean amount of trips per day is 4 and the driving pattern for a weekday commuter shows four peaks at 08:00, 12:00, 16:00 and 17:00 h.

Charging point hogging

Within the charging behaviour of EV drivers, a phenomena called "charging station hogging" can be recognized. This is the behaviour in which EV drivers stay parked at and connected to a CP longer than their necessary charging time. Data analysis found that in the Netherlands, only 15% to 25% of the time the CP is actually used for charging (Wolbertus & van den Hoed, 2020). They found that this CP hogging is a significant problem for the efficient use of public CPs in cities. Municipal policies, like introducing fees, could be effective to solve these problems.

2.1.5 Trends and future developments in EV driving and charging

During the early years of EV adoption in between 2012 and 2015, buying a EV was subsidised. This leaded to an increase in the amount of EV drivers, which were mostly lease drivers (Vermeulen, Helmus, Lees, & van der Hoed, 2018). With an ongoing increase in the number of EVs in the Dutch vehicle fleet, this mode of transport is likely to replace the conventional combustion vehicles in the future. There is a number of technologies currently in development to support this EV market penetration. Un-Noor, Sanjeevikumar, Mihet-Popa, and Hossain (2017) are overlooking five major trends in EV charging and driving technologies, as summarized in Figure 2.4.

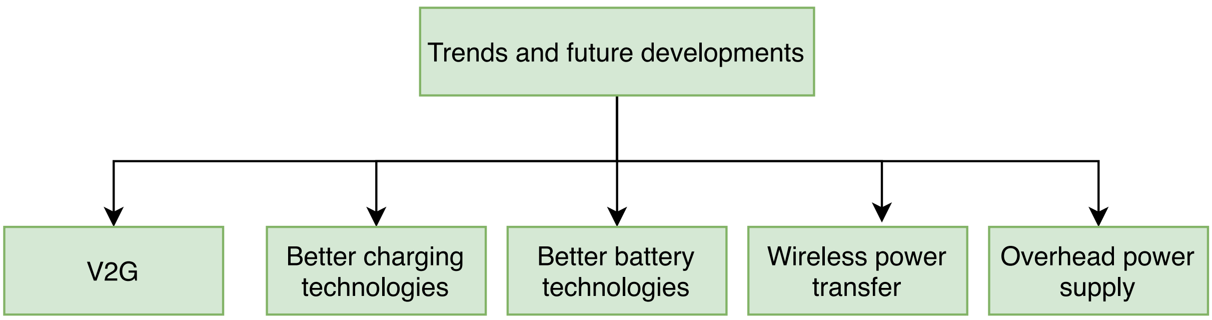


Figure 2.4: Trends and future developments for EV charging and driving, adapted from Un-Noor et al. (2017).

The first trend is the one of 'Vehicle to Grid' (V2G) charging, which makes it possible for EVs to communicate with the electricity grid for making bi-directional charging and other smart charging technologies possible. In this way EVs can be used as batteries to deliver power back to the grid during peak hours. Secondly, better charging (faster charging) and battery (more capacity) technologies are needed to take the EV technology to a higher level. This is to increase the range of EVs and to reduce the need of charging. Another technology which may appear in the future is the wireless charging through roads or the overhead charging through power lines like trains have (Un-Noor et al., 2017).

2.2 Modelling and simulation

In order to understand the spatial dynamics and behaviour of EV drivers, ABM simulations are used to build behavioural models. A model is a simplification of the reality, used to study the real-world. Simulations are using models to study the behaviour of a functioning system, a simulation can use models to explore scenario's which might not be possible in the original system (Andradóttir, Healy, Withers, Nelson, & Maria, 1997). Simulations are used to study complex systems by developing models. Those models are build using computers with computationally underlying models (Winsberg, 2003).

When building a model, choices have to be made in simplification as it is not possible to completely recreate a real-world environment. This section explains concepts concerning modelling and simulation techniques, which are used for making the right choices when developing this research's model.

2.2.1 Microscopic vs. macroscopic

Two main approaches can be distinguished in simulating traffic and driving behaviour; microscopic and macroscopic. In modelling traffic flows, macroscopic is used the most often. "Macroscopic simulators use mathematical models that describe the flow of all vehicles. These models are often derived from fluid dynamics and treat every vehicle the same (Ehlert & Rothkrantz, 2014)". In real life, vehicles are not the same and each vehicle has its own unique behaviour based on for example vehicle types and driving styles. Microscopic simulations allow for this individual behaviour of drivers to be modelled; "each element is modelled separately, allowing it to interact locally with other elements (Ehlert & Rothkrantz, 2014)". When modelling driver behaviour, both approaches have to be considered as the individual movements of drivers resulting in collective traffic flows. However, the model developed in this thesis will represent a system-based individual behaviour and can therefore be seen as microscopic model. Microscopic modelling uses a bottom-up approach as it simulates individual behaviour. When aggregating these individual behaviours, patterns at a higher level can be observed such as traffic flows (Macal, 2016).

2.2.2 Agent-based modelling

In the problem section (section 1.2), a definition of ABM is already given and it is pointed out that ABM seems to be the appropriate modelling method for simulating EV driving and charging behaviour. In addition to that, van Dam (2009) argued the following; "The key distinguishing element, that sets agent-based models apart from other models, is a focus on modelling individuals who can make decisions". In this sense, ABMs are microscopic models as it concerns behaviour of individuals. These individuals are called "agents" of which their behaviour can be modelled using algorithms, called behavioural rules. Macal and North (2010) distinguished the following three elements which are typical for any ABM:

1. A set of *agents*, together with their attributes and behaviours,
2. A set of agent *relationships* and interaction methods,
3. The agents' *environment*: Besides interacting with other agents, agents interact with their environment.

In Figure 2.5, a typical structure of an ABM is showed. Agents can interact with their environment as well as with other agents. The environment can be used to add spatial context, as for example the locations of agents relative to other agents. An ABM may also provide geographic information, with the use of GIS (Macal & North, 2010).

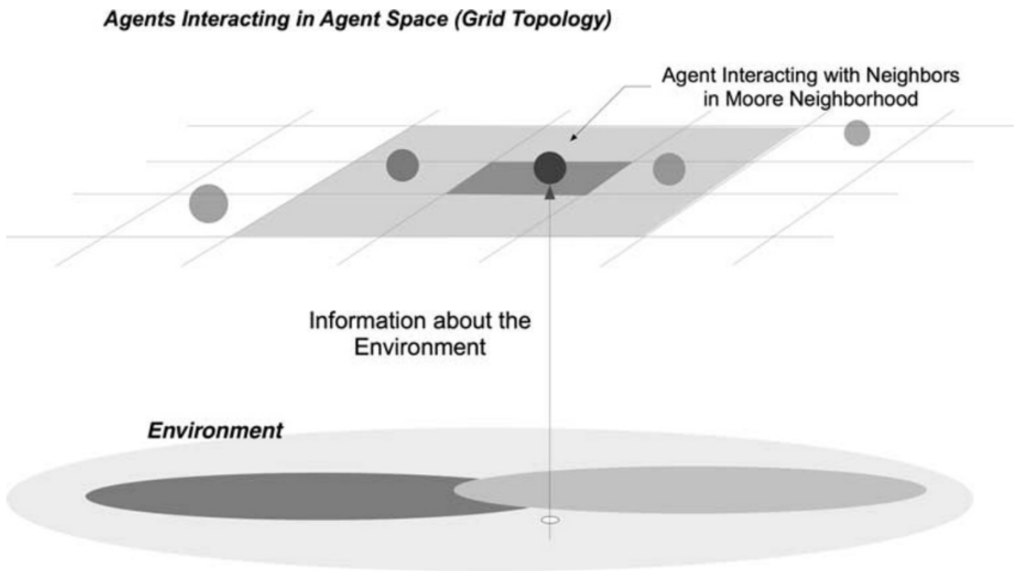


Figure 2.5: Structure of a typical ABM (Macal, 2010)

To standardize the description of ABMs, the 'ODD' (Overview, Design concepts and Details) protocol is published. This protocol makes it easier to understand and reproduce models (Grimm et al., 2010). The protocol is presented in Table 2.2 and will be used in this research to describe the agent-based model.

Table 2.2: The ODD protocol reprinted from Grimm et al., (2010)

	Elements of the ODD protocol
Overview	1. Purpose 2. Entities, state variables and scales 3. Process overview and scheduling
Design concepts	4. Design concepts - Basic principles - Emergence - Adaptation - Objectives - Learning - Prediction - Sensing - Interaction - Stochasticity - Collectives - Observarion
Details	5. Initialization 6. Input data 7. Submodels

2.3 Previous studies and existing models in EV driving behaviour modelling

Multiple simulation models exist nowadays on the topic of EV driving behaviour (Daina, Sivakumar, & Polak, 2017; Hoekstra, 2017; Kangur, Jager, Verbrugge, & Bockarjova, 2017; Chaudhari, Member, Kumar, Krishnan, & Member, 2018; Marmaras, Xydas, & Cipcigan, 2017). This section describes some of the major previous studies and existing models in EV driving behaviour modelling.

Vincenzo (2014) provided an outline of modelling approaches in EV transport and traffic. The following is argued:

> ...a modelling framework including activity-based travel demand models and agent-based dynamic traffic simulation models seems the best suited for investigating the introduction of e-mobility and its complex interactions with both the transport and the electricity networks (Vincenzo, 2014).

It is stated that validation of those ABMs is the major challenge, as those modelling frameworks can be complex and there is a lack of validation data. Vincenzo (2014) also mentioned some needed variables for a simulation model. These variables are: The State of Charge (SoC), departure and arrival times, stopping locations and daily travel plans. An evaluation of methods for modelling EVs, is also given by Daina et al. (2017). The outcome of this review of diverse modelling approaches is that ABM is the most attractive modelling approach for time of day analysis in EV simulating. It is also found that there is a lack of realistic representations of charging behaviour.

The most comprehensive ABM which simulates EV behaviour in the Netherlands might be the ABCD model, as introduced by Hoekstra and Hogeveen (2017). This ABM takes into account the buying, charging and driving (ABCD) of EVs. This model integrates different sub-models on these elements at different levels, with representative Dutch neighbourhood data. This model results in real-life simulations which can support decision making on the following subjects; policy making for public space, electricity grid balance, CP supply & demand, and technological developments like smart charging. Regarding the CPs, the so-called 'disapPoints' are introduced in the model: "every time an EV driver wanted to use a specific charger but that charger was occupied (meaning the EV driver was disappointed) the charger received an extra point (Hoekstra & Hogeveen, 2017)". Vijayashankar (2017) further developed the charging module of the ABCD module, for simulating the CP infrastructure usage and rollout in Dutch neighbourhoods. Two representative neighbourhoods are chosen for the presence of a mix between residential spaces, business offices, visiting places and parking spots. For the model, EV agents have been distinguished as both resident agents living inside the neighbourhood and commuters which visit the neighbourhood from outside.

More research on CP infrastructure deployment with ABM is conducted; Sweda and Klabjan (2011) developed an ABM for analysing patterns in residential EV driving and ownership. These patterns enable a strategic deployment of new CPs. The model can be mainly used for identifying EV adoption patterns based on different scenario's, which supports strategic CP placing. Spatial patterns are not taken into account within the scope of this ABM.

ElBanhawy, Dalton, Thompson, and Kottor (2015) discussed the potential of simulations of built environments with ABM to study electric mobility. Multiple ABM simulation platforms are evaluated, and the aspects visualization and simulation are taken into account. The following relevant attributes of agents and model assumptions where summarized:

- The EV agents starts with defining the origin and destination (O-D matrix).
- The time interval is updated on a daily basis.
- At every destination the EV agents chooses a new destination and checks the EV SoC.

The model is presented through a case study of the Newcastle-Gateshead area and the model is calibrated and validated with real-world urban transportation data.

A comprehensive ABM containing multiple detailed behavioural choices regarding charging behaviour, competition for scarce CPs and driver adaptations is the PEVI model, proposed by Sheppard, Harris, and Gopal (2016). Multiple assumptions are made and tested for their impact on outcomes. An important assumption made is that of the *Driver Rationality.* This is the assumption that a driver is completely rational during the seek for CPs. This means that a driver will always choose the option with the least costs, whereas in real-life the choices are unlikely to be perfectly rational. The outcomes of the model are used to site CPs and to explore the impact of the EV trends on the need for CPs and on the electricity grid.

Another model that simulates the charging demand of EVs, it that of Chaudhari et al. (2018). The model considers factors related to the social characteristics of EV drivers and focuses on economic elements. The results of the simulation facilitate an efficient process of optimal CP siting. The model uses various detailed parameters to predict the charging demand, some of them are; the category of EV, range anxiety, SoC, charging modes and driver experience. The authors advised to perform a comprehensive sensitivity analysis for future studies, with a wider selection of variables. A research that performed a comprehensive sensitivity analysis is that of Olivella-Rosell et al. (2015). A probabilistic ABM of EV charging demand is developed to analyse the impact on distribution networks. The model is stochastic for considering different random distributed variables. This is done using the Monte Carlo method, which allows for the iteration of the model with stochastic variables to analyse the sensitivity of those variables.

2.4 Summary

To conclude, this chapter outlined different theories about EV driving behaviour what created an understanding about which factors to include in the simulation model. Agent-based modelling seems to be a sufficient method to realise this kind of behavioural simulation model. The first sub question, *'what are important factors that affect EV driver behaviour and which modelling methods exists for developing a simulation of EV driver behaviour?'*, have thus been answered. This chapter provided the base for the modelling framework, what will be deliberated on in the next chapter. In the beginning of that methodology chapter, the key findings of the literature study will be further discussed.

Chapter 3

Methodology

This chapter describes the methods this research uses to reach the research objective. This will start with summarising the key findings of the theoretical framework and the definition of the case study area. After this, the conceptual model will be introduced following the ODD protocol as presented in Section 2.2.2. Furthermore, this chapter will deliberate on the process of implementing the model into the modelling software. The methods for evaluation will be explained in the final section of this methodology chapter, followed by a short summary.

3.1 Theoretical framework: key findings

After the problem formulation, the theoretical framework is developed by reviewing literature. This framework relates to the first research question; determining which factors affect EV driver behaviour and which modelling methods exists for developing a simulation of EV driver behaviour. This section gives a summary of the key findings from the theoretical framework, which form the input for the conceptual model. This sections also sets out the model assumptions which followed from the literature study.

It is found that possible parameters which might have an impact on EV driving and charging behaviour can be grouped in these major classes: vehicle related and driver related factors. Vehicle related factors concern mostly technical aspects of electric vehicles, such as the type, battery characteristics and the range of EVs. Driver related factors are considered to be the social characteristics of the EV drivers and the factors influencing behavioural decisions of the EV drivers. These are likely to differ from conventional vehicle drivers; mainly because of their need to recharge the vehicle. The individual behaviour of a driver can be seen as the result of both long-term and short-term decisions. Short term decisions include the timing of the trip, the destination, the path, transport mode and the frequency of the trips. The use of a EV affect these short-term decisions. A recurring term in literature concerning EV driving behaviour is that of 'range anxiety' which refers to the fear of stranding with a discharged battery. This fear causes the drivers to charge longer and more often than needed.

Another parameter which have an impact on EV behaviour, is the charging infrastructure. This is an external parameter, meaning that the behaviour will be affected by environmental means. CPs are located in the drivers' environment and enough charging possibilities have a positive effect on EV adoption. EV charging takes place at different modes, indicating the power level and charging times. Three different types of CP locations can be distinguished; private CPs, semi-public CPs and public CPs. The charging behaviour of EV drivers can be determined by the following parameters: the charging frequency, the charging time of day and the charging duration. An often considered concern is that of occupancy rates of CPs, which are often either too low or too high. Occupancy rates differ between CPs and also differ in time. Differences between CPs are likely to be affected by the location of the CP, residential locations show high occupancy rates during the night while office locations show high rates during the day.

The key concepts found in literature, as described above, are summarized in Figure 3.1. Besides the two major groups 'vehicle' and 'driver', 'environment' can be seen as a group of factors influencing the behaviour of EV motorists. Within these groups, the factors can be either having an impact on the driving behaviour or on the charging behaviour of EV motorists.

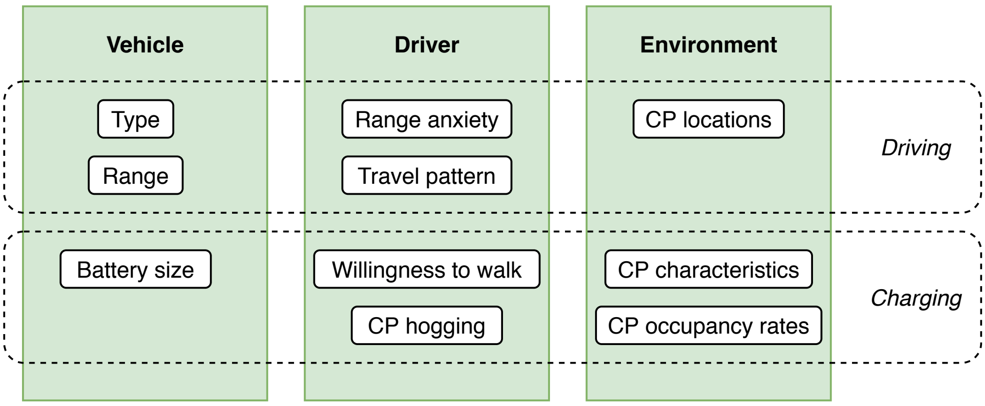


Figure 3.1: Key concepts found in literature

Section 2.2 reviewed modelling and simulation approaches and this led to the following finding for developing the simulation model: **The appropriate approach for simulating EV driving and charging behaviour is agent-based modelling, which allows for modelling the individual behaviour of EV drivers (microscopic) and shows patterns at higher level (macroscopic) such as traffic flows.**

After reviewing various concepts in literature, the following model assumptions are constructed:

- **The EVs** simulated in the model will be battery electric vehicles (BEVs) only, other types of EV are not taken into account (section 2.1.1).

- **The EV driver types** are based on partly random distributed variables. Social characteristics of the EV drivers are not considered in the simulation (section 2.1.2).
- **The behaviour of EV drivers** is mainly determined by their need to recharge the vehicle (section 2.1.2).
- **The behaviour of EV drivers** can be seen as the result of multiple decisions (section 2.1.2).
- **EV drivers** mostly cope with some degree of range anxiety. For this model, this fear is translated in a higher threshold in state-of-charge of the battery for at which state-of-charge the driver wants to recharge (section 2.1.2).
- **The simulation model** will only include short term decisions of drivers, within the time scope of one day. Long-term decisions are out of scope (section 2.1.2).
- **CPs** in the model are assumed to be (semi-)public and charge in mode 3 (section 2.1.3).
- **EV drivers** in this neighbourhood depend on public CPs since they don't have a driveway for a private CP. Private CPs are out the scope of this model (section 2.1.3).
- **EV drivers** can be both residents living inside the neighbourhood or commuters who visit the neighbourhood from outside (section 2.3).
- **EV drivers** start with defining their origin and destination (O-D matrix) (section 2.3).
- **EV drivers** are assumed to be fully rational in their decisions. A driver is completely rational, so also during the seek for CPs. In this study it is assumed that a driver will always choose the option with the least costs, whereas in real-life the choices are unlikely to be perfectly rational. Drivers will always choose the least-cost path to their destination and they will search for the CP nearest possible CP (section 2.3).

3.2 Case study area

Amsterdam has been selected as case study for this research. Section 1.1 elaborates on why Amsterdam is a suitable case. The city of Amsterdam copes with a poor air quality, which resulted in planning to having a complete emission-free city by banning all patrol vehicles by 2030. In this, Amsterdam is at the global forefront of stimulating EV driving. Furthermore, Amsterdam encounters problems concerning an overcrowded city. With a smart distribution of CPs, the government could affect the mobility behaviour of EV drivers.

As the whole area of Amsterdam is too large for the scope of this modelling research, one district is chosen as case study area. The municipality of Amsterdam consists of 479 neighbourhoods, called *buurten* and these are grouped in 99 districts, called *wijken*. The case study area for this research is the district *Apollobuurt* and is displayed in Figure 3.2. The *Apollobuurt* is densely populated with around 9.775 inhabitants per square kilometre. In 2018, 4.110 households were located in this area with a total number of 8.640 inhabitants. In 2018, altogether the inhabitants of this area owned 3.365 residential vehicles (CBS, 2018). Also in 2018, 1.800 business establishments were registered in this area. The CBS (2018) uses a standard classification of business activities called SBI (*Standaard Bedrijfsindeling*). Among the businesses in the area are 210 are assigned to the SBI codes G+I, which means hotels, restaurants, cafes and bars and 210 businesses in recreation, art, culture and sports (SBI codes R+U). This makes the *Apollobuurt* an area with inhabitants as well as businesses, which attract non-resident people like visitors, tourists and employees. This mixed-used district of Amsterdam is therefore a useful case to investigate the EV mobility of both inhabitants and visitors.

Figure 3.2: The municipality of Amsterdam and the case study area.

For this research, a dataset with static charge point data in Amsterdam is retrieved from Eco-Movement (2019). The dataset shows the locations of all the public and semi-public CPs in the municipality with attributes like the operator and power in kWh of the CP. At the 22th of October, 2019, the dataset counted 4729 CPs in Amsterdam. In the Apollobuurt, 96 of them are located. Figure 3.3 shows the area with its roads (red lines) and CPs which are displayed as grey pins. It might seem that there is way less than 96 CPs in this area, however at one location multiple CPs might be located and CPs can include more sockets to charge multiple EVs at the same time. Each socket is counted as a different CP in the dataset.

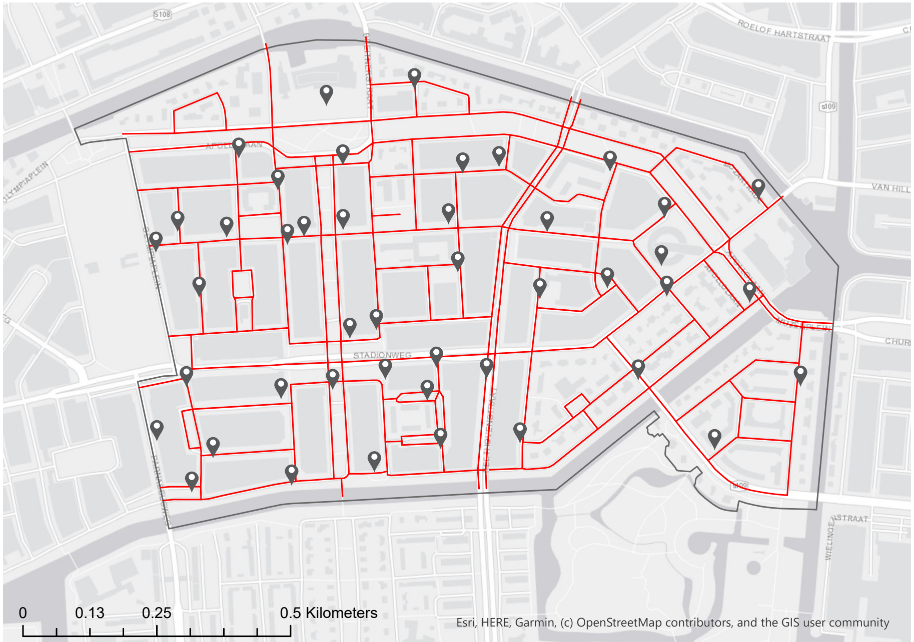


Figure 3.3: The case study area with its roads and CPs.

3.3 Model overview

The outcomes of the literature study as described before, are the input for this next step where the conceptual model will be designed. This step tackles the following research question: 'How can behavioural aspects, influencing EV driving and charging, be conceptualized in a framework suitable for modelling?'. These factors are derived from the first step, and form the base for the ABM agents' behaviour and characteristics. In order to present the conceptual model, the ODD protocol is used as described in section 2.2.2.

3.3.1 Purpose

This models aims at simulating the behaviour of EV drivers to create an understanding of their spatial behaviour and dynamics in relation to CP placement in the case study area. It is designed in order to easily expand the model with additional (behavioural) aspects and integrate different scenarios.

One run of the simulation model shows a daily pattern of EV motorists with their driving and charging behaviour. Therefore, the model shows a cycle starting at 6:00 and ending when all the EV drivers returned home (around 22:00). Each step in the model is 10 seconds in time.

These small time step causes a relatively long run time of the model, but it allows for including realistic driving speeds and modelling decision making at a detailed level.

The model takes the case study area as input. At the initial state of the model all agents are described by specific inputs, for example by parameters controlling their driving behaviour. This model is partly stochastic, meaning that a variety of decisions and processes in the model are based on random chance. This is to avoid conclusions which suit one particular set of circumstances.

3.3.2 Entities, state variables, and scales

The model takes into account four types of entities:

- The moving *EV agents*.
- The *CPs* in the area.
- The *buildings* which can have different functions.
- The *roads* forming the network.

The basic relations between those entities are depicted in Figure 3.4.

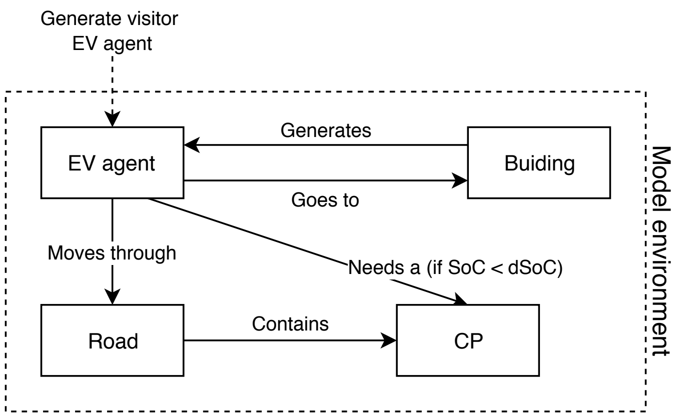


Figure 3.4: The basic relations between the models' entities; Electric Vehicle (EV) agents, Buildings, Roads and Charging Points (CP). *SoC = State of Charge, dSoC = desired State of Charge*

As shown in the figure, EV agents can be either residents, generated from a building entity, or visitors. Visitors are generated in simulation from 'outside' of environment of the model, meaning they enter the simulation from 'origin points' at the edges of the road network ending at the neighbourhood boundaries. Those EV agents move through the road network to their destination, which is a destination building in the model. The EV agents need a CP when their

State of Charge is less than their desired State of Charge. Those CPs are placed along the road network.

For this model, the environment is created by using GIS data of the case study area. Figure 3.5 shows the model environment at its initial state at the beginning of the simulation. The data used in this model consists of the road network over which the EV agents can move, the CP locations and the buildings in the neighbourhood. The buildings are divided in two classes; residential and destination buildings. Destinations are buildings with a main function different than a residential function. These buildings are mostly hospitality companies, offices and retail stores. In the model, as displayed in Figure 3.5, the destination buildings are displayed in blue and the residential buildings in grey. The CPs are coloured orange. Section 3.4.2 eleborates on the data used in this model and what also explains the modifications made to the data.

Figure 3.5: Initial state of the model in simulation environment GAMA. The buildings are represented in grey (residential buildings) and blue (destinations). The orange dots represent the CPs.

Besides the GIS data, the most important input for the simulation is the population of the EV agents. The number of EV agents in the simulation is based on the estimated number of visitors arriving by car in the neighbourhood and the share of EV ownership in percentage of the total vehicle ownership. As there is no data available indicating the number of visitors, assumptions are made based upon the number of destination buildings and their main function described in the used dataset. With a total number of 167 destination buildings in the neighbourhood, the calculation gives a total of 6,295 estimated number of visitors arriving by car during the day. These estimations and the calculation can be found in Appendix A. In the initial state of the model, the number of EV agents are calculated by using the parameter indicating share of EV ownership. Since this parameter is expected to have an significant influence on the outcomes of the simulation, each scenario is run with four different values of this parameter. The chosen values are 1.6%, 10%, 30% and 85%. The percentage of 1.6 is according to the most actual data (December 2019) by RVO (2019a) of the share of EV ownership at this moment. The number of 30% is based on calculations of the SparkCity model (Hoekstra, 2017), in which it is expected to have an EV ownership share of around 1/3 in 2030. The value 85% is based on the policies of the municipality of Amsterdam in their 'Action Plan on Clean Air' (Gemeente Amsterdam, 2019), in which the municipality aims for a completely emission free vehicle fleet in the city by 2030. For this simulation it is chosen to downgrade the 100% to 85%, because it is assumed that this policy will cause a decrease in the total amount of vehicles visiting in the city, alternative means of transport will be used instead. The EV ownership share of 10% is chosen because it is assumed to be a realistic scenario for the near future.

This section further explains the entities of the model and their variables. These variables are mostly based on assumptions, which are explained per entity. These assumptions are either based on data, theories or hypothesis. At last, also some additional global parameters with their assumptions are being explained. The methods used to make assumptions for stochastic variables in the model, are supported with built in functions of the simulation software. These methods are briefly explained before the entities and their variables are discussed;

- **Random variable**; this method is used to determine a random value for a parameter, within a given interval. These values can be randomly assigned at the initial state of the model or during the simulation at a certain time step. This causes differences in parameters between single agents and between runs of the simulation.

- **Samples based on weights**; this method can be used to take a sample of elements. Input elements can be given (for instance a list) and these elements can be given a certain weight, which are further related to as the probability. This number indicates how likely an element is to be chosen. This method also causes stochasticity within the model and between simulation runs.

- **Normal Gaussian distribution**; this function returns a stochastic value. This is based on a Gauss distribution with a given expected value (mean) and variance (standard deviation).

The EV agents

The EV agents are the main agents of the model, and exists of both the EV driver with its behaviour and decision making and of the EV characteristics like the battery and energy

Table 3.1: The EV agent most relevant variables with their descriptions.

Variable	Description
Origin	Whether the EV agent is a resident (living at a resident building within the case study area) or a visitor (coming from outside of the case study area). This variable is decided based on an assumed probability; 0.9 for being a visitor and 0.1 for being a resident.
Type of activity	This variable indicates whether the type of activity of the agent is working (probability of 0.7) or leisure (probability of 0.3).
Departure time	The time of departing from their starting location.
Staying time	The amount of time in hours the agent is staying at its destination.
Destination	The location of the destination of the EV agent. This is a randomly assigned destination building. The EV agent moves from their starting location to their destination over the road network.
Battery capacity	The amount of stored energy by the battery when it's fully charged.
Range	The range of the battery, indicating the amount of kilometres the EV can drive with a full battery.
Speed	The driving speed of the agents, which is a random value between 15.0 and 25.0 km/h.
Initial SoC	The initial state of charge of the vehicle.
Desired SoC	After a certain threshold of desired SoC, the need to charge for the EV agent increases exponentially. The phenomena of range anxiety causes this threshold to be higher. This threshold is a random value following a normal distribution between 5% and 25%.
Willingness to walk	This includes the distaste for parking far away from the destination. The threshold is assumed to be Gauss distributed around 200 meters with a standard deviation of 50 meters, based on theory (Pagany et al., 2019). A higher walking distance influences the satisfaction of the agents.
Satisfaction	The level of need satisfaction, decreasing per EV agent during simulation based on the searching minutes and their willingness to walk. (Jager, Janssen, De Vries, De Greef, & Vlek, 2000)
CP Hogging	Whether the agent is likely to cling at the CP after charging or not, based on a probability which is used as input for the sensitivity analysis. This probability is a global parameter in the model. When this Boolean variable is false, the EV agent will leave the CP after around 60 minutes.

consumption. The most important variables are further explained in Table 3.1 and some of the calculations are described in this section. The 'Type of activity' variable has an influence on the departure time and staying time of the EV agents. For the working agents the departure time is a random value between 6:00 a.m. and 9:00 a.m. Their staying time is a value following a Gauss distribution with a mean of 8 hours and a standard deviation of one hour. Agents with leisure as activity type have a random departure time between 6:00 a.m. and 18:00 a.m. as their departure times are more likely to be distributed throughout the day. They have a staying time based on a random amount of hours between one and four hours.

Some important variables are the vehicle related ones, which are determined per EV agent at the initial state of the simulation. The first is the battery capacity, this amount is expressed in kWh, following a Gauss distribution with a mean value of 56.8 kWh and a standard deviation of 22.6 kWh. This mean capacity and standard deviation is based on the average capacity of all EVs registered in the Dutch EV database (EV-Database.nl, 2020). Following this value for capacity, the range of the vehicle in the model is calculated in the following way:

$$range\ in\ km = \frac{Capacity\ (kWh)}{Vehicle\ efficiency\ (km)} \tag{3.1}$$

The average vehicle efficiency is assumed to be 17.5 kilometres. Besides these two variables, the EV agents have an initial State of Charge (iSoC) and a desired State of Charge (dSoC), both set at the initial state of the model. The iSoC is set as a random value between 10% and 100%. The SoC decreases while driving and increases while charging. The dSoC is based on the range anxiety of the EV agent, which is set in the global parameters of the model and is therefore the same for every agent throughout the simulation. This range anxiety is a factor between 0 and 1 which influences the mean value for the Gauss distribution of the dSoC. A range anxiety factor of 0 means the driver wants to recharge around a SoC of 5% and a factor of 1 means 45%. Some variables which are not discussed in Table 3.1 are; the walking distance from the CP to destination, the number of minutes the agent is searching for a CP, the status of the agent (either resting, driving, searching or charging). These variables are dynamic and are used to generate the outputs of the model.

The charging points

The CPs represent the installed charging points in the case study area. The locations of these CPs, the number of sockets and their energy rate are adapted from the dataset of Eco-Movement (2019). Table 3.2 shows the CPs agents' variables and descriptions. One global parameter which influences the CPs is the CP occupancy probability, which is assumed to be 0.4, based on data of the occupancy rate of CPs in Amsterdam (Wolbertus et al., 2016). Based on this probability, a CP can be either occupied or not at the beginning of the simulation. During the night, inhabitants in the neighbourhood charge their EVs at the public CPs, causing occupied CPs in the morning. This occupancy rate is around 40%.

Table 3.2: The CP agent most relevant variables with their descriptions.

Variable	Description
Location	Where the CP is indicated.
Energy rate	The rate at which the CP delivers power to the vehicle (kWh).
Number of agents charging	The count number of agents currently charging at the CP, which is continuously updated through the simulation.
Sockets	The number of sockets at the CP, which indicate the number of vehicles who can charge at the CP at the same time.
Occupied	This Boolean variable turns true when the number of charging agents is equal to the number of sockets of the CP.
Occupied at start	When this Boolean variable is true, the CP already is (partly) occupied at the beginning of the simulation.
disapPoints	Adapted from Hoekstra (2017): "Every time an EV driver wanted to use a specific charger but that charger was occupied (meaning the EV driver was disappointed) the charger received an extra point. When chargers accrued too many disapPoints, more chargers could be placed in their vicinity"

The buildings

The buildings are polygons corresponding to the real buildings in the study area with their functions. The type of the building is the only variable of this entity, a building can be either a residential building or a destination building.

The road network

The roads are determined by the study area and are represented by a polyline and consists of different links. The EV agents are driving along this road network from their origin to their destination based on the shortest path. The most important variable of a road is its length, used for driving distance calculation through simulation.

3.3.3 Process overview and scheduling

This section gives an overview of the processes which are built into the model. These processes can be either individually per agent or environmental. First, the main simulation process of an EV agent will be described. After this, the section will explain the smaller process of CP hogging within the model. In the end, the process of choosing the CP on the hand of a list will be elaborated. The descriptions of these processes will be supported by flow charts.

Main simulation process

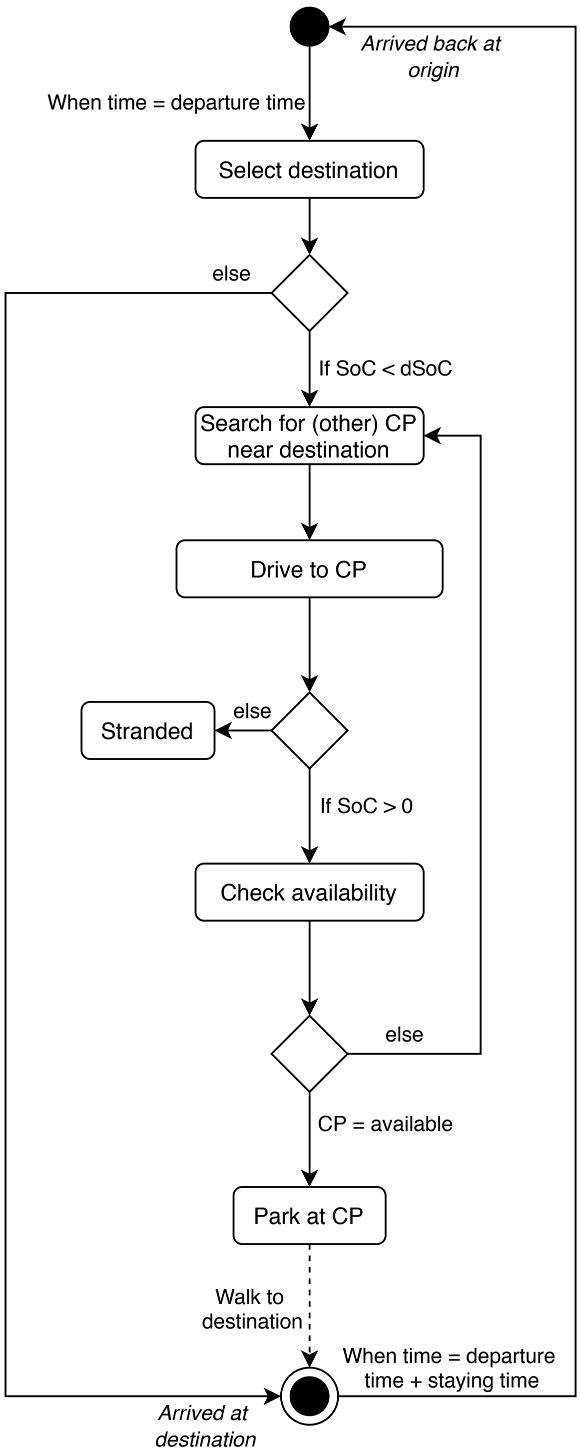


Figure 3.6: Flowchart of the simulation process.

Figure 3.7 shows a flowchart of the main simulation process of the EV agent. One step in the simulation represents 10 seconds. The most important dynamic process in the model is the driving of the EV agents. With each step, the agents move over the road network from their origin to a selected destination. The driving speed is not dynamic and set beforehand by the *speed* variable agent. The EV agent moves towards the destination and during this movement the SoC decreases (State-of-Charge). The initial SoC ($iSoC$) is set at the beginning of the modelling cycle, this is a stochastic variable for a realistic representation of EV drivers who arrive in the model area with different SoC's. If the EV agent reach the destination, it stops. However, when the SoC passes underneath a certain threshold which represents the desired SoC ($dSoC$), the EV agent will start searching for the CP nearest to the destination. At the beginning of the simulation, the distances from the CPs to the destination of the agent will be calculated. After the agent stayed at the destination for a certain staying time, the agent will return home.

If the CP is available, the EV agent will park at the CP and walk to the destination. This walking is not simulated, but the walking distance will be calculated and saved as output. If the CP is not available, the EV agent again searches for another CP near to the destination. This cycle of searching ends when the SoC is zero, which will leave the EV agent stranded.

Charging Point Hogging

As described in Section 2.1.4, CP hogging is the behaviour in which EV drivers stay parked at a CP longer than necessary. This process can lead to a higher occupancy rate of the CPs than needed, resulting in more pressure on the CPs in the neighbourhood. This aspect is a behavioural aspect of EV charging and can have a high influence on the dynamics of EV motorists in relation to CP placement. Therefore, this process is included in the simulation and tested in the sensitivity analysis. Whether an agent is likely to show the behaviour of CP hogging is decided at the beginning of the simulation, by the use of the CP hogging probability (global parameter). When the EV is fully charged (SoC = 100) and the variable CP hogging is false, meaning the agent does not show that hogging behaviour, the agent will remove its car from the CP making place for new EVs. The agent will not move the car directly when it is full, but after a leaving time decided beforehand (see Section 3.3.2).

Updating the CP list

An ongoing process during the simulation is the updating of the dynamic CP lists per EV agent. This process simulates the behaviour of EV motorists when they are searching for a CP to recharge their vehicle. When they are near the CP, they check for its availability and eventually search for another available CP nearby. At the start of the simulation, two lists are created for each agent. One lists all the CPs in the simulation and the other calculates the distance of each of these CPs to the destination of the agent. These lists always stay the same length and the indexes are corresponding with each other. When the EV agent is in need of

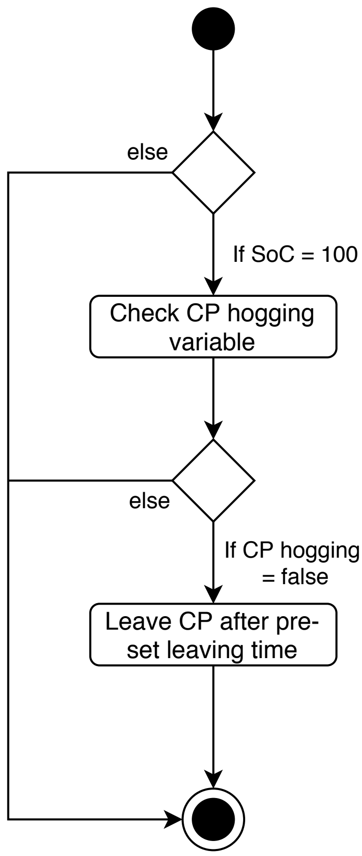


Figure 3.7: Flowchart of process of CP hogging during the charging of the EV agent.

charging (if SoC < dSoC), the agent checks for the lowest value in the distances list. This is the charging point nearest to the destination of the agent. After this, the agent moves to the corresponding CP. This is the item on the CPs list with the same index as the one in the distances list with the lowest value. When the distance to the CP is less than 100 meters, the agent checks for its availability. If the CP is occupied, the CP and its corresponding item in the distance list will be removed. During this action, the removed CP adds a disapPoint to itself. By counting these disapPoints per CP, it can be indicated which CPs are often left by a disappointed EV motorist because the CP was occupied. When the occupied CP is removed from the list, the agent selects the next CP with the lowest distance to the destination. This goes on until the agents finds an available CP to recharge its vehicle. During this process, the agent will count the searching time in minutes.

Satisfaction

For this simulation model, a variable is introduced to indicate the drivers' satisfaction. This satisfaction score can vary between 0 (completely unsatisfied) and 100 (completely satisfied). All agents start with a score of 100 and when an agent strands it will end up with a score of 0. There are two other parameters influencing the drivers' satisfaction; the searching time and the

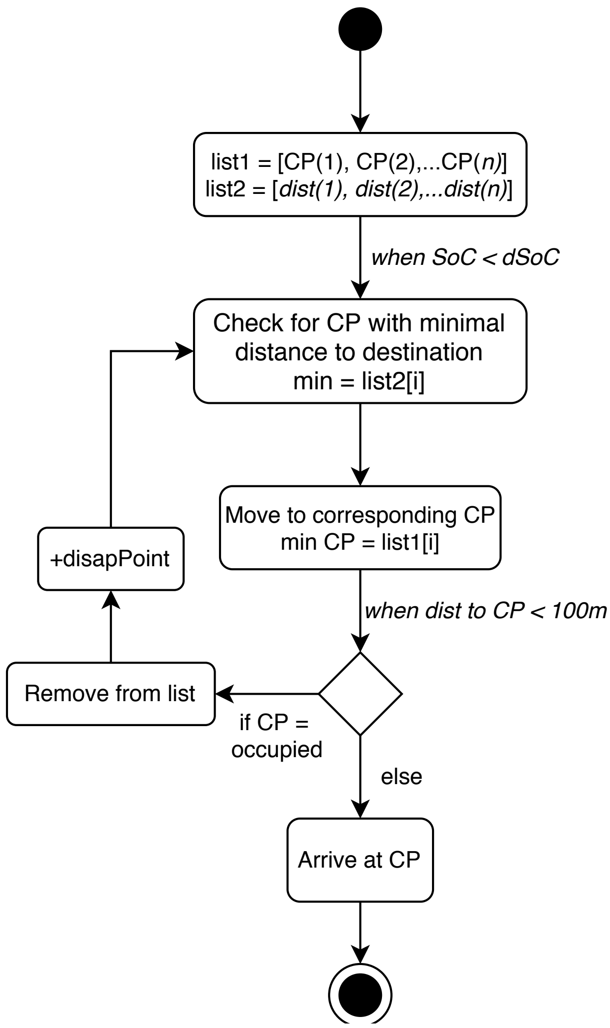


Figure 3.8: Flowchart of updating the CP list during the simulation.

walking distance to the destination. For every minute the agent is searching, the satisfaction score decreases with 5. This means that a higher searching time causes a lower satisfaction score. The other influencing parameter is the walking distance from the CP to the destination of the agent. For this, the variable *willingness to walk* is used. The walking distance is of influence if this is higher than the willingness to walk of the agent. When this is the case, every meter walking further than the willingness to walk threshold accounts for a decrease of 10 for the satisfaction score. This score can be used to give an indication of the satisfaction per agent as well as the total satisfaction during the simulation.

3.4 Implementation of the model

During the implementation phase, the conceptual model is implemented in ABM software using the data of the case study area as input. This will answer the third research question: 'How can this framework be implemented in an agent-based model?'.

3.4.1 Software choice

The ABM model is developed using the GAMA-platform, which is a "...modelling and simulation development environment for building spatially explicit agent-based simulations" (Taillandier et al., 2018). This platform can be chosen over other ABM software like NetLogo for its ease in use and open-source code. Moreover, it is good in use with GIS data as it is easy to load-in shapefiles for defining real-life environments. The language used is called GAML (GAma Modelling Language) and is intuitive and user-friendly in use. GIS datasets will be pre-processed in ArcGIS Pro. The data can be exported as Esri shapefiles, which will be the input for the environment of the model in GAMA.

3.4.2 Used data

This section will elaborate on the used datasets in the simulation model and how this data is processed before using it in the model. The datasets contain spatial data which is used to populate the model. GAMA allows for making a connection to these GIS datasets. A complete overview of these datasets can be found in Appendix B.

Neighbourhood data

The *CBS wijken en buurten* map is retrieved through pdok.nl for indicating the case study area. The neighbourhood Apollobuurt in Amsterdam is selected and exported as a new shapefile. This shapefile is used to extract the other datasets and is used in GAMA to define the boundary of the simulation.

Road network and entry points

The agents move in the simulation along the road network, which means it is important that the dataset is of high quality. A small gap in the dataset can cause a distortion in the network. The network dataset is retrieved from the Wageningen University & Research, where the data is pre-processed and used before in other research. In ArcGIS the data is checked for its quality and completeness. With the 'clipping' tool, the network is clipped to the area of the Apollobuurt.

At each open end of the network (at the boundary of the neighbourhood) an entry point is created and saved in a new shapefile. These are used as origins of the visitor EV agents.

Buildings and their functions

For the representation of buildings in the model, two datasets are combined. The first one is the BGT, which consists of all registered objects with their topography. The building objects are selected from this dataset and clipped to the Apollobuurt boundaries. The second one is the 'Functiekaart', a dataset containing all functions of non-residential accommodations in Amsterdam. This dataset consists of points and is joined to the buildings layer, resulting in a shapefile representing all buildings in the case study area with their functions.

Locations of current CPs

A dataset of all the current public CPs in Amsterdam is retrieved from the organisation Eco-Movement. The data was retrieved at the 22th of October 2019 in a csv file with coordinates to geolocate the points. These points are clipped to the shapefile of the case study area. This dataset shows the locations of the charging points, and counts every socket as a new CP with a unique id. In the GIS software, this dataset is merged in a way that multiple sockets count as one charging point. An attribute 'sockets' is added to count the number of sockets for each CP, indicating how many EVs can charge at the same time. The dataset also contains the energy rate for each CP, this is used in simulation to see at what rate the CP can deliver power to the vehicle. This can be either 11kWh or 22kWh. The charging points are public charging points from different providers.

3.4.3 The modelling process

The next step in the implementation of the conceptual model, is to code the model in GAMA. This is an iterative process, in which small pieces of the code are developed and tested. When those meet the expectations, other functionalities can be designed and coded. Figure 3.11 shows the process of the model development. In this EV behavioural simulation model, a test environment is created before implementing the model in the case study area. As can be seen in the figure, functionalities are designed and coded first in the test environment. When a functionality is tested and considered done, a new functionality is built. When pieces of code fail the testing, the code was being reassessed and adjusted until the code works well. When the basic functionalities in the test environment worked, the code was implemented in the case study area with the real-life spatial datasets.

When the functionalities worked in the real-life environment, this model was extended with more complex functionalities. In this way, new elements and rules were added step by step and these were continuously tested and adjusted until the model was complete. After this, the model if verified and validated. Additionally, a sensitivity analysis is performed and the results are being analysed.

A model in GAMA is organized by the following structure (Taillandier et al., 2018);

- The definition of the global parameters.
- The definition of the different species with their parameters.

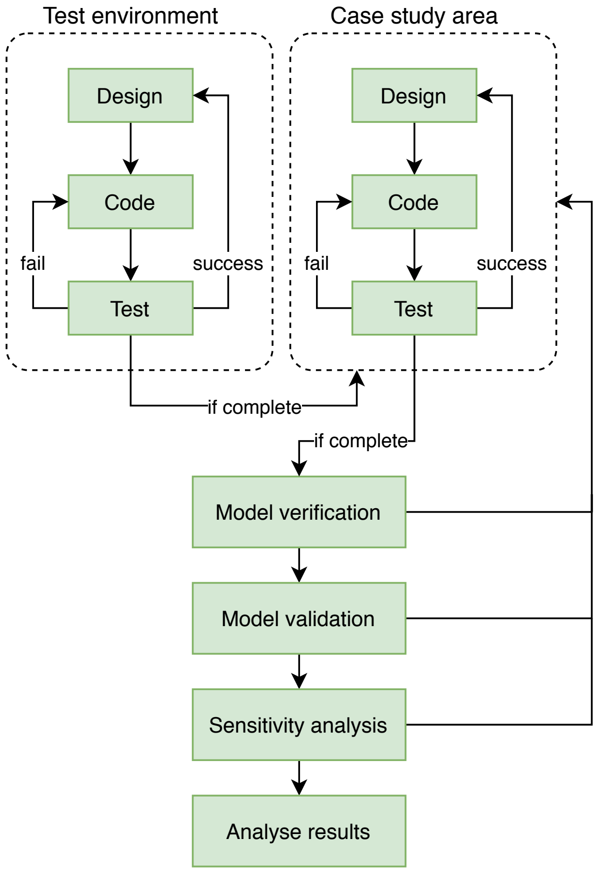


Figure 3.9: Process of the model development

- The definition of the different experiments.

This section further clarifies how the conceptual EV behaviour model is implemented in GAMA following this structure.

Global attributes

The model file begins with the global parameters, which can be used to defining values which apply for the entire model. This section contains the imported shapefiles, definitions of global variables and the initialization of the species. Some variables which are defined in this global section are the time indications, the total number of vehicles, the share of EV ownership, driving speeds, the willingness to walk, range anxiety factor and the different probabilities. This also contains variables used for creating output. For example, attributes such as searching minutes and level of satisfaction are being summarized over all the agents. The global section also contains of code which writes lines of results to a list every hour in simulation. In doing so, daily patterns can be observed. Besides this, the species, representing the agents of the model, are created with their initial attributes.

Definition of the species

In GAMA, the agents of an ABM are specified by a species. In this section of the file, the different species of agents are defined together with their attributes, actions and the way how they are visualized in the model. The actions of the species are defined in GAMA as 'reflexes' which are executed in every time step, following the coded order. In this way, the processes as described in Section 3.3.3 are converted in pieces of code which are being executed every time step. 'When statements' are used as rule in order to define when the reflex can be executed. For example; the reflex *time_to_go_home* is being conducted when: *cycle* = *end_drive*. This reflex make the agents return back to their origin after their staying time at the destination.

Figure 3.11 shows how the reflex which updates the agents' CP list in GAMA, as described in Section 3.3.3. In this way, all the actions of the species are translated in coded reflexes resulting in a complete model.

```
//reflex of updating CP list
reflex cp_list {
    //update list at every new cycle
    tobe_removed <- [] ;
    //add CP to the removed list when the cp is occupied
    loop thecp over: remaining_cps {
        if (thecp.occupied=true) and (thecp in tobe_removed) != true and (location distance_to thecp) < 100  {
            add thecp to: tobe_removed ;
        }
    }
    //use index to remove the CP from the cps lists
    loop elt over: tobe_removed {
        if elt = destination_cp {
            elt.disapPoints <- elt.disapPoints + 1 ;
            }
        int ind <- remaining_cps index_of elt ;
        remove index: ind from: distances_cps ;
        remove elt from: remaining_cps ;
    }
}
```

Figure 3.10: Code of the reflex updating the CP list.

Experiments and output

The last part of the code contains the settings of the experiments, with the parameters and its outputs. Experiments in GAMA are meant for executing and controlling the simulation models. They can be seen as an agent and its behaviour is specified by an experiment plan. The modeler can choose to execute either one of the defined experiments. The first experiment is the general one, with a map display of the actual simulation with adjustable parameters (Figure 3.11). The output of this experiment is the 'monitor' at the right with values of parameters and the map with the species visualized based on their aspect. The destination buildings are displayed as blue, and the EV agents are moving through the network. Their colour is either red (in need of charging) or green (fully or partly charged). The *disapPoints* of the CPs are displayed as a transparent red circle around the points, increasing based on the number of *disapPoints*. In this way, it is visible in which part of the neighbourhood the CPs are congested. The outcomes of this experiment matches the expectations; the CPs close to destinations are the most congested.

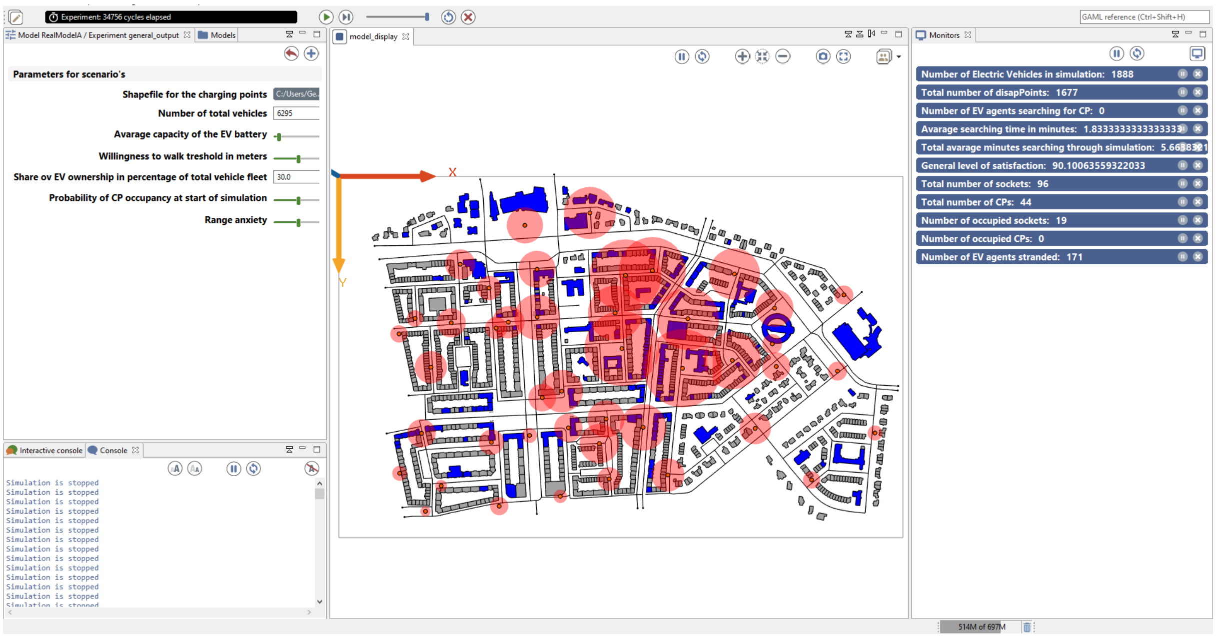


Figure 3.11: Layout of the general model output containing the map display.

The second experiment is that of the batch output, where the tested parameters and their values are set. "Batch experiments allow to execute numerous successive simulation runs. They are used to explore the parameter space of a model or to optimize a set of model parameters" (Taillandier et al., 2018). For this batch experiment, numerous parameters are tested among a couple of values for the sensitivity analysis as well as the scenario analysis. This will be further explained in the next section.

The outputs of the simulation are obtained during several simulation steps, as the value of some variables may change during the simulation time. Furthermore, outputs of agents are generated at the time agents 'die' in simulation. The 'die' reflex in GAMA is used to remove agents from the simulation. In this simulations, the EV agents die when they don't have any more actions to follow. The outputs are saved as lists and saved to local files defined in the experiment part of the code. The following outputs are obtained:

- **Output of EV agents**; obtained after an agent 'dies' with for each agent a comma separated line (.csv file per run).
- **Output of CPs**; obtained at the end of the simulation, with for each CP a line (.csv file per run). This csv file can be joined to the GIS shapefile to observe spatial patterns.
- **Output per hour**; obtained after each hour in simulation (a line per hour) to analyse patterns in time (.csv file per run).
- **Batch output data**; obtained after a batch simulation run with a line for each run (.csv file per batch run).

Large quantities of output csv files are generated, but the aggregated batch output data files are used to evaluate the general outputs and to indicate which other files should be analysed.

3.5 Evaluation

The last step is to evaluate the model, and answers the following question: 'How plausible and useful are the resulting patterns of the proposed behavioural agent-based model?'. Verification and validation of the model is one of the main challenges of the ABM, as there is no validation data available. Different methods need to be used. The model will be evaluated with two methods: face verification and validation, and a sensitivity analysis. This section of the explains the used methods for the evaluation, the results are presented in the following chapters.

3.5.1 Methods for verification and validation

The two processes of verification and validation are essential for making the ABM a functioning tool. Verification is the process to confirm that the developed model in GAMA is working as designed following the conceptual model (Rand & Rust, 2011). This process is carried out during the early stages of the simulation development. The verification consists of three elements; animation assessment (observation of the overall visual simulation), immersive assessment (observation of one particular agent during the model run) and output assessment (check for consistency of the outputs) (Klügl, 2008).

The validation process is to assess whether the model represents the real world, which is carried out during the analysis of the working model (Rand & Rust, 2011). This can be done by evaluating simulation runs with different parameters to test if the model reacts to it in the way it is expected to do, corresponding to real-world situations. Rand and Rust (2011) state that "It is impossible to completely validate or verify a model (p. 187)". Therefore, the verification and validation of this model is limited to a few methods. The current model will be verified and validated using the following methods:

1. The verification during the implementation of the model, with the test model and the verification of small pieces of code.

2. The observation of the overall visual simulation (animation assessment, (Klügl, 2008)).

3. The observation of one specific agent during the model run (immersive assessment, (Klügl, 2008)).

4. The validation of the output data, to assess whether the model produces useful outputs (output assessment, (Klügl, 2008)).

5. The validation of the model with exploring different parameters, as described in Section 3.5.2.

6. The validation of the model with testing two different scenarios, as described in Section 3.5.3.

3.5.2 Sensitivity analysis

This research consists of a separate sensitivity analysis for validation purposes. With the sensitivity analysis, different parameters and their values are assessed. These parameters can be both particular behaviour of agents or overall model outputs (Klügl, 2008). It can be used to approach the behaviour of complex systems where simplifying assumptions must be made (Fox & Burks, 2019). The model is an exploratory agent based model, what means that the simulation is run with different parameters and scenarios to explore and report the way it behaves. The outputs of the different runs are interpreted. For the parameters in the model, quite some assumptions are made (as described in Section 3.3.2). Due to time and complexity restrictions of this research, it is decided to restrict the sensitivity analysis to testing three parameters. These parameters with their tested values are explained before in Section 3.3.3. This section will elaborate on the choices made regarding the parameters for the sensitivity analysis.

The selection of parameters

After analysing the first outcomes of the model, the following parameters are chosen to assess their influence on the model outputs:

1. The probability of the agents being a 'CP hogger'

2. The range anxiety index

3. The share of EV ownership

The first two parameters are behavioural parameters which are strongly related to assumptions made by the modeller, as it is complex to base those parameters on real-life data. Considering this, these parameters are examined to assess their impact on the model's output. The outcomes of this analysis can be used in additional research to calibrate the values of the parameters in the model.

The share of EV ownership is expected to have a very high influence on the outputs of the model, and is therefore chosen to be included in the tested parameters. The reason for this, is that this parameter influences the amount of EV agents in the model. A higher number of agents would hypothetically lead to a longer searching time, more disapPoints and a lower satisfaction level. To examine this, the model will be run for the EV share values of 1.6%, 10%, 30% and 85%. The reason for this selection of values is explained before in Section 3.3.2. The differences in this parameter can be seen as different scenarios of EV market penetration in the city of Amsterdam.

3.5.3 The scenario testing

The aim of the scenario analysis is to evaluate the impacts on the system when testing different scenario's. Three scenarios are proposed and they are either corresponding with the current situation, with policies of the municipality of Amsterdam or with future developments in the technologies of electric mobility. The model is run with these different scenarios to test the model on its usefulness. This can be also seen as an additional validation of the model. The three scenarios are summarized in Table 3.3.

Table 3.3: The selected scenarios with their affected parameters.

Scenario		**Description**	**Ajusted parameter(s)**	**Modifications**
Baseline	Current situation	The initial model result, with the current situation regarding EV characteristics and CP locations.	None.	-
I	Policies	An exploratory scenario with the placement of more CPs, regarding policies of the Municipality of Amsterdam.	Shapefile of the CPs.	Modified in GIS based on the outcomes of the baseline scenario.
II	Technologies	An exploratory scenario with the impact of future developments in the techniques of EVs and CPs.	Average capacity and range.	An increase in average capacity from 56.8 kWh to 180 kWh.
			Charging speed of CPs.	An increase in power of CPs from 11/22 kW to 55 kW.
			Desired State of Charge	Increased to ratio of the increased capacity.

The first scenario can be seen as the baseline scenario, with the **current situation**. This scenario is the final model as implemented in the case study area. The dataset with the charging points corresponding with their real locations is used and the parameters are the most likely to correspond with the current situation in the case study area. The current situation is used as a scenario to assess how the simulation comparable to the current situation is influenced by different parameters. For example, the outcomes of this scenario will show what will happen when the share of EV ownership increases without the placement of new CPs.

Scenario I is based on **policies** in the 'Action Plan on Clean Air' of the Municipality of Amsterdam as discussed in the introduction of this research (Gemeente Amsterdam, 2019). The city of Amsterdam is banning all the petrol vehicles by 2030 in order to be emission-free in the future. In order to facilitate this policy, new CPs will be placed through the city of Amsterdam. In the year of 2018 the number of public CPs in the city grew with 16%. It is expected that in the year of 2025, 23,000 CPs are needed in the city in order to supply enough capacity. This means the current number of CPs in the city (around 3,000) needs to be multiplied by almost 8. For the Apollobuurt, this increase could mean an increase from 96 CPs (individual sockets) to a number of 736 CPs. After the baseline scenario is analysed, a new distribution of additional CPs is proposed for Scenario I.

The last scenario, Scenario II, is based on **future technologies**, as found in literature (Section 2.1.5). It is assumed that better charging and battery technologies will be developed in the near future, allowing an increasing share of EV ownership. This means that the capacity of batteries will be greater and the charging speed of CPs will be faster. It is expected that these technologies will have a positive impact on the satisfaction of EV motorists as the need to recharge is less and the charging will be faster. Table C.1, which can be found in Appendix C, presents a summary of the selected simulation experiments with the settings for the different input parameters.

3.6 Summary

This chapter successfully answered the second research question: *'How can behavioural aspects influencing EV driving and charging be conceptualized in a framework suitable for modelling?'*. The previously conducted literature study has provided outlines for the conceptual ABM, which have been designed in this methodology chapter. After summarizing the key findings of the theoretical framework and explaining the case study selection, a overview of the conceptual model is given. This model is implemented in GAMA using an iterative process which already covered a part of the model verification and validation. Thereby, the third research question, *'how can this framework be implemented in an agent-based model?'*, is answered as well. Investigating the plausibility and usefulness of the ABM will be further accomplished in the following chapters containing the model verification and validation, the sensitivity analysis and the scenario testing.

Chapter 4

Model verification and validation

This chapter contains the verification and validation of the model, in order to confirm that the EV driving and charging behavioural model works as it is designed and to assure it is representing the real-world in a valuable way for stakeholders as policy makers. Section 3.5.1 provides the methodical outlines for this part of the research, in this chapter the results of the verification and validation are presented. First, the model verification during the coding process is described at the level of the test model and the final model. After this, the model is analysed at the individual level of agents and the model outputs are validated. Furthermore, a sensitivity analysis is conducted. The validation is also carried out by testing different parameters in scenarios. These results are described in Chapter 5.

4.1 Verification of the test model

The model is in the first place implemented in a test environment. At this stage of modelling, the functionalities were still limited, and the number of agents was constrained to allow analysing the test model in detail. After adding each small piece of code, the model was run to see whether the added functionality works as designed in the conceptual model. Once the test model contained some first basic functionality, the verification of the model in the test environment was conducted.

The test environment, as displayed in Figure 4.1, is created in ArcGIS Pro with the use of the editing tools. It is created to match the real-world entities at a simplified level and scale, based on the case study area. The road network consists of 15 segments and has two origins for the visitor agents. The buildings are either residential (grey) or destination buildings (blue). In the initial phase of the simulation, the EV agents are diffused around the residential buildings and the two origins. The CPs are displayed as orange points and diffused along the road network. Visualisation possibilities in GAMA are used to make the agents differ in colour for their SoC (agents turn red when in need of charging), and a semi-transparent red circle appears around the CPs based on their number of disapPoints.

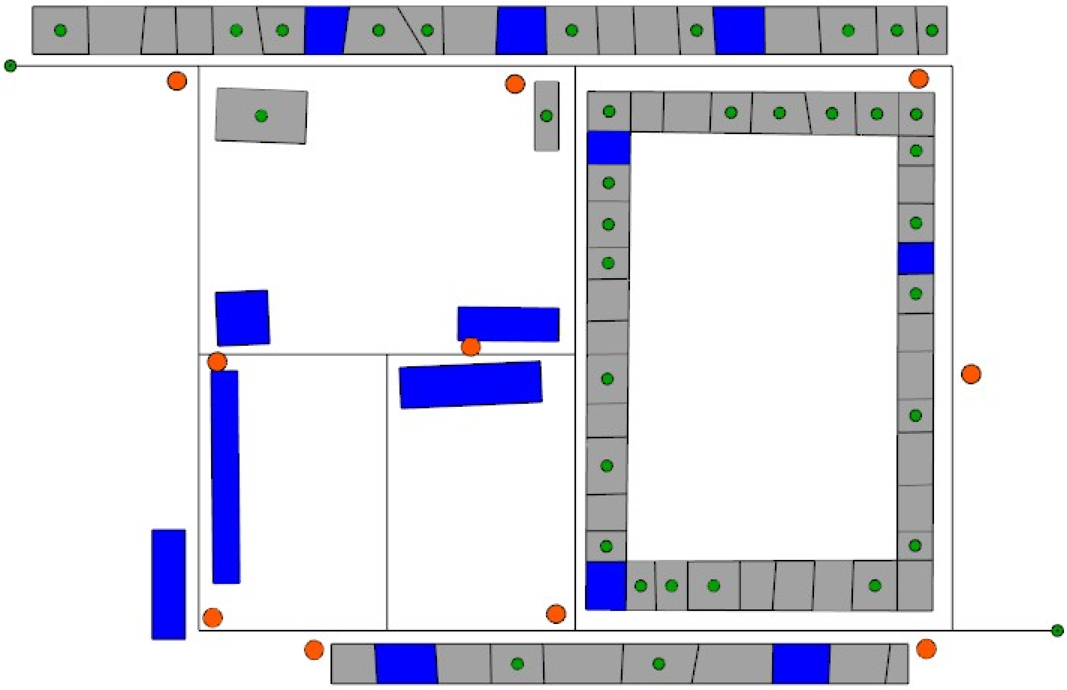


Figure 4.1: Setup of the test environment.

The test model is initially run with a number of 80 EV agents in simulation. Simplified parameters are used to see if the model is functioning in the fundamentals of the model. In this test, the SoC of the agents is decreasing based on the time steps instead of the driving distance along the road network. There are no statistical outputs generated. Therefore, the test model is only verified by visual observation. The running simulation already gave realistic mobility patterns; agents are moving to their destination when it's time to leave their origin. When it's time to recharge, they move to the CP closest to their destination. These patterns match the expectations of the conceptual model. During this test run, only two disapPoints were generated and no agents stranded. The EV agents in need of charging were able to find a CP close to the destination.

After the first test run the number of EV agents is incremented to 240 agents in order to see what will happen when the CPs are likely to be overburdened. In order to see how the model responds to the expected overload of the system, the spatial temporal patterns of the simulation at four different time steps (Figure 4.2). At 06:00 (upper left), the simulation is initialised, and the agents are diffused around the residential buildings and the two origins. At 09:00 (upper right) a large share of the agents left their origin. Some of them moved directly to their destination, as there are some agents located in the destination buildings. Some of the CPs are occupied and red circles around them appeared indicating the disapPoints. At 14:00

(bottom left), most of the agents left their origin and the number of disapPoints increased. This indicates the overuse of the CPs and the disappointment of the EV agents. Some agent left already because their staying time expired. Spatial differences in the disapPoints can be observed, as the number of disapPoints is higher around clusters of destination buildings (in the bottom left corner of the test environment). At 22:00 (bottom right), the simulation ended and all agents left (died in terms of simulation). The patterns in the test environment match the expectations of the conceptual model.

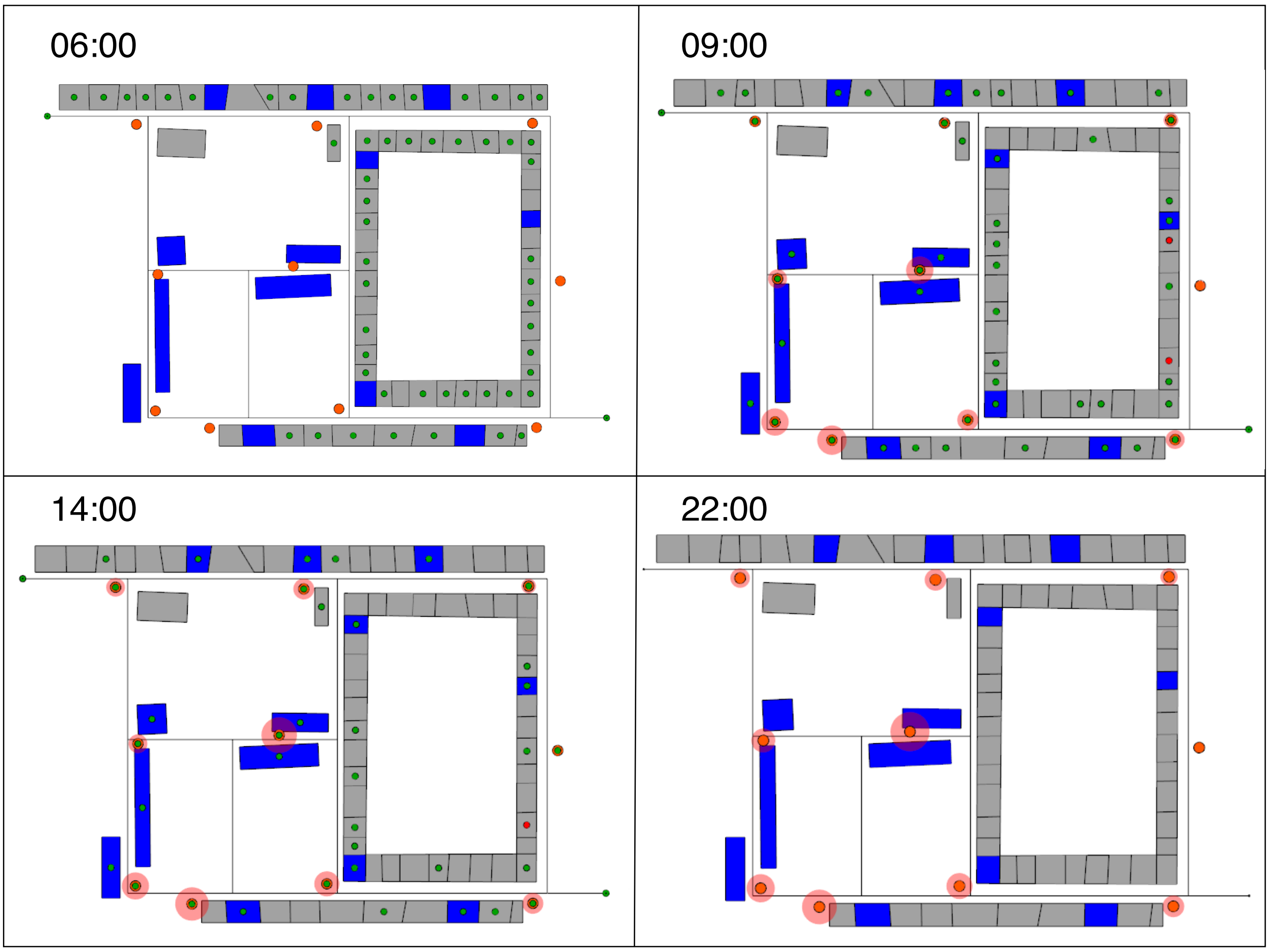
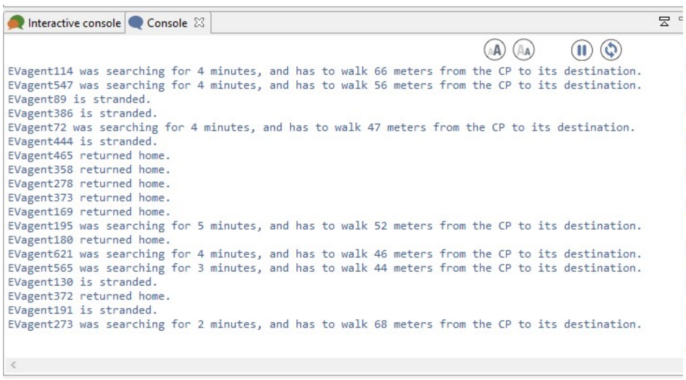


Figure 4.2: Spatial temporal patterns of the test simulation run with 240 agents.

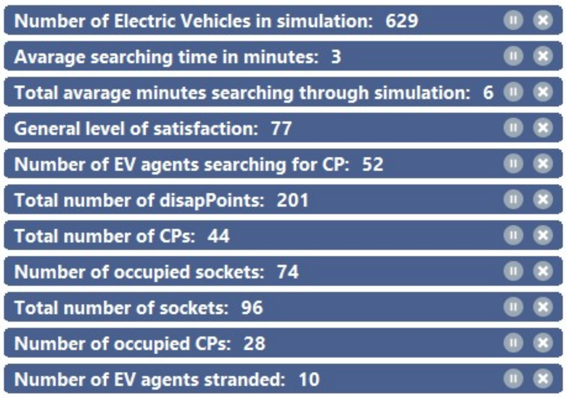
4.2 Visual observation of the final model

In this section, the running model will be verified following the method 'Animation assessment' proposed by Klügl (2008). This process is already integrated in the development of the model. The previous described test model was also part of this process. After successfully testing and debugging the test model, the code was implemented in the case study area by changing the shapefile document paths to the case study datasets. For the case study model, additional functionalities where coded and tested step by step resulting in a more complex model reflecting the real life situation in a more accurate way. This model development process continued until the simulation contained all the desired functionalities as designed in the conceptual model (as described in Section 3.4.3 0. Once the model reached this point, the verification of the running final model started.

As described in the previous section, GAMA consists of different visualisation options to support the animation assessment. The same layout options as used for the test model are chosen. However, for the final model two additional layout options are added: the console and the monitor. The console is used to display messages during the run time of the model, created with 'write' statements in the code. This provides a visual real-time display with information about events in the model. It logs the events of when an agent; arrives at a CP, has arrived at destination, left the CP without hogging, returns home and when the agent strands. When an agent arrives at a CP, the console logs the time the agents spend on searching in minutes and the walking distance to the destination. The monitor keeps track of some variables which are summarized over all the agents. For example, it monitors the number of occupied sockets and CPs, the searching time and the general level of satisfaction. These layout options allow for an extensive visual observation of the model while running. Figure 4.3 shows these layout options with the console messages and the measured values in the monitor. This figure captured the console and monitor at 09:00 in simulation.



(a) Console



(b) Monitor

Figure 4.3: Console and monitor during the animation assessment, at 09:00 in simulation.

The model is assessed during different runs with an EV ownership share of 10%, resulting in a number of 629 EV agents in the simulation. Observing the model, the moving of the agents is occurring as attended with the conceptual model. The agents are moving along the road network to their destinations and to a CP when they need to recharge. When this CP is occupied, the agent moves to another CP close to the destination and a disapPoint is visualised around the CP. Figure 4.4 shows the model environment at 09:00 during simulation time. Some of the agents already reached their destination or the charging point. This animation shows similar patterns as was observed in the test environment; higher numbers of disapPoints are clustered around destination buildings. Most op the time, CPs around residential buildings are not occupied.

Figure 4.4: The model environment during the simulation run at 09:00.

Running the model multiple times shows small differences in the visual patterns, which is caused by the stochastic aspects of the model. However, the behaviour of EV agents is relatively similar with every run and the spatial distribution of the disapPoints is not varying significantly. The impressions after conducting the animation assessment is that the behaviour of the agents seems to be matching the expectations and is able to represent real-world mobility patterns.

4.3 Observation at individual level

This part of the verification and validation process contains the 'immersive assessment' (Klügl, 2008), this entails the observation of one specific agent during the model run. This assessment is conducted to see if an individual agent in the model behaves the way it was designed and whether it corresponds with the expectations of real-life behaviour. For this, two single EV agents are tracked to observe their variables and behaviours.

GAMA consists of different tools which allow for tracking an agent at individual level. It is possible to study different elements in the model, such as the total population of the agents as well as an individual agent. Two agents who are likely to be in need of charging are chosen to be able to investigate their charging behaviour, because not every agent will be in need of charging during the simulation. Table 4.1 shows the initial variables of the two tracked agents during the immersive assessment. These variables are verified and validated by observing their behaviour during the simulation run, this will be described below.

Table 4.1: The initial variables of the two tracked EV agents

	Agent 1	**Agent 2**
Type	Visitor	Resident
Capacity	35.5 kWh	52.7 kWh
Activity type	Working	Leisure
iSoC	21.00%	23.00%
dSoC	28.95%	19.06%
Start drive	06:40	15:55
Staying time	9 hours	3 hours and 18 minutes
Destination building	Building(1182)	Building(1071)
CP Hogger	false	true

At 06:40, Agent 1 leaves its origin and the model starts computing its target and path to that target. The target is the CP closest to its destination building because the State of Charge is below the desired State of Charge. It moves along the road network and its driven distance is increasing while the State of Charge is decreasing. Because the CP is not occupied yet, the EV agent successfully arrives at the CP and starts charging. The agent was searching for 20 seconds and had to walk 23 meters from the CP to its destination. This distance is checked with the use of the measure tool in ArcGIS Pro which gave a distance of 22.93 meters, so the distance in the simulation is correctly calculated. At the time of 15:02, the EV agent was fully charged and turned green. Because the agent is not a CP hogger, the agent should leave the CP after around 1 hour. However, the agent had a staying time of 9 hours so at the time of 15:40 the agent already returned home and died in the simulation.

At the simulation time of 15:55, Agent 2 leaves its home and moves over the road network to the destination building. During the drive, the SoC decreases to a level lower than the desired SoC. At that moment, the agent starts searching for a CP. Within this time of the simulation, around half of the CPs is occupied (47 out of 96). Some of the agents returned back to their origin already. The agent drove to the CP closest to the destination and when the distance to this CP was less than 100 meters, noticed it was occupied. After continuing with the search, agent 2 successfully arrived at the second CP and started charging.

The agent was searching for 4 minutes and had to walk 55 meters. However, measuring the walking distance in ArcGIS Pro gave a result of 120 meters. As this difference in measured and modelled walking distance is quite remarkable, this discrepancy has been further studied. The difference is probably due to simplification assumptions by GAMA, as can be seen in Figure 4.5. When measuring distance along the road, the distance of 55 meters from the CP reaches to a point where the Euclidean distance to the destination might be relatively short. However, in the real world the building can only be reached by walking to the front side of the building facing the road. In the case as showed in Figure 4.5, the building can be reached in real-life by walking around the corner. This causes some calculated distances in GAMA to be too short, compared to the real-life situation. This flaw in the simulation can be further studied in future research to optimize the model.

Figure 4.5: Assessment of difference in walking distance of Agent 2.

After assessing the initial variables and tracking two individual agents, it can be concluded that in general the model behaves as designed and matches real-life behaviour as expected. However, the immersive assessment as conducted could be extended by including more variables and study more agents with different parameters. For further research, it would be interesting to track the routes of some individual agents and plot these routes on a map showing the spatial patterns of EV motorists searching for an available CP.

4.4 Verification and validation of the model output

The last step of the verification and validation 'output assessment' (Klügl, 2008). In this part of the process the outputs of the model are validated. This section aims to validate the initial variables and global outputs by comparing it to the input values. Due to limited data availability for the validation and calibration, an attempt is made with limited data sources. This step of the validation process is conducted with the results of 10 model runs to achieve the desired variance stability.

4.4.1 Distribution of the initial variables

To determine if the distribution of the initial variables matches the given input parameters, the final model is run 10 times and some major variables of the EV agents are compared to the model input. This is analysed with a share of EV ownership of 10%, resulting in a total number of 629 agents in the simulation. The compared variables are the following: the desired State of Charge (*dSoC*), the capacity, the leaving time and the staying time. In Table 4.2 the input for the *dSoC* and *Capacity* variables are compared to the values of the model output summarised over 10 runs. Based on this, it can be concluded that the distribution of the model is almost identical to the input mean and standard deviation for the Gaussian variables. The outputs for these values in the simulation matches the expectations as designed, and are therefore verified. However, during this assessment a flaw in the model is discovered as some agents have either too low or values below zero for the capacity variable, which is not realistic when comparing it with the real-world. This is caused by a relatively high value for the standard deviation. For future analysis, the negative values for the Gaussian distribution of this variable should be truncated. The values of *dSoC* for each run with the total number of agents are displayed in Graph 4.6, this shows the Gaussian distribution along the values for capacity.

Table 4.2: The initial Gauss variables of the model compared to the input values.

	Input distribution		**Model distribution (average of 10 runs)**	
Variable	**Mean**	**SD**	**Mean**	**SD**
dSoC (%)	21	5	20.93	5.01
Capacity (kWh)	56.8	22.6	56.92	22.88

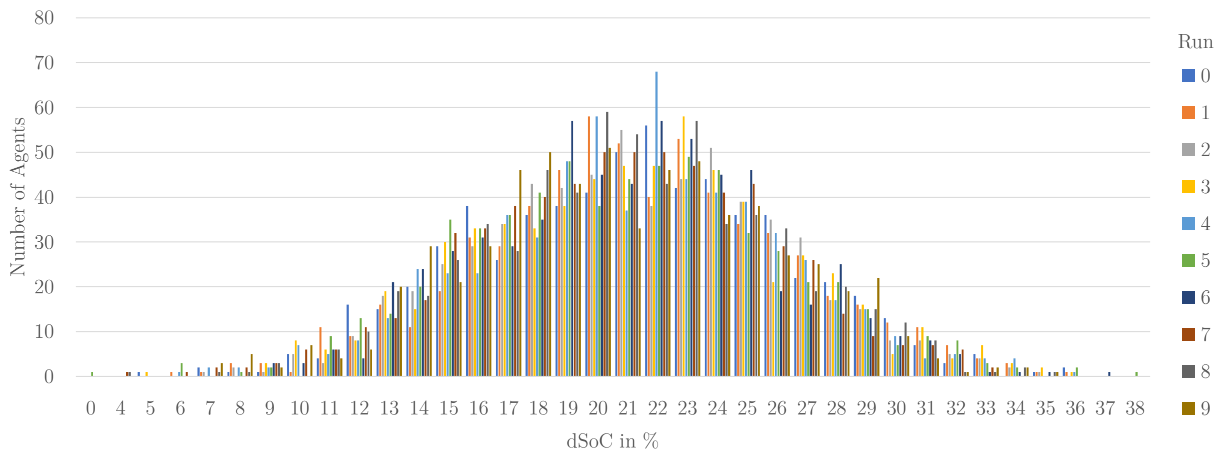


Figure 4.6: The distribution of the desired State of Charge ($dSoC$) over 10 runs.

Additionally, the initial variables determining the staying time and the start of the drive are compared. These vary between the activity type of the EV agent, which can either be working or leisure. As can be observed in Table 4.3, different methods are used for setting the staying time. For the agents with a 'working' profile, the time spent on destination is distributed along a Gaussian distribution with a mean of nine hours and a standard deviation of 1 hour. The model shows similar outputs with the values for 10 runs summarised. The staying time for the leisure activities is a random value between one hour and four hours. For this the outputs are as expected, with a mean staying time around 2.5 hours. The start times for both working and leisure typed agents are also based on a random value between a minimum and a maximum time. For both the starting times, the output values are matching the input values.

Table 4.3: The initial leaving time and staying time of the model compared to the input values.

		Input distribution		**Model distribution (average of 10 runs)**	
Activity type	**Variable**			**Mean**	**SD**
Working	**Staying time (hours)**	Mean: 9	SD: 1	9.02	1.01
	Start Drive (time)	min: 06:00	max: 09:00	07:28	00:52
Leisure	**Staying time (hours)**	min: 1	max: 4	2.56	0.86
	Start Drive (time)	min: 06:00	max: 18:00	08:31	01:01

4.4.2 Verification of the probability values

The distribution of the EV agents is based on assumed input probability values. As illustrated in Table 4.4 the model behaves as expected because the model gives similar output distribution percentages as the probability values. For example, with an input probability of 0.7 for activity type 'working' it is expected that around 70% of the agents will be of this type. After 10 runs this average share for this activity type is 69.81%, which is almost identical to the expected share. Another conclusion that can be drawn from this is that the number of 10 runs is adequate for levelling out the variation.

Table 4.4: Input probability values compared to the output distribution.

		Input probability	**Output distribution (average 10 runs)**
Type	**Visitor**	0.9	90.49%
	Resident	0.1	9.51%
Activity type	**Working**	0.7	69.81%
	Leisure	0.3	30.19%
CP Hogging	**True**	0.8	79.81%
	False	0.2	20.41%

To illustrate the differences between different model runs, the distribution of activity type is compared and studied over the 10 different runs. Table 4.5 shows the variation that exists in between the different model runs. However, the shares for each run are still relatively similar to the input probabilities and the distribution values are stable.

4.4.3 Validation of occupancy rates

In this section, the hourly occupancy rate of the sockets is displayed for the 10 simulation runs in Figure 4.6. The model is in the first place run with an EV ownership share of 10%, to be able to clearly see patterns in the output data. After this, the validation is repeated with an EV ownership share of 1.6% to be able to compare it with the available real-world data. The occupancy rate is calculated as the share of occupied sockets against the total amount of sockets. The average occupancy rate during the day over the 10 runs is 68.83% for an EV ownership share of 10%. This rate is not comparable to the real-life occupancy rate in Amsterdam (40% in the beginning of 2016, see Section 2.1.3) as an EV ownership share of 10% is higher than the current situation (1.6% in 2019, see Section 3.3.2). Nevertheless, the occupancy rates show similar patterns as an 'office-charger' profile as displayed in Section 2.1.3. This is due to the fact that the simulation aims to simulate charging behaviour of EV motorist

Table 4.5: The distribution of activity type compared over 10 runs.

Run	Share of agents with activity type 'leisure'	Share of agents with activity type 'working'
1	30.68%	69.32%
2	29.89%	70.11%
3	31.64%	68.36%
4	31.48%	68.52%
5	25.12%	74.88%
6	27.98%	72.02%
7	34.50%	65.50%
8	30.21%	69.79%
9	30.05%	69.95%
10	30.37%	69.63%

which visit the neighbourhood for leisure or work. The biggest share of EV agents are having a 'working' profile which means they leave home early, causing the steep increase early in the graph in Figure 4.7. At the start of the simulation, the occupancy rates are starting with a share around 40%. This is due to the assumption of the modeler that some of the CPs will already be occupied by residents at beginning of the day.

To be able to compare the occupancy rates with real-life data, the model was run 10 times with the EV ownership share of 1.6%, which reflects the current real-world situation. This gave an occupancy rate of 44.13%, which is rather similar to the real-world occupancy rate of 40% (in the beginning of 2016, see Section 2.1.3). This similarity shows that the resulting occupancy rate can be validated when comparing it to real-life occupancy rates. However, the occupancy rate data dates from 2016 and the EV ownership share dates from 2019. This could cause minor differences in between the simulation output and the real-life data. After all, the output of the model is highly influenced by the assumptions made by the modeler. This could cause similarities to real-life data to be a coincidence rather than a strong validation of the model. When more (recent) validation data is available, the model could be further calibrated in future research.

4.5 Sensitivity analysis

A sensitivity analysis has been carried out to explore how the model reacts when parameters change. As the model contains multiple stochastic variables, the output of each individual run will differ from another run. Due to this reason, the model will be run 10 times for each

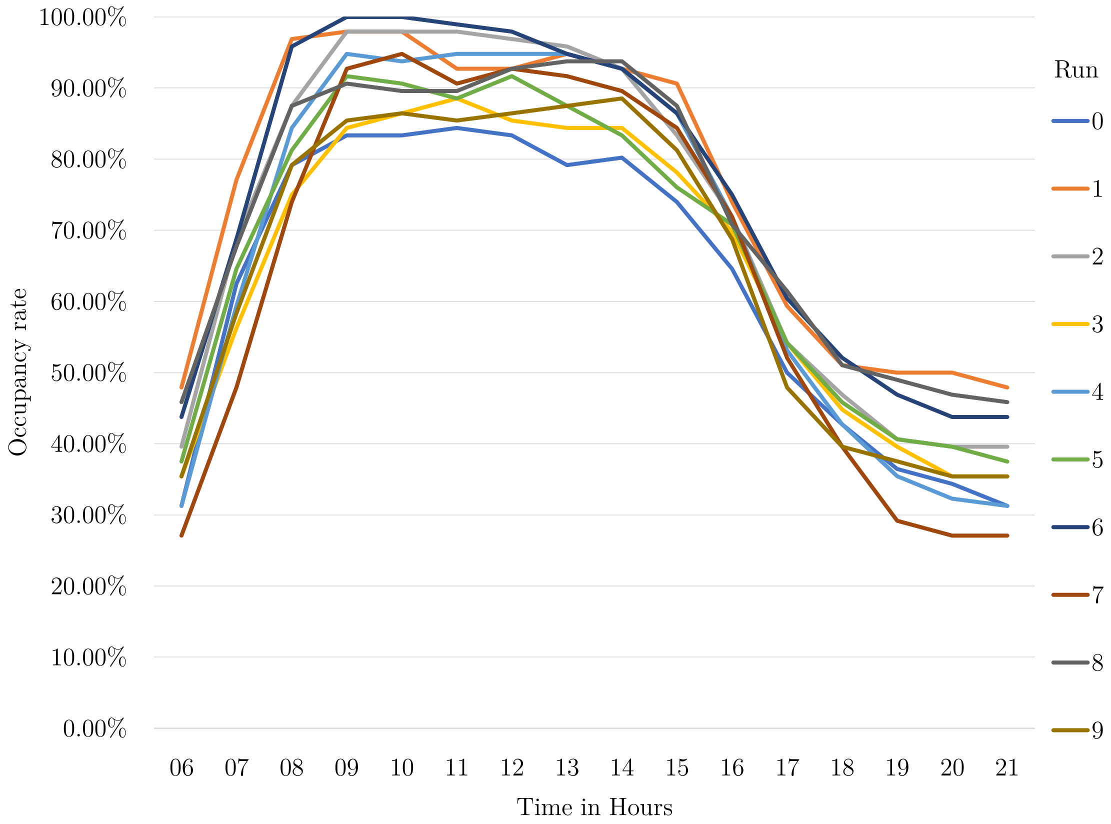


Figure 4.7: Hourly occupancy rate over 10 model runs, for an EV ownership share of 10%.

parameter setting and the outcomes will be averaged over the runs. As explained before in Section 3.5.2, the chosen parameters are the following: the probability of the agents being a 'CP hogger', the range anxiety index and the share of EV ownership. The presence of CPs, the capacity of an EV and the charging speeds are parameters to be explored by experimenting with different scenarios. The results of the scenario testing are presented in Chapter 5.

4.5.1 CP hogging and range anxiety

First, the parameters 'CP hogging' and 'range anxiety' are explored. For the first parameter, the probability of the agent being a CP hogger, five configurations are used (0.2, 0.4, 0.6, 0.8 and 1). With a probability value of 0.2, it is likely that for the most part EV agents will leave the CP within an hour after the vehicle is fully charged. With a probability value of 1, all EV agents will keep their vehicle parked at the CP until they leave for home. For the range anxiety parameter, six values are explored varying from 0 to 1 with steps of 0.2. This parameter indicates a factor determining the degree of range anxiety amongst EV agents in simulation. With a range anxiety score of 0, agents are in need to recharge their vehicle around a State of charge of 5%. With a score of 1, the need to recharge is around a State of Charge of 45%.

The different parameter configuration combinations are tested with a share of EV ownership of 10%.

For this part of the sensitivity analysis, each possible combination of the parameter settings is run 10 times and the outputs are summarized over these 10 runs. Four kinds of output values are generated for each combination of parameter settings:

1. The average **searching minutes** per agent,
2. The total number of **disapPoints** in the simulation,
3. The average level of **satisfaction**,
4. The total number of **stranded agents** during simulation.

The results of these four output values are displayed and visualised in Figure 4.8. A green to red colour scale is used to clearly visualise the differences in the output values. A green colour is used for a positive output (for example, a low number of disapPoints) and a red colour is used for the negative output values (for example, a low satisfaction score).

Search min. CH \ RA	0	0.2	0.4	0.6	0.8	1
0.2	1.36	2.43	3.86	4.95	5.96	6.69
0.4	1.57	2.45	3.66	5.04	5.99	6.74
0.6	1.45	2.58	3.83	5.06	6.19	6.61
0.8	1.56	2.54	3.89	5.21	6.18	6.99
1	1.48	2.15	3.96	5.25	6.39	7.03

(a) Average searching minutes per agent.

disapPoints CH \ RA	0	0.2	0.4	0.6	0.8	1
0.2	6.30	75.50	355.00	713.40	1199.10	1680.70
0.4	5.50	71.60	328.30	708.60	1217.10	1721.10
0.6	8.10	100.30	333.90	760.20	1284.20	1657.10
0.8	6.50	87.60	344.90	752.00	1244.70	1790.30
1	5.70	61.00	367.10	775.70	1331.90	1736.70

(b) Total number of disapPoints.

Satisfaction CH \ RA	0	0.2	0.4	0.6	0.8	1
0.2	99.51	98.88	94.07	88.16	80.20	73.75
0.4	99.56	98.78	94.66	88.14	79.77	72.90
0.6	99.63	98.23	94.42	87.23	79.09	73.62
0.8	99.51	98.49	94.26	87.09	79.01	70.94
1	99.57	98.83	93.88	86.65	78.10	71.81

(c) Average level of satisfaction.

nb. Stranded CH \ RA	0	0.2	0.4	0.6	0.8	1
0.2	2.6	2.9	27.5	60.3	109.5	147.1
0.4	2.2	3.7	23.6	61.4	111.8	152.9
0.6	1.7	6.6	25.9	67	115.4	148.3
0.8	2.5	5.6	27.1	68.6	117.9	167.2
1	2.1	4.1	29.2	71.3	124.3	162.2

(d) Total number of stranded agents.

Figure 4.8: Output values for different configurations of the CP Hogging (CH) and Range Anxiety (RA) variables, averaged over 10 model runs.

The influence of the different parameter configuration combinations is clearly displayed in Figure 4.8. First of all, it can be concluded that the CP Hogging probability (CH) variable does not have a considerable influence on the different output values in the simulation. The differences in the output for each setting of the CH variable are unremarkable, in contrast to the outputs for the different values of the range anxiety (RA) factor. As can be seen in the different figures, the configuration for the RA parameter greatly influences the output values of the simulation. This is visualised with use of the green to red color scale. The RA factor and the output values correlate mainly in a positive way, meaning that when the RA factor increases the output value increases as well. Except for the Satisfaction output; when the RA factor increases, the satisfaction decreases because a lower satisfaction score indicates a more negative output. In general, it can be said that a higher RA factor relates to less positive output of the model.

4.5.2 Share of EV ownership

For this sensitivity analysis, the different shares of EV ownership are tested determining the number of EV agents in the simulation. It is expected that this parameter has a considerable influence on the outputs of the model. This parameter is tested with the use of a 'one-at-a-time' (OAT) analysis, this entails that variations of the tested parameters are applied while the other parameters are kept the same. The tests will be run with the original CP hogging probability of 0.8 and a range anxiety factor of 0.4. The following configurations for the EV ownership share are used:

- EV ownership share of 1.6%, resulting in 100 EV agents in simulation.
- EV ownership share of 10%; resulting in 629 EV agents in simulation.
- EV ownership share of 30%; resulting in 1888 EV agents in simulation.
- EV ownership share of 85%; resulting in 5350 EV agents in simulation.

Large differences in between the shares are used to show the extremes in the results. The effect of the EV ownership share configurations on the different output values can be observed in Table 4.6 with the mean values averaged over 10 simulation runs. First, it can be concluded that a larger number of agents in simulation increases the demands which results in a higher pressure on the charging point infrastructure. This led to a higher number of average searching minutes, more disapPoints, a lower satisfaction score and more stranded agents. Additionally, the table shows the stability of the results in the different simulation runs, expressed by the standard deviation and the coefficient of variation. The coefficient of variation (CV) is the ratio of the standard deviation (σ) to the mean (μ);

$$CV = \frac{\sigma}{\mu} \tag{4.1}$$

A lower share of EV ownership means more variability in between the runs, resulting in a higher coefficient of variation. With a higher share and more agents in the simulation, the outputs are more stable.

Subsequently, the daily patterns in the CP occupancy are observed for the different EV ownership shares. The results of the four configurations show differences in occupancy rates, but similar patterns can be recognised (Figure 4.9). All configurations start and end with

Table 4.6: The mean, standard deviation (SD) and coefficient of variation (CV) in the outputs for different shares of EV ownership (EV%).

EV%		**Searching min.**	**disapPoints**	**Satisfaction**	**nb. Stranded**
1.6	Mean	2.66	22.50	97.58	0.60
	SD	0.39	11.56	0.89	0.66
	CV	0.15	0.51	0.01	1.11
10	Mean	3.97	375.70	93.71	30.20
	SD	0.52	97.59	2.26	14.21
	CV	0.13	0.26	0.02	0.47
30	Mean	5.44	1567.90	89.54	183.50
	SD	0.18	124.37	0.86	16.38
	CV	0.03	0.08	0.01	0.09
85	Mean	6.23	5293.30	86.90	679.90
	SD	0.09	175.93	0.51	28.73
	CV	0.01	0.03	0.01	0.04

an occupancy rate around 40% because of the occupancy probability of residents. The four configurations show a similar curve: steep at the beginning of the day and a gradual decrease after 14:00. The higher the EV ownership share, the steeper the line will be in the begin of the day. With a share of 1.6%, the occupancy will not exceed an occupancy rate around 50% during the day, meaning there are fewer temporal differences to be observed. An increase to 10% already causes significantly higher occupancy rates and the daily pattern is more diverse. With the shares of 30% and 85%, the occupancy rate of 100% is already reached around 7.00 in the morning. For most of the day, the CPs are occupied causing more stranded agents and a lower satisfaction score.

At last, this part of the sensitivity analysis investigates the effect of the EV ownership share on the spatial distribution of the CPs' disapPoints. Output maps with the disapPoints per CP averaged over 10 simulation runs, for the different EV ownership shares can be found in Figure 4.10. It is clear that a higher share, thus a higher number of agents, causes more disapPoints through the simulation. Similar patterns can be observed in this simulation run; higher numbers of disapPoints are clustered in the middle of the neighbourhood (due to the presence of destination buildings) and CPs with less disapPoints are to be found close to the borders of the neighbourhood. However, with a share of 1.6% those patterns are less visible considering the maximum disapPoint value of 2.4. With the share of 85% the maximum amount of disapPoints is 326, making it harder to distinguish details on the map as seen below.

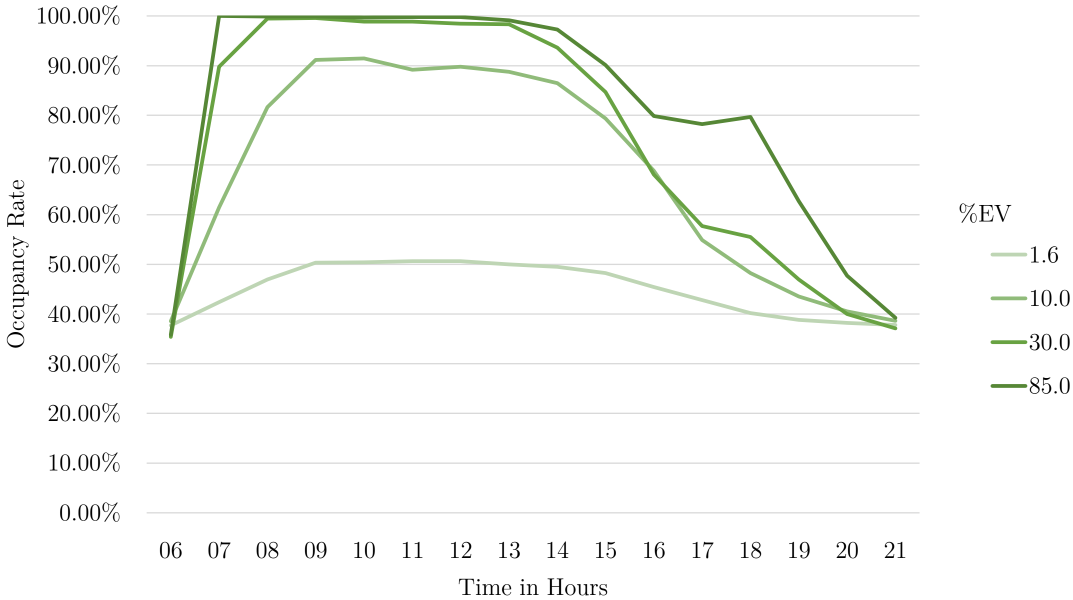
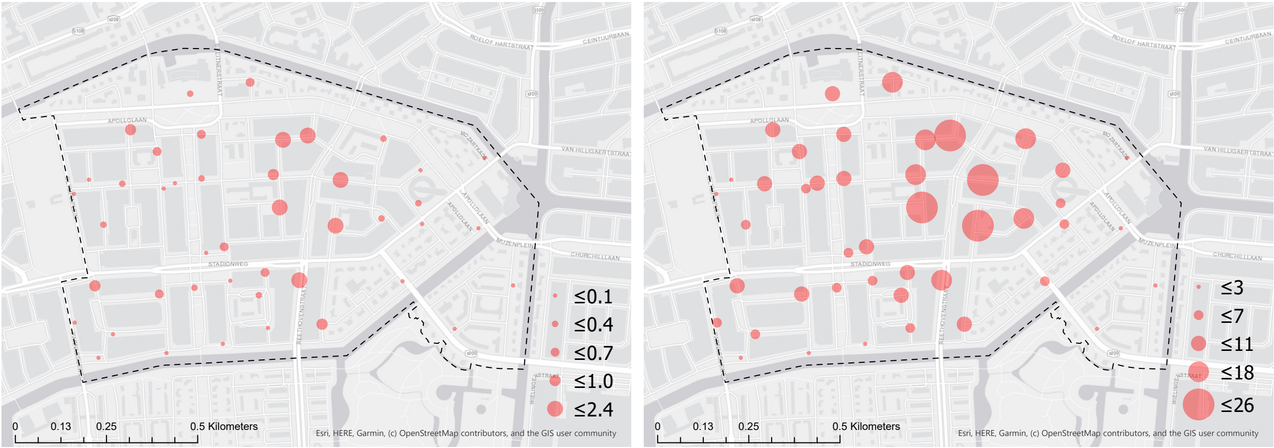


Figure 4.9: Hourly occupancy rate for different shares of EV ownership (EV%).

4.6 Summary

Based on the processes described in the sections above, it can be said that the model is successfully verified; it matches the expectations of the designed conceptual model. During the process of modelling, the process of animation assessment is already conducted by developing and testing a test model, and with the iterative process of coding the case-study model. Besides matching the conceptual model as designed, it also corresponds with the behaviour as expected in real-life as realistic everyday mobility behaviour is observed. For example, disapPoints are clustered around destination buildings. If the CP is further away from destination buildings, it means it has less disapPoints. When tracking 2 individual agents, it can also be concluded that they behave the way it is designed, and they are performing real-life behaviour with moving along the network and searching for CPs. Some flaws where found in the calculation of walking distances. When verifying and validating the outputs of the model, it can be concluded that output values represent the values for the Gaussian distributions and probability values used as input.

A sensitivity analysis was carried out to observe the model behaviour after altering various parameter settings. The tested outputs are not sensitive to the variable 'CP Hogging', in contrast to the outputs for the different range anxiety values. The configuration of the range anxiety factor has a high influence on the simulation outputs; a higher factor causes a higher pressure on the CP infrastructure of the neighbourhood. This results in higher searching minutes, more disapPoints, a lower satisfaction score and more stranded agents. Furthermore, different EV ownership shares are tested to see the impact of the number of agents on the sim-



(a) EV ownership share of 1.6%.

(b) EV ownership share of 10%.

(c) EV ownership share of 30%.

(d) EV ownership share of 85%.

Figure 4.10: Output disapPoints per CP for different configurations of the EV ownership share variable.

ulation. This variable has, as expected, a high influence on the output values of the simulation; a higher share causes the CP infrastructure to be overburdened. However, similar spatial and temporal patterns can be observed for each EV ownership share. These patterns are less visible when the number of agents is either too low (with a share of 1.6%) or too high (with 85%).

All performed methods of verification and validation can be extended and elaborated upon for further research, however; it can be concluded that the simulation model is a valid environment to test different scenarios in EV driving and charging behaviour in the case study area. Thereby this chapter partly answered the fourth research question, *'How plausible and usefulness are the resulting patterns of the proposed behavioural agent-based model?'*. The next chapter will further explore the usefulness of the ABM with analysing different scenarios.

Chapter 5

Scenario analysis

After the verification of the model in Chapter 4, this chapter demonstrates how the model can be used to test different scenarios. Thereby it provides the answer to the research question considering the usability of the simulation model. For each scenario, different parameters are altered to analyse its effect on the models' output. Therefore, this scenario analysis is considered as a part of the sensitivity analysis. For the baseline scenario (the current situation), an extended sensitivity analysis is carried out to see which parameters should be considered for the calibration of the model. The methods for the scenario testing have been explained before in Section 3.5.2, containing the argumentation for the scenario choice. To summarize, the three scenarios are the following:

- Baseline Scenario: the main simulation model with the current situation in the case study area.
- Scenario I: Policies; the placement of more CPs, regarding policies of the Municipality of Amsterdam.
- Scenario II: Technologies; testing the impact of an increasing capacity and charging power.

Each scenario is run with three different EV ownership shares to be able to observe what happens to the system when the number of EV drivers increases. The sensitivity analysis showed that the EV ownership shares of 10% and 30% allow for the observation of patterns without losing sight of the details (as found in the Sensitivity Section 4.5). It has also been found that the increase in EV ownership share from 10% to 30% has a significant impact on the output values. To be able to further study this impact, an EV ownership share in between these two is added (20%) for the scenario analysis. The testing is limited to these three different EV ownership shares due to time and scope limits. Especially with testing an ownership share of 85%, the computational time will be way longer, making it less convenient for this thesis' scope. For future research, exploring the scenarios for a wider range of EV shares could be interesting.

Each scenario is run 10 times and is summarised over these runs, making it able to compare them with each other. This chapter presents the results of Scenario I and Scenario II and compares them with the baseline scenario. The results of the baseline scenario are discussed before with the sensitivity analysis. The chapter ends with a short summary and a comparison of the two future scenarios.

5.1 Scenario I: Policies

This section describes the results of Scenario I, the scenario based on policies of the Municipality of Amsterdam. For this scenario, additional CPs are added with the edit function in ArcGIS Pro. It is expected that the presence of more CPs should relieve pressure of the charging infrastructure in the neighbourhood. This section first explains the method used for the placement of these CPs. Hereafter, the results of this scenario will be presented and compared with the baseline scenario.

5.1.1 Allocation of the new charging points

This section explains the process of allocating possible Charging Points based on the outcomes of the baseline scenario. The placement of the new CP points is done manually and is based the outcomes of the baseline scenario and on the presence of destination buildings. According to the 'Action Plan Clean Air' (Gemeente Amsterdam, 2019), the Municipality of Amsterdam strives for complete fulfilment of the needs to provide enough capacity for future EV drivers. The Municipality expects that a number of 23,000 CPs will be needed in Amsterdam by 2025. At the time the report was published, the city counted 3,000 CPs. That means an increase in CPs with the factor of 7.67 is needed to meet these policies. For the case study area this directs to an additional 736 CPs to be allocated. These calculations can be found in Table D.1 in Appendix D. It is assumed that one sockets accounts for one charging point.

For this scenario, it is decided to allocate an additional 200 CPs in the case study area to test its impact on the simulated system. An amount of 200 is expected to be enough to analyse the impact of intensifying the CP infrastructure in the case study area. The result of the CP allocation can be found in Figure 5.1. An amount of 50 points are placed, with four sockets each, resulting in 200 additional sockets in the case study area. The locations of the new CPs are based on the results of the baseline scenario, as presented in the sensitivity analysis (Section 4.5). As observed in the maps in Figure 4.10, spatial patterns in the diffusion of disapPoints in the neighbourhood can be identified. The disapPoints are centred around the destination buildings, and for this reason most of the new CP points are also allocated around destination buildings as well. Some additional CP points are placed along the edges of the neighbourhood. They are mainly placed in proximity of existing CPs which got a significant number of disapPoints in the baseline scenario. The new CPs are more clustered than the original CPs, intending to smooth out the peak pressure on some of the centrally located CPs.

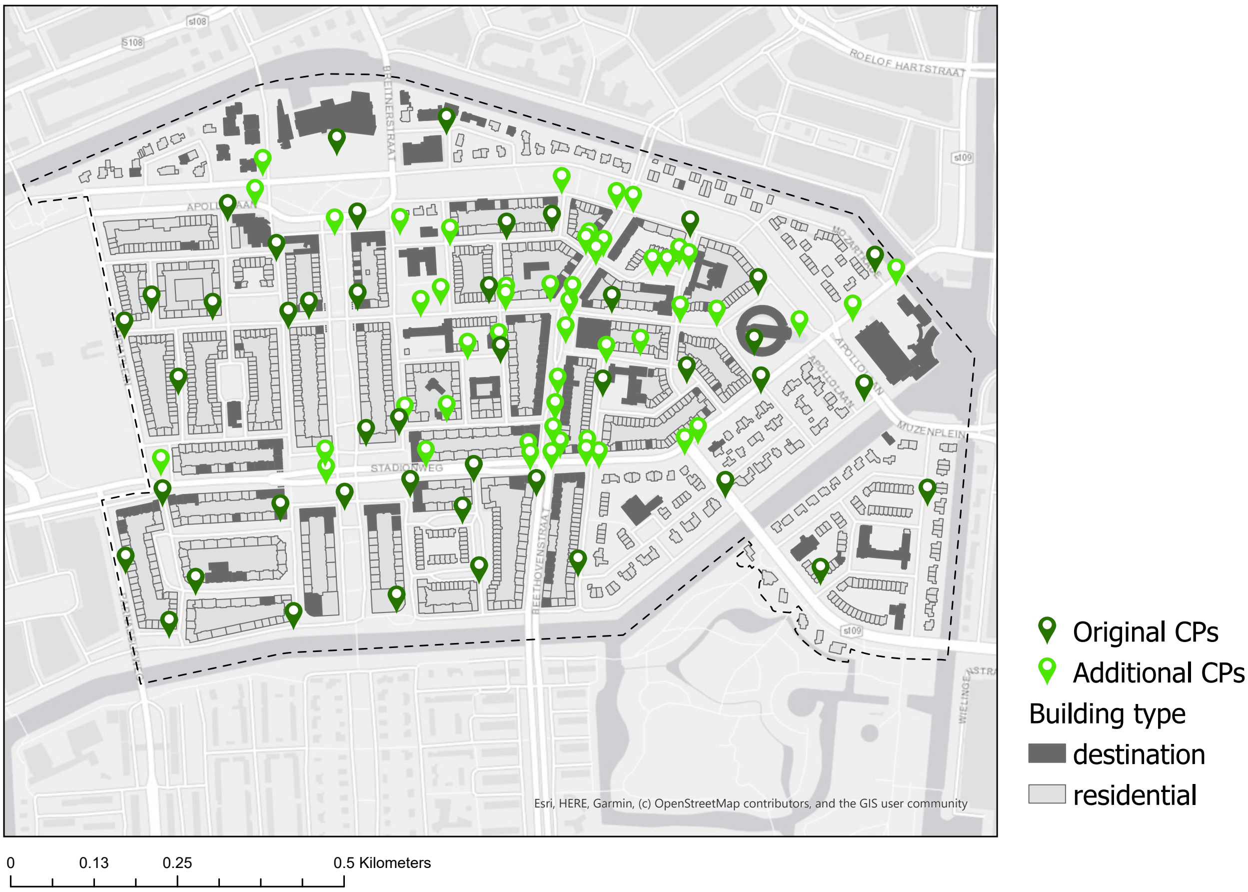


Figure 5.1: Map displaying the locations of the new allocated CPs and the original CPs.

5.1.2 Results

As described before, the allocation of additional 200 CPs (sockets) is expected to have a positive impact on the EV driving and charging dynamics in the neighbourhood. 'Positive' in this context would mean a reduction of the searching time, disapPoints and walking distances for EV agents. It should also reduce the number of stranded vehicles and should cause a higher satisfaction score. In Figure 5.2, the average searching time of agents is compared for both scenarios. The searching time has been significantly reduced: for the 10% EV ownership share it has decreased from 3.75 to 2.19 minutes, for 20% from 4.95 to 2.39 minutes and for 30% it reduced from 5.55 to 2.84 minutes. It is also remarkable that the difference between the three ownership shares is smaller for Scenario I. In the baseline scenario, the EV ownership share has a bigger impact on the searching time.

Another remarkable outcome of this scenario is the massive reduction of the number of stranded agents in simulation. It seems that the increase of stranded agents follows a linear

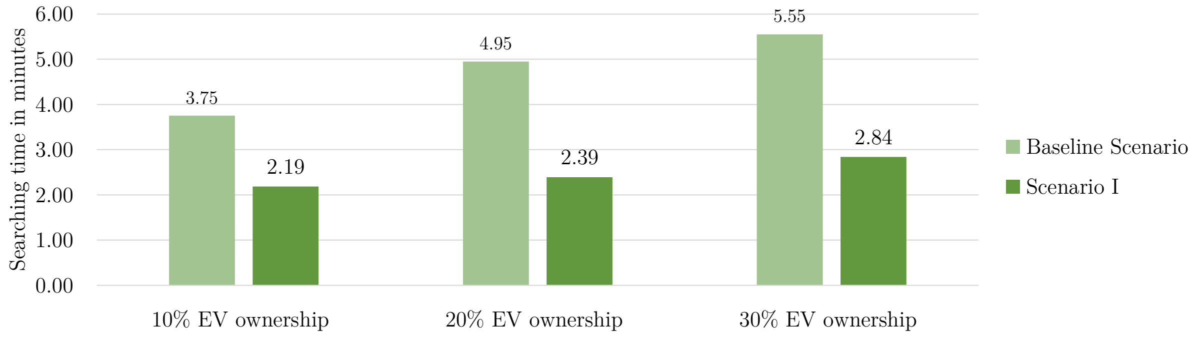


Figure 5.2: Average searching time for Scenario I compared to the baseline scenario.

trend for the baseline scenario: the number of agents increases with 83.3 from 10% to 20% EV ownership and with 84.7 from 20% to 30%. For Scenario I the outputs imply that there is a tipping point after the 20% EV ownership share. For 10% and 20% the number of stranded agents stays relatively low. This is probably due to the fact that the increased number of CPs cover the charging need of the EV agents (nearly) completely. For an ownership share of 30% the number increased to 27.70, indicating the first signs of the system overload. For the baseline scenario, these signs already show at an ownership of 10%.

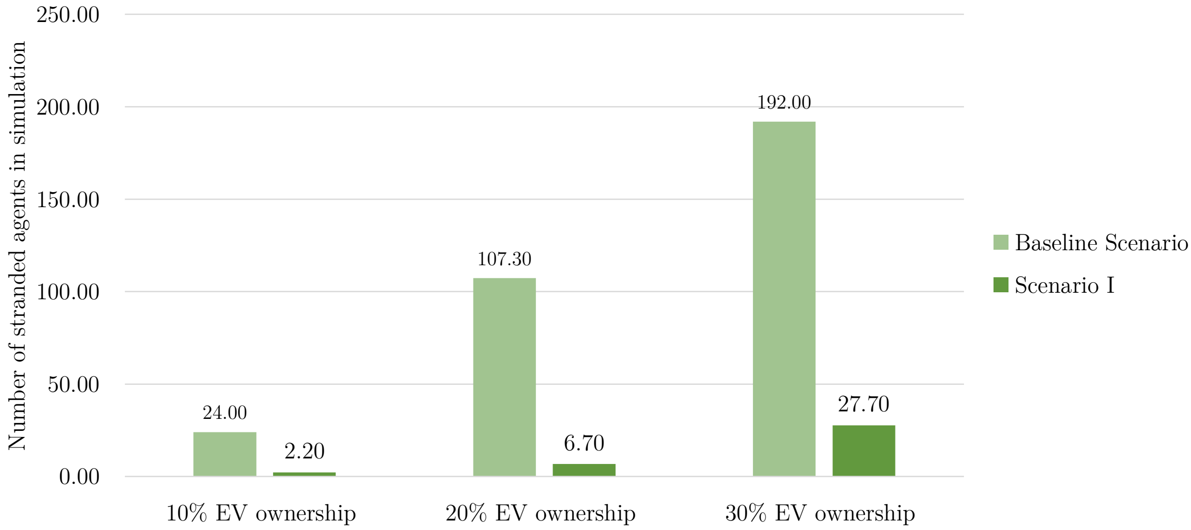


Figure 5.3: Number of stranded agents in Scenario I compared to the baseline scenario.

The last two main output values important for comparison are the average satisfaction score and the total number of disapPoints. An overview of all main output values for the scenario analysis can be found in Appendix E. As can be seen in Table E.1, the average satisfaction score is higher for Scenario I compared to the baseline scenario. For the baseline scenario the score decreased from 94.66 to 90.46 and 89.07, on sequence of the increasing EV ownership share. For Scenario I the satisfaction stayed more stable and the score was higher (98.34, 98.00 and 97.03 for the three ownership shares).

The spatial distribution of the disapPoint through the three simulations for Scenario I can be found in the maps in Figure 5.4. For each map, the disapPoints are visualised on the same scale. For the share of 10% and 20% the average amount of disapPoints per CP are 1 and 3.7. With an ownership share of 30% the average number of disapPoints per CP increased to 9. This number is much less than the average number of disapPoints for the baseline scenario (7.6, 23 and 38 on sequence of the increasing EV ownership share). However, especially for the ownership share of 30%, the number of disapPoints did not cut down completely. Meaning that with this higher amount of CPs, the EV agents still encounter occupied CPs in their search for a charging point. The spatial distribution of the disapPoints for this scenario is less clustered than for the baseline scenario. This is due to the allocating of the new CPs based on the outcomes of the baseline scenario and the locations of destination buildings. There are still some patterns to observe: the disapPoints are mostly located around the centre and the west side of the neighbourhood. This is explained by the higher ratio of CPs as opposed to the amount of destination buildings.

Figure 5.4: Spatial distribution of disapPoints in Scenario I for the three EV ownership shares; a) 10%, b) 20% and c) 30%.

The next measure used to study the impact of Scenario I is the walking distance (Table 5.1). This distance is averaged over all the EV agents who arrived at charging points. In general, the average walking distance for Scenario I is lower than that of the baseline scenario. It is remarkable that the walking distances stayed somehow stable for each ownership share in the baseline scenario, whereas the distance increased over the ownership shares in Scenario I. This is probably caused by the fact that in the baseline scenario, agents encounter occupied CPs already with a share of 10%. For Scenario I, the impact of the EV ownership share has a significant impact on the walking distance.

Table 5.1: Average walking distance of Scenario I compared to the baseline scenario.

EV ownership	**Baseline Scenario**	**Scenario I**
10%	53.60 meters	42.30 meters
20%	54.75 meters	43.84 meters
30%	54.30 meters	46.29 meters

The last discussed result for this scenario is the occupancy rate per hour, as displayed in Figure 5.5. It can be concluded that with the additional placed CPs, 100% occupancy is not reached for each of the EV ownership shares. Because the number of CPs is higher, less CPs are occupied at the start and the end of the simulations (around 25% instead of 40% for the baseline scenario). In the baseline scenario, the occupancy rate of 100% is already reached around 08:00 in simulation for an ownership share of 30% (as described in Section 4.5). For Scenario I the maximum occupancy rate is 90%, which is reached at 09:00. For 10% the rates stay below 50% during the day, and with a share of 20% the maximum occupancy rate is 72%. With the additional placement of 50 CPs for this scenario, it is likely that the system does not get overburdened completely.

5.2 Scenario II: Technologies

This scenario is based on the expected future development in technologies concerning EV driving and charging. In the simulation runs, the parameters of EV capacity and CP charging speed are increased. This parameter modifications are discussed before in Section 3.5.3. It is expected that these technologies should have a positive impact on the outcomes of this simulation scenario. This means, the charging system will be less overburdened and less agents should strand because of their increased capacity. This section presents the results of Scenario II and compares them to the baseline scenario.

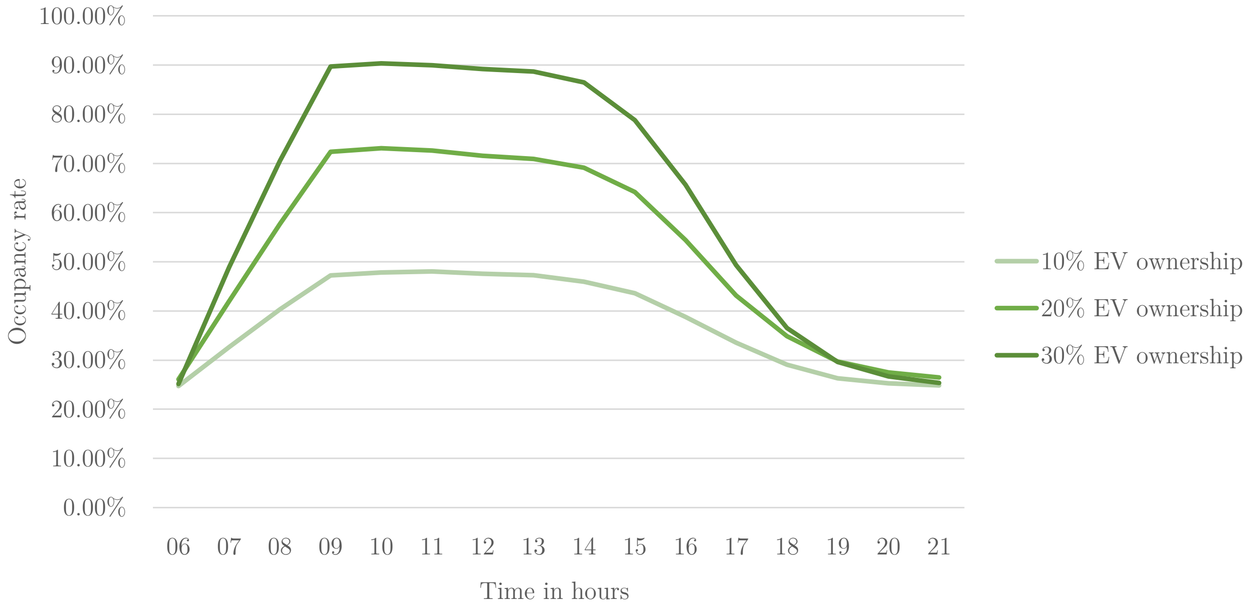


Figure 5.5: The occupancy rate during the day in Scenario I for the three EV ownership shares.

5.2.1 Results

Figure 5.6 shows the average searching time in minutes for Scenario II compared to the baseline scenario. In the first place, it can be concluded that simulating Scenario II reduced the searching time of EV agents relative to the baseline scenario. It is remarkable that for this scenario the searching time nearly stays the same for each EV ownership share (2.53, 2.41 and 2.52 minutes). This indicates that an increase of EV ownership share from 10% to 30% does not have any impact on the searching time of agents.

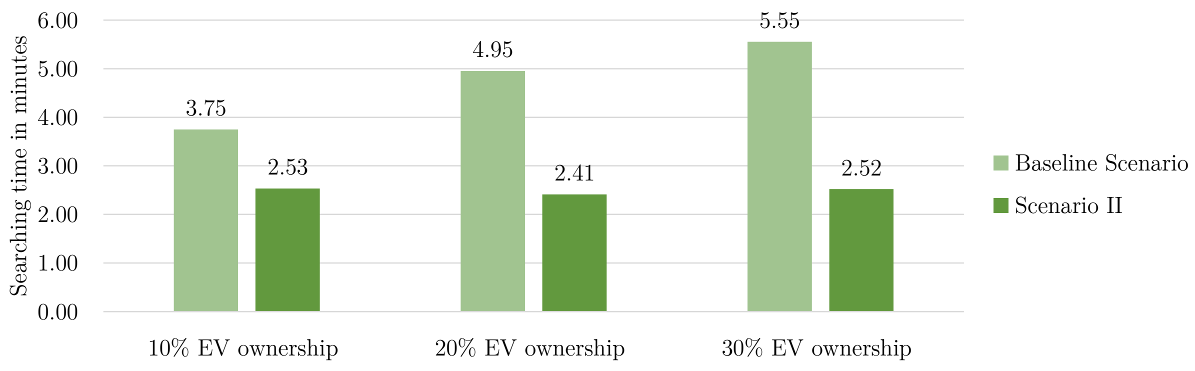


Figure 5.6: Average searching time for Scenario II compared to the baseline scenario.

The output of the satisfaction score for Scenario II shows similar patterns. In comparison to the baseline scenario, the satisfaction score throughout the simulation is high (near 100) and this stays nearly the same for the three ownership shares. Another remarkable outcome of this scenario that for each EV ownership share setting, the number of stranded agents stayed zero. This is a very big reduction as the number of stranded agents for the baseline scenario was much higher: 24, 107 and 192 on sequence of the increasing ownership share. Also, the amount of disapPoints stayed remarkably low. It increased from a total amount of 5.90 for 10% to 14.80 for 20% and 36.40 for 30%. This results in less than one disapPoint per CP for each ownership share. As this number is minimal, no spatial patterns can be observed.

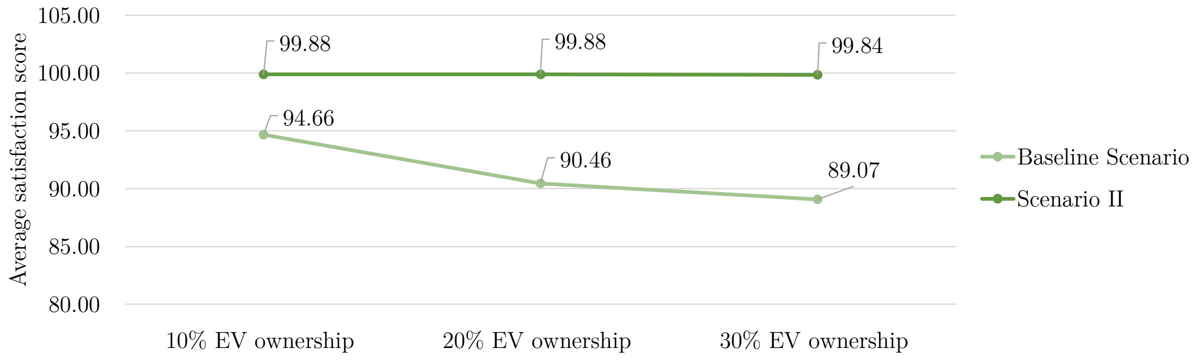


Figure 5.7: Average satisfaction score for Scenario II compared to the baseline scenario.

Furthermore, the differences in walking distance are observed (Table 5.2). The average walking distance of the EV agents who arrived at CPs in Scenario II is lower than that of the baseline scenario. Just as for the baseline scenario, the walking distances stayed considerably stable over the ownership shares. For both the scenarios, the walking distance is a little higher for the EV ownership share of 20%. In both scenarios the difference is less than 1 meter, what makes this difference insignificant.

Table 5.2: Average walking distance of Scenario II compared to the baseline scenario.

EV ownership	**Baseline Scenario**	**Scenario II**
10%	53.60 meters	52.61 meters
20%	54.75 meters	53.17 meters
30%	54.30 meters	52.88 meters

Finally, the occupancy rates per hour of the CPs in this scenario are analysed. The daily temporal pattern of the occupancy rates for each EV ownership rate, are displayed in Figure 5.9. It can be observed that for Scenario II the occupancy rates are strongly decreased relative to the baseline scenario. Furthermore, the differences in between the ownership shares are smaller. The maximum occupancy rate is increasing as the EV ownership share is increasing from 42% to 49%, and 55% for the 30% EV ownership. These maximums are reached for each run around 09:00, and after 16:00 the rates are decreasing again to the occupancy rate from the start (around 35%). This occupancy rate from the start differs a bit between the three runs, probably due to the stochastic variable indicating this rate.

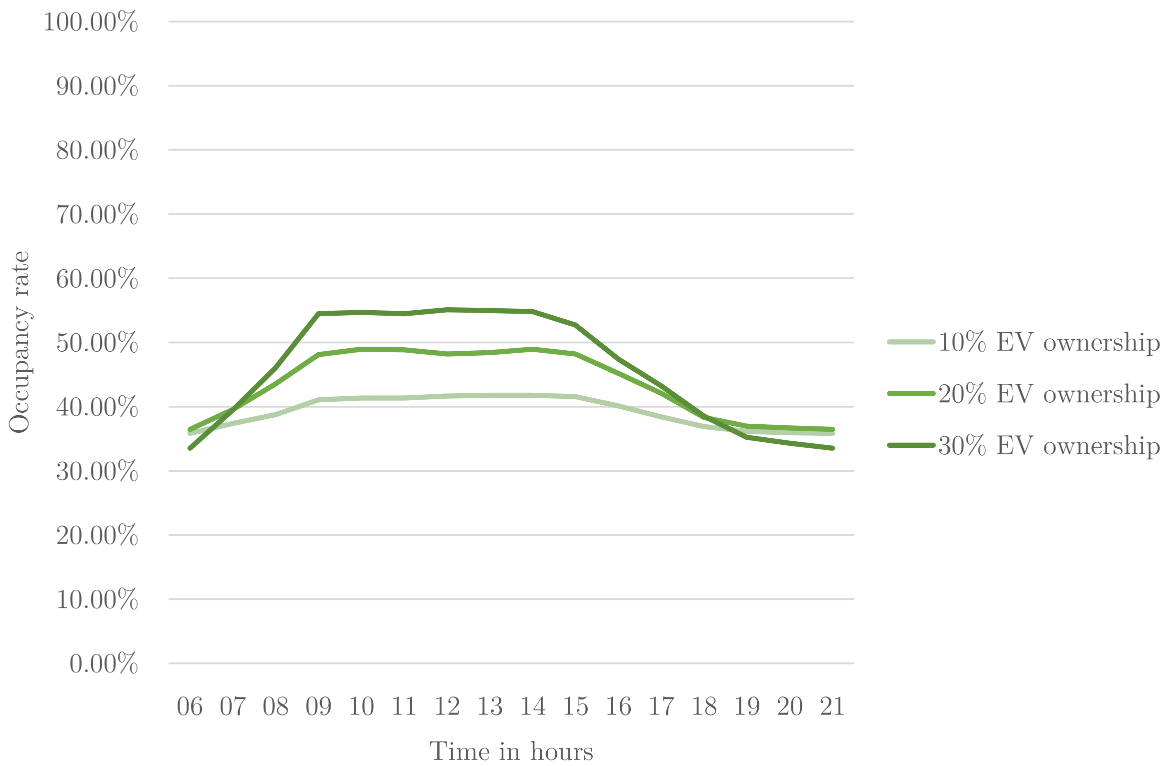


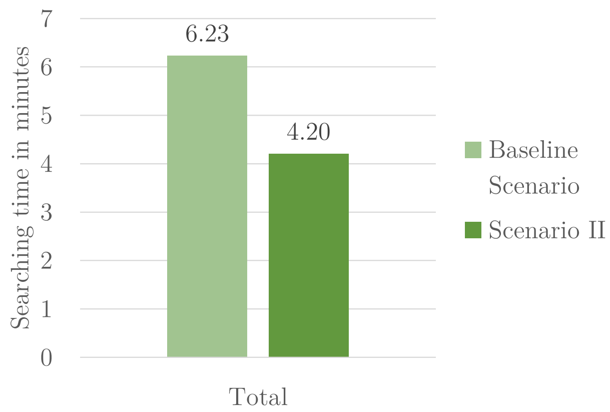
Figure 5.8: The occupancy rate during the day in Scenario II for the three EV ownership shares.

5.2.2 Testing the extreme

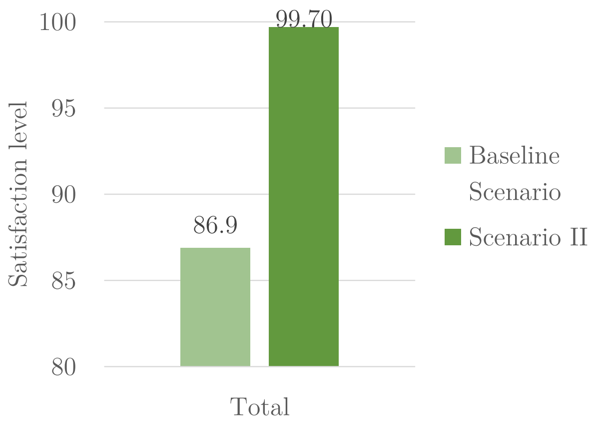
The results of Scenario II are promising: the searching time and the number of disapPoints are relatively low, the satisfaction score is near 100 and no agents stranded. Furthermore, the impact of increasing the EV ownership share on the output values is minimal. The occupancy rates show that even for an EV ownership share of 30%, during peak hours, less than 60% of the CPs are occupied. To further explore this scenario and investigate the potential uses of this simulation model, it is decided to test Scenario II for the extreme EV ownership share of 85%. This share indicates a number of 5350 EV agents in the simulation. The ownership share of 85% is tested before in the sensitivity analysis, showing outrageous outputs: in the baseline scenario the system was already overburdened around 07:00 in the simulation. In order to experiment with Scenario II, the simulation is run again 10 times and averaged in the output data for an EV ownership share of 85%. This section presents the results of this experiment, compared to the results from the baseline scenario (as presented in the sensitivity analysis).

It can be concluded that the system as proposed in Scenario II can still manage an EV ownership share of 85%. First of all, the searching time increased from 2.52 minutes for 30%

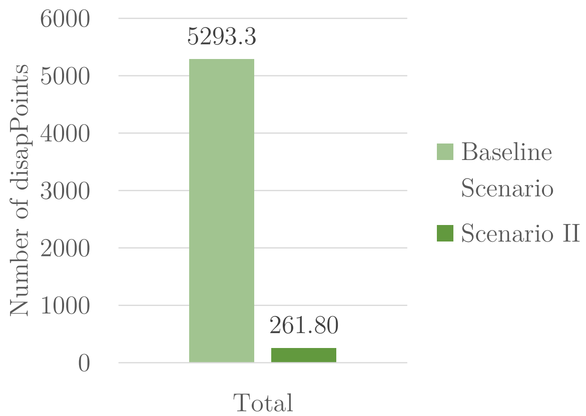
to 4.20 minutes for 85%. This is 2 minutes lower compared to the baseline scenario, as shown in Figure 5.9a. The level of satisfaction is still high with an ownership share of 85%: 99.70 compared to 86.9 in the baseline scenario. Up to an ownership rate of 30%, the number of disapPoints and stranded agents stayed around zero. This increased for the ownership share of 85%. However, these values are still remarkably low compared to the baseline scenario as shown in Figure 5.9c and Figure 5.9d. The results show an average of 6 disapPoints per CP, compared to 123 in the baseline scenario. Less than 6 agents stranded, what can be explained by the higher capacity of the vehicles. For the baseline scenario this number was almost 700.



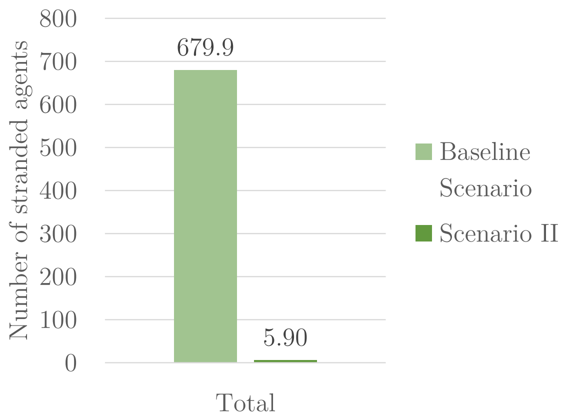
(a) Searching time.



(b) Level of satisfaction (out of 100).



(c) Number of disapPoints.



(d) Number of stranded agents.

Figure 5.9: Output values for the 85% ownership share of Scenario II compared to the baseline scenario.

As the number of disapPoints per CP for the EV ownership share of 85% is noteworthy, spatial patterns in the distribution of those points can be explored. The map in Figure 5.10 shows the distribution of the disapPoints over the CPs in the case study area. Similar patterns can be observed when compared to the baseline scenario: higher numbers of disapPoints are mainly located around the middle of the neighbourhood, where destination buildings are clustered. The maximum amount of disapPoints per CP is 20.2, which means that during the day around 20 EV agents arrived at this CP when it was occupied already. This number is strongly reduced compared to the baseline scenario, in which the highest amount of disapPoints counted 326. Even the EV ownership share of 10% in the baseline scenario exceeded the maximum amount of 20 disapPoints.

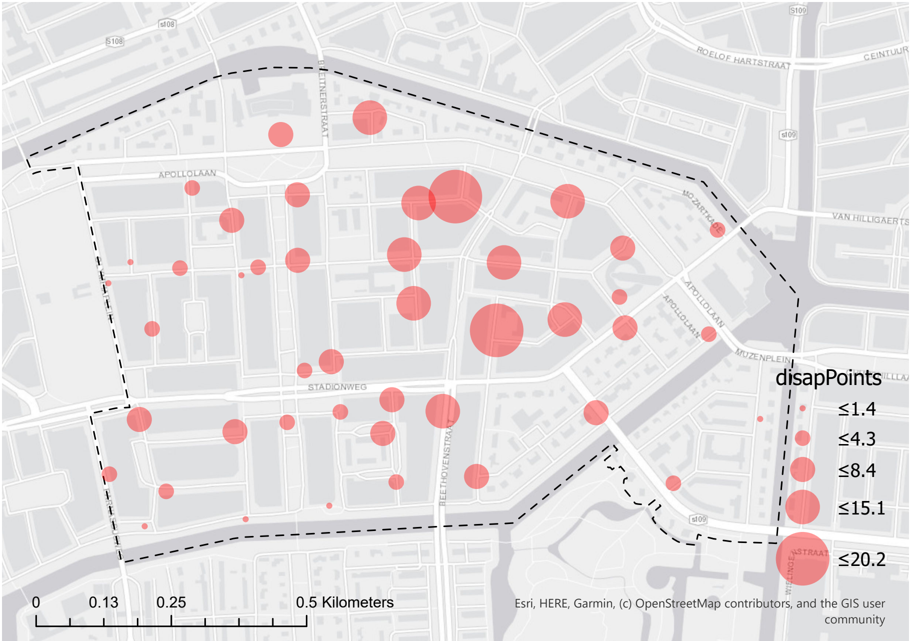


Figure 5.10: Spatial distribution of disapPoints in Scenario II for the EV ownership of 85%.

The final result that needs to be researched in this experimentation, is the occupancy rate during the day for the EV ownership of 85% (Figure 5.11). During the peak hours, the occupancy does not exceed the rate of 86%. This maximum rate is reached around 09:00 after a steep gradual increase. After 14:00, the rate is decreasing slowly till it reaches the beginning occupancy rate of 35%. As can be concluded from these results, the system will not be overburdened with an occupancy rate of 85% in Scenario II as the CPs are never fully occupied.

5.3 Summary

The behavioural EV driving and charging ABM has been applied to two scenarios based on policies of the Municipality of Amsterdam and technologies. Thereby, this chapter answered the 'usable' part of the fourth research question: *'How plausible and usable are the resulting patterns of the proposed behavioural agent-based model?'*.

For Scenario I, based on policies, an additional 200 CPs are situated in the case study area. This had a positive impact on the system, meaning the searching time, disapPoints, stranded agents and walking distances are reduced compared to the baseline scenario and the satisfaction score is higher. Furthermore, this scenario is less sensitive for the increase in EV ownership

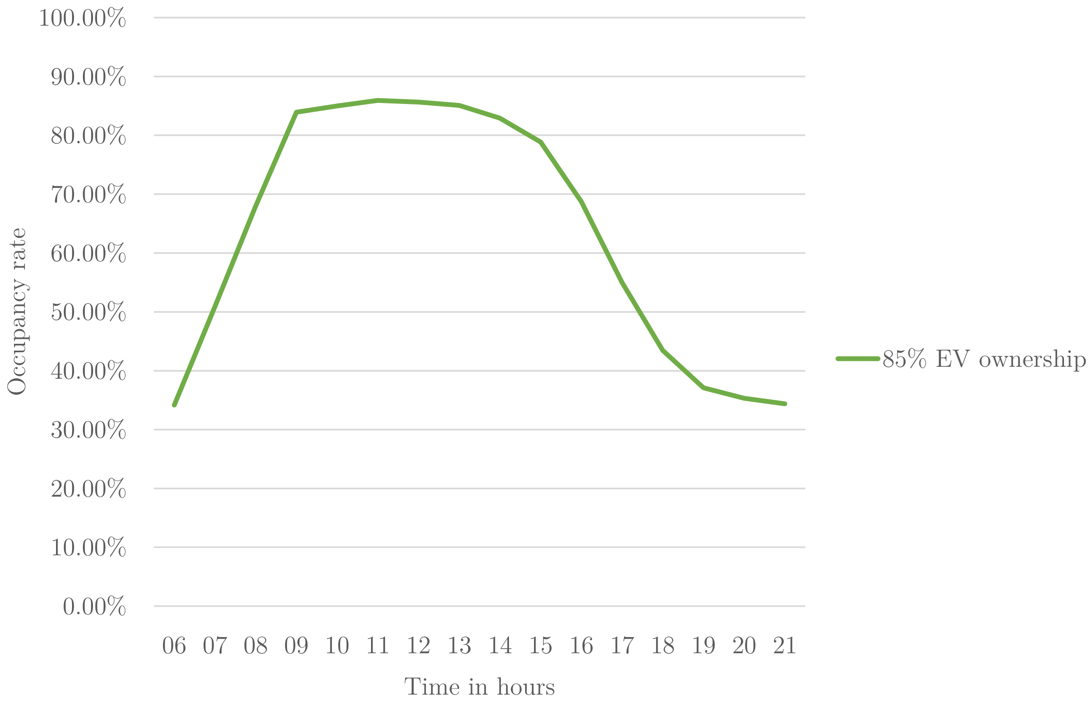


Figure 5.11: The occupancy rate during the day in Scenario II for the EV ownership of 85%.

rate. For the output number of stranded agents, there seems to be a tipping point after the EV ownership of 20%. This number increased significantly for the EV ownership of 30% compared to that of 20%. The placement of additional CPs caused the spatial distribution of disapPoints to be less clustered than in the baseline scenario.

Results of Scenario II show strongly reduced output values which are not sensitive to the increasing EV ownership shares. The satisfaction score stayed nearly 100 for the three EV ownership shares. The only visible effect of the increasing ownership share can be noticed when observing the occupancy rates. To further experiment with this scenario, the simulation was run again with an EV ownership share of 85%. The results showed that this increase of the number of EV agents has a remarkable impact on the output values. However, these outputs are still strongly reduced compared to the baseline scenario.

Chapter 6

Conclusion and discussion

In this chapter, the conclusions of this thesis are presented, followed by a discussion. The aim of this research is to develop and demonstrate a behavioural based agent-based model that allows to explore the spatial behaviour and dynamics of electric motorists in relation to CP placement in the city of Amsterdam. The proposed agent-based model proved itself adequate to meet this aim. This is researched with the help of four research questions around which the following conclusion is structured.

6.1 Conclusions

The first research question is the following: *'What are important factors that affect EV driver behaviour and which modelling method is suitable for developing a simulation of EV driver behaviour?'*. This question is answered by conducting a literature review. As there was no convenient dataset available for developing this simulation model, the model is mainly based on theoretic grounded assumptions. For this, it was needed to create an understanding of the factors influencing the choices of the EV driver. The main factors, as found in literature, can be divided into three classes: Vehicle related, driver related and environmental factors. Comprising the vehicle related factors: features and characteristics of an EV such as its type, range and battery size, are of major influence on the charging and driving behaviour of the EV drivers (Franke & Krems, 2013). The driver related factors are all determined by the drivers' need to recharge the vehicle, which causes the driving patterns of EV drivers to be different from conventional vehicle drivers (Azadfar et al., 2015). Within this need to recharge the vehicle, two factors influencing the travel choices can be distinguished: the range of EVs (range anxiety) and the recharging times of EVs (Vincenzo, 2014). Walking distances between CPs and destinations should be considered when modelling EV driver behaviour. This is translated into the drivers' willingness to walk, which can differ between different type of drivers (Pagany et al., 2019). Environmental related factors which have impact on EV behaviour are all concerning the charging infrastructure. Within this category, the locations, characteristics and occupancy rates of CPs are of influence on either the driving or charging behaviour of EV drivers.

Agent-based models have been chosen as method for this research' behavioural simulation model. As the model developed in this research will represent individual behaviour in a system at microscopic, ABM has proven as an appropriate approach because it allows for modelling decision making at individual level (van Dam, 2009). In an ABM, agents can interact with their environment as well as with other agents. Geographic information can be used as input for information about the environment or to populate the model (Macal & North, 2010).

The second research question, *'How can behavioural aspects influencing EV driving and charging be conceptualized in a framework suitable for modelling?'*, is answered with designing the conceptual model. The key elements found while researching the previous questions together with the constructed model assumptions are the foundations for the conceptual model. After this, the Apollobuurt in Amsterdam is chosen as case study area and spatial datasets are collected. The model is designed in order to easily expand the model by adding more behavioural aspects and by integrating different scenarios. During designing the conceptual model, decisions had to be made concerning the variables and behavioural rules of the EV agents and other entities in the model. These assumptions could be mainly based on literature review, but some additional assumptions had to be made by the modeler.

The main simulation process is that of the EV agent moving over the road network from their origin to a destination, following its O-D matrix. When an agent is in need of recharging, it searches for a CP near its destination. It checks its availability and searches for another CP when its occupied. When the EV agent finds an available CP, it parks there, and the model calculates the walking distance. Each agent has its own dynamic CP list, which simulates the behaviour of EV drivers searching for CPs. It will be updated with the distances from CPs to the agents' destinations, and information about the occupation of those CPs. Other processes included in the conceptual model are that of charging point hogging and updating the satisfaction level of the agents.

The following research question is as follows: *'How can this framework be implemented in an agent-based model?'*. This question concerns translating the previous described conceptual model in rules for developing the ABM. The simulation processes are translated in code in the modelling software GAMA, which allows for importing GIS shapefiles for defining real-life environments. The GIS data used for populating the model is retrieved through different open GIS datasets. After the data collection, the conceptual model was translated to GAMA code. This was an iterative process, with adding and testing small pieces of code. The model was first tested in a test environment before implementing it in the case study area.

The question *'How plausible and useful are the resulting patterns of the proposed behavioural agent-based model?'* is the last research question of this thesis. This question is two-folded, meaning it researches on the one hand the plausibility of the model, and on the other hand the usefulness of the model. The plausibility of the model is tested by conducting the verification of the model, the validation of the model and a sensitivity analysis. The verification of the model is to see if the model works as designed. This is done by observing the test model, the final model and the individual behaviour of agents in the model. It is found that the model behaves as it was designed and the final model is bug-free, therefore the verification of the model was successful. The validation of the model is conducted to test if the model successfully represents the real-world situation. Due to the lack of validation data, different methods needed to be used. The validation process is conducted by visual observing the model and validating the model outputs by comparing it to the input variables. Furthermore, the output occupancy rates are compared to a real-world occupancy rate. The model is found valid by observing it, the agents perform real-life behaviour with their search for CPs and moving along the road network. The occupancy rates are compared to real-world data and the outputs show results similar to the real-world situation. However, full calibration and validation of the model is not possible as there is not enough validation data available. Finally, a sensitivity analysis is performed to test the reaction of the model when adjusting different parameters. For this, three parameters where tested. It was found that the share of EV ownership and the range anxiety have a notable impact on the model. These parameters could be further researched in order to improve the model with model calibration. Additional data on these parameters will be needed to fully calibrate the model.

The second part of the last research question concerns the usefulness of the model. With experimenting using two scenarios, the model was tested on its usefulness for stakeholders as the Municipality of Amsterdam and other parties interested in EV dynamics in urban environments. Besides this, the testing of the scenario shows how the model reacts after changing the parameters chosen for the scenarios. Two scenario tests are conducted, the first based on policies and the second based on technology. Both scenarios are compared to the baseline scenario and are tested for three EV ownership shares to see what will happen when the number of EV agents increases. For Scenario I, the CPs shapefile is adjusted with the placement of additional CPs. The results are compared to the baseline scenario and show improvements in the system: a higher number of CPs has a positive impact on measures as searching time and satisfaction of drivers. The model is still sensitive for the increasing EV ownership share, but less sensitive than the baseline scenario. In Scenario II, the parameters capacity of EVs and charging speed are incremented to match expectations of future technologies. This scenario has a very positive impact on the systems, there are no signs of the EVs overloading the charging infrastructure. Because the model is not sensitive for the increasing EV ownership share, the extreme share of 85% is tested. This extreme showed remarkable impact on the output values, but the impact is still low relative to the baseline scenario.

The finding of the scenario experimentation is that a higher number of CPs will reduce the pressure on the charging infrastructure, but the developing of EV technologies will eventually cause even more positive results. Furthermore, with this scenario analysis, the ABM showed clear potential for testing real-life scenarios. ABM is a helpful tool for policymakers as the policies can be tested in a simulation environment corresponding to the real-world. With this, there can be reflected again on the main aim of this thesis: *developing and demonstrating a behavioural based agent-based model that allows to explore the spatial behaviour and dynamics of electric motorists in relation to CP placement in the city of Amsterdam.* The ABM developed in this research proved itself as an adequate simulation model, tested on its plausibility and usefulness. This thesis contributed to the field of EV behavioural modelling, with simulating EV driving and charging on individual level.

6.2 Discussion

In the past section, it is concluded that the developed and demonstrated behavioural based ABM is considered adequate for exploring the spatial behaviour of EV drivers. The model is tested on its plausibility and usefulness in the best possible way what fits within the scope of this thesis, without the availability of validation data. The model presented in this thesis is grounded in theory on EV driving and charging behaviour and proved itself for exploring this behaviour within a real-world environment. The model enables the users to integrate a variability of scenarios and to test its impact on the simulation system. Even though the model aimed to represent the real-world situation, it should be noted that a simulation is always a simplified version. Therefore, many assumptions have been made during the modelling process. This section discusses some of these assumptions, the model validation and provides opportunities for further research.

Discussion on model assumptions and simplifications

The model as presented works as it is supposed to do but it is highly depending on the input data. As found in Section 3.5.2, the model is highly sensitive for the parameters of range anxiety and the share of EV ownership. These parameters are based on assumptions as there were no exact calculations possible. The range anxiety reoccurs in literature as one of the main obstacles for the success of EV (Section 2.1.2). However, range anxiety is a fear and this behavioural aspect is complex to express in numbers. In this research, an attempt is made with expressing the range anxiety as a factor influencing the desired state of charge of the EV drivers. It is shown that the model results are sensitive to this parameter, the model could be improved when this parameter is further researched or included in a model calibration.

The share of EV ownership in the model determines the number of EV drivers in the simulation. The model results are highly depending on this number, that is why it was decided that the scenario test is run for different shares of EV ownership to be able to compare the outcomes. Furthermore, the number of total vehicles visiting the neighbourhood is calculated using estimations based on the number of the different types of destination buildings. For future research it is valuable to base these numbers on exact data, if that data is available. An extensive calibration of the number of agents in the model would improve the quality of the model, making it able to represent the real-world in a more realistic way.

A behavioural output value which is initiated by the modeler is that of the satisfaction score. The calculation of this value during the modelling is questionable as it is not grounded in literature. An attempt has been made to express the satisfaction of the EV drivers in the simulation, which have proved itself as a usable score for comparing the different scenarios. This part of the model output can be highly improved when more insight in expressing satisfaction in models is gained.

Another point of discussion are the variables based on a normal distribution. Some of the initial variables of the agents are based on a Gaussian distribution in order to create a realistic population of agents. During the assessment of the model outputs, it was found that some agents had initial values which are too low to match the reality (for example, negative values for the capacity variable). For future analysis, these distributions should be reconsidered in order to more realistically represent EV drivers on individual level.

Discussion on model validation

One part of the aim of this research the testing of the model on its plausibility. At the same time, the method for the assessment of the model plausibility is one of the main points of discussion. As there was no specific dataset available to validate the model, other methods have been chosen to research the plausibility of the model. As Rand and Rust (2011) already stated, it is near impossible to validate the model completely. During the model validation process, the output values are compared to the input values to check for variation and inconsistency between the input and output data. In Section 4.4.3 a limited attempt with external data is made by validating the occupancy rates. The output occupancy rate is compared to the real-world occupancy in Amsterdam, and this proved valid. However, the correctness of this validation is questionable as this similarity to real-life data could be a coincidence. A proper validation of this model should be carried out using empirical data. The data platform for charge point locations, Eco-Movement (2019) could provide access to dynamic charge point data, which was not accessible within the scope of this thesis. This dataset consists of exact information about the occupancy of singular CPs, which can be used for extensive model calibration and validation.

Another validation method that was used is that of the scenario testing. This was mainly focused on testing the model on its usefulness. The scenarios are constructed based on policies and future technologies. However, the scenarios could still be improved, and it would be relevant to test them on all EV ownership shares between zero and 100%. In this way tipping points could be better identified, and results would be more valuable for policy makers. Furthermore, the CP placement for Scenario I could be done with more care. For example, by conducting a multi criteria analysis for examining the best locations of new CPs. In the scope of this thesis, the scenario testing proved that the model is useful for exploring scenarios. However, the validation process should be extended in order to fully rely on the outcomes of the scenarios.

Further elements to include

The EV behavioural ABM as presented in this research could be improved by including more elements. The first thing to include would be the improvement of the distances. For example, the walking distance is now calculated based on Euclidean distance. It would be useful to calculate this distance along the road network. Furthermore, the desired State of Charge of agents is now based on a percentage of the total capacity. An improvement would be to base this threshold on distance, or on a percentage of the total distance of the trip (as proposed by Franke and Krems (2013)). Another element what can be added to the model is including more different profiles of EV drivers and base these profiles on empirical data and social characteristics. In this model, distinction is made between visitors & residents and agents with a working or leisure activity profile. However, the distributions are based on assumptions and the different profiles are not very decisive in the simulated behaviour. More comprehensive driver profiles could be included.

In relation to previous research

In perspective to the existing research field as discussed in the theoretical framework, this research on the one hand endorses previous research and on the other hand complements to the field of EV behavioural simulation modelling. Vincenzo (2014) provided outlines for modelling EV traffic and already argued that ABM seems the best option for investigating the complex interactions within EV behaviour. The same is argued by Daina et al. (2017). This is in line with the results of this thesis in which ABM is proved as a suitable method. One recommendation of Vincenzo (2014) which has not been implemented, is that of modeling detailed daily travel plans, which could be included in further development of the model.

The model in this research could best be compared to the ABCD model (Hoekstra & Refa, 2017) as this is the most comprehensive EV behavioural ABM in Netherlands at the moment. The ABCD model covers the broader spectrum of EV behaviour, including EV buying behaviour. The EV behavioural model in this thesis covers the EV charging and driving in a more detailed way with more comprehensive behaviour and it includes individual decision making. A strong point of the ABCD model is that it includes the power grid in the simulation, allowing analysis on the electricity grid balance and smart charging developments. The PEVI model (Sheppard et al., 2016) also includes the electricity grid, to explore the impact on this of EV trends. It would be interesting to include the element of the power grid in this research' model as well. In that case, scenarios can be constructed with keeping the overload of the electricity network in mind.

Some last notes

The main aim of the model is to explore spatial behaviour and dynamics of EV drivers in Amsterdam, in which it succeeded. As discussed in this section, this research has its limitations and there are many opportunities for further research. When more extensive datasets are retrieved for validation and calibration, the quality of the model will increase, and it will even better represent the real-world. The model as presented in this research should be considered as a step in the right direction to further develop a realistic model which simulates EV driving and charging behaviour. As stated in the introduction, the transport sector still accounts for around a quarter of all the greenhouse gas emissions in Europe. Moving towards complete electric mobility is a major challenge. The need for understanding the processes behind EV development keeps increasing and this thesis together with many other studies contribute to this field of knowledge. This knowledge will eventually guide the transition towards fully sustainable road transport.

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Appendices

Appendix A

Estimation of visitors

Table A.1: Estimated number of visitors by car, based on the main function of the building.

Destination type	**Estimated number of visitors per building**	**Number of buildings in case study area**	**Total estimated number of visitors**
Retail	50	55	2750
Hospitality	60	7	420
Offices	30	60	1800
Accomendation	30	5	150
Education	30	18	540
Religion	20	2	40
Sport & Leisure	20	3	60
Healthcare	40	13	520
Unknown function	5	3	15
Total		166	6295

Appendix B

Used datasets

Used in model for	Dataset	Description	Source	Accessed at	Format	Retrieved from
Boundary	CBS wijken en buurten 2018	Geometry of all Dutch neighbourhoods with statistical data.	CBS	28-10-2019	WFS	*
Roads	Nationaal Wegen Bestand	Data of all roads in the Netherlands, adapted and modified by the WUR for the Amsterdam road network.	WUR	14-01-2020	Shp	Email contact with Arend Ligtenberg
Buildings	BGT	Basic registration Large-scale Topography, including all physical building objects.	Kadaster	06-01-2020	Shp	Esri living atlas
Functions of buildings	Functiekaart Amsterdam	Functions of buildings without a residential function in Amsterdam.	Gemeente Amsterdam	25-01-2020	CSV	**
Charging Points	Laadpunten Amsterdam	Static data of all charging points in Amsterdam.	Eco-Movement	22-10-2019	CSV	Email contact with Falco van Vloten, founder of Eco-Movement.

* https://www.pdok.nl/geo-services/-/article/cbs-wijken-en-buurten

** https://maps.amsterdam.nl/open_geodata/?k=49

Appendix C

Simulation experiments

Table C.1: The different simulation experiments with the number of simulations and the values for input parameters

Simulation experiment	Sensitivity analysis	Baseline scenario	Scenario I	Scenario II
# of simulations	120	2	2	2
EV ownership share (%)	[1.6, 10.0, 30.0, 85.0]	[10.0, 20.0, 30.0]	[10.0, 20.0, 30.0]	[10.0, 20.0, 30.0, 85.0]
CP hogging probability	[0.2, 0.4, 0.6, 0.8, 1.0]	0.8	0.8	0.8
Range anxiety index	[0.0, 0.2, 0.4, 0.6, 0.8, 1.0]	0.4	0.4	0.4
Capacity average (kWh)	56.8	56.8	56.8	180
Charging speed (kW)	11/22	11/22	11/22	55
CP shapefile	Main	Main	Placement additional CPs	Main

Appendix D

Calculations for the allocation of additional CPs

Table D.1: Calculations for the number of needed CPs in the case study area, based on policies of the Municipality of Amsterdam (Gemeente Amsterdam, 2019).

	Amsterdam	**Apollobuurt**
2019	3,000	96
2025	23,000	736
To be allocated	20,000	640

Increase factor **7.67**

Appendix E

Main output values of the scenario analysis

Table E.1: The main output values for each share of EV ownership for the three scenarios. Each value is summarized over 10 simulation runs.

	Share of EV ownership	**Searching time in min.**	**Av. DisapPoints**	**Satisfaction**	**Nb. of stranded agents**
Baseline Scenario	10%	3.75	7.63	94.66	24.00
	20%	4.95	23.04	90.46	107.30
	30%	5.55	37.98	89.07	192.00
Scenario I	10%	2.19	0.99	98.34	2.20
	20%	2.39	3.70	98.00	6.70
	30%	2.84	9.00	97.03	27.70
Scenario II	10%	2.53	0.14	99.88	0.00
	20%	2.41	0.34	99.88	0.00
	30%	2.52	0.85	99.84	0.00
	85%	4.20	6.09	99.70	5.90