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Expanding charging infrastructure for large scale introduction of electric vehicles

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Executive Summary

Currently EVs constitute only 1% of all vehicles on the road. We are at the eve of the large scale introduction of EVs. Large scale introduction requires a significant growth in charging infrastructure. In an urban context, in which many rely on on-street charging facilities, policy makers deal with a large number of concerns. Policy makers are uncertain about which charging deployment strategy to follow. This paper presents results from simulating different strategies for charging infrastructure roll to facilitate a large scale introduction of EVs using agent based simulation. In contrast to other models, the model uses observed charging patterns from EVs instead of travel patterns of fossil fuelled cars. The simulation incorporates different user types (Inhabitants, visitors, taxis and sharing) to model the complexity of charging in an urban environment. Different scenarios are explored along the lines of the type of charging infrastructure (level 2, clustered level 2, fast charging), the intensity of rollout (EV to Charging point ratio) and adoption rates. The simulation measures both the success rate and the additional miles cruising for a charging station. Results shows that scaling effects in charging infrastructure exist allowing for more efficient use of the infrastructure at a larger size.

1 Introduction

The demand driven rollout of charging infrastructure in urban areas has been one of the key success factor in the Dutch electric vehicle (EV) case [1]. Yet, EVs constitute only 1% of all vehicles on the road [2]. Currently we are at the eve of the large scale introduction of EVs. Large scale introduction requires a different approach to planning charging infrastructure. Demand driven roll-out [1] is a slow process which is not sustainable for scaling up. Policy makers in cities face concerns with electricity grid integration [3], business case development [4], [5] and public space and parking integration [6]. Strategic decisions have to be made on the long term, as infrastructure investment costs are high and payback periods long. One of the major questions is which EV to charging station ratio is optimal. Uncertainty in before mentioned decisions increases due to technological developments related to the vehicles (i.e. battery sizes) and charging equipment (i.e. higher charging speeds) and the expected but uncertain reciprocal effects between the EV adoption pace and infrastructure roll-out [7], [8].

Effective utilisation of the infrastructure is key for public space integration and the business case, but due to the rival nature of the charging stations it is not sure which scale effects might exist. The aim of this study is to (1) Provide insight into possible scale effects of EV charging infrastructure in an urban context. With a growing network it is expected that charging infrastructure is used more efficiently, in terms of successful charging sessions. (2) Explore and compare different roll-out strategies based on different charging technologies in terms of successful charging sessions, cruising for parking distances and business case perspective. (3) Investigate the reciprocal relation between charging infrastructure and EV adoption. This allows for a measurement of how effective charging station roll-out is a policy measure to promote EV adoption.

To study scenarios of EV charging infrastructure roll-out, an agent based model (ABM) approach is used. The ABM approach is used as the modelling context provides a large number of interactions between agents (both between EV agents and charging point operator agents) and the charging process takes place within a geo-spatial context. These features are best examined using an ABM approach. It is therefore that various researchers have used ABMs to model the uptake of EVs [9]–[11], the charging behaviour of EVs [12]–[14] or more recently the relation between charging infrastructure and EV uptake [15].

In the remainder of this paper we first analyse previous work done on EV adoption and charging in relation to charging infrastructure deployment. In section 3 we present the method for this paper including the data to support the choices in the design of the ABM. In section 4 some of the results of the simulations are discussed from which conclusions are derived in section 5.

2 Previous work

Research interest in electric vehicles and charging infrastructure has grown extensively over the past years in line with the rise in the number of EVs on the road. In this section an overview of some the work done on EV adoption and its relationship to charging infrastructure and on roll-out strategies for charging infrastructure is given. As both fields are researched intensively, the overview focuses on agent based model approaches on the two aspects.

2.1 EV adoption and charging infrastructure

Literature overviews on EV adoption studies [16]–[18] show that charging infrastructure availability is one of the main barriers for consumers when buying an EV. Hardman et al. [19] and Gnann et al. [20] reviewed papers with an explicit focus on the relationship between EV adoption and charging infrastructure and found that home charging availability is the most important factor in the decision to adopt electric vehicles. Hardman et al. find that these studies rely on structural equation modelling of survey results or multinomial logit models from stated choice experiments and hardly on revealed preferences. Notable exception is the research by Sierzchula et al. [7] which analysed data on EV adoption in 30 countries and found charging infrastructure to be the main predictor.

Besides previous mentioned research techniques EV adoption has also been studied using agent based models. The main reason behind using agent based modelling is to model the interactions with the environment, usually other agents. This allows for social relations such as the neighbour effect [21] to be studied. Most models used an “if-then” decision model for the agents’ purchase decision [11], [22]–[24]. In these models the observed parameter (e.g. utility or cost) has to higher or lower than other available options for the agent to purchase an EV. Other studies [25][26] use more advanced multinomial logit models for the EV adoption choice. The input parameters estimate a choice probability for each agent after which a random wheel procedure is applied. These models seem to be more in line with the latest choice models and allow for more validation of decisions made of which variables to include [27]–[29].

The interactions modelled in the ABM studies are often other agents and relatively few models take available charging infrastructure into account [11], [24]–[26]. If so, they mostly do so in a static sense in which charging infrastructure is a given and no interaction between the purchase decision and infrastructure development is given. Notable exception is the work by Gnann, Plötz and Wietschel [15] which also modelled the charging point operator as agent to study how charging infrastructure develops in line the number of electric vehicles. The stock of charging stations also influences the assessment of potential EV buyer agents of their ability to fulfil their travel needs. This work however assumed that all agents had home charging availability without competition of other agents making the analysis less suitable for urban environments with a large share of inhabitants that rely on on-street parking and charging.

Currently research on EV adoption has identified charging infrastructure availability as one of the main barriers to a large scale introduction. In ABM studies however charging infrastructure has been hardly considered or only in a static sense. The reciprocal relationship between EV adoption and charging infrastructure has received very little attention and certainly not in an urban context.

2.2 Charging infrastructure utilisation

As for EV adoption, the number of studies on charging infrastructure utilisation has risen in the last few years. Research has changed from early stated choice work [30], [31] or estimations using travel data [32]–[34], to using actual recharging data for descriptive [35][36][37] and modelling research [38][37][39]. In general, the research confirms the need of home, workplace and opportunity driven charging stations and fast charging along corridors. This research has resulted in several key performance indicators to measure charging infrastructure utilisation [40][41].

These studies however focussed on past usage of charging infrastructure. Studies that try to predict charging infrastructure roll-out often make use of travel patterns from gasoline driven vehicles and try to fit charging infrastructure in optimal manner accordingly. For EV fast charging, Motoaki [42] observes two approaches to do so: a node-serving and a flow-capturing approach. He concludes that the flow capturing works best to predict inter-city charging demand but that in practice local motivations play a much larger role. For slower level-2 charging infrastructure researchers mainly make use of dwell time as a proxy for charging demand [43].

The number of studies using agent based modelling for both charging infrastructure roll-out and utilisation is limited. The available models use driving behaviour to estimate charging demand. The models assume that the driver will charge at the end of a trip (or under certain conditions) when a charging station is available [14], [44]. Additionally the charging point operator is modelled in the decision to place a charging station [15], [45]. The decision to place a charging station is based on a business case proposal. Results from Gnann [15] show that level 2 charging stations for opportunity charging hardly ever become profitable and will need subsidies for the foreseeable future. These studies assume that vehicles have private charging facilities for overnight charging. The only exception to our knowledge is a paper by Vermeulen et al. [46] using charging patterns as input and only assuming public charging infrastructure. This paper however only models a static environment and does not consider growth scenarios and with a CPO agent.

2.3 Contribution

This study adds to previous studies on the following aspects. First, a large dataset on actual charging patterns is used to model the charging behaviour of agents. Previous models have instead mainly relied on travel patterns from gasoline vehicles and have made assumptions about charging choices. The approach used here, more closely resembles the new behavioural patterns EV drivers have, which is an interplay between parking and refuelling [38]. Secondly, an urban area in which most of the home and workplace charging is done on public charging stations is modelled. The model therefore includes much more interaction between EV drivers than previous models, more accurately representing the complex system of on-street EV charging. Previous models assumed home and workplace charging on private and therefore always available charging stations without any interaction. Moreover, this model includes traffic from visitors and charging demand from other modalities such as shared vehicles and a taxi fleet adding to the complexity to more realistically simulate the urban environment. Thirdly, this research models the relationship between the charging infrastructure and EV adoption based upon a choice experiment, while previous models have been using assumptions about this relationship. Lastly, it is the first to compare roll-out strategies based upon different charging technologies (regular charging, charging hubs and various fast charging speeds). This allows us to model emerging patterns due to changes in technology that current models could not yet foresee.

3 Methodology

3.1 Overview

In this study a data-driven agent-based-modelling approach is used. Three types of processes are simulated. These are (1) the charging process in which the EV driver interacts with available charging infrastructure and other EV drivers, (2) the process of purchasing a vehicle of non-EV car owners in which they take current charging infrastructure utilization into account and (3) the process of installing new charging stations by the charging point operator as part of the placement strategy, which depends on the charging station utilization (ratio EV : Charging station). An overview of the elements and their interactions in the model is given in *Figure 1*.

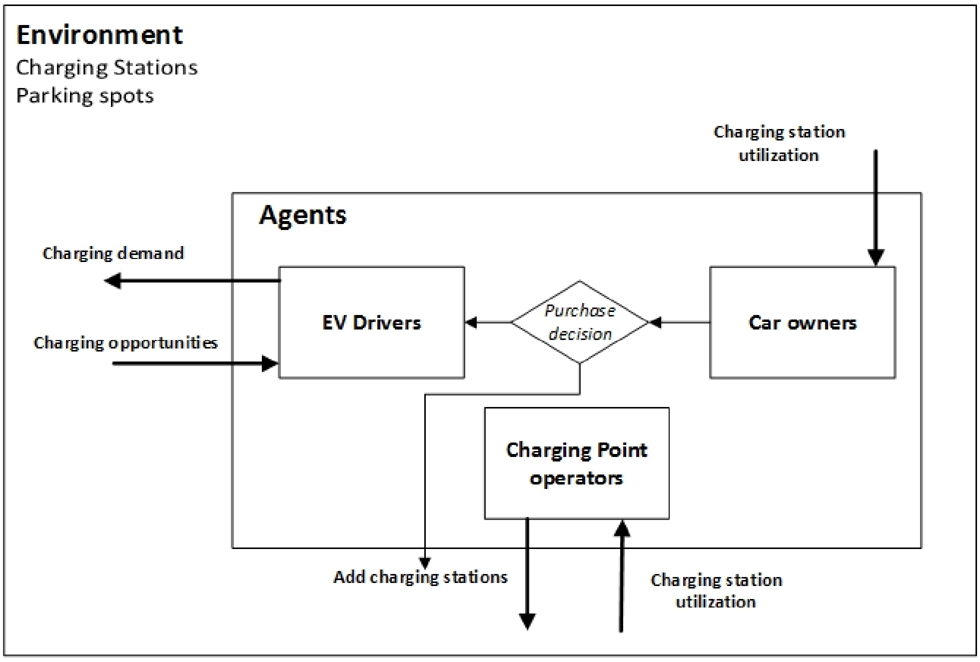

Figure 1 Model overview

3.2 Description

The description provides details of the elements in the system, their characteristics and how they interact with different elements in the system. An overview of elements in the ABM with their parameters is given in *Table 1*.

Table 1 Overview of elements in ABM with their parameters

Agent/Element	Parameters
EV Drivers	- Favourite charging location - Charging demand o Connection time o Time in-between charging sessions o kWh - Battery size
Charging stations	- Location - Capacity (No. of EVs)

	- Charging speed (Regular/Fast 50-350kW)
Car owners	- Purchase decision moment - Attitude towards EV - Home Location
Charging Station Operator	- Number of charging stations to be added - Type of charging station to be added

3.2.1 EV drivers

In contrast to other EV ABMs, this model uses actual charging data instead of travel patterns to simulate the charging behaviour. Previous studies have found that charging behaviour is often habitual and therefore suited to be modelled using ABM. To capture these charging habits we first define a charging profile per agent on the basis of observed charging patterns, secondly explain the charging process and thirdly present how we model the charging behaviour of those which are less habitual or insufficient data is available to create charging profiles.

3.2.1.1 Charging profiles

The charging profile per agent is determined on the basis of historical charging data. The same dataset as in [35][41][8] is used. In this research we use a subset focussed on the city of Amsterdam. Data from 2017 is used to create the charging profiles per agent and 2018 data to validate the model. The RFID tag of the charging card used is used as an indicator for a single person. Only RFID tags that were found to charge more than 20 times at a same location were used to create a charging profile. Further the data was filtered to exclude taxi and car sharing schemes as they were found to display unhabitual behaviour (see. 3.2.1.3).

Table 2 Example of charging pattern per agent

Agent	Favourite Location	Weekday	Time	Possible Connection Time	Probability Connection Time	Possible Disconnection Time	Probability Disconnection Time
….	….	….	….	….	….	….	….
1	14	Monday	17:00	3.5 hours	0.2	4 hours	0.1
1	14	Monday	17:00	14.5 hours	0.3	15 hours	0.4
1	14	Monday	17:00	15.5 hours	0.5	16 hours	0.5
1	14	Monday	17:30	15 hours	0.25	1 hour	0.1
1	14	Monday	17:30	16 hours	0.25	1.5 hour	0.3
1	14	Monday	17:30	16.5 hours	0.5	16 hours	0.6
…..	…..	…….	…..	…..	…..	…..	…..

The charging profile is defined by (i) a favourite charging location, (ii) the connection time, (iii) number of kWh to be charged and (iv) the time until the next charging session. The model sets a favourite charging location per agent, based upon the most used charging station in the data. The charging pattern in terms of connection and intervals between sessions is determined for each half our and day of the week based on historical charging sessions. For each timestamp (rounded to half an hour) observed (dis-)connection times are gathered for an agent as shown in *Table 2*. The probability of choosing a (dis-)connection time while running the model is based upon the relative number of times a (dis-)connection time has been observed at a particular given time of day and day of the week. For the pattern of the number of kWh to be charged a similar probabilistic approach is used. The difference however is that there is no relationship between the time and the number of kWh.

In *Figure 2* an overview of the charging patterns of all agents in the system is given. The figure shows (a) the distribution of sessions over the day, (b) the distribution of connection times, (c) the distribution of intervals between sessions and (d) the distribution of the number of kWh charged.

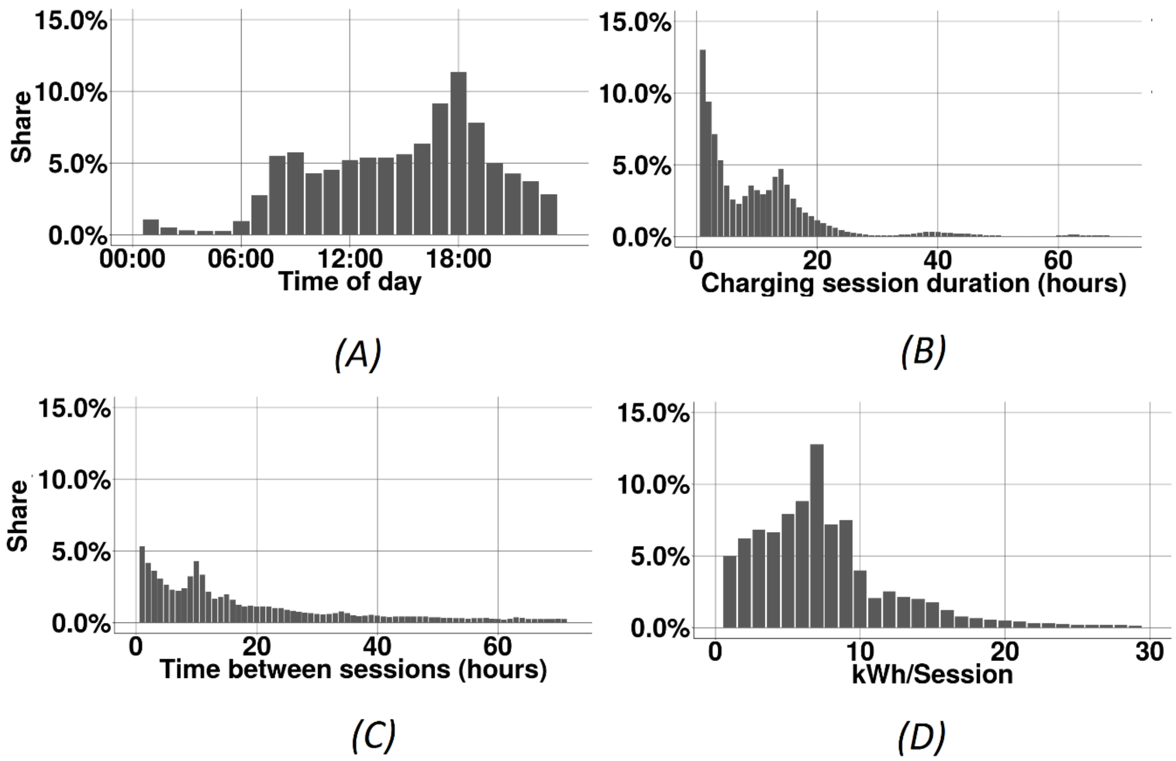

Figure 2 Descriptive statistics of charging behaviour captured in the model

3.2.1.2 Charging process

The charging process is modelled as displayed in *Figure 3*. For each time stamp the models check if an agents wants to charge. If so, the agent will try to charge at the given favourite charging location. The agents checks the availability of the charging station. If the charging station is not available it will select a charging station within the given radius of the favourite charging station. The agent will then again check the availability until no more options are available. The model tracks the distance between the charging stations travelled to check availability. The agent is presumed to have no knowledge about charging station availability upfront. If a charging station is available the agent will connect and the number of cars connected to charging station is updated. When connected the agent will select a connection time (based upon the time in the system) and the number of kWh to be charged. If the charging session is noted as failed, the agent still determines its disconnection time as if the session has succeeded. Data about the connection time, kWh location, and distance travelled and the success of the charging session is stored in a charging session database. Based upon the connection time, the time when the agent should disconnect from the charging station is determined.

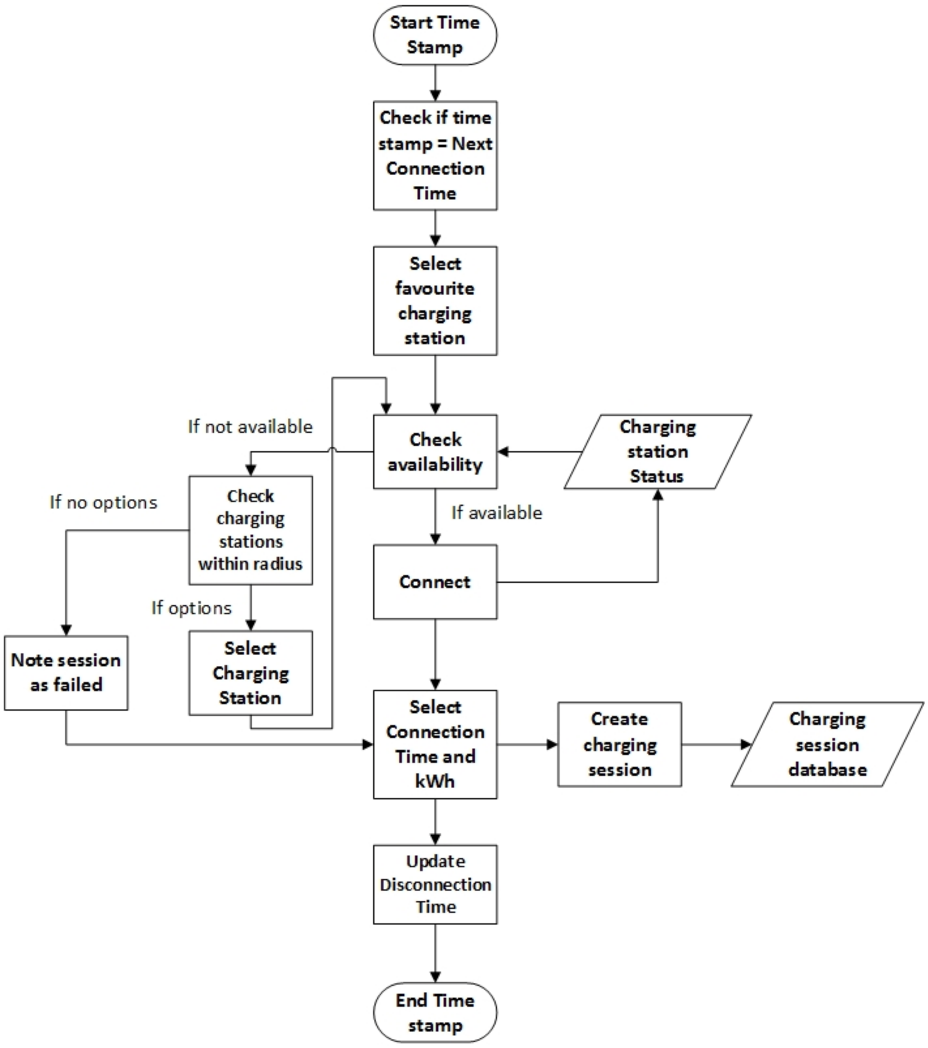

Figure 3 Overview of the charging process

3.2.1.3 Unhabitual charging

To account for the charging sessions of EVs that are not modelled as agents (users with less than 20 charging sessions/year) a probabilistic approach is used. These sessions represent visitors, shared vehicles and taxi drivers. Given a certain time, the model assumes (based upon patterns found in the data) a certain number of sessions to take place. Locations are chosen based upon previously observed distributions across the charging stations. It is assumed that the number of so-called non-habitual EV charging sessions grows at a similar pace as the number of agents in the model.

3.2.2 Charging Stations

Charging stations are objects modelled within a spatial context. They have a fixed location, a capacity for the number of EVs that can be charged simultaneously and a charging speed. The location is based upon GPS coordinates and the walking distance between the charging station is calculated using the OSRM routing engine [47]. Capacity for a regular charger is 2 agents, which can be expanded. Fast charging stations have a larger charging speed (which can be varied between 50-350 kW). The connection time of the EV-driver agents is altered depending on the charging speed of the fast charging station. Connection times at fast charging stations are calculated on the basis of the amount of kWh to be charged and the charging speed as given in *Formula 1*.

$$Connection\ time_{Fast\ charging} = \frac{kWh}{Fast\ charging\ speed} \quad (1)$$

3.2.3 Car Owners

Car owners are agents in the model that do not own an EV. The purchase decision of a new vehicle for these agents is modelled as shown in *Figure 4*. To this end the discrete choice model on purchase decisions in Wolbertus, Kroesen, van den Hoed, & Chorus [48] is used. This model estimates the choice probabilities of full electric, plug-in hybrid electric and gasoline driven cars. Factors that are taken into account are a general tendency towards EVs, the price and the ratio between the number of EVs and charging stations. Other factors used in the model by Wolbertus et al. are kept constant. The car owners are separated into different neighbourhoods. For each of these neighbourhoods the general attitude towards electric vehicles is determined, based upon previous sales. This attitude is represented by the constant for EVs in the choice model. The price of the car is based upon a fixed price for the glider of the car and a battery price. The initial prices are determined using the share of electric vehicles sold in the Netherlands. The price of the battery is discounted with 18% each year, the average drop in battery price over the last years [49]. The battery is estimated to be 47% of the total car costs when initialised for a full electric vehicle and 10% for a plug-in hybrid electric vehicle.

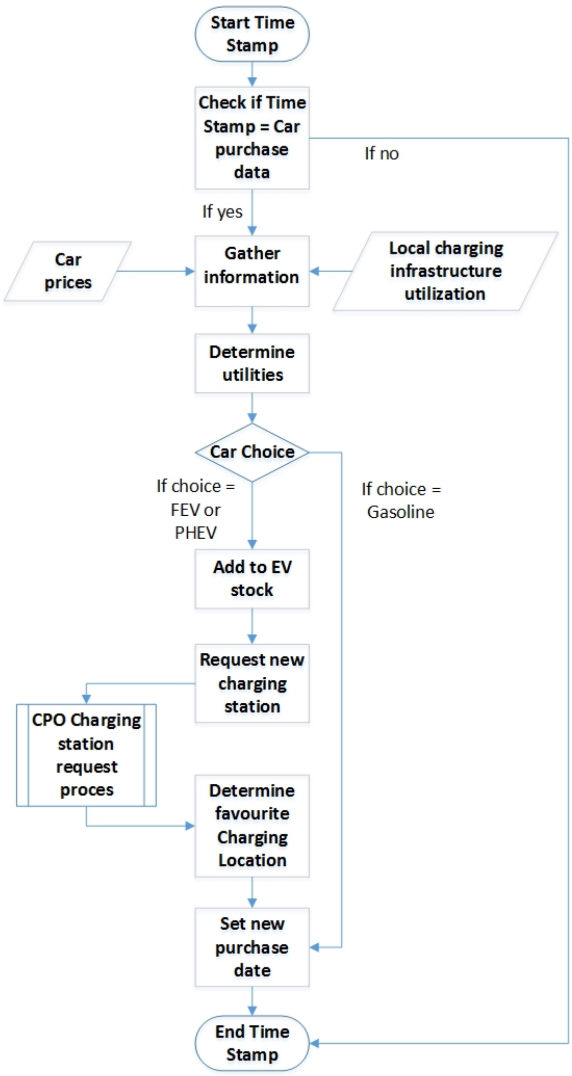

Figure 4 Overview of Car purchase process

When car owners decide on which vehicle to purchase, they monitor the ratio of number of frequent users and charging stations within the set radius of their home location. Each of the car owners is given a home location which is one of the parking spots in the neighbourhood identified by a unique identifier and GPS coordinates. The total number of car owners is equal to the number of car owners in the city of Amsterdam. Depending on the decision to purchase a plug-in hybrid or a full electric vehicle, a charging pattern of one of the already existing agents is copied. If the choice is a full electric or a plug-in hybrid vehicle, the behavioural pattern of agent with more or less than 25 kWh is copied, respectively. The new EV agent is then added to the existing stock of agents. The first connection date is sampled from connection dates of existing agents which are beyond the current time in the model.

3.2.4. Charging station operator

The charging station operator decides on whether to place an additional charging station after a new electric vehicle has been purchased. The charging point operator evaluates the number of users within a radius of 550 meters of the newly purchased vehicle. If the ratio exceeds a certain threshold, the charging station operator can decide to place an additional charging station. The charging point operator has three options which is to (1) add a regular charging station (at the home location of the new EV owners), (2) to increase the capacity of existing stations or (3) to add a fast charging station. Fast charging stations are only placed on locations of existing gas stations. Decisions to add new charging stations are done on a monthly basis after the vehicle choice decision.

4 Results

The simulation period starts on the 1st of January 2018. Agents are initialised being either connected or disconnected based upon charging data. If disconnected the first connection time is retrieved from the validation data. The simulated environment is the city of Amsterdam which contains 1148 charging locations and 3128 agents at the start of the simulation. The simulation period runs until the end of 2022 with a time interval of 30 minutes. Fast charging speed is set at 50kW, making the minimal fast charging time one timestamp. In this simulation single charging stations were added for a variety of threshold (1.5 to 6.5) for the charging point operator. Each model is run 4 times, mean results are displayed. The walking preparedness for EV drivers was set at 550 meters. Data is analysed on a weekly basis for a comparable number of days to be present in the data.

4.1 Descriptive results

Figure 5 shows the descriptive results of the model. It shows that for the lower thresholds (1.5 and 2.5) the number of EV Agents, the number of charging stations and sessions grow at an exponential rate. Due to the low threshold for the charging point operator, the number of charging stations grows fast, for nearly every new EV agent a charging station is placed. This in the longer run results (from 2020 a clear difference becomes apparent) in a higher number of new EV agents as the car owners see that the ratio between EVs and charging stations is very low. This clearly illustrates the reciprocal effect between EVs and available charging stations. A higher number of EV agents then also results in more charging sessions.

For the lower threshold the growth in EV agents stays linear and the number of charging stations nearly equal as the threshold to place a new charging station is barely reached. Despite this, still a number of car owners decide to purchase an electric vehicle, mainly on the basis of prices becoming lower. The charging station availability has the ability to accelerate this linear growth into an exponential one in a few years time.

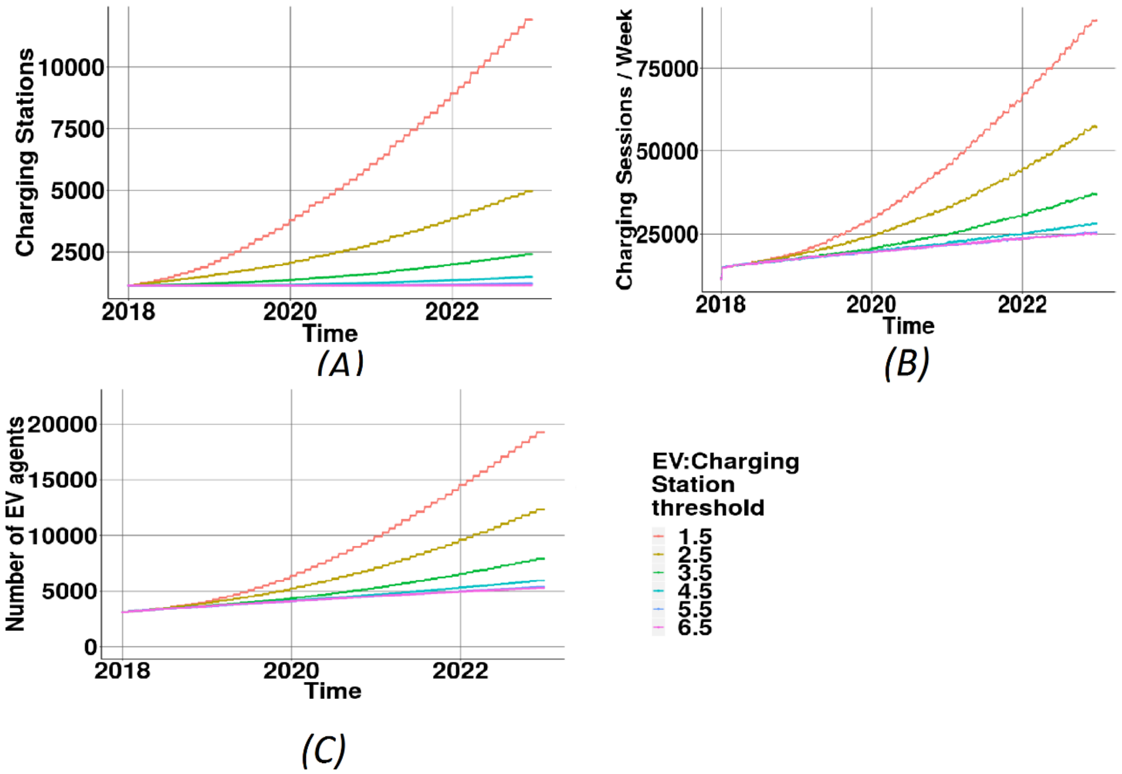

Figure 5 Descriptive results (A) Number of charging stations (B) Number of charging sessions (C) Number of Agents

4.2 Failed sessions

For each of the thresholds the number of failed sessions as of the total per week is analysed. On average the results show that approximately 0.6% of sessions fail due to a lack of available charging stations at the start of the simulation (*Figure 6)*. It is not possible to validate this data (failed sessions are not registered) but in general the number of failed sessions is thought of as low in Amsterdam due to the extensively available charging infrastructure. Sensitivity analysis shows that the percentage of failed is dependent on the walking preparedness of EV drivers. The 550 meter chosen in the data is the median maximum observed walking preparedness. A lower preparedness results in a higher share of failed sessions due to fewer alternative charging stations becoming available for the EV agent.

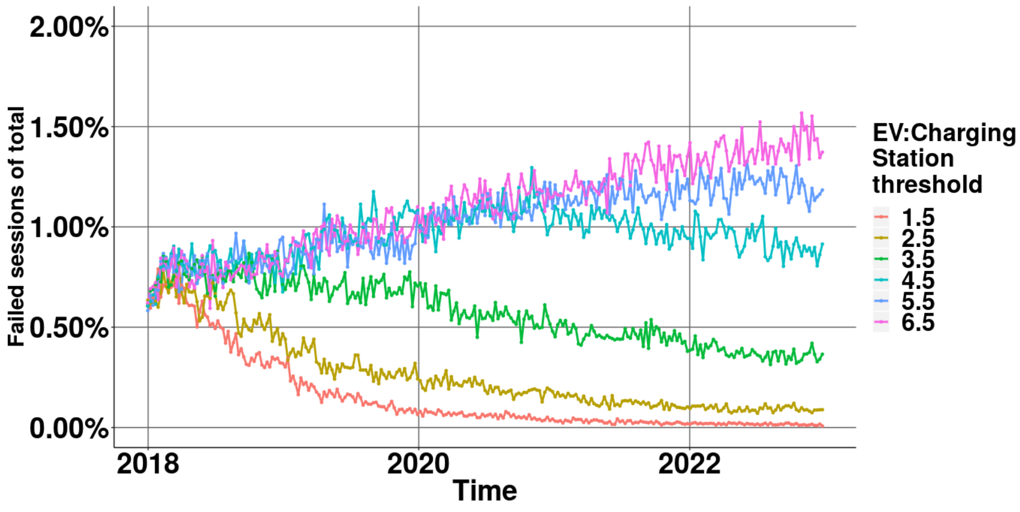

Figure 6 Shared of failed sessions per threshold over time

The results show that for the lower threshold the share of sessions that fail goes down to nearly zero quite quickly. Maintaining such a low threshold would result in a well available charging infrastructure for the long term. The ratio at the start of the simulation was approximately 2.7, slightly above the 2.5 modelled. With a threshold of 3.5 EVs per charging station before a new charging station gets placed the number of failed sessions stays equal for the first two years. After this the share also drops. We account this result due to scale effects: every EV agents gets a larger number of charging station alternatives when the favourite location is occupied. This results in more efficient utilization of the charging infrastructure in general.

This idea is supported by the fact that the number of charging sessions per station increases with the 3.5 threshold, while the share of failed sessions decreases (*Figure 7)*. The system as a whole starts operating in a more efficient manner. A higher number of sessions per charging station will also result in a positive business case on the long run.

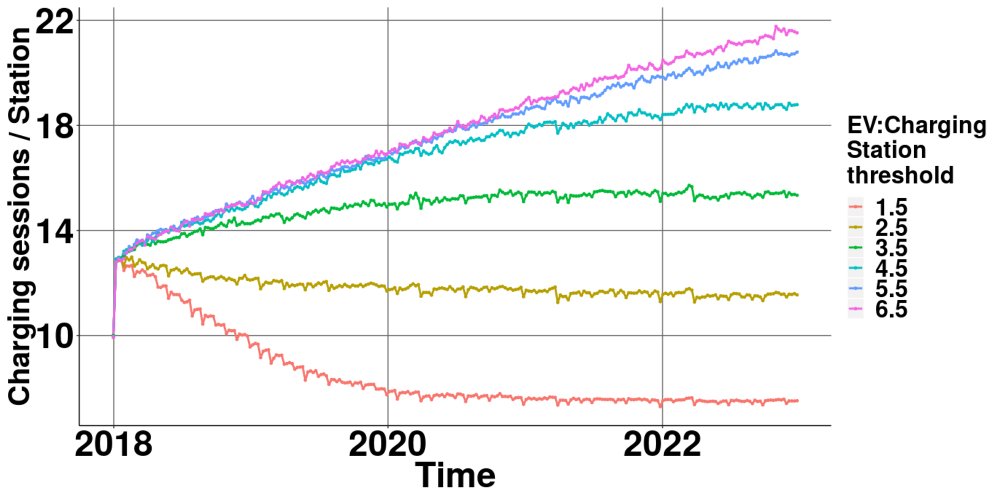

Figure 7 No of charging sessions per week per charging station

4.3 Cruising for charging stations

The last analysis of the result shows the number of kilometres on a weekly basis EV agents are cruising to find a charging spot. *Figure 8* shows that initially the lower thresholds also result in a lower number of cruising kilometres due to better availability. On the longer run however the number of cruising kilometres for the lower thresholds surpasses the total cruising kilometres of the higher thresholds.

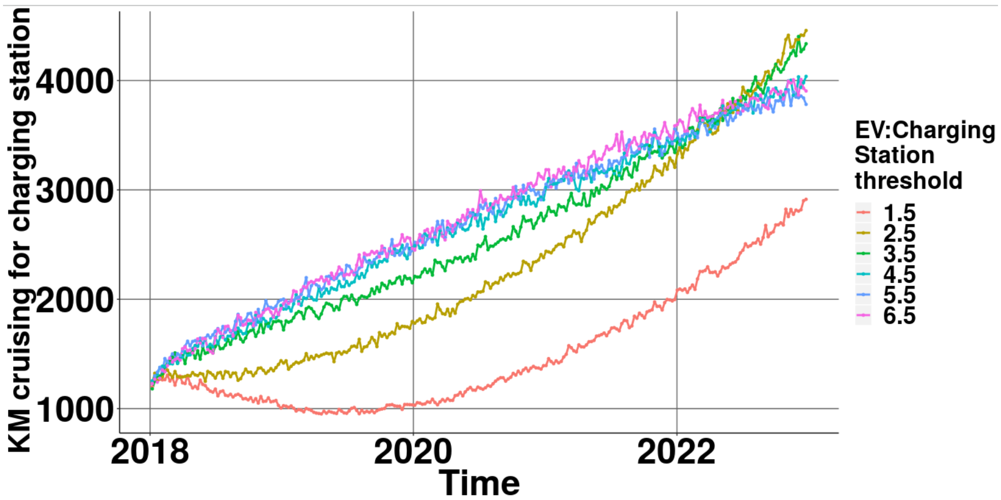

Figure 8 Sum of kilometres cruising for charging stations per week

This result does however not show that these higher thresholds create a more efficient system in terms of cruising. The number of kilometres is lower due to the lower number of agents in the system. As *Figure 9* shows the average cruising kilometres per charging session is much lower for the lower thresholds. This is due to better charging station availability at the favourite charging location of the EV agent.

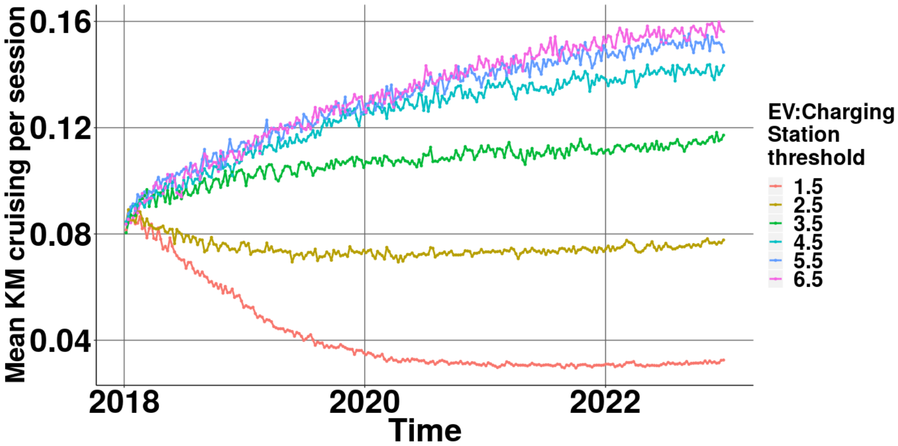

Figure 9 Mean number of kilometres cruising for charging stations per session

5 Conclusions

This paper has presented a methodology for assessing roll-out strategies for EV charging stations in the urban environment. A new agent based model was formulated to be able to more closely assess charging behaviour of electric vehicles and its specificities, while previous models have mainly been built on assumptions about charging behaviour. Using a large dataset on charging behaviour in the public realm, this model allows agent to be built on actual charging patterns.

This paper has further specified a charging point operator agent which decides on when to place a new charging station. This agent does so on the basis on the ratio between EV drivers and charging stations available in area. Potential EV drivers also take this ratio into account when evaluating the decision to purchase a new vehicle. In this way it has been possible to model the reciprocal effect between EV purchases and the charging station availability.

The results of a first simulation of the model, in which new single charging stations were placed, has shown that this reciprocal effect indeed exists. A lower threshold for placing new charging stations resulted in exponential growth of new EV owners. A higher threshold, and therefore a lower number of stations, resulted in more linear growth. This shows for policy makers that investing in sufficient charging stations for those that rely on on-street charging facilities will results in an increased adoption pace.

If the threshold was kept at slightly higher levels than the system currently was working on, did not result in more inconvenience for EV drivers in terms of finding an available charging station. Due to scale effects, in which a network of charging stations results in more alternatives becoming available, the share of failed sessions declines after a period even though similar number of charging stations is added to the system. This shows that policy makers and charging point operators can in time increase the threshold for placing a charging station without effecting service levels. This increases efficiency with lower impacts on the grid and public space and has a positive impact on the business case due a higher number of sessions per charging station.

In general the model has proved to be able to calculate a large range of different roll-out scenarios and assess these on multiple aspects. This should aid policy makers to make decisions on the long term about these strategies and adjust them when necessary. Such flexibility will be key for policy makers and industry partners to provide sufficient charging infrastructure in the future with an exponential growth in EVs on the road.

Acknowledgments

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