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Charging infrastructure roll-out strategies for large scale introduction of electric vehicles in urban areas: An agent-based simulation study

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ABSTRACT

On the eve of the large-scale introduction of electric vehicles, policy makers have to decide on how to organise a significant growth in charging infrastructure to meet demand. There is uncertainty about which charging deployment tactic to follow. The main issue is how many of charging stations, of which type, should be installed and where. Early roll-out has been successful in many places, but knowledge on how to plan a large-scale charging network in urban areas is missing. Little is known about return to scale effects, reciprocal effects of charger availability on sales, and the impact of fast charging or more clustered charging hubs on charging preferences of EV owners. This paper explores the effects of various roll-out strategies for charging infrastructure that facilitate the large-scale introduction of EVs, using agent-based simulation. In contrast to previously proposed models, our model is rooted in empirically observed charging patterns from EVs instead of travel patterns of fossil fuelled cars. In addition, the simulation incorporates different user types (inhabitants, visitors, taxis and shared vehicles) to model the diversity of charging behaviours in an urban environment. Different scenarios are explored along the lines of the type of charging infrastructure (level 2, clustered level 2, fast charging) and the intensity of rollout (EV to charging point ratio). The simulation predicts both the success rate of charging attempts and the additional discomfort when searching for a charging station. Results suggest that return to scale and reciprocal effects in charging infrastructure are considerable, resulting in a lower EV to charging station ratio on the longer term.

1. Introduction

In most countries electric vehicles (EVs) constitute less than a 1% of all vehicles on the road (International Energy Agency, 2018). Rapid growth in the number of vehicles is expected in the next years due to a decrease in battery costs and increase in driving ranges (Nykvist et al., 2019). At the eve of the large-scale introduction of EVs, policy makers are looking for the optimal approach to scale up charging infrastructure to facilitate increased charging demand. The chicken-or-egg dilemma related to charging infrastructure could prove to be the largest bottleneck to facilitate a rapid transition to electric mobility.

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Policy makers face difficult decisions about the right approach to deploy charging infrastructure. The main question(s) they face is *how many* and *which type* of charging stations should be installed *where*. These are long-term tactical decisions, as infrastructure investment costs are high and payback periods long. Insight into the effect of different roll-out strategies is therefore considered crucial. The main questions come down to operational decisions for policy makers such as: how many charging stations should be installed relative to the number of EVs on the road? Which EV to charging station ratio is optimal to service EV drivers and provides business opportunities for charging point operators (CPOs)? What is the trade-off in service to EV drivers between accessibility (ability to charge) and convenience (e.g. proximity and charging time)? Are charging stations best clustered in centralised hubs or should they be spread throughout a city to provide maximum geographical coverage? Can return to scale effects be expected? Can new fast charging technologies with increased charging speeds (from 50 kW up to 350 kW) provide an alternative centralised solution in urban environments? Policy makers urgently need insights into which reciprocal effects between investments in charging infrastructure and EV adoption exist, to be able to capitalize on them in their decision making.

To address these policy questions, charging infrastructure can best be seen as a complex system (Helmus et al., 2019a, 2019b) in which EV drivers compete and interact with each other for available charging stations. Charging stations are a rival good, in the sense that charging at a particular station prevents other EV drivers from access to that location. Competition takes place within geo-spatial boundaries and between different types of users such as residents, taxi drivers or shared EVs (Helmus and van den Hoed, 2015). EV drivers not only interact with each other but also with the CPO as this stakeholder monitors the utilisation of current stations to adjust the supply of new charging stations. Potential new EV drivers take into account charging convenience when they decide which cars to purchase. Therefore, reciprocal effect between the EV adoption pace and infrastructure roll-out is expected (Sierzchula et al., 2014; Wolbertus et al., 2018a, 2018b) but the extent to which this plays out is uncertain. Additionally, when charging infrastructure is expanded, return to scale effects might exist. Yet, due to the rival nature of the charging stations it is uncertain if and to which extent a larger charging network is used more efficiently. It is necessary to address these complexities in research on charging infrastructure, to be able to provide accurate and meaningful impact assessments of different roll-out strategies.

To study the effect of charging station roll-out strategies on the EV charging system, an agent-based model (ABM) is built and employed. The ABM presented in this paper addresses three related processes; (i) the charging choice, (ii) the charging station deployment and (iii) the vehicle purchase process. The agent based approach is ideally suited to investigate the EV charging system, since it is able to handle two important features, namely, it allows simulation of interactions between agents (between EV agents, CPO agents and non-EV car owners) and it acknowledges the fact that the geo-spatial context is highly relevant. Due to these specificities, various researchers have already used ABMs to model the uptake of EVs (Krupa et al., 2014; Noori and Tatari, 2016; Silvia and Krause, 2016), the charging behaviour of EVs (Olivella-rosell et al., 2014; Sweda and Klabjan, 2015; Torres et al., 2015) and more recently the relation between charging infrastructure and EV uptake (Gnann et al., 2018). In contrast to this previous work, this study uses a data-driven approach to operationalise the ABM. In particular the charging behaviour is derived from an empirical dataset which contains approximately 2 million actual charging sessions. It focusses on the urban area in which competition between different user groups for public charging infrastructure is intense since many users rely on on-street charging infrastructure for their daily charging needs. Furthermore, it uses established research to address the relationship between EV adoption and charging infrastructure. This gives new and empirically rooted insights for policy makers in their roll-out strategy decisions.

In the remainder of this paper, first previous work carried out on EV adoption and charging in relation to charging infrastructure deployment is reviewed after which the research gap is identified (Section 2). In Section 3 we present the method and the data to support the choices in the design of the ABM. Section 4 discusses the results of the simulations and the conclusions are presented in Section 5.

2. Previous work

Research interest in EVs and charging infrastructure has grown extensively over the past years in line with the rise in numbers on the road. In this section an overview is given of the work done on (i) EV adoption and its relationship to charging infrastructure and (ii) on roll-out strategies for charging infrastructure. As both fields are researched intensively, the overview focuses (albeit not exclusively) on ABM approaches on these two topics.

2.1. EV adoption and charging infrastructure

Literature overviews on EV adoption studies (Coffman et al., 2016; Liao et al., 2015; Rezvani et al., 2015) show that a lack of charging infrastructure is one of the main barriers for consumers to purchase an EV. Hardman et al. (2017) and Gnann and Plötz (2015) review papers with an explicit focus on the relationship between EV adoption and charging infrastructure and found that availability of home charging is the most important factor in the decision to adopt electric vehicles. Studies in this area mostly rely on data from surveys or stated choice experiments, while the use of revealed preference data is scarce (Hardman et al., 2017). A notable exception in this regard is the research by Sierzchula et al. (2014) which analyses data on EV adoption in 30 countries and found charging infrastructure to be the main predictor of adoption rates (although causality may operate in both directions).

Besides stated and revealed preferences techniques, EV adoption is also studied with ABMs. Typically, the main reason to use an ABM is to model the interactions with other agents. This allows for studies on social relations such as the neighbour effect (Axsen et al., 2009). Most models use an "if-then" decision rule for the agents' purchase decisions (Eppstein et al., 2011; Gnann et al., 2015; Kangur et al., 2017; Silvia and Krause, 2016). In these models the utility or cost parameter is compared to other available options and the most favourable option is chosen. Other studies (Kieckhäfer et al., 2017; Shafiei et al., 2012) use more advanced multinomial logit models for the EV adoption choice. The input parameters result in a choice probability for each agent after which a random wheel procedure is applied. These models are more in line with the latest choice models and allow for more validation of the decisions on which variables to include (Araghi et al., 2014; Holm et al., 2016; Le Pira et al., 2017).

Although ABM studies consider the relation with other EV agents, relatively few models take available charging infrastructure into account (Kangur et al., 2017; Kieckhäfer et al., 2017; Shafiei et al., 2012; Silvia and Krause, 2016). If included, the relation is modelled in a static sense, in which charging infrastructure is a given and no interaction between the purchase decision and infrastructure development is allowed for. An exception is the work by Gnann et al. (2018) which models the CPO as an agent which decides on charging station deployment. The stock of charging stations also influences the assessment of potential EV buyeragents of their ability to fulfil their travel needs. This work however assumed that all agents had home charging availability without competition from other agents. This makes the analysis less suitable for urban environments in which a large share of inhabitants relies on public on-street parking and charging.

To conclude, research on EV adoption has identified charging infrastructure availability as one of the main barriers to a large scale introduction of EVs. However, in ABM studies of EV adoption charging infrastructure has hardly been considered or only in a static sense. The reciprocal relationship between EV adoption and charging infrastructure development has received very little attention in ABMs, despite other research pointing out that charging infrastructure is a key barrier in uptake of EVs.

2.2. Charging infrastructure utilisation

In line with the number of papers on EV adoption, the number of studies on charging infrastructure utilisation and charging behaviour increases. Research has progressed from stated choice studies (Jabeen et al., 2013; Latinopoulos et al., 2017) and estimations with travel data (Brooker and Qin, 2015; Shahraki et al., 2015; Xi et al., 2013), to revealed charging data for descriptive (Morrissey et al., 2016; Sun et al., 2016; Wolbertus et al., 2018a) and explanatory research (Sun et al., 2016; Wolbertus et al., 2018a; Zoepf et al., 2013). In general, the research confirms the need for home, workplace and opportunity driven charging stations and fast charging along corridors.

These studies focus on past usage of charging infrastructure. Studies that try to optimise charging infrastructure roll-out often make use of travel patterns from gasoline driven vehicles. For EV fast charging, Motoaki (2019) observes two approaches in the literature 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 in actual deployment strategies. For slower level 2 (up to 22 kW) charging infrastructure researchers make use of dwell time as a proxy for charging demand (Paffumi et al., 2015; Shahraki et al., 2015).

The number of studies that use ABMs for both charging infrastructure roll-out and utilisation is limited. The available models use travel behaviour to estimate charging demand. The models assume that the driver charges at the end of a trip (under certain conditions) when a charging station is available (Torres et al., 2015; Vijayashankar, 2017). Additionally, the CPO is modelled in the decision to place a charging station (Gnann et al., 2018; Pan et al., 2019). The decision to place a charging station is based on the potential business case. Results from Gnann et al. (2018) show that level 2 charging stations for opportunity charging hardly ever become profitable and requires 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 model developed and applied by Helmus et al. (2019a, 2019b) and Vermeulen et al. (2018). This model uses charging patterns from actual charging events instead of travel information as input and only assumes public charging infrastructure for home charging. These papers however only model a static environment and do not consider growth scenarios with a CPO agent.

2.3. Contributions

This study contributes 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 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 (Wolbertus et al., 2018a). Secondly, an urban area is modelled in which most of the home and workplace charging is done on public charging stations. Previous models assume home and workplace charging at private charging stations. These are always available and used without any interaction with other EV drivers. The proposed model includes considerably more interaction between EV drivers compared to previous models, to more accurately represent the complex system of on-street EV charging in an urban context. Moreover, this model includes traffic from visitors and charging demand from other modalities such as shared vehicles and a taxi fleet which allows a more realistic simulation of the urban environment. Thirdly, this research models the relationship between the charging infrastructure and EV adoption based upon a choice experiment, while previous models use assumptions about this relationship.

The developed ABM is used to evaluate three case studies in the city of Amsterdam which address prominent questions by policy makers. These questions evolve around the three main aspects of charging infrastructure deployment which are *how many* and *which type* of charging stations should be placed *where*. The first case study addresses the ratio between EVs and charging stations. The case studies vary the threshold for the number of new EV drivers to place a new charging station. The second case study compares a clustered approach in which charging hubs are created to an approach in which single charging stations are placed across the city. The last case study compares fast charging stations to level 2 charging stations, to see if high powered charging stations can be a substitute for lowered stations. The city of Amsterdam is used as a case study as it is a city that already has a substantial number of charging stations in place and expects considerable growth due to the city plans to ban all non-electric vehicles by 2030 (City of Amsterdam,

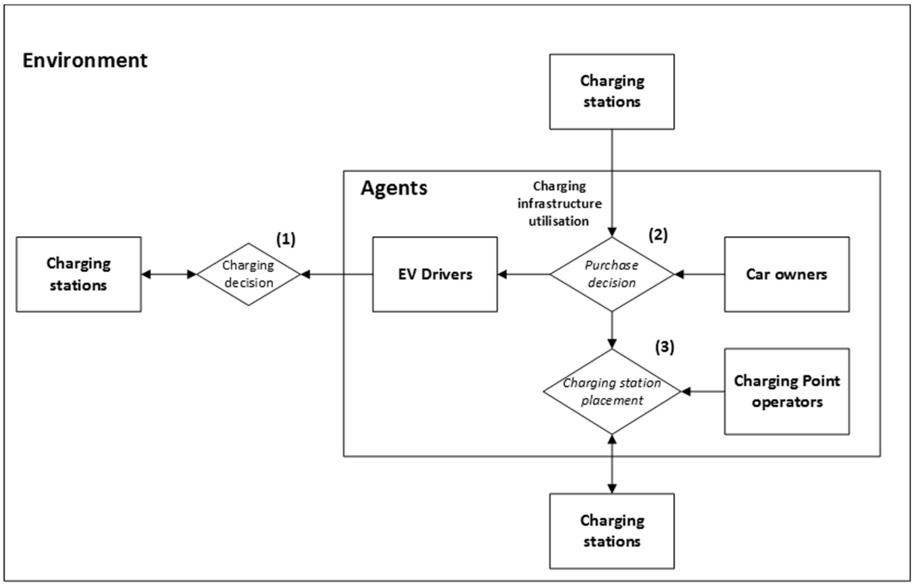

Fig. 1. Conceptualisation of Agent based model.

2019). All simulations run up to 2025, a period in which substantial growth infrastructure has to be made.

All three studies aim at investigating patterns due to changes in technology that current models could not yet foresee. The results allow policy makers to make well informed decisions on the charging infrastructure roll-out tactics with clearly defined performance indicators in mind. These performance indicators include amongst other things the service level in terms of successful charging sessions but also the convenience in terms of additional miles travelled to find an available charging station. In addition to performance indicators for the charging infrastructure, the research provides insights in the reciprocal effect between charging infrastructure and EV adoption. Together with information on the return to scale effects in charging infrastructure deployment it gives policy makers more insight in how their tactics contribute to policies at the strategic level.

3. Methodology

3.1. Conceptualization

3.1.1. Overview

The model contains three types of agents that operate in the environment of the city of Amsterdam in which charging stations are situated. The agents are EV drivers, non-EV car owners and the CPO. The interaction between these agents in simulated in three processes. These are (1) the charging process in which the EV driver interacts with available charging stations 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 instalment process of new charging stations by the CPO as part of the placement tactic, which depends on the charging station utilization. An overview of the elements and their interactions in the model is given in Fig. 1. The concepts behind these processes are discussed below.

3.1.2. EV drivers

Charging behaviour is the result of the choice of an individual EV driver to charge its car. Charging behaviour is here defined by its location, the time connected to the charging station, the energy transferred and the time until the next charging session. Analysis of charging patterns reveals heterogeneity in charging behaviour across users and different user types (Helmus and Van den Hoed, 2015). Each EV driver has her own distinct charging patterns. The behaviour at the individual level is habitual, e.g. EV drivers charge at a limited amount of locations (Wolbertus and Van Den Hoed, 2017) and often around the same time. It is therefore assumed that EV drivers attempt to charge at their favourite charging location, closest to their destination. Note that this location is often the home location or workplace, as can been derived from the charging patterns in Appendix A. The model gives room for flexibility of different user types and does not fixate only on inhabitants of the city. If the favourite location is not available, the driver searches for an available charging station in its proximity. It is assumed that distance is an important factor in location choice (Axhausen and Polak, 1991) and that drivers have a maximum willingness to walk (Waerden et al., 2017), which varies across drivers. Charging station locations are assumed to be known to the driver, but current occupancy is unknown.

Once the EV driver has chosen a charging station, she determines how long and how much she wants to charge. Previous research (Wolbertus et al., 2018a) has shown that the charging process conceptualised as 'charge when empty', is an insufficient explanation for observed charging patterns. Charging an EV is an interaction between refuelling and parking behaviour. Connection time and energy

Table 1
Overview of elements in ABM, their parameters and assumptions.

Agent	Parameters	Assumptions
EV Drivers habitual	- Charging profile • Favourite charging location • Connection duration • Interval between charging sessions • kWh - Battery size - Maximum walking distance - State (Connected or disconnected)	- First charging attempt at favourite charging station - Maximum walking distance varies between 200 and 600 m - Battery size between 4 and 100 kWh
EV Drivers non-habitual	- Charging profile • Number of sessions • Distribution of locations • Connection duration • kWh - Maximum walking distance	- Maximum walking distance at 450 m - Distributions of locations based on 2017 historic distribution - Charging sessions grow at similar rate as habitual drivers
Car owners	- Purchase decision moment - Attitude towards EV - Home Location - Maximum walking distance	- Purchase decision is monthly – Choice between petrol, PHEV and FEV - Battery prices drop 18% yearly - Battery price 47% of total cost (FEV) or 10% total cost (PHEV) - Attitude towards EV dependent on historic EV adoption in neighbourhood - Home Location based on public parking place location - Maximum walking distance varies between 200 and 800 m
Charging Point Operator	- Number of charging stations to be added - Type of charging station to be added	- Places charging station if ratio between EV drivers and charging stations exceeds threshold
Environment		
Charging stations	- Location - Capacity (No. of EVs) - Charging speed (Regular/Fast 50–350 kW)	- Capacity of regular charging station is 2 - Fast charging stations placed at locations of current gas stations

transferred are therefore correlated to the starting time of the charging session. The best proxy to simulate charging behaviour is to observe charging patterns across time from current EV drivers.

In the urban environment not only habitual users such as residents and commuters make use of charging infrastructure. Visitors, taxi drivers and electric car sharing services are important users of the systems. It is of interest how these different user types interact with each other and how a single infrastructure can serve the demand from different user types. The behaviour of these other user types is not habitual but does have distinct patterns (Van der Poel et al., 2017). The charging sessions of these types of users are therefore conceptualised as a homogeneous group of one-time visitors to the charging infrastructure in the city.

3.1.3. *Car owners*

Car owner agents that consider purchasing a vehicle are conceptualised to make a choice between a gasoline driven, a plug-in hybrid (PHEV) or a full electric vehicle (FEV), all with similar performances. For the latter two, it has been found that purchases have been restricted by three main barriers: price, driving range and available charging infrastructure (Coffman et al., 2016; Liao et al., 2015). The price and range of the vehicle are connected to developments of battery technology (Nykvist et al., 2019). These developments are considered a given and thus exogenous. To overcome the charging infrastructure barrier, home charging availability is considered the most important. Home charging in urban environments is often done at the kerbside located charging infrastructure. As awareness of public charging positively correlates with the willingness to purchase an EV (Bailey et al., 2015) the car owner considers charging availability near home during the purchase decision.

Charging availability differs between neighbourhoods, but is not enough to explain different adoption rates across these areas. Purchase decisions are found to be heterogeneous across different user groups (Bjerkan et al., 2016; Gnann et al., 2015). Differences between these users groups are attributed to factors such as income (Montfort et al., 2016) and environmental awareness (Kangur et al., 2017). This paper conceptualises these factors in a single preference for an electric or gasoline driven vehicle. The factors and thus preferences are often concentrated at the neighbourhood level (Kangur et al., 2017; Rodrigues et al., 2019). The preference for EVs is therefore assumed heterogeneous across but homogeneous within neighbourhoods. To best asses the preferences, past adoption rates per neighbourhood are used as a proxy.

3.1.4. *Charging point operator*

In the charging station placement process three important factors play a role. Namely where, how many of which type of charging stations should be placed (Motoaki, 2019). The decision to place a charging station is made by the CPO. The CPO optimises its business case and accordingly only places a new charging station if there is sufficient demand. In the urban area demand is best expected where home charging is needed, i.e. where the (prospective) EV owner lives. This is a so-called demand driven roll-out strategy (Helmus et al.,

Fig. 2. Charging stations within different ranges of walking distance in the Amsterdam-South area.

2018). The CPO adds a charging station in case a new EV is bought and insufficient charging infrastructure within walking distance is available. The CPO decides on the number and type of charging stations to be placed.

3.2. Operationalization

To operationalise the model both a description of the agents and their relevant parameters and the processes of each of the agents is given. Table 1 provides the operationalization of the elements in the system and their characteristics. These characteristics are discussed in more detail in the following paragraphs.

3.2.1. EV drivers

3.2.1.1. Charging profiles habitual. The charging profile is defined by (i) a favourite charging location, (ii) the connection duration, (iii) number of kWhs to be charged and (iv) an interval until the next charging session. These profiles are determined on the basis of charging data from the city of Amsterdam (see Section 3.3) in which an anonymous RFID-tag (from now onward "agent") is used to determine which charging sessions are performed by the same user. A favourite charging location per agent is selected, based upon the most used charging station. The charging pattern in terms of connection duration and interval between sessions is determined for each time of day (per half hour) and day of the week. The probability of a specific connection duration or interval is based upon the relative number of times the duration/interval has been observed at a particular time of day and day of the week. The number of kWhs to be charged is determined with the same approach, with the difference that there is no relationship with the day of the week. Evidently there is a strong relation between the kWh and the agents' battery size. Each agent tracks its own state, be it connected or disconnected. If disconnected, an agent has a time at when it wants to charge next, the so called Next Connection time. If connected, the agent's status is updated and the time it disconnects is determined based upon the selected connection duration.

The model allows EV agents to use different charging stations if the favourite charging station is occupied by other agents. It is assumed that an agent only uses charging stations within the maximum walking distance of the favourite charging station. Fig. 2 gives an illustration of charging points within given walking distances of a charging station in the Amsterdam South area. Note that the figure displays distances *as the crow flies* for illustrative purposes albeit the model calculates actual walking distances through the OSRM package in R (Luxen and Vetter, 2011).

Analysis of the maximum walking distance based on observed charging events away from the favourite charging station, reveals that this distribution is nearly uniform (see Appendix C). The agent in the model is randomly assigned a maximum walking distance between 200 and 600 m rounded to 50 m. Agents can travel up to 1500 m to a fast charging station despite their maximum walking

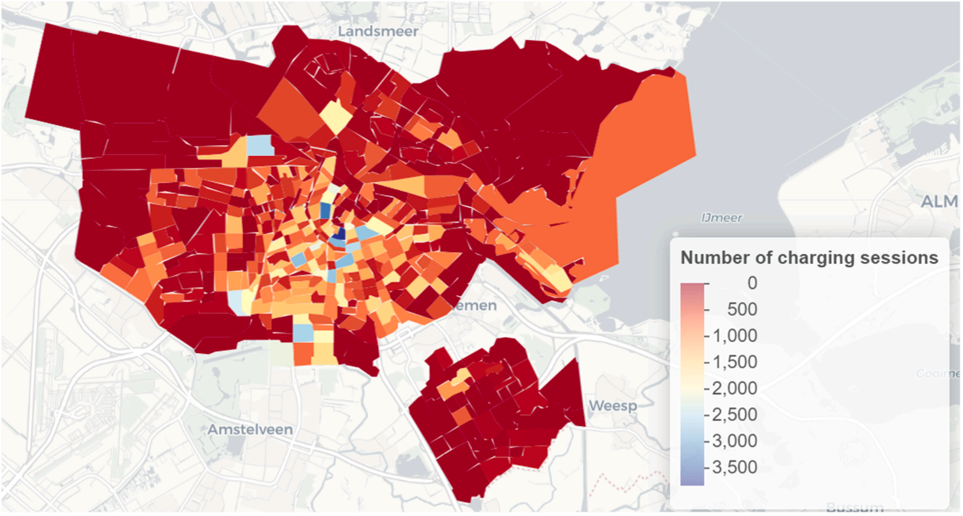

Fig. 3. Distribution of non-habitual charging session in 2017 in Amsterdam.

distance. Agents are assumed to travel to a fast charging station by car back and forth without walking.

3.2.1.2. Non-habitual charging. To account for the charging sessions of EVs that are not explicitly modelled as agents, a probabilistic approach is used. These charging sessions for example include visitors, car sharing vehicles and taxi users (if not residing in the city). These charging sessions are modelled as the result of behaviour of temporary agents whose charging behaviour is sampled from a single distribution. The number of sessions is determined from past observations of the number of non-habitual charging events. A visual overview of how these sessions are distributed across the city is given in Fig. 3.

Given the time of day and day of the week in the model, a number of temporary agents attempt to charge. The location the temporary agents want to charge is sampled from the distribution across the charging stations. In line with the habitual profiles the connection duration is sampled only from the occurrences that happened at the same time and day of the week. The amount of energy is selected independent from the time of day, but it is adjusted if the energy could not be transferred within the given time. The connection process is similar to the agents. The maximum walking distance for temporary agents is fixed at 450 m. The agent's identifier is set to "*Non-habitual*" when data on the charging sessions is gathered. When the non-habitual charging session ends, no new time is set for a next charging session.

3.2.1.3. Charging process. The charging process is modelled as displayed in Fig. 4. At each time stamp the model controls for which agents the next connection is equal to the time in the model and how many non-habitual agents want to charge. The agent selects and checks the availability of their favourite (or assigned in case of non-habitual agents) charging station. If the charging station is not available, it considers the charging stations within the maximum walking distance of that agent. From these stations, the next station to connect to is sampled with choice probabilities that are calculated using a multinomial logit model. This model is estimated with a combination of 2017 revealed charging data and a stated choice experiment described in Wolbertus and Van den Hoed (2019). This model includes walking distance and an identifier for charging hubs or fast charging stations as variables (see Table 2). The agent checks the availability of the chosen station and continues this process until no more options are available. If no options are available, the session is considered as failed. The model tracks the distance between the charging stations travelled.

If a charging station is available, the agent connects and the number of cars connected to the charging station is updated. When connected, the agent samples a connection duration (depending upon the time of day and day of the week) and the number of kWh to be charged. When the agent has no data in its charging profile for the given day of the week, only the time of day is considered. Based upon the connection duration, the time to disconnect is determined. If the charging session is noted as failed, the agent still determines its connection time and the energy charged (kWH) as if the session has succeeded. This is done to be able to set the time it next connects. Data about the connection duration, kWhs charged, location, and distance travelled and the success of the charging session are stored in a charging session database. When an agent disconnects, the time between charging sessions is sampled depending on the time of day and day of the week. The charging process in case of fast charging is similar, but connection duration are determined differently; the connection time is the amount of kWh to be charged divided by the charging speed. Only FEV vehicles (battery size >24 kWh) have the ability to fast charge.

3.2.2. Car owners

The purchase process of a new vehicle for car owner agents is modelled as shown in Fig. 5. Each car owner has a specific purchase date, which is randomly attributed to the agents. Dates across 15 years were used, approximately the ratio between new cars sold and the stock of cars in the Netherlands. If the date in the model is equal to the purchase date, the purchase process is initiated. To this end

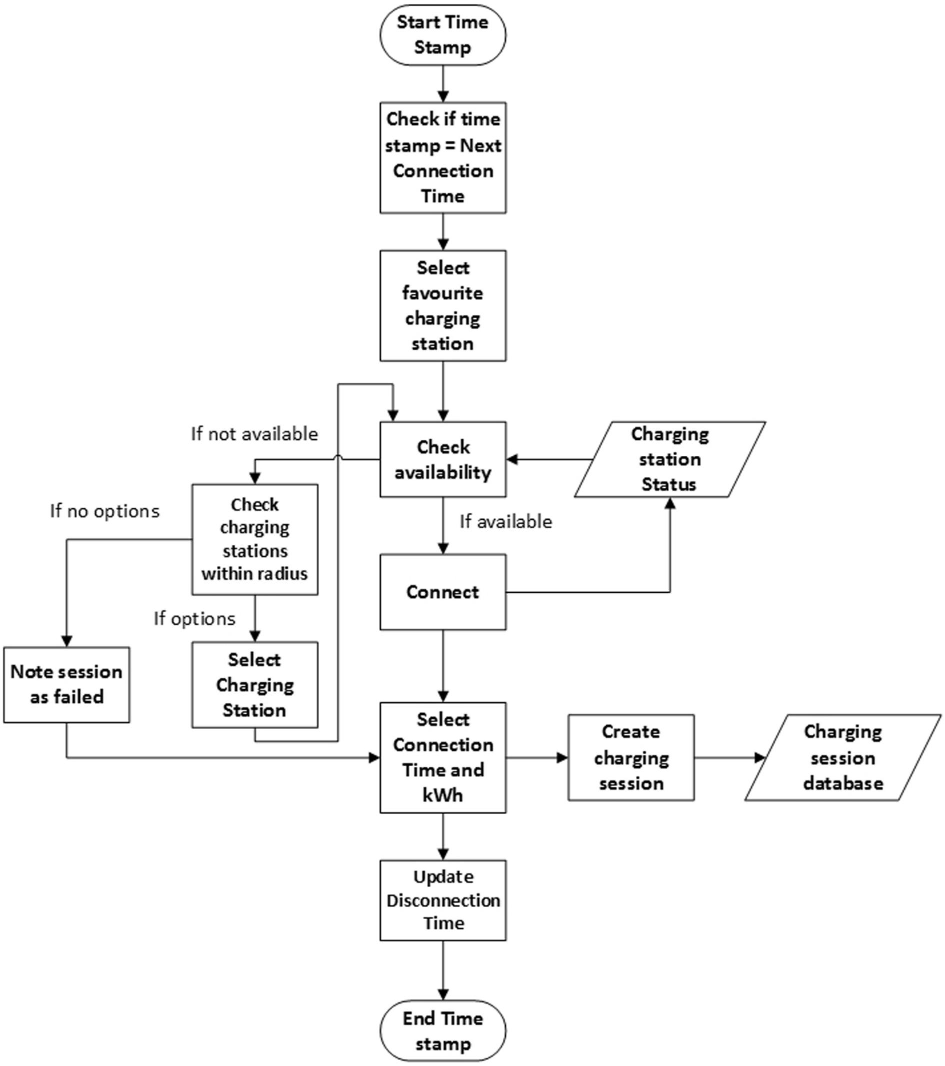

Fig. 4. Overview of the charging process.

Table 2
Choice Model for charging station selection.

Variable	Parameter
Constant Fast Charger	2.95
Constant Charging Hub	−3.99
Distance	−0.001417
Charging Time at fast charger (minutes)	−0.0437

the discrete choice model on purchase decisions in Wolbertus et al. (2018b) is used (see Appendix E). 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 (EV constant), the price and the ratio between the number of EVs and charging stations. Other factors used in the model by Wolbertus et al. (2018b) are kept constant. Car owner agents observe the ratio of number of frequent users and charging stations within the maximum walking distance of their home location. This ratio is obtained from the previous month of the simulation. The price of the cars is related to the exogenous developments of battery technology. The car owners are separated into different neighbourhoods. For each of these neighbourhoods the general attitude towards electric vehicles is determined, based upon the share of EVs (agents) from the total number of cars in the neighbourhood (see Section 3.3 last paragraph). Each of the car owners has a home location linked to a parking spot in the neighbourhood. Longitude and latitude information on public parking space information was retrieved from the city of Amsterdam (Municipality of Amsterdam, 2019b). The maximum walking distance of each car owner varies randomly

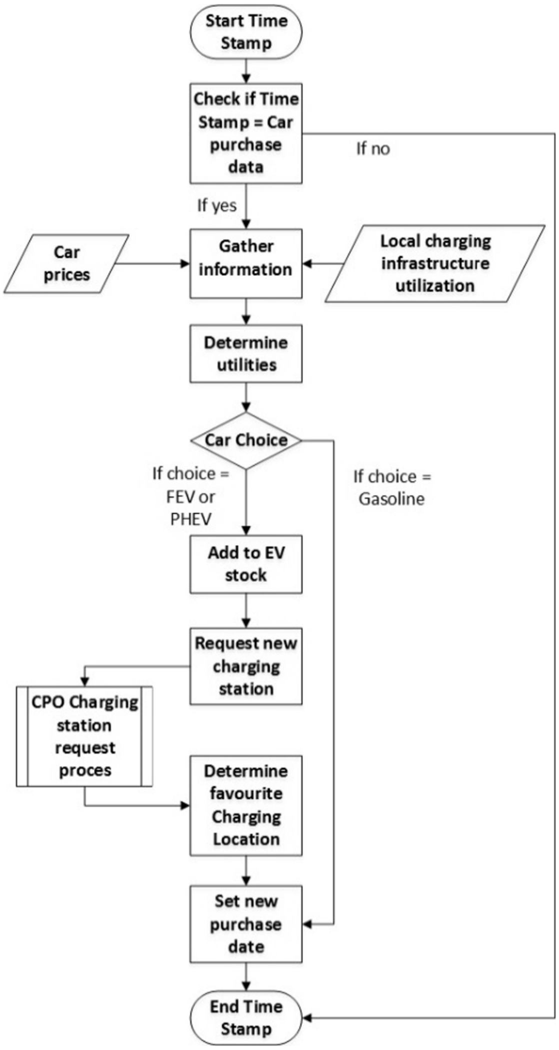

Fig. 5. Overview of Car purchase process.

between 200 and 600 m. Once all information is obtained, the agent calculates the different utilities for each option and the corresponding choice probabilities, consequently the car choice is sampled

When a PHEV or a FEV is purchased, the new EV agent is assigned a charging pattern of an existing EV agent. Depending on the choice of a FEV or a PHEV, a pattern of an agent with more or less than 24 kWh is sampled from the original stock and copied, respectively. The new EV agent is added to the stock of agents. The first connection date is sampled from connection dates of EV agents which are beyond the current time in the model. The favourite charging station is chosen on the basis of proximity to the home location. If the CPO (see 3.2.3) adds a new charging station at the home location, this station is chosen. After the charging station is placed all other agents check if the new charging station is closer to their home location and update their favourite charging location accordingly. 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. At each month the number of non-habitual charging sessions to be created at each time of day is updated on the basis of the number of agents.

3.2.3. Charging point operator

The charging station placement process is initiated after the purchase process, as if the EV drivers requests a charging station. The CPO measures the ratio between users and charging stations within the walking distance of the particular agent that requests a new charging station. If the ratio exceeds a threshold (which is varied in the simulation), the CPO decides to place an additional charging station. This is done in order to prevent multiple charging station placements in the same area. The CPO has three options which is to (1) add a regular charging station (at the home location of the new EV owners, capacity two agents), (2) to increase the capacity (with two agents) of the closest existing station or (3) to add a fast charging station. Fast charging stations are placed on locations of existing gas stations.

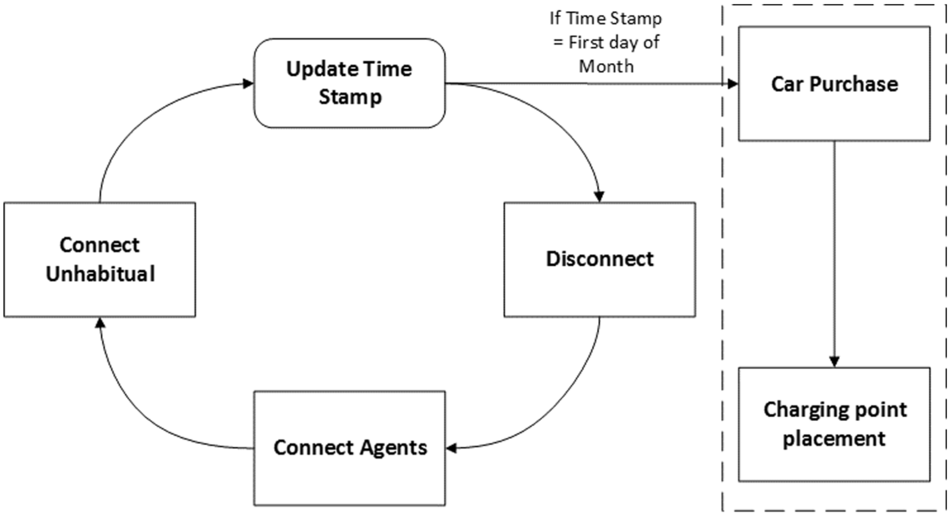

Fig. 6. Simulation iteration process.

3.2.4. *Charging stations*

Charging stations are objects modelled within a geo-spatial environment. They have a fixed location, a capacity for the number of EVs that can be charged simultaneously and a charging speed. The location is indicated with GPS coordinates and the walking distance between the charging stations is calculated with the Open Source Routing Machine (Luxen and Vetter, 2011). Standard capacity for a charger is two agents, which can be expanded. Fast charging stations have a larger charging speed (which can be varied between 50 and 350 kW).

3.3. *Data*

The charging profile per agent is created from data of the public charging infrastructure in Amsterdam (Wolbertus et al., 2018b, 2018a). Data from 2017 (682.709 charging sessions) are used to create the charging profiles and the data from 2018 (1.080.925 charging sessions) are used for verification. Data on the time of day, energy transferred (kWh), connection time and location of the charging session are stored per unique EV driver that is identified by a RFID-tag which is used to activate the charging station. Only RFID tags that are found to charge more than 30 times at a same location are used to create a charging profile. In addition, the data are filtered to exclude agents that are taxi drivers and shared car schemes as they are found to display non-habitual behaviour. These types of users are identified as their RFID tags are identified as such using external databases from car sharing and taxi companies. Data on the start and end times of charging sessions are rounded to the nearest half hour. For each RFID a probability distribution per half hour and day of the week is created for the connection duration and the time between the charging sessions. An overview of the distributions across all agents is given in Appendix A. In total 3941 unique charging profiles are extracted from the data. These represent 10% of all users in the system but these users account for 58% of all charging sessions.

For those charging sessions that are not performed by RFID tags with more than 30 sessions, data were merged into a single distribution. The distribution of connection durations is made per half hour of the day, per day of the week. The kWh distribution is per half hour of the day. Additionally, two other distributions are made. First, a distribution of the average number of sessions per half hour, which serves as a proxy for the number of charging sessions that should be started on that timestamp. Second, as the created temporary agents do not have a favourite location, a probability distribution of the locations was made. In case a new charging station is added, it is given the mean probability. The distribution of charging behaviour for non-agent charging sessions is shown in Appendix B.

In total 201.339 car owners are modelled in Amsterdam. The home location is determined by the GPS locations of publicly available parking spots in Amsterdam (Municipality of Amsterdam, 2019a). Each car owner agent has a specific attitude towards EVs related to the share of EV in its neighbourhood. This share is based on the ratio of agents to the total number cars per neighbourhood (CBS Statline, 2016). To determine the EV specific attitude per neighbourhood the share of EVs is compared to the national average in the Netherlands in 2017 (RVO.nl, 2019). The initial price of the car is determined with the choice model from Wolbertus et al. (2018a, 2018b) and the share of EVs sold in 2017 as input. The price of the car is split into a fixed price for the car without battery and a battery price. The price of the battery is discounted with 18% each year, the average drop in battery price over the last years (Nykvist et al., 2019). The battery is estimated to be 47% of the total car costs for a full electric vehicle and 10% for a plug-in hybrid electric vehicle when initialised.

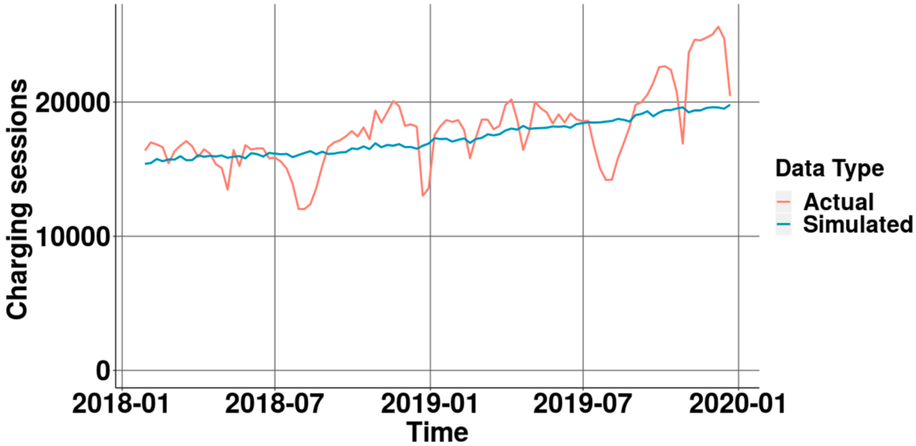

Fig. 7. Comparing validation set and simulation in terms of number of charging sessions.

3.4. Simulation process

3.4.1. Initialisation

The simulation period starts on the 1st of January 2018 with the 3941 EV drivers in the model. The connection and location status or first time to connect for an agent are retrieved from the verification data and thus resembles the actual situation at the time. From the 3941 EV drivers, 438 are connected. Non-habitual drivers are not connected at the initialisation. The simulated environment is the city of Amsterdam which contains 1148 charging locations at the start of the simulation, each with at least 2 sockets. At the start of the simulation 18% of the charging sockets are occupied. Standard fast charging speed is set at 50 kW. Each model runs four times, mean results are displayed. The simulation period runs from 1st of January 2018 until the 31st of December 2024. The time interval in the simulation is set to 30 min. Simulation takes places in RStudio (RStudio Team, 2015).

3.4.2. Simulation order

An overview of the simulation steps is shown in Fig. 6. The order of simulation is as follows. At each timestamp agents first disconnect from the charging station. After the disconnection process, the simulation connects agents whose next connection time is equal to the time stamp in the model. The selection process for charging stations is looped in a random order. If multiple agents attempt to charge at the same station, the agent first in the loop is allowed to connect. After the agents have connected, the temporary non-habitual agents connect. If the time stamp is equal to the first day of the month the car purchase and charging station placement process is initialised. As a result, the stock of EVs and the charging stations are updated.

At the end of each time stamp data are gathered about the charging sessions. For each agent and non-habitual charging session data are gathered on the location, time of day, session length and number of kWh charged. Additionally, the system checks at each time stamp how many EV agents and charging stations are active within the system. Analysis of the data occurs at a weekly basis as this provides a consistent time frame across which the system can be evaluated.

3.4.3. Verification

The simulation is verified with 2018 and 2019 charging data from the same dataset as described in Section 3.2.1.1. Verification is done over the period of a year to compare if charging patterns match those that were observed in real life. To check if simulated charging patterns match those actually observed, distributions across the day for the start time, end time, connection time were compared. Wilcox tests are used to compare distributions of charging behaviour. Generally, the model validates well on all charging parameters. For example, Wilcox test ($p = 0.82$) verifies that the model validates well on the connection duration of agents. Additionally, we compared the number of charging sessions over the period of 2018–2019 as shown in Fig. 7. The simulation validates the general upward trend in the number of sessions well. The simulation however misses the seasonal variation with a lower number of sessions during summer and somewhat higher demand in winter. This was expected as charging patterns are based only on weekly variations and the model does not capture end of the year spikes in sales due to changes in tax regulations. With regard to the aim of the simulation, comparing different roll-out strategies, the validation is considered sufficient as it estimates within a reasonable range.

3.5. Experiments

The model is used to test three types of hypothetical roll-out strategies which are being considered by policy makers. These roll-out strategies are single level 2 stations, clustered level 2 stations and fast charging stations.

Study 1: Charging station placement threshold variation

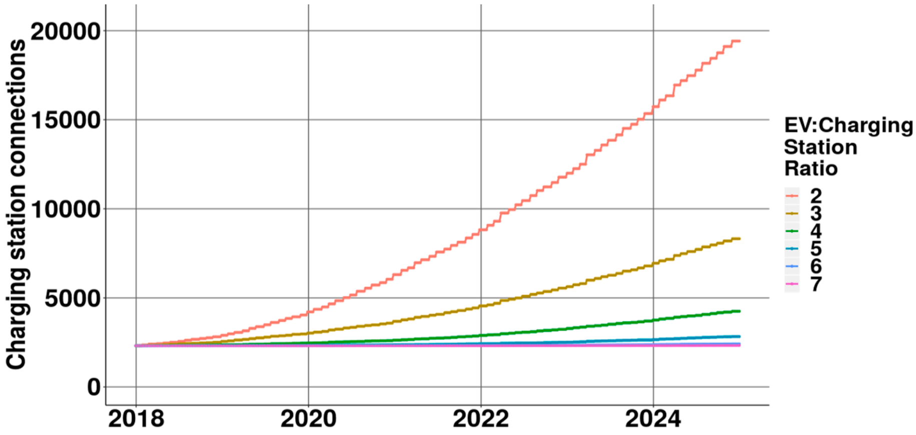

Fig. 8. Charging station connections for each EV:Charging station ratio simulated over time.

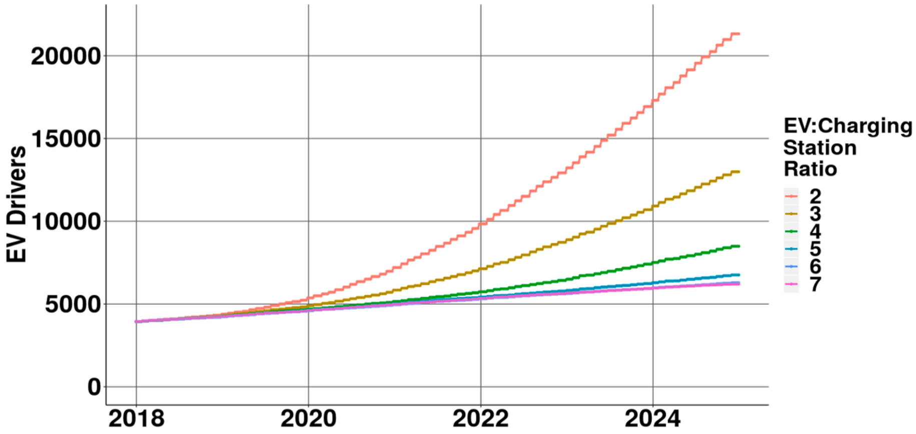

Fig. 9. Number of EV Driver for each EV:Charging station ratio simulated over time.

This study uses a roll-out strategy in which the CPO places a new level 2 charging station at the home location of a new EV owner. This is done if the ratio of agents to charging stations within the walking distance of an EV driver exceeds a threshold. This threshold is varied in the first study between 2 and 7 with a step of 1. At the start of the simulation, the ratio between agents and charging stations is 3.4, the current ratio. With a low ratio of e.g 2, a higher number of charging stations shall be placed as this threshold more easily exceeded. Higher thresholds lead to a lower number of stations relative to the number of EVs. Results are evaluated in terms of number of charging stations, reciprocal effect on EV sales, charging point utilisation (number of sessions and kWhs) and the share of failed sessions.

Study 2: Comparison of a charging hub to single charging station tactic

The single charging station strategy of study 1 is compared to a charging hub roll-out strategy. In the charging hub tactic, level 2 charging stations are added to the closest existing location, expanding the capacity at that location. If no locations are available within the given range, an additional charging station is added. The threshold for adding a charging station is fixed at three (which is the integer closest to the current ratio). Evaluation takes place in terms of the total number of locations and stations, the share of failed sessions, the share of sessions at favourite location and the number of kilometres of cruising for charging stations. The results of the charging hubs station tactic are compared to a single charging station roll-out.

Study 3: Fast charging station roll-out at different charging speeds

This study adds fast charging stations instead of level 2 charging stations. In this scenario, fast charging stations are not placed at the home location but at locations of gas stations in the city (see Appendix F). In this scenario the fast charging speed is varied for the charging stations placed. These charging speeds are 50 kW, 175 kW and 350 kW along the common standards for fast charging in the market. Iteration time of the model is set to 30, 15 or 5 min accordingly, to be able to fully simulate the effect of faster charging speeds.

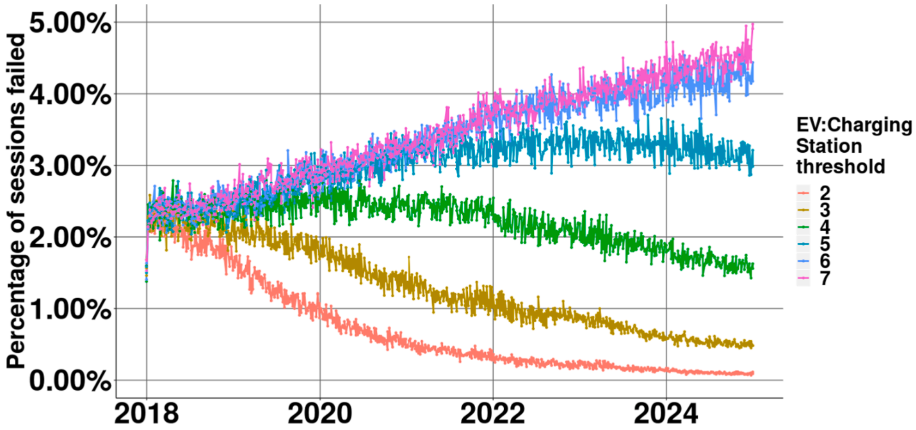

Fig. 10. Share of failed sessions per threshold over time.

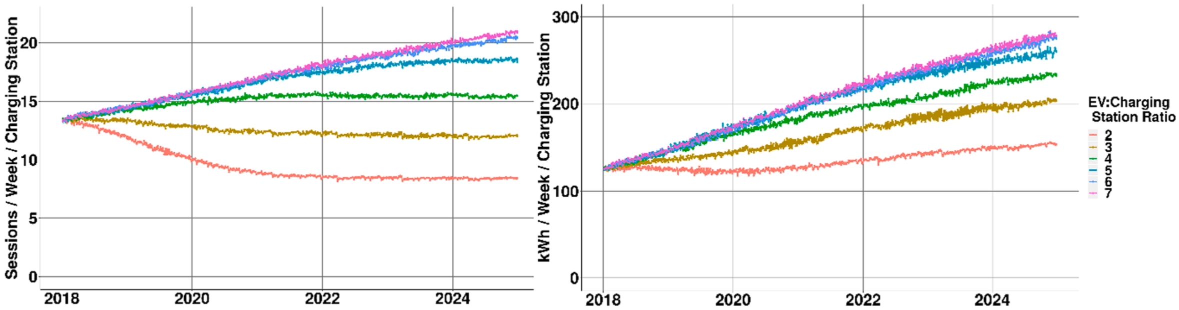

Fig. 11. Frequency of use in number of sessions per charging station (Left) and kWh per charging station (right) per week.

No restriction is assumed on the charging speed by the vehicle, except that PHEVs cannot fast charge. Agents can travel up to 1500 m to a fast charging station despite their maximum walking distance. During the purchase and charging station placement process the capacity for a fast charging station (50 kW) is assumed to be 10 times as big as regular charging station, which corresponds to the ratio of connection times between regular and fast charging speeds. This capacity is adjusted according to the speeds (50-175-350 kW) of the added fast charging stations. Threshold is again set at 3 EVs per charging station. Results are evaluated in terms of number of stations, failed sessions and additional kilometres travelled.

4. Results

4.1. Study 1: Charging station placement threshold variation

Figs. 8 and 9 show the model results in terms of number of charging stations and EVs respectively. For the lower thresholds (2 and 3) the number of EV agents and charging stations grow at an exponential rate. Due to the low threshold for the CPO, the number of charging stations grows fast, as for every second EV agent added a charging station is placed. In the long run this results in a higher number of new EV agents; prospective owners are more inclined to buy an EV because of the low ratio between EVs and charging stations and the resulting high availability of charging nearby. The results illustrate the reciprocal effect between EVs and available charging stations. A higher number of EV agents then also results in more charging sessions. For the higher thresholds the growth in EV agents remains approximately linear in the short run. The number of charging stations barely grows as the threshold to place a new charging station is almost never reached. Despite this, still a number of car owners decide to purchase an electric vehicle, on the basis of decreased purchase prices. Deploying the right EV:Charging station ratio can result in the acceleration of EV sales.

Fig. 8 shows that the number of charging stations to be added for the lower threshold is significant. If a threshold of 2 is maintained this means a near tenfold increase in 7 years' time. If a similar ratio as in the current system is maintained (~3) the number of stations should grow by a factor of 4. The big difference in size can be attributed to the lower number of expected EV drivers (Fig. 9). For the higher thresholds, limited growth is expected as the number of electric vehicles remains small.

For each of the thresholds the share of failed sessions of the total per week is shown in Fig. 10. On average the results show that approximately 2.2% of sessions fail due to a lack of available charging stations at the start of the simulation. It is not possible to empirically validate this number (failed sessions are not registered) but in general the actual number of failed sessions is thought of as being rather low in Amsterdam, due to the extensive charging infrastructure.

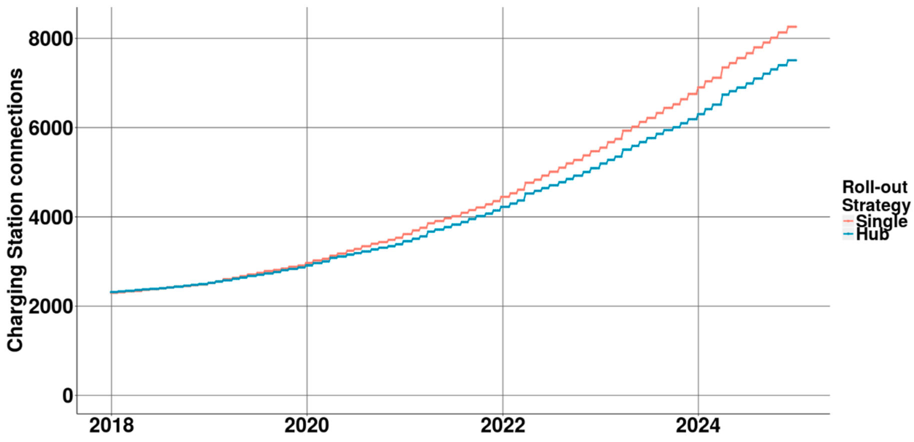

Fig. 12. Charging connections for single (red) and hub (blue) roll-out tactic. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

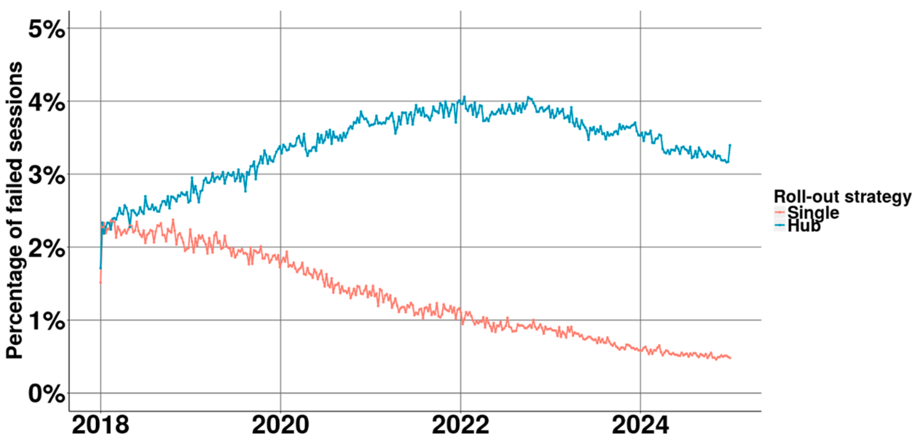

Fig. 13. Share of failed sessions for single and hub roll-out tactic.

The results show that there are return to scale effects in charging infrastructure in terms of serving the EV driver. If a similar EV: Charging station ratio is deployed as in the current situation (~3), the number of failed sessions decreases with nearly 75% over the period of seven years. This decrease can be attributed to network formation of charging infrastructure. With an increasing charging network size, each agent gets multiple options to charge within their acceptable walking distance. Such return to scale effects are absent for the higher thresholds, because these networks have not yet reached the critical density for such effects to exist. This suggests that in time, policy makers and charging point operator can maintain higher EV:Charging station ratios without reducing the chance for EV drivers in finding an available charging station.

Results show that CPOs can expect increasing 'returns on investment' in time for any EV:charging station threshold. Despite that the number of sessions per charging station decreases for the lower thresholds (Fig. 11 *Left*), the number of kWh sold increases over time (Fig. 11 *Right*). This is mainly due to the higher number of FEVs. The largest share of newly added agents (99%) drives an FEV (see Appendix D for the distribution of battery sizes). FEVs charge more kWh per session. At a ratio in which the number of failed sessions stays approximately equal, the turnover in terms of number of kWh roughly doubles in 7 years' time. This results in a substantially better business case for CPOs. For higher EV:Charging station ratios the business case can be nearly twice as good for the lower thresholds as idle times are reduced. For policy makers this implies reduced investments of public funding to facilitate the charging infrastructure for EVs.

4.2. Study 2: Comparison of a charging hub to single charging station tactic

In the second study a roll-out tactic with single charging stations or charging hubs is compared at the equal threshold level of 3. For the charging hub tactic, charging stations were added to existing locations (blue). The total number of charging connections (Fig. 12*)* however is only slightly less than in a tactic in which single charging stations were placed at new locations (red). In the longer term charging hubs can facilitate the same EV:Charging station threshold with fewer charging connections, although the difference is

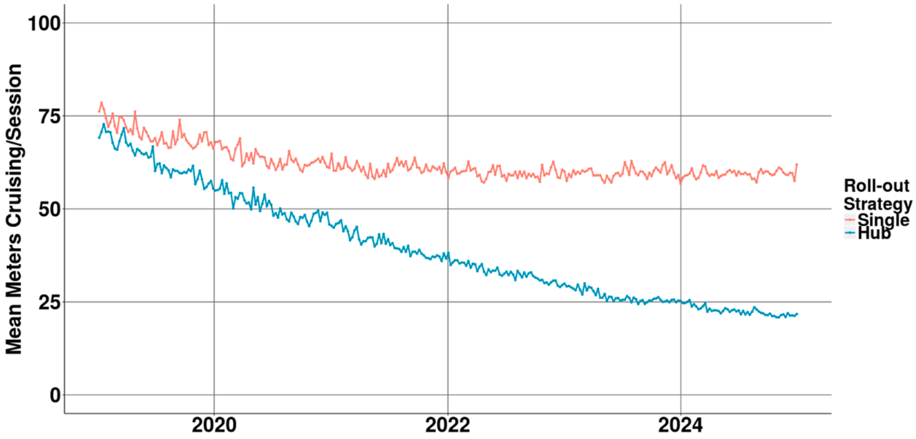

Fig. 14. Cruising for charging stations per roll-out tactic in mean meters travelled.

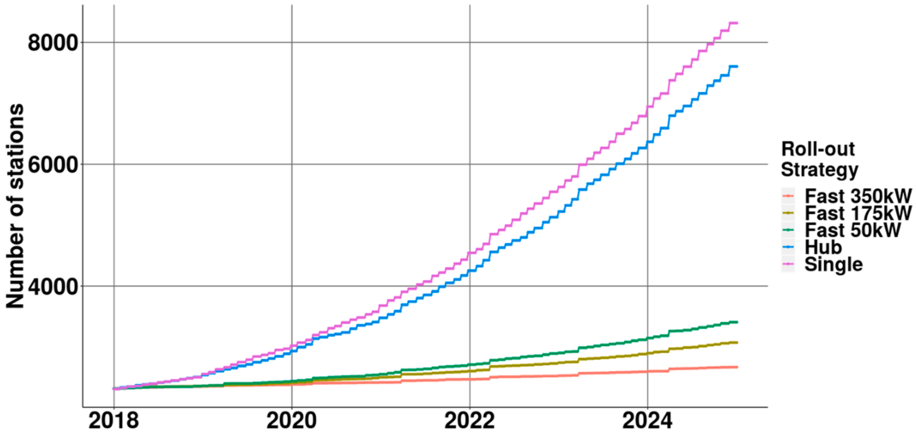

Fig. 15. Number of installed charging stations per simulated roll-out strategy over time.

minimal. The centralisation incentivizes agents mainly use a single location. Therefore agents are not counted as frequent users across multiple locations, leading to slightly lower EV:Charging station ratios. The hub scenario did not have a big impact on the adoption rate of EVs. This was only slightly lower as the number of charging station connections was slightly lower. The dynamics stayed similar as to the single charging station strategy.

Despite having to install slightly fewer charging stations, the hub roll-out tactic performs significantly worse (Fig. 13) in terms of providing available charging stations for EV drivers. The share of failed sessions is up to four times as large in 2024 compared to the single roll-out tactic. This is due to the fact that there are hardly any increasing returns of scale for the hub tactic. The number of alternatives at different locations does not increase for EV drivers and networks effects stay similar to the start of the simulation. Especially charging stations that are placed in locations without alternatives within given walking distances perform significantly worse (share of sessions that fail are up to 20%). Despite the initial increase in number of failed sessions the charging hub simulation also shows a decrease in the share of failed sessions. Part of the decrease in both roll-out strategies can be attributed to the shift towards full electric vehicle compared to the large base of lug-in hybrid vehicles that are initially present as already mention in discussing the results of study 1. These vehicles tend to charge less often than plug-in hybrid vehicles, while the model adds the same number of charging stations, which leads to a reduced number of failed charging sessions.

The charging hub roll-out tactic performs less in terms of failed sessions but better in terms of a reduced number of kilometres vehicles are cruising to find a charging station (Fig. 14). The number of charging attempts that succeed at the first try is significantly higher for the hub (95% at the end of simulation) than for the single station tactic (80%). This culminates in a significantly smaller distance that agents are driving to find an available charging station. Across the board the variance across users decreases, as those not living close to charging hub are given nearby new charging stations. Results show a higher convenience level for the EV driver, which has more certainty that charging stations closest to her or his preferred destination are available, despite the fact that there is a lower probability of having the possibility to actually charge. This result suggests that policy makers face trade-offs between providing charging accessibility on the one hand and convenience on the other, and could consider a hybrid roll-out tactic to optimise both factors.

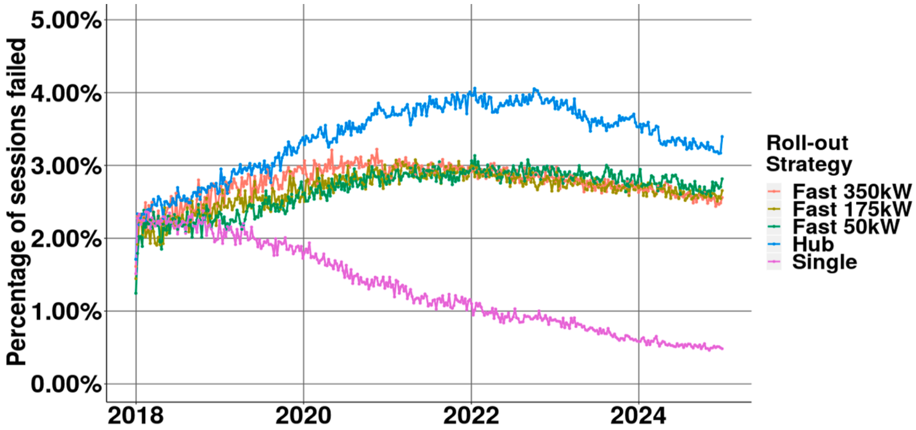

Fig. 16. Percentage of sessions failed per roll-out strategy over time.

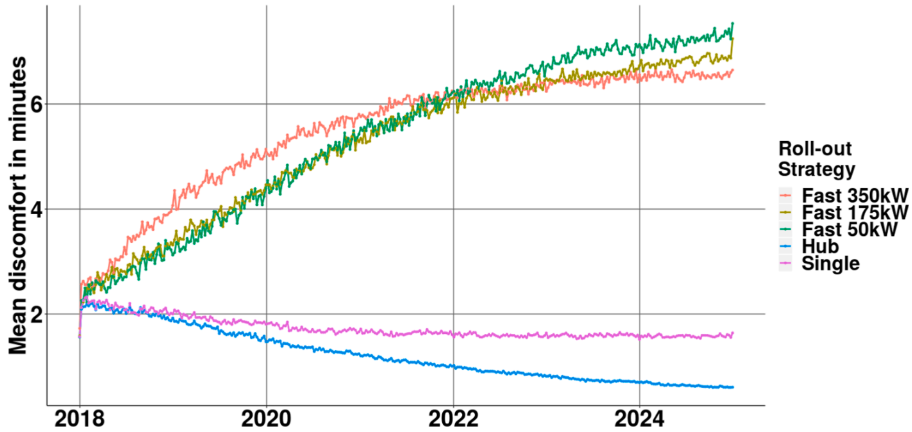

Fig. 17. Mean discomfort per charging session in time per roll-out strategy over time.

These results show be interpreted in the light that one of the model assumptions is that the agents have no information about charging station availability. Although mobile applications can provide this information, the authors are unaware about studies on how often and when EV drivers use this information. Interpretation is that cruising distances could be cut in half if perfect information was available in case the favourite charging was occupied. The agent still has to walk half the distance to her home.

4.2.1. Study 3: Fast charging station roll-out at different charging speeds

The third study compares the single and hub tactic with three different roll-out strategies in which fast charging stations are placed at current locations of gas stations. Simulation shows that up to a factor 4–5 less fast charging stations (in absolute terms) are needed compared to regular chargers, as is to be expected (1000–2000 fast chargers in 2025 versus 7000–8000 stations for hubs/regular chargers – see Fig. 15). When accounted for the model assumption that fast charging stations are considered having the capacity of 10 regular chargers (for 50 kW), then number of stations grows more substantially in the fast charging station scenario in relative terms. This is due to the fact that charging demand becomes more centralised. Centralisation results in a higher number of unique users per station. Therefore the CPO will add new charging stations more frequently than in the single station strategy. When evaluated in terms of costs (Schroeder and Traber, 2012), the results suggests that in total costs the fast charging option is more economical than the single charging station model. This would however require a substantial number of chargers at a single site sharing the same grid connection (Nicholas and Hall, 2018).

The service level in terms of number of failed sessions at fast charging stations is lower than the charging hub strategy but significantly higher (up to 3-4x times) than the single charging station model (Fig. 16). Differences between the different charging speeds are minimal. Increased charging speeds do not lead to a lower share of failed sessions as the number of charging stations is lower. The number of failed sessions at the fast charging stations themselves is very low (~0.1%). Some level 2 charging station have a very high share of failed sessions (20–30%), which indicates that some areas are underserved by the locations of fast charging stations as agents have a limited driving distance. New sites for fast charging stations or adding more regular chargers in the vicinity of those locations that are underserved may solve these issues.

In terms of discomfort for drivers, the additional number of kilometres travelled is higher in case of fast charging stations. This

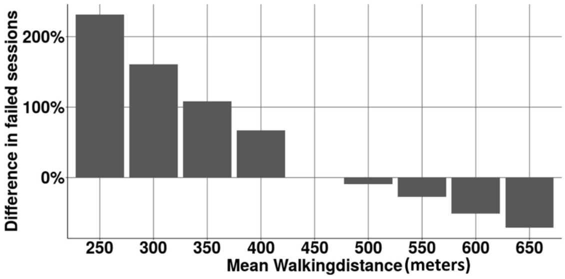

Fig. 18. Sensitivity Analysis on share of failed sessions due to variations in walking preparedness.

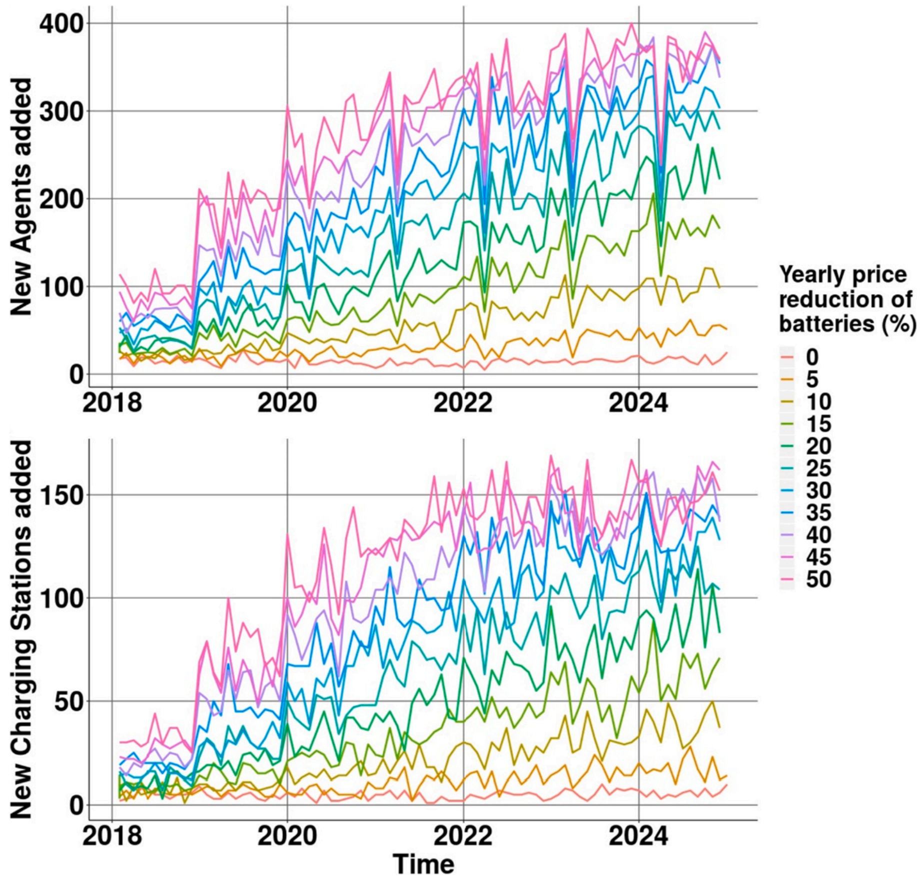

Fig. 19. Sensitivity analysis on agents and locations added due to differences in yearly price reduction of batteries.

finding can be supported by several intuitive reasons. First, the additional distance that agents are willing to travel is larger than with level 2 chargers. Secondly, agents prefer to first charge at a level 2 station rather than at a fast charging station. With a growing number of agents and thus higher occupancy of level 2 stations, more agents are diverted to fast charging stations, resulting in additional cruising traffic. Travelling to and from the fast charging stations occurs by car, while travelling from an alternative level 2 stations is by foot. Comparing the additional inconvenience for the EV drivers therefore should be calculated in time (not in kilometres), which should include the time spent at the fast charging station. Fig. 16 compares the additional time per session spent for the different roll-out strategies. It is assumed that travel speed by car is 22 km/hour (CROW, 2015), travelling by foot is 5 km/hour. Travel times to fast charging stations are calculated as twice the one-day distance by car. The time charging at fast charging stations is added to the travel time. For level 2 charging stations, the travel time is regarded as covering the distance once by car and two times by foot.

Fig. 17 shows that roll-out strategies with fast charging stations result in more discomfort (in terms of time) for the EV driver. Remarkably, despite shorter charging times, the 350 kW charging stations lead to more discomfort during the first years of the simulation. This is because agents are more likely to detour to these stations because the higher charging speed makes them more preferable as an alternative and thus the first alternative. On the short run, the additional travel time to the charging station plays a bigger role, but on the longer run it is the charging time which is dominant. In the model EV drivers are assumed to first try to connect at the level 2 station closest to their home. If agents learn that a fast charging station along their route to home is always available, it could lead to a significant reduction in discomfort time. In that case discomfort for drivers in a 350 kW fast charge strategy is comparable to level 2 roll-out strategies with an EV:Charging station ratio of four to five.

4.3. Sensitivity analysis

To assess the impact of the different assumptions (see Table 1) on the model result a sensitivity analysis has been performed. The analysis focuses on the two most important assumptions, the maximum willingness to walk for EV drivers and the price reduction for battery. The maximum willingness to walk varies for habitual drivers but is fixed for non-habitual but these have the same average. The variation in the sensitivity analysis is applied to both type of EV driver agents. Results are displayed as a percentage change to the model assumptions. Results of the sensitivity analysis in Fig. 18 show that this variable has a big impact on the results of the analysis. Especially if the mean walking distance gets smaller the results in up to two times more failed charging sessions. In case of a mean walking distance of 250 m some of the agents have no willingness to walk. A careful estimation of this variable is necessary to interpret the results.

Sensitivity analysis on the price reduction (Fig. 19) for the batteries of the electric vehicles shows that differences can have a significant impact on the number of agents and locations that should be added to the system. A quick price reduction results a lot of new EV drivers in the system and consequently more charging stations. In the later stages this reduction is less important as the battery starts to play a smaller role in the total price of the electric vehicle. It does not result in any structural differences on how the model results should be interpreted.

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Sensitivity analysis on the price reduction (Fig. 19) for the batteries of the electric vehicles shows that differences can have a significant impact on the number of agents and locations that should be added to the system. A quick price reduction results a lot of new EV drivers in the system and consequently more charging stations. In the later stages this reduction is less important as the battery starts to play a smaller role in the total price of the electric vehicle. It does not result in any structural differences on how the model results should be interpreted.

5. Conclusion

5.1. Results, their interpretation and implications for policy

This paper has built and applied an ABM to assess roll-out strategies for EV charging stations in the urban environment. The model aids policy makers in making long-term decisions on how many of which type of charging stations should be placed where. Previous models have mainly been built on assumptions about charging behaviour with the use of travel patterns, while this model uses a large dataset of actual charging behaviour to distil charging patterns. This has resulted in a more realistic simulation of the charging behaviour and the effect on charging infrastructure roll-out. This paper has further specified a CPO 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 an 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 the first study, in which new single charging stations were placed, show that the reciprocal effect can be substantial. A two-fold increase in the number of charging stations could lead to more than a doubling in the number of EV drivers. A higher threshold for placing new stations (resulting in less stations relative to new EVs), resulted in (approximately) linear growth in the short term. This shows that sufficient charging infrastructure can be a powerful catalyst in driving EV adoption. This effect is especially present if the ratio between EVs and charging stations is very low. Investing in sufficient charging stations for those that rely on on-street charging facilities results in an increased adoption pace. If the threshold is kept at similar levels as the current system's ratio between EVs and charging stations (3.4), the systems' performance in terms of successful sessions will increase. This result is due to return to scale effects, in which growth in network provides more alternatives to EV users. This suggests that policy makers and CPOs may in time increase the ratio between EVs and charging stations without affecting service levels. This increases efficiency with lower impacts on the grid and public space and would have a positive impact on the business case of public chargers due a higher number of sessions per charging station.

Comparison of the charging hub and single charging stations roll-out strategy (study 2) reveals that policy makers deal with trade-offs in charging accessibility (always able to charge) and convenience (measured in additional cruising distance and time). Charging hubs provide less, up to a factor 3, accessibility due to reduced network effects and return to scale, but provide more convenience (reducing average cruising distance by up to ~70%). This higher convenience results from the idea that EV drivers have their favourite charging location available more often and have to cruise less to find an available spot. The charging hub tactic has less negative impact on public space and grid integration but a there is a trade-off with charging accessibility. A possible solution lies in the use of a hybrid roll-out strategy in which empty spots are filled to create networks with critical densities and central locations are expanded.

Results of the fast charging station deployment study (study 3) suggest that fast charging stations can be a replacement for level 2 stations, especially if charging speeds are high (175–350 kW). Location choice for fast charging stations is important as underserved areas can be a potential bottleneck. Level 2 charging stations without a fast charging station near, are often occupied. Fast charging requires the EV driver to detour additionally, but learning behaviour by drivers could minimize the detour. Additional discomfort comes from charging times, but as charging speeds increase and battery packs of EVs increase, this could result in comparable levels of discomfort to gasoline cars or roll-out strategies with a limited number of level 2 charging stations. Charging times however remain the largest barrier for fast charging stations to become the preferred charging option in urban areas. Due to technological constraints it can still take multiple years before the majority of EVs can reach higher charging speeds. Policy makers should therefore monitor developments in charging speed both the charging as the vehicle side and adjust their policies to these developments.

All three studies revealed that policy makers face a trade-off in their roll-out strategies between providing sufficient charging accessibility (able to charge) and charging convenience (charging with minimal time loss) from the EV driver perspective. Mixed roll-out strategies, in which sufficient charging stations create network formation, and thus return to scale benefits, and charging hubs and possible back-ups of fast charging stations provide possible solutions in which the policy maker can best satisfy the EV driver demand both in terms of accessibility and convenience. Note that such solutions are often very location specific, as the results of the fast charging simulations show, and thus optimal solutions may vary from city to city. The general idea however of creating network with hubs as often available places serves EV drivers the best. This idea could change the perspective for the policy makers in the way it views increased local demand. Many municipal policy makers look at new demand at if a new EV driver enters at a specific location. The network approach advocated based on these results would imply a strategy to look at demand in a wider area and not solely look at demand from single users but as well include their differences in charging infrastructure demand. This also allows the policy maker to evaluate charging options (such as the ultra-fast charging at 350 kW) in this perspective although this technology is not applied in the market at a large scale.

The results also showed that with increasing network size the business case for charging point operators improves. Together with increasing battery packs this provides good opportunities for a viable business case for CPOs in the near future. This also allows policy makers to better handle the interest of other stakeholders such as grid operators, which for example can allocate places in the grid where higher demand from fast charging stations or hubs is possible.

5.2. Limitations and future work

The ABM in this paper presented a new approach to simulate the charging behaviour and demand of EVs. The model has shown that is possible to model the aspects of both EV purchase decisions, infrastructure roll-out strategies, infrastructure utilisation and the interactions between these processes. The model assumed that charging demand is not directly correlated with travel patterns but rather is the result of an interplay between parking and charging needs. With the use of a large dataset of revealed charging patterns the large-scale introduction of EVs in the urban area is simulated. The charging patterns of future agents are copied from existing agents. This approach has limited flexibility in terms of representing learning behaviour of EV drivers. Most prominently, this is an issue in the fast charging scenarios in which the EV drivers are assumed to drive to their favourite level 2 charging location before considering a fast charging station. If the agent could learn from previous attempts in which they find level 2 stations mostly occupied and fast charging stations available and choose to first attempt fast charging, this could result in less cruising traffic. Future work should implement learning algorithms for agents as this in time could lead to new patterns.

Furthermore, the results should be interpreted in the light that these are charging patterns from early adopters. Although, the market in the Netherlands is relatively mature, the EV driver population is characterised by a group of drivers that drive more on average than the general population. This could have specific consequences for the length of the connection duration and the energy transferred. Further specification of such user groups is relevant for future work. The model does have the flexibility to address technological changes, both in battery capacity and fast charging speed, addressing the two most prominent advancements. This also leaves the flexibility in the model to model alterations in consumer preferences for different type of vehicle models.

The model has focussed on the urban environment as this environment has a unique public charging demand which so far has been lacking in earlier research. The combination of on-street overnight and office charging combined with different electric modes creates a different dynamic. The focus and use of data only in this urban environment provides a limited view on the total charging demand of EV drivers. For example, EV drivers that charge overnight in the city can also have access to workplace charging elsewhere. A reduced availability of public charging in the city could result in a shift in their charging behaviour in place and time to the workplace. Such a scenario becomes more likely as battery capacity of EVs grows and the need to recharge daily decreases. EV drivers have to option to choose which charging mode they prefer instead of simply choosing the available charging station. Other factors such as price and parking preference could become more dominant in charging choices. An example in this case would be to examine the effect of time-based prices to incentivize EV drivers to move their car once fully charged.

Our results suggest that charging behaviour is a result of a combination of travel and parking behaviour and the interaction of the EV driver with various technological constraints. The technical properties in this research have only been addressed by distinguishing between PHEVs and FEVs. Yet, battery and charging capacity also can play a dominant role in charging choices. The model for example relies on previous charging patterns of FEVs in which short (up to 40kWh) and long-ranged (>70 kWh) are most prevalent as these vehicles were available during the initialisation period. Yet, mid-ranged FEVs can get a substantial share in the years to come. As these cars are not yet on the market, it is difficult to estimate what their charging behaviour will look like. Further research in how technological features of the car, such as battery capacity, level 2 and fast charging capabilities are needed to enrich ABMs. This would allow for even more realistic simulation of the EV charging system.

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 helps policy makers to make decisions on the long term about these strategies and adjust them when necessary. Such flexibility is crucial for policy makers and industry partners to provide sufficient charging infrastructure in the future with an exponential growth in EVs on the road.

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Appendix A. Charging patterns of agents

See Fig. 20.

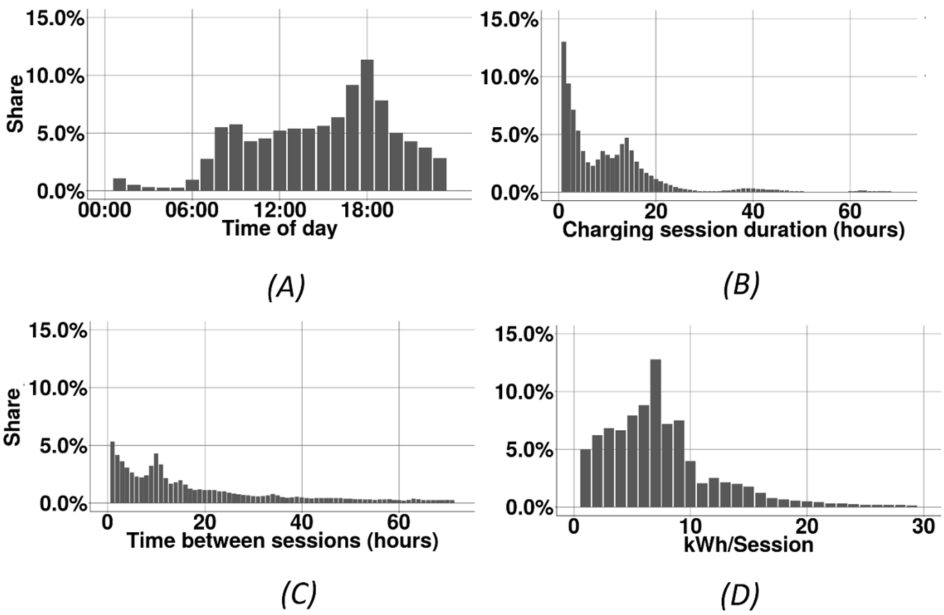

Fig. 20. Charging patterns of agents, with (A) distribution of start times, (B) Connection duration and (C) Time between sessions and (D) kWh distribution.

Appendix B. Charging patterns of non-habitual users

See Fig. 21.

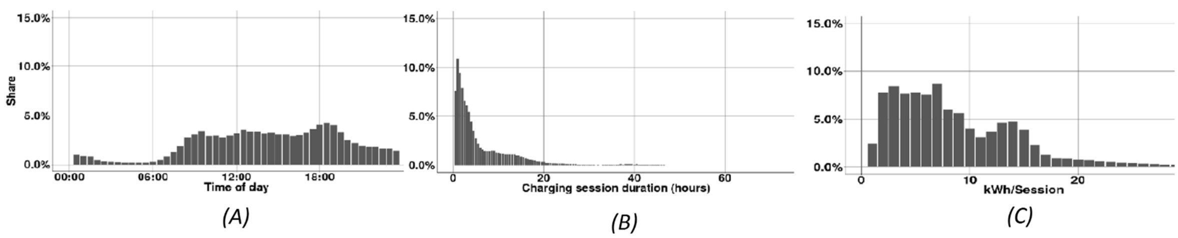

Fig. 21. Charging patterns of non-habitual users, with (A) distribution of start times, (B) Connection duration and (C) kWh distribution.

Appendix C. Distribution of observed maximum walking distances

See Fig. 22.

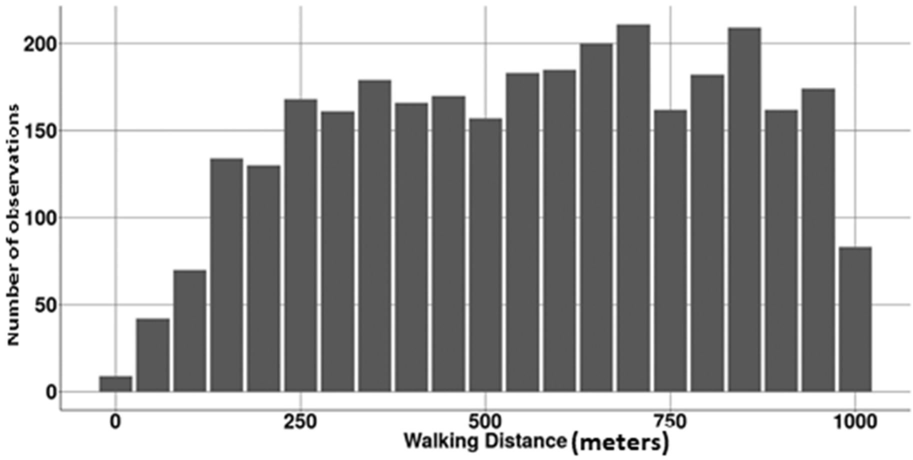

Fig. 22. Distribution of maximum walking distance per agent.

Appendix D. Distribution of battery size vehicles

See Fig. 23.

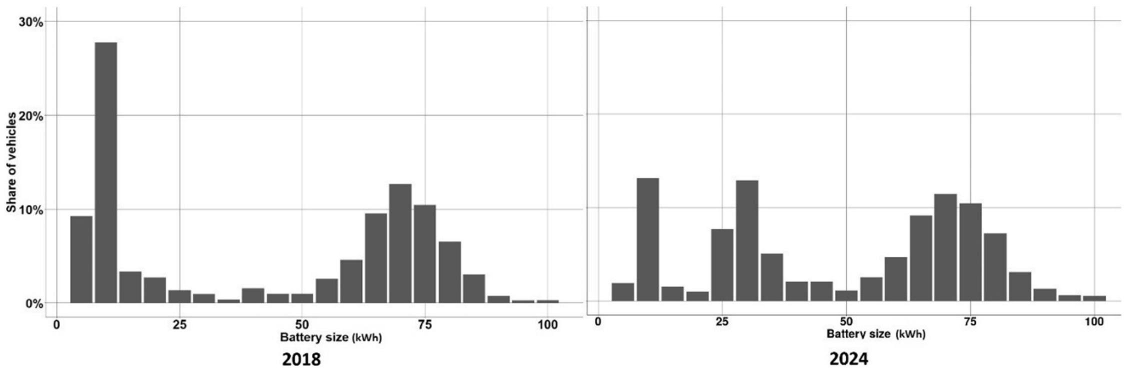

Fig. 23. Distribution of battery size across EV drivers at start (2018) of simulation and at the end (2024).

Appendix E:. Choice parameters vehicle choice

See Table 3.

Table 3
Choice Parameters vehicle choice.

Estimates	Value	Fixed/Variable in the model
Constant EV	6.410	Fixed
Constant Conventional	−0.071	Fixed
Price	−0.217	Variable
Range EV	0.005	Fixed
EV: Charging station ratio	−1.110	Variable
EV: Charging station ratio PHEV	−0.485	Variable
Parking Fee EV	−0.617	Fixed
Parking Fee PHEV	−0.000	Fixed
Availability EV	0.448	Fixed
Availability PHEV	0.000	Fixed

Appendix F:. Locations of gas stations

See Fig. 24.

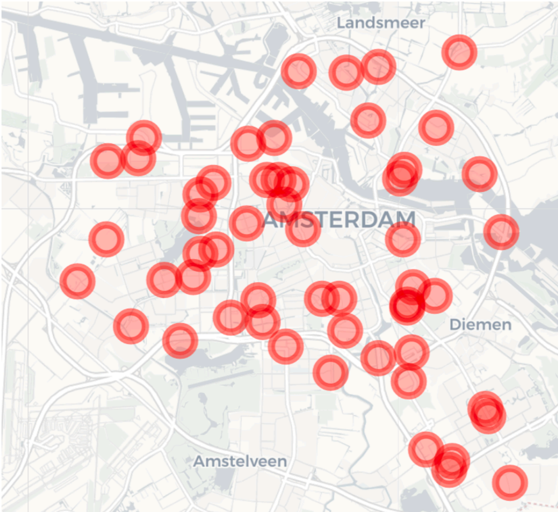

Fig. 24. Locations of Gas Stations.

Appendix G:. Locations of charging stations over time (Single strategy, threshold 3)

See Fig. 25.

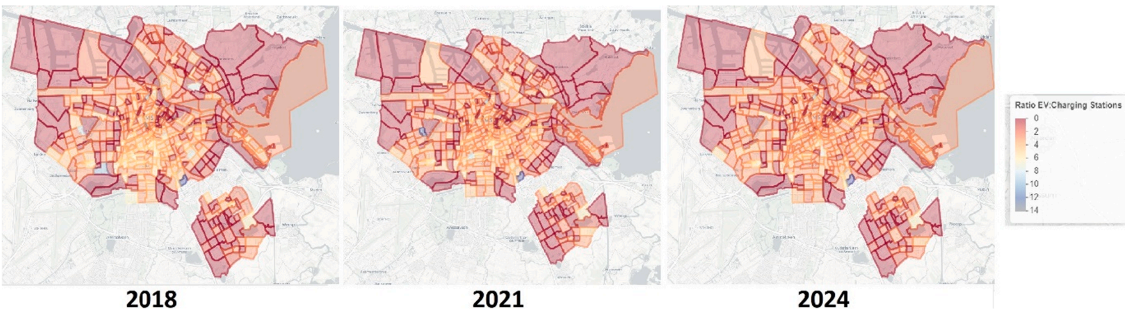

Fig. 25. Ratio between EV drivers and Locations per district across time in the simulation.

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