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Multiple roads ahead: How charging behavior can guide charging infrastructure roll-out policy

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ABSTRACT

A key challenge for the roll-out of public charging infrastructure is that electric vehicles are needed to function both as a clean mode of transportation and as part of a sustainable electricity system, while being cost-effective. Translating these high-level policy goals to a coherent roll-out strategy is not trivial. We address this by analyzing local charging behavior and linking behavior indicators to specific policy measures through a decision tree. We analyze how policy measures for: (1) *increasing the number of charge points*, (2) *reducing hogging*, (3) *vehicle-to-grid*, (4) *overnight charging*, and (5) *solar charging* align with overall goals *and* characteristics of specific neighborhoods. More specifically, we analyze a dataset containing one million charging sessions in the Netherlands, and (1) link this data to neighborhood characteristics and (2) evaluate the coherency of policy mixes. Our analysis shows great spatial variation in charging behavior and consequently in the suitable policy mixes.

1. Introduction

Electric vehicles (EVs) are envisioned to play an important role in future sustainable transport *and* energy systems. EVs contribute to reducing greenhouse gas and local pollutant emissions in the transport sector (Malmgren, 2016; Nikitas et al., 2017). In the energy sector, EVs can contribute to load balancing using smart charging and vehicle-to-grid (V2G) (Mwasilu et al., 2014). This also facilitates the integration of intermittent renewable energy sources in the electricity grid, for instance by shifting charging demand to times of high photovoltaic (PV) solar power production. Recognizing these benefits, governments throughout Europe stimulate the transition to e-mobility in their efforts to reach the European climate targets set by the Paris agreement (European Commission, 2015). This in turn creates a challenge to develop coherent policy mixes for stimulating and supporting EV adoption. The development of coherent policy mixes is important for accelerating the transition towards sustainability, but is complex especially when multiple sectors are involved, as is the case for e-mobility (Kern et al., 2019; Rogge and Reichardt, 2016).

There are tensions between the different functions of an EV as (1) a mode of transportation, and (2) part of a sustainable energy system. More specifically, the optimal EV charging pattern is different for each function. An example is the duration of charging sessions: On the one hand, the time needed to charge to a sufficient state-of-charge (SOC) of EV batteries is preferably short. Short charging sessions enable more efficient use of vehicles and charging infrastructure. On the other hand, cost-effective integration of charging infrastructure in the existing electricity grid requires longer charging sessions, allowing the use of the EV battery for grid balancing and matching EV demand with renewable energy production.

Strategies for public charging infrastructure roll-out need to take these trade-offs into account. While private charge points can

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fulfil the needs of many EV drivers, public charging infrastructure will most likely continue to be important for certain groups of EV drivers. Examples are EV drivers that cannot install a private charge point at their home, drivers of EVs with small batteries, and EV drivers wanting to travel long distances (Hardman et al., 2018). In Europe, various governmental levels are stimulating the build-up of public charging infrastructure. A directive from the European Union states that member states should build sufficient public charging infrastructure to support their national EV fleet (European Parliament and The Council of the European Union, 2014). National governments have implemented a variety of policy measures, which include setting of national targets, subsidizing public charging stations, and information campaigns (Cansino et al., 2018). Furthermore, member states decide whether and how to implement dynamic energy tariffs (Greening, 2010), which could be used to stimulate shifting of EV charging demand. Municipalities also play an important role, as this is typically the level at which decisions about charge point placement are taken (Egnér and Trosvik, 2018; Heidrich et al., 2017; Helmus et al., 2018).

The Netherlands has the highest market share of EVs within the EU-28 in 2018 and has been very active in building public charging infrastructure (ACEA, 2019). The Dutch government has expressed the ambition that by 2030 all new vehicles sold in the Netherlands are zero-emission vehicles (Rijksoverheid, 2019a). The number of EVs registered in the Netherlands is 18% of the total EVs registered within the EU-28 countries (EEA, 2018), but the country contains 28% of all public charge points (ACEA, 2018). A recent publication of the Dutch Ministry of Economic Affairs presents the vision that charging infrastructure should optimally accommodate smart electric transport in the Netherlands, but also be cost-effective as part of a future smart energy system which will increasingly be based on sustainable energy (Ministry of Economic affairs, 2017). Furthermore, they have recently announced to invest 5 million Euro in bidirectional charging stations, supporting the integration of intermittent renewable sources via V2G technology (Rijksoverheid, 2019b). Dutch municipalities, the government layer responsible for charging infrastructure, are thus tasked with developing charging infrastructure that supports high EV adoption, doing so cost-effectively, and integrating the charging infrastructure in a smart and sustainable energy system.

The extent to which charging infrastructure aligns with these high-level goals also depends on the charging behavior of EV drivers. For example, in a neighborhood where the charge points are often occupied, charging infrastructure expansion may be needed. However, if many of these EVs only charge for a short time but continue to be connected to the charge point, so-called "charge point hogging" (Wolbertus and Van den Hoed, 2017), it might be better to incentivize EV users to remove their EV after having charged.

In this paper, we demonstrate how charging behavior can inform decision making for public charging infrastructure roll-out. Our main research question is: How well does actual EV charging behavior fit with different implementations of high-level policy goals? To answer this question, we link charging behavior to several policy measures commonly found in the literature for further charging infrastructure roll-out, which contribute to achieving the high-level policy goals availability, cost-effectiveness, and integration with intermittent renewable energy sources of charging infrastructure: (1) *increasing the number of charge points*, (2) *reducing hogging*, (3) *vehicle-to-grid*, (4) *overnight charging*, and (5) *solar charging*. Furthermore, we consider the characteristics of the neighborhoods where certain behaviors are common, including the charge point density, charge rate of charging stations, and type of EV users charging there. We base our analysis on a large dataset of around one million charging sessions at public charge points in the Netherlands. Note that we only consider policy measures aimed at the roll-out of public charging infrastructure, and not measures stimulating private charge points or general EV adoption.

Our analysis consists of several steps. (1) We identified high level policy goals for the roll-out of public charging infrastructure (as above). (2) We identify more specific policy measures (Section 2 and Section 3.1). (3) We identify several indicators that characterize the charging behavior relevant for evaluating which policy measure would fit best for a certain area (Section 3.2). (4) We calculate the value of these indicators and other characteristics for each neighborhood in our dataset (Sections 4.1–4.3). (5) We link these indicators to neighborhood data on charging infrastructure and EV users via regression analysis (Section 4.4). (6) We link aggregate charging behavior at neighborhood level (four-digit postal code) to the policy options in a multi-criteria analysis, and compare the results of the multi-criteria analyses of the neighborhoods (Section 4.5). (7) Based on our results, we identify lessons for policy makers concerned with public charging infrastructure roll-out (Sections 5-7). Together, these steps provide (1) a method to link charging behavior to charging infrastructure related policy, and (2) identification of potentially coherent policy mixes, and (3) further insight in charging behavior. Fig. 1 presents an overview of our analysis. The rest of this paper is organized as follows: Section 2 presents a concise review of the literature on charging infrastructure roll-out. Section 3 presents our framework, containing the policy targets

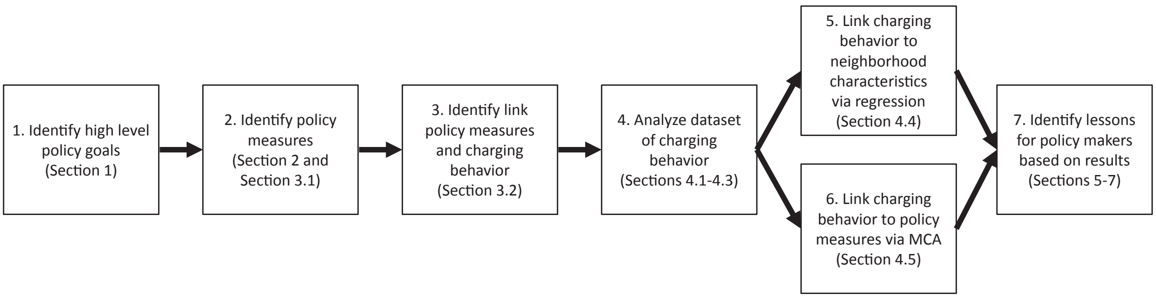

Fig. 1. Overview of the research approach.

we investigate and which charging behavior indicators are relevant to assess the suitability of pursuing these targets. Section 4 presents our data, how we calculate the indicators from our data, and the method we use in our multi-criteria analysis. Section 5 presents our results. Section 6 discusses the contributions and limitations of our research, and Section 7 concludes the paper.

2. Background

A growing body of literature addresses the challenges for charging infrastructure roll-out. Several relevant environmental, economic and societal factors for charge point placement have been identified (Guo and Zhao, 2015), of which demand for charging is one of the most important (Chakraborty et al., 2019). Challenges for public charging infrastructure roll-out are the need for viable business models (Madina et al., 2016; Zhang et al., 2018), the increased pressure on the electricity grid from EV charging (Eising et al., 2014), and the public space used by charge points, the latter is especially relevant when parking spots with charge points are reserved for EVs (Steinhilber et al., 2013).

Studies on demand prediction typically consider both the location of the demand and the variation over time using mobility research data (Andrenacci et al., 2016; De Gennaro et al., 2014; Jiang et al., 2018; Olivella-Rosell et al., 2015; Smith et al., 2011; Wang et al., 2015), data on EV pilot projects (Azadfar et al., 2015; Khoo et al., 2014; Speidel and Bräunl, 2014; Sun et al., 2016), surveys (Kristoffersen et al., 2011), or a combination of these (Mallig et al., 2016; Xu et al., 2018). Most studies thereby take the perspective of electricity grid managers and investigate the impact of EV charging on the electricity grid, and how this can be mitigated through smart charging and V2G (Azadfar et al., 2015; Hu et al., 2016a). These studies focus on the variation of demand over time rather than location (Bauman et al., 2016; Blasius and Wang, 2018; Daina et al., 2017; Van der Kam and Van Sark, 2015; Weis et al., 2014; Wolinetz et al., 2018), or use a coarse spatial resolution (Ensslen et al., 2018; Van der Kam et al., 2018; Waraich et al., 2013).

As EV adoption increases, large datasets on public charging sessions become available. These have been used for descriptive studies (Morrissey et al., 2016; Neaimeh et al., 2017; Van den Hoed et al., 2013), distinguishing different types of EV users (Helmus and Van den Hoed, 2015), and evaluating public charging infrastructure roll-out strategies (Helmus et al., 2018). Other studies have used surveys among EV drivers to construct charging patterns, for instance to show how charging behavior of BEV and PHEV drivers differs (Tal et al., 2014), investigate choice of charge points (Lee et al., 2020), and determine the impact of EVs on greenhouse gas reduction (Axsen et al., 2011).

Other studies have focused on explaining charging behavior. Travel behavior and EV range play an important role in deciding where to charge (Lee et al., 2020), as do charging tariffs (Chakraborty et al., 2019), but there is often also a strong habitual component (Zhang et al., 2018) as well as influences of socio-demographic characteristics (Lee et al., 2020), social norms (Caperello et al., 2013), and range anxiety (Franke et al., 2012; Franke and Krems, 2013b, 2013a; Geske and Schumann, 2018).

In order to inform policy, studies have compared the effects of financial incentives, access to carpool lanes, and the build-up of charging infrastructure on EV adoption. Presence of financial incentives and the build-up of charging infrastructure are often correlated with EV adoption (Hardman, 2019; Mersky et al., 2016; Sierzchula et al., 2014; Vergis and Chen, 2015), though the causal relation between the presence of charging infrastructure and EV adoption remains an open question. Jenn et al., (2018) conclude that monetary incentives are more effective when combined with non-monetary incentives such as access to carpool lanes and awareness campaigns. Furthermore, it is important to note that the effectiveness of policies can differ for different EV types (Mersky et al., 2016; Vergis and Chen, 2015) and different regional travel characteristics (Hardman, 2019). Policies stimulating changes in EV charging behavior are not widespread yet, but recent survey-based studies have investigated how to shift demand to off-peak times to avoid grid congestion. Demand shifting can be stimulated by financial incentives (Chakraborty et al., 2019; Ensslen et al., 2018; Nicolson et al., 2017), and by giving EV users feedback on how demand shifting helps with load balancing and reducing CO_2 emissions (Bailey and Axsen, 2015; Will and Schuller, 2016). Furthermore, range anxiety and preferences for a minimum range should be taken into account for users to accept smart charging and V2G (Geske and Schumann, 2018; Will and Schuller, 2016). The early stages of EVs deployment are a good opportunity to influence charging behavior as new social norms are still forming, especially for people who recently purchased an EV (Roy, 2017).

Regarding charging behavior, studies have also looked into the connection time of EVs (Khoo et al., 2014; Morrissey et al., 2016; Wolbertus et al., 2018) and charge point hogging (Speidel and Bräunl, 2014; Wolbertus and Van den Hoed, 2017). Since charge points are used not solely for the purpose of recharging but also as a parking spot (Faria et al., 2014), it is often attractive for EV users to leave their EV plugged until they make their next trip, especially in cities where parking pressure is high. Wolbertus & Van den Hoed (2017) show that this behavior is indeed very common for public charge points with up to 11 kW maximum power output in the four major Dutch cities. For fast chargers, often placed along the highway, connection times are much shorter and charge point hogging is not as common (Morrissey et al., 2016; Wolbertus et al., 2018). With low levels of EV adoption charge point hogging is not a major issue, but this will change as EVs become more mainstream. Inefficient use of public charge points will lead to a high number of charge points needed to meet charging demand. This results in increased costs for charge point instalment and operation, use of public space, and pressure on the grid, as many EVs charging at the same time can cause high peaks of electricity demand. Measures to reduce idle plug-in time include fees, rewards, connecting EV users via an app denoted as “social charging”, valet charging, and unplugging (Wolbertus and Van den Hoed, 2017).

Summarizing, the spatial and temporal aspects of charging demand, efficient use of charging infrastructure, and integration of charging infrastructure in smart grids are all important topics in the scientific literature on charging infrastructure roll-out. Where earlier studies had to rely on EV pilot projects, surveys, or general mobility data, the empirical basis of studies of charging behavior is increasingly large datasets of charging sessions and surveys among EV drivers. Such studies have been used to inform or evaluate charge point placement, and incentives for behavioral change, e.g. regarding smart charging and charge point hogging. However, a holistic approach to policies for charging infrastructure roll-out is missing. Our contribution lies in developing a framework that links charging behavior to a set of policy measures that explicitly address the different functions of EVs in sustainable transport and energy, and applying this framework to a large dataset of charging sessions. In doing so, we clarify the trade-offs for policy makers who must consider the availability, efficiency, and sustainability of public charging infrastructure.

3. Framework

Based on our literature review, we identified five policy measures that contribute to the high-level policy goals to support large EV fleets, cost-effective charge point roll-out, and charging with sustainable energy. These are: (1) *increasing the number of charge points*, (2) *reducing hogging*, (3) *vehicle-to-grid*, (4) *overnight charging*, and (5) *solar charging*. Measures 1 and 2 contribute to the availability of charging infrastructure; 2, 3, and 4 to cost-effectiveness; and 3 and 5 to the integration of renewables. The measures are not mutually exclusive, but reducing charge point hogging (measure 2) will limit the flexibility needed for shifting EV charging demand (measures 3–5). Section 3.1 shortly discusses each measure, and Section 3.2 presents a decision tree that links charging behavior and neighborhood characteristics to these policy measures.

3.1. Policy measures

Increasing the number of charge points: Additional charge points increase the availability of charging infrastructure, and thereby increase the comfort and reduce range anxiety of EV users (Dong et al., 2014; Neubauer and Wood, 2014). Disadvantages of building more charge points are that increasing the number of charge points leads to higher total cost for installation, maintenance and operation, and the local electricity grid may have to be strengthened in order to supply enough electricity for EV charging (Eising et al., 2014). Moreover, building a high number of charge points can be a problem in cities that have limited public (parking) space available, and could lead to push back by internal combustion engine (ICE) vehicle-owners if parking space with charge points will be reserved exclusively for EV drivers.

Reducing hogging: EVs are often plugged in longer than they need to be fully charged, sometimes called charge point hogging (Khoo et al., 2014; Morrissey et al., 2016; Speidel and Bräunl, 2014; Wolbertus et al., 2018; Wolbertus and Van den Hoed, 2017). Reducing charge point hogging increases the availability of existing infrastructure, resulting in a more cost-effective charging infrastructure. Furthermore, policies to reduce charge point hogging would also discourage ICE vehicle owners to block charge points. Disadvantages are that to reach this policy target EV users would have to be incentivized to move their EV (Wolbertus and Gerzon, 2018), and moving an EV is problematic in areas with high parking pressure.

Vehicle-to-grid: EVs can be used for grid management, such as ancillary services and storage for renewable energy. These kind of services are enabled with V2G technology (Kempton and Tomić, 2005). One of the earliest applications of V2G was to use EVs as a source of emergency power supply after the 2011 earthquake in Japan (Corchero and Sanmarti, 2018). Next to using V2G technology in emergency situations, it can also play an important role in smart grids, and it has emerged as a major research theme in smart grid as well as e-mobility research (Mwasilu et al., 2014; Sovacool et al., 2017). The promise of V2G is underlined by the subsidy for bidirectional charging stations by the Dutch government (Rijksoverheid, 2019b), even at a time where the number of EVs able to be used in V2G systems is low (Hofs, 2019). There are several disadvantages of V2G for EV users. Implementing V2G systems requires flexibility of EV users (Gerritsma et al., 2019), as it will lead to longer charging time In V2G schemes. Furthermore, EV users will have to give control of the charging process to an algorithm, grid manager or aggregator, since using EVs for grid management will require real-time information grid conditions. Also, participating in V2G schemes may increase degradation of EV batteries (Wang et al., 2016). Given these disadvantages for EV users, they will have to be incentivized to participate in such a system.

Overnight charging: One peak in EV charging demand typically occurs in the evening, when EV users return home, coinciding with peaks in household electricity demand (E-Laad, 2013). Encouraging EV users to shift their charging demand to the night is beneficial for grid management, since large peaks in electricity demand can be avoided, also called valley filling (Zhang et al., 2014a). However, EV users have to be incentivized to shift their demand, for instance by offering cheaper electricity for charging during the night (Dunckley and Tal, 2016; Hu et al., 2016b). Already, nighttime tariffs can significantly decrease the total costs of ownership of EVs (Ernst et al., 2011). Overnight charging can be achieved manually by EV users waiting to plug in their EV until nighttime, or a system could be implemented which does this automatically (Zhang et al., 2014b). Charging EVs at lower power than the maximum power capacity will lead to longer charging times.

Solar charging: EVs are an especially clean mode of transportation when charged with PV solar power, and they can contribute to integration of PV solar power when EV charging is aligned with times of high PV solar power production (Denholm et al., 2013; Nunes et al., 2015; Van der Kam and Van Sark, 2015). Next to the evening peak, EV charging demand peaks in the morning (E-Laad, 2013), which is typically linked to commuters arriving at their location of work. This peak can be shifted to better align with generation of PV solar power, which is highest in the late morning and early afternoon. For automatic shifting of charging demand, a form of automated smart charging based on algorithms would have to be implemented. *Solar charging* is interesting for EV users wanting to reduce their carbon footprint, but EV users could also be incentivized with lower charging fees for *solar charging*.

Table 1 presents an overview of the policy measures and suggestions for further reading.

Table 1
Advantages, disadvantages, and optimal conditions for different policy targets to further develop public charging infrastructure and suggestions for further reading.

Policy measure	Contributes to high-level policy goal	Advantages	Disadvantages	Effective measure in neighborhoods with	Further reading
Increasing the number of charge points Increasing the number of charge points	● Availability	● Comfort of EV drivers ● Comfort of EV drivers ● Reduces range anxiety ● Reduces range anxiety	● High costs ● Increased pressure on grid ● Increased pressure on grid ● Increased use of public space and parking space ● Increased use of public space and parking space	● Low idle connection time ● Low idle connection time ● High total connection time ● High total connection time	● Dong et al. (2014) ● Hardman (2019) ● Mersky et al. (2016) ● Neubauer and Wood (2014) ● Sierzchula et al. (2014)
Reducing hogging	● Availability ● Cost-effectiveness	● Less charge points needed to support EV fleet	● EV users have to move EV when charged sufficiently	● High idle connection time ● High total connection time	● Morrissey et al. (2016) ● Speidel and Bräunl (2014) ● Wolbertus and Gerzon (2018) ● Wolbertus and Van den Hoed (2017)
Vehicle-to-grid	● Cost-effectiveness ● Sustainability	● Decreased pressure on grid ● EVs as storage for renewables	● Incentives and automation system needed ● Long charging times ● Potentially decreased battery life	● High idle connection time	● Corchero and Sanmarti (2018) ● Kempton and Tomić (2005) ● Lund and Kempton (2008) ● Sovacool et al. (2017)
Overnight charging	● Cost-effectiveness	● Decreased pressure on grid	● Incentives and automation system needed ● Long charging times	● High charging time during evening peak ● High idle connection time during night	● Dunckley and Tal (2016) ● Ernst et al. (2011) ● Z. Hu et al. (2016) ● Zhang et al. (2014)
Solar charging	● Sustainability	● Integration with renewables ● Decreased pressure on grid	● Incentives and automation system needed ● Long charging times	● High charging time during morning ● High idle connection time during solar hours	● Denholm et al. (2013) ● Nunes et al. (2015) ● Van der Kam and Van Sark (2015)

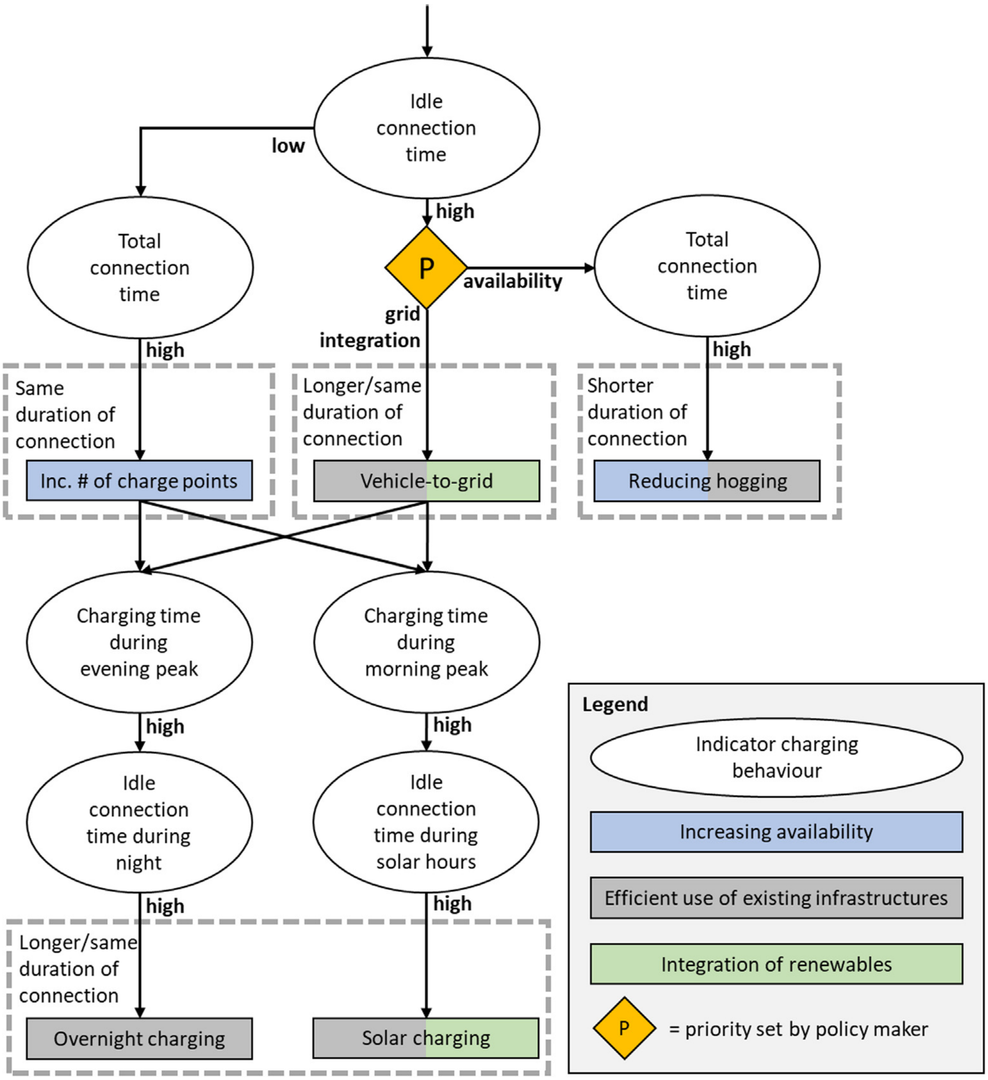

Fig. 2. Decision tree for implementation of policy measures for public charging infrastructure roll-out.

3.2. Decision tree

Fig. 2 presents our literature-based policy decision tree. The logic underlying the decision tree is as follows: the *idle connection time*, i.e., the time connected to a charge point but not charging, is an indicator for potential flexibility in EV charging. When *idle connection time* is low, and total connection time is high, the number of charge points should be increased in that area to prepare for higher EV adoption (left hand branch of tree). If the *idle connection time* is high, there is opportunity to increase the cost-effectiveness of the charging infrastructure. This can be done either through better integration with the grid and use of renewable energy sources (*vehicle-to-grid*, middle branch) or by increasing the availability of charge points (*reducing hogging,* right hand branch). This last option is relevant only when the charge points are thus often occupied, and the total connection time is thus high. Policy makers must decide which of the overall goals is more relevant for a particular area.

Overnight charging and *solar charging* are compatible with *more charging points*, *vehicle-to-grid* and with each other, and are relevant options depending on charging behavior on specific times of the day. When many EVs charge in the evening and stay connected during the night, the evening peak can be reduced by charging the EVs overnight, thereby reducing the impact on the electricity grid. When many EVs charge in the morning and stay connected when solar energy production is high, demand can be shifted such that EVs charge with solar energy, thereby decreasing the impact of EV charging *and* renewable energy on the grid. *Reducing hogging* can in principle be compatible with *overnight charging* and *solar charging*, but for these two policy measures case demand shifting is the main priority rather than shortening the duration of charging sessions, which is why we have not included it in our scheme.

Table 2
Description of dataset of charging sessions after data cleaning process.

Variable name	Description	Unit
user_postal_code	Postal code of EV user residence	PC6
start_datetime_local	Start time charging session	Date (minutes)
end_datetime_local	End time charging session	Date (minutes)
duration	Duration of charging session	Seconds
volume	Energy charged	kWh
charge_point_postal_code	Postal code of charge point	PC6
charge_point_country	Country of charge point	Netherlands
make	EV producer	1 of 27 companies
model	EV model	1 of 78 models
batterycapacity	Battery capacity	kWh
user_id_cat	ID of EV user	1 of 5337 unique IDs
charge_point_serial_cat	ID of charge point	1 of 15348 unique IDs
max_power	Maximum power output of charge point	W

4. Data and methods

This section presents our data sources (Section 4.1) and methodology (Section 4.2 - 4.5) addressing the steps outlined in Fig. 1.

4.1. Data

4.1.1. Charging sessions

Our dataset contains 1048575 charging sessions that took place in in the period 27 December 2016 to 2 September 2018 by cardholders of NewMotion, a large e-mobility service provider (EMSP) in the Netherlands. The dataset contains 6895 unique EV users and 24,955 unique charge points in total. Table 2 presents an overview of the cleaned dataset. We have added two variables on the technical specification of the EV models, using the database of e-mobility company EV-Box (EVBox, 2019): the type of vehicle (battery electric vehicle (BEV), plug-in hybrid electric vehicle (PHEV), or e-motorcycle), and (2) the maximum charging rate of the EV. These variables are relevant for our analysis, but not present in the NewMotion dataset available. 42% of the EV users in the dataset drive a BEV, and 58% a PHEV (there are 9 users of e-motorcycles, whom we do not consider in our analysis). Supplementary Table A.1 in Appendix A presents summary statistics.

In our analysis, we only used data on charging sessions for which (1) the data is complete, (2) the charge point is located in the Netherlands, (3) the charged volume does not exceed the battery capacity of the EV, and (4) the charged volume divided by the duration of the charging session does not exceed the maximum power output of the charge point. These data cleaning steps resulted in 847,433 usable charging sessions (81% of the total dataset). Steps 3 and 4 of the data cleaning process excluded technologically impossible charging sessions, but we expect that some errors remain due to errors in measurement or registration. We restrict the analysis to the two full years 2017 and 2018 in the dataset to reduce the influence of monthly changes in charging behavior on the outcome. While the weekly charging profile does not change substantially throughout the year, we do see lower EV charging demand during holidays, such as summer holidays and Christmas. We include charging sessions starting in 2016 and ending in 2017 and charging session starting in 2018 and ending in 2019, resulting in 744,400 charging sessions for our analysis (71% of the total dataset and 91% of the complete data).

4.1.2. Population and area data

To calculate charge point density, we use data on the number of inhabitants and the area size per four-digit postal code (PC4). For the number of inhabitants per postal code we use 2018 data from Statistics Netherlands (CBS) of the Netherlands (CBS, 2018). For the area size we use data from the 2018 cadastral map as published by The Netherlands' Cadastre, Land Registry and Mapping Agency. The Netherlands is divided in 4052 four-digit postal codes with an average of 4173 inhabitants (with standard deviation 4130). Given the size of PC4 areas, we refer to PC4 level as neighborhood level. In our analysis, we only consider PC4 areas with at least one charging session in the dataset. These are 2511 postal codes, with an average of 6233 inhabitants (with standard deviation 4348). PC4 areas are always part of a municipality, but there are no separate governmental bodies for PC4 areas. However, policies can be formulated specifically on the level of PC4 areas (Kausika et al., 2017).

4.2. Calculation of indicators

This section describes how we calculate the indicators (*total connection time*, *idle connection time*, and *charging time*) from our data. We aggregate the time-steps to 15 min and calculate the indicators on PC4 level.

Our dataset gives the start (*start_datetime_local*) and end times (*end_datetime_local*) of charging sessions. We define the *total connection time* as the total time that EVs are connected to charge points. For each PC4 area (*user_postal_code*) we take the average connection time per charge point.

To calculate the *charging time* and *idle connection time*, we need to determine the charging profile for each charging session. Often,

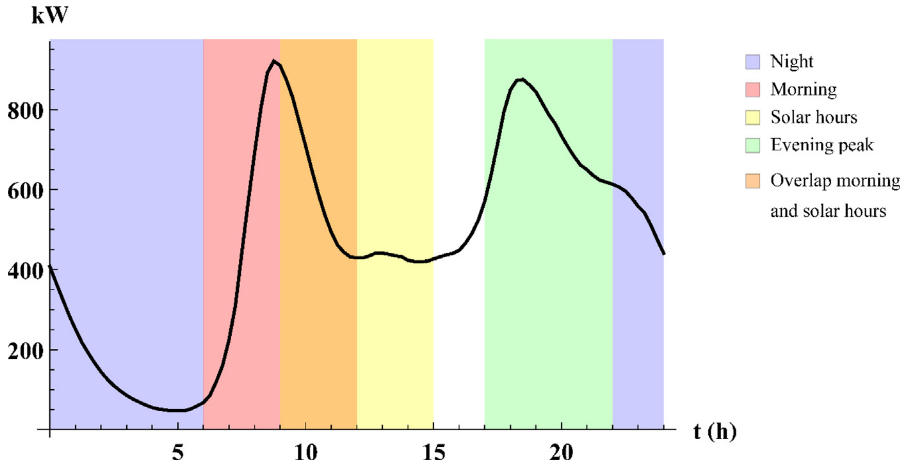

Fig. 3. Resulting charging profile for weekdays including defined cut-off times.

an EV does not charge at maximum power (Gerritsma et al., 2019); the charging profile depends on factors such as power losses, the EV type, the state of charge (SOC) of the battery, the outside temperature, the grid conditions, the car battery management system, etc. As our dataset does not provide this information, we must make some significant simplifications to calculate charging profiles using data on the volume that was charged (*volume*), the maximum power output of the charge point (*max_power*), and the maximum charge rate of the EV (as found on EVBox (2019)). The power output over time is then calculated by assuming the EV charges at either the maximum power of the charge point or the maximum charge rate of the EV at 100% efficiency and use the lower value of these two. This means that we overestimate the actual power output over time and the time the EV needed to be charged. It is therefore important to interpret the results regarding *charging time* and *idle connection time* as indicators suitable for comparing neighborhoods and users, but not as absolute measures.

Based on the estimated charging profile we calculate the *charging time* as the time the EV was connected to a charge point and charging. The *idle connection time*, then, is the time the EV was connected to the charge point and *not* charging.

For *overnight charging*, we observe that the evening peak starts around 17:00 and ends around 22:00 (see Fig. 3). Charging demand is lowest overnight, and starts increasing from around 6:00. Therefore, we set the time of the evening peak from 17:00–22:00 and define night-time as 22:00–6:00. Furthermore, we calculate the *idle connection time in the night* for EVs that charged during preceding the evening peak, because this indicates the charging demand that can be shifted.

Under the policy measure *solar charging*, EVs postpone their charging needs in the morning to times of high PV solar power production. Based on the charging profile (see Fig. 3), we define morning charging to be between 6:00, when charging demand starts rising after the night, and 12.00, when the morning peak is over. The cut-off points for high PV solar power production is somewhat arbitrary, as it depends on weather conditions, such as cloudiness and temperature, which vary throughout the day and the year (seasonal changes). On average, PV solar production in the Netherlands is high in mid-to-late morning and early afternoon.[1] We define the solar hours to be between 9:00 to 15:00. As with *overnight charging*, we calculate *the idle connection time during solar hours* of EV drivers that also charge during the morning on the same day in order to measure charging demand that can be shifted.

4.3. Additional neighborhood statistics

In order to identify the types of neighborhoods where a specific charging behavior is often observed, we link the indicators to several neighborhood-specific variables of charging infrastructure and EV users.

First, the data contains unique IDs (*charge_point_serial_cat*) and the postal codes of the locations of the charge points (*charge_point_postal_code*). We calculate charge point density in two ways: by dividing the total number of charge points within each PC4 area by the total population, and by dividing it by the area size. These are not the same because (a) the penetration levels of EVs in the Dutch car fleet differ between neighborhoods (Van der Kam et al., 2018), (b) public charge point placement is decided by municipalities, who might not follow the same strategies (Helmus et al., 2018), and (c) public charge points are not only placed in residential areas, but also at other places (e.g. offices, commercial centers, along the highway). The data also contains information on the maximum charge rates of the charge points (*max_power*). We take the average maximum charge rate of the charge points within a PC4 area.

Second, our data contains unique user IDs (*user_id_cat*) and the postal code of their residence (*user_postal_code*). For each PC4 area, we determine the ratio of EV users who have charged there more than once to the total number of EV users. We also determine whether an EV user is charging near home, by comparing the five-digit postal code (PC5) of the EV user with the PC5 of the charge point. The PC5-level is more detailed than the PC4-level, and each PC4 area contains several PC5 areas. If these are the same, we

[1] See Fig. 2 in Van der Kam et al. (2018)

consider the EV user to charge near home. Dutch PC5 areas have a median area of 0.15 km^2.

4.4. Regression model

We use a negative binomial regression model to link indicators and neighborhood characteristics. This is a suitable model for our data as the distributions of the dependent variables are highly skewed, even after log transforming, and the variance is much greater than the mean. A negative binomial regression model requires count data. All our dependent variables measure time, and as input for the model we use a resolution of 15 min. The neighborhood characteristics we include are related to local charging infrastructure and type of EV users. These are charge point density (per inhabitant and per km^2), the average maximum charge rates of charge points, recurring EV users, and EV users charging in the same PC5 area as where they live (home users). As a control variable, we also include the number of charge points in our regression model. Supplementary Table A.2 in Appendix A presents summary statistics for the variables used in the regression model.

We include charge point densities (per inhabitant and per km^2) as key indicators for the characteristics of charging infrastructure in a neighborhood. We do not have any prior expectation on how these link with charging behavior. A low charge point density could lead EV drivers to move their EV to another parking spot when having charged sufficiently, but they would have to be aware of this low density and be concerned about other EV drivers wanting to charge. We expect the average maximum charge rate of charge points to have a negative correlation with the *connection time* and *charging time*, because a higher charge rate will lead to the EVs being charged sufficiently in a shorter time. This could also lead to longer *idle connection times*, but it could also be the case that the maximum charge rate has a negative effect on *idle connection time*, as hogging behavior has been found to be less common at fast chargers (Morrissey et al., 2016; Wolbertus et al., 2018).

We include two variables on the EV users that visit the charge points: EV users that visit a neighborhood more than once (recurring users), and the EV users that charge near their home (home users). Charging behavior has a strong habitual component (Zhang et al., 2018) and is influenced by social norms (Caperello et al., 2013). We have no a priori expectation on how the percentage of recurring users influence charging behavior, but we do have expectations on the link between charging behavior and the percentage of home users. We expect home users to have longer *connection* and *idle connection times*, because they will have their EV parked often overnight and throughout the weekends. Furthermore, we expect the evening peak to be higher, because this peak results mostly from EV users coming home after work. During the day however, we expect many EV users do not charge near home, but near their work, which is why we expect a negative effect on *charging time during the morning* and *idle connection time during solar hours*.

4.5. Multi-criteria analysis

To identify suitable policy mixes for neighborhoods, we perform an MCA. An MCA allows to incorporate multiple criteria that measure different qualities in a decision process. We perform an MCA for each of the policy measures and compare the results. The criteria we use in the various MCAs are (1) *connection time*, (2) *idle connection time*, (3) *charging time during the evening*, (4) *idle connection time during the night*, (5) *charging time during the morning*, and (6) *idle connection time during solar hours*, as described in Section 4.2. These criteria are all numeric variables measured with a time resolution of 15 min. Therefore, we take a simple MCA approach, namely the weighted product method, because the fit of a policy measure depends on *all* formulated criteria being a good match, e.g., if many EVs charge during the evening peak, but none of them stay connected after having charged during the night, the demand cannot be shifted to night-time. Furthermore, we divide the criteria by the maximum value for that criterion, so that the scales are comparable. This results in the following calculation:

$$s_i = \prod_n w_n \frac{x_{i,n}}{\max(x_n)} \tag{1}$$

where s_i is the MCA score for PC4 area i, w_n is the weighing factor for criteria n, $x_{i,n}$the value of criterion n for PC4 area i, and $\max(x_n)$ the maximum value of criterion n.[2] The preferred values for w_n might differ for different policy makers depending on their priority and other factors such as grid capacity. As stated above, the fit of a policy measure depends on all formulated criteria being a good fit, which is why we weigh each criterion$n$ equally by setting $w_n = 1$.

We correlate and plot the results of the MCA for neighborhoods. This way, we can observe patterns in the results and identify coherent policy mixes for specific neighborhoods.

5. Results

This section presents our results. Section 5.1 presents the indicators and includes several maps and aggregated charging profiles.

[2] How to standardize the criteria for performing an MCA is not obvious *a priori*. In our case, the distributions of the relevant variables follow a power law, see Fig. 6. Because the variables have similar distributions, the outcomes of our MCA are not sensitive to using the median or mean instead of the maximum. If the variables would follow a different distribution (e.g. a normal distribution), a different standardization method might be more appropriate. We recommend readers who want to follow this method to first check the distributions of the relevant variables, and then to choose the standardization method.

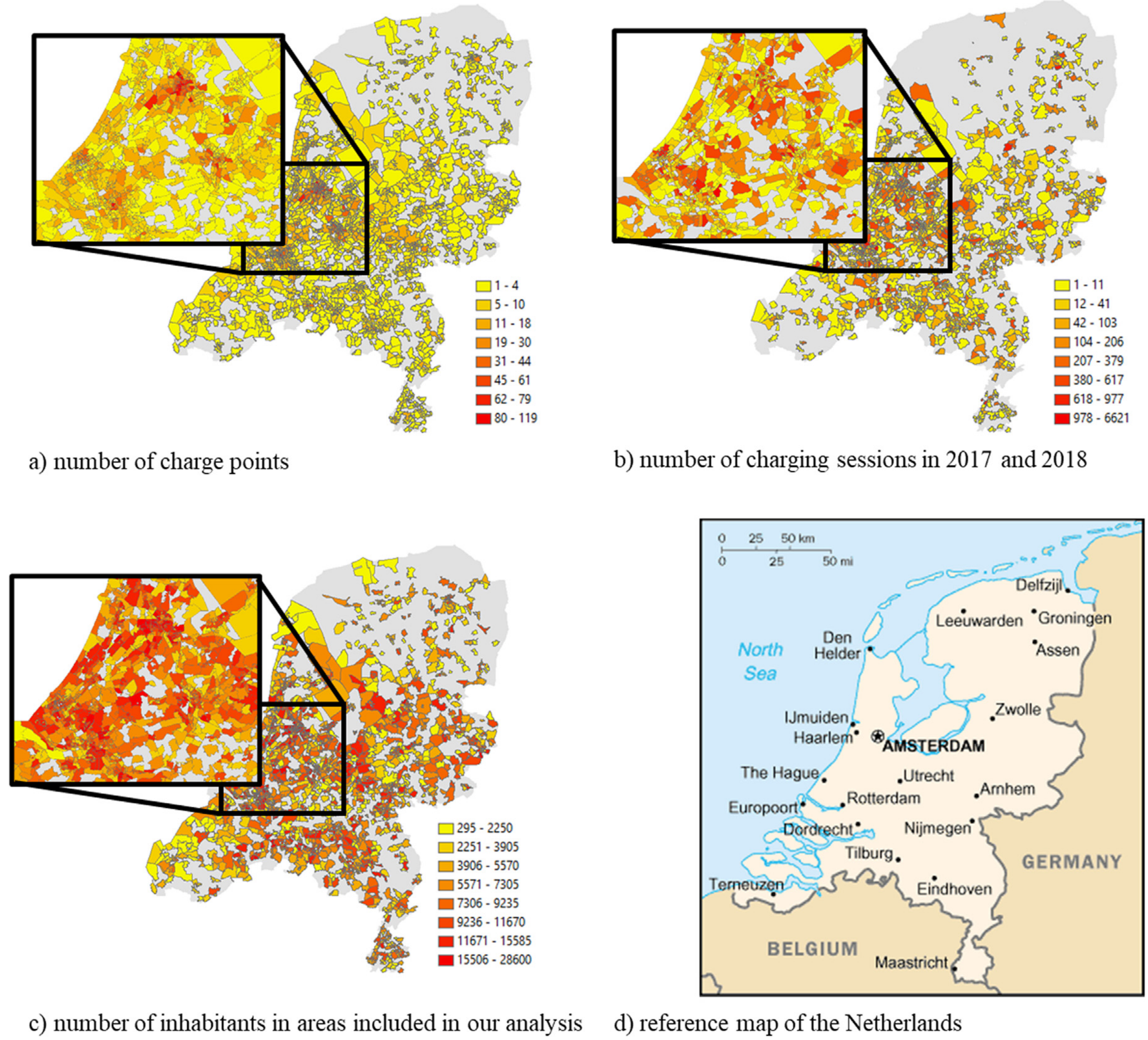

Fig. 4. Number of charge points, charging sessions, and inhabitatants in PC4 areas considered in our analysis. The densely populated Randstad area is enlarged. The figure also includes a map of the Netherlands for reference (d). Grey areas do not have a data point.

Section 5.2 presents the results from our regression analyses, and Section 5.3 presents the results from the MCA.

5.1. Charging infrastructure and charging behavior

Fig. 4 shows maps for the charging locations and the number of charging sessions in 2017–2018 (for reference, we have included maps of the number of inhabitants and of the Netherlands, see Fig. 4c and d). The maps show that these factors are unequally distributed throughout the Netherlands. Taking into account population density, the charging locations are concentrated in Amsterdam, Utrecht, and Rotterdam. However, most charging sessions take place outside of the major city centers in suburban areas.

Fig. 5 shows the resulting weekly charging profile averaged over 2017 and 2018. The figure shows clear morning and evening peaks for weekdays, while in the weekends the peak is in the late afternoon. The patterns for PHEVs and BEVs are very similar. One difference is that the evening peak lasts longer for BEVs, due to larger battery size and thus longer charging of BEVs. For the morning peak this is not the case. This could indicate that BEV drivers do not charge their EV in the morning as often as PHEV drivers, but have sufficient range to only charge in the evening. Another thing to note is that the charging demand for both types is roughly the same. BEVs make up roughly 42% of the EV users in this analysis. It is not surprising that PHEVs charge less than BEVs given that PHEVs can also use the internal combustion engine. Assuming other factors, such as efficiency and driving patterns, are equal between the two EV types, it seems that PHEV users, at least the ones in this dataset, mainly use the battery when driving.

Fig. 6 and Table 3 show the variation of the indicators per PC4 area. All distributions follow a power law, which is why the x-axes and y-axes of the histograms have a logarithmic scale (we added 1 before log transforming to include zeroes). This power law

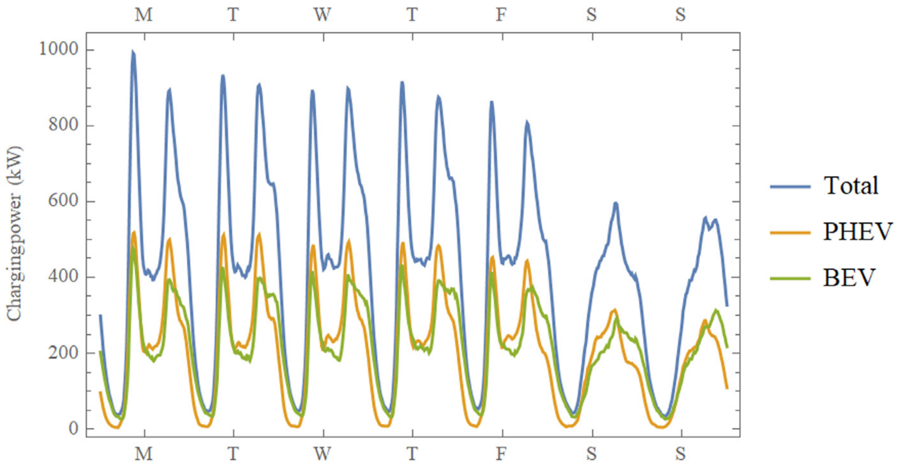

Fig. 5. Resulting week profile of average charging power. Ticks on the horizontal axes indicate 12.00.

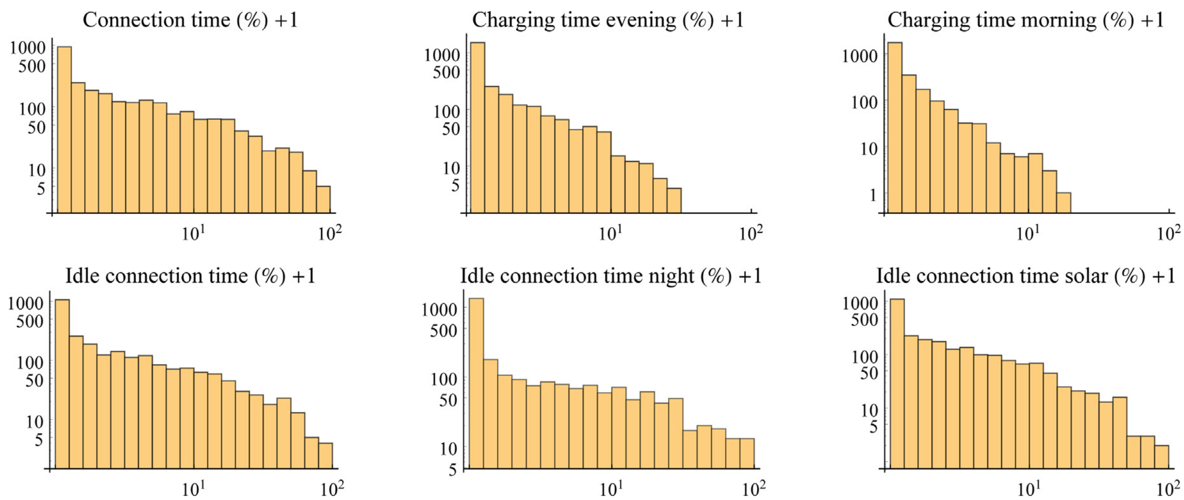

Fig. 6. Histograms of charging behavior indicators at PC4 level (log–log scale, the unit is time divided by the total time considered in this analysis for that indicator. The total time considered in the analysis is (a) 2 years for the *connection* and *idle connection time*, (b) 5 h / 24 h * 2 years for the *charging time evening*, (c) 8 h / 24 h * 2 years for *idle connection time night*, and (d) 6 h / 24 h * 2 years for *charging time morning* and *idle connection time solar*).

Table 3
Summary statistics of charging behavior indicators at PC4 level (the unit is time divided by the total time considered in this analysis for that indicator. The total time considered in the analysis is (a) 2 years for the *connection* and *idle connection time*, (b) 5 h / 24 h * 2 years for the *charging time evening*, (c) 8 h / 24 h * 2 years for *idle connection time night*, and (d) 6 h / 24 h * 2 years for *charging time morning* and *idle connection time solar*)). Q1 indicates the first quartile, Q3 indicates the third quartile.

Variable	N	Mean	St. Dev.	Min	Q1	Median	Q3	Max
Connection time (%)	2511	4.375	9.843	0.003	0.090	0.694	3.845	95.033
Idle connection time (%)	2511	3.714	8.815	0	0.047	0.483	3.051	90.595
Charging time during evening peak (%)	2511	1.053	2.570	0	0.007	0.121	0.805	28.027
Idle connection time during night (%)	2511	4.494	11.445	0	0	0.160	3.027	93.086
Charging time during morning (%)	2511	0.426	1.112	0	0.011	0.094	0.367	17.477
Idle connection time during solar hours (%)	2511	2.884	6.964	0	0.032	0.462	2.469	89.806

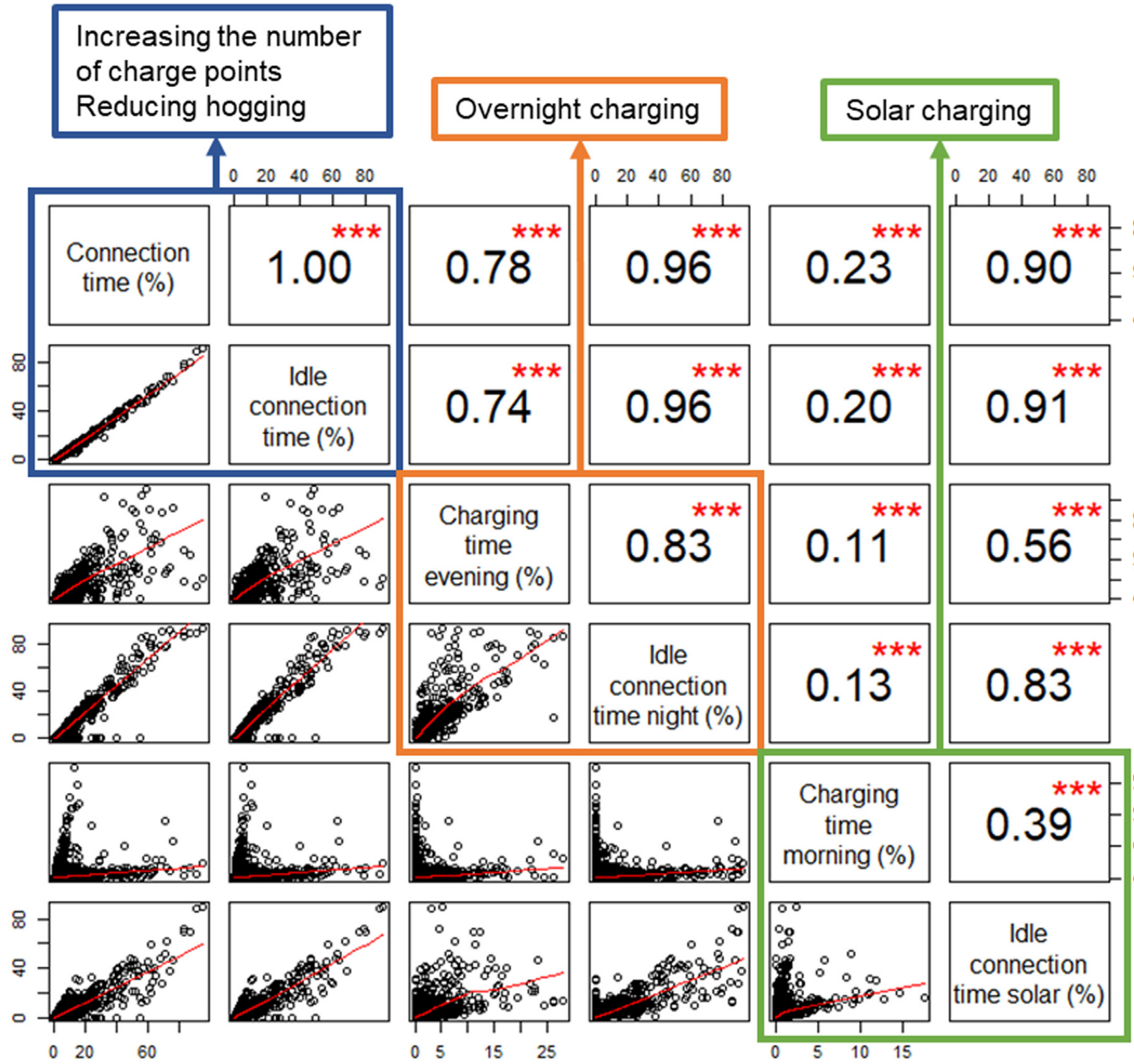

Fig. 7. Comparison of charging behavior indicators at PC4 level. The lower left triangle contains pairwise plots, and the upper right triangle contains correlations, and indications of p-values resulting from an ANOVA analysis, *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. The red trend line is drawn using the LOWESS smoother function (Cleveland, 1981). The figure highlights pairs of indicators relevant for a specific policy measure.

indicates that EV charging and idle charging is highly concentrated in specific neighborhoods. We can also see that there is a large variation in *connection time*, the *idle connection time*, and the *idle connection time during night* and *solar hours*, varying from 0% to around 90% of the total time considered. The *charging time in the evening* varies from 0% to 28% of the total time considered, and the *charging time in the morning* varies from 0% to 17% of the total time considered.

Fig. 7 shows the relation between these indicators via pairwise plot, correlations, and analysis of variance (ANOVA) tests.[3] First, we can see that *connection time* and *idle connection time* are strongly correlated. This is currently not a problem because of the high availability of public charging infrastructure, but if long idle times become routine behavior it will become a problem as the EV fleet grows. This result also indicates that in areas where charge points are occupied often, there is a lot of flexibility to either reduce hogging or implement V2G. Furthermore, *charging time in the evening* and *idle connection time in the night* have a strong correlation, indicating that for neighborhoods with a large evening peak postponing charging may be a good option. Finally, *charging time in the morning* and *idle connection time during solar hours* have the weakest correlation out of these examples; many neighborhoods either have a lot of EV charging in the morning *or* a lot of EVs hogging in the afternoon, while having both would be best for solar charging.

[3] In our robustness analysis, we checked whether these relationships exist in areas with either high or low availability of charging infrastructure (measured both as charge point per km^2 and as charge point per person). We found that the relationships between variables that are considered together in the MCA (as indicated by the colored rectangles) are not sensitive to charge point density (significance levels stay the same, correlation values vary with maximum 0.03). This indicates that our results are robust for areas with high as well as low availability of charging infrastructure.

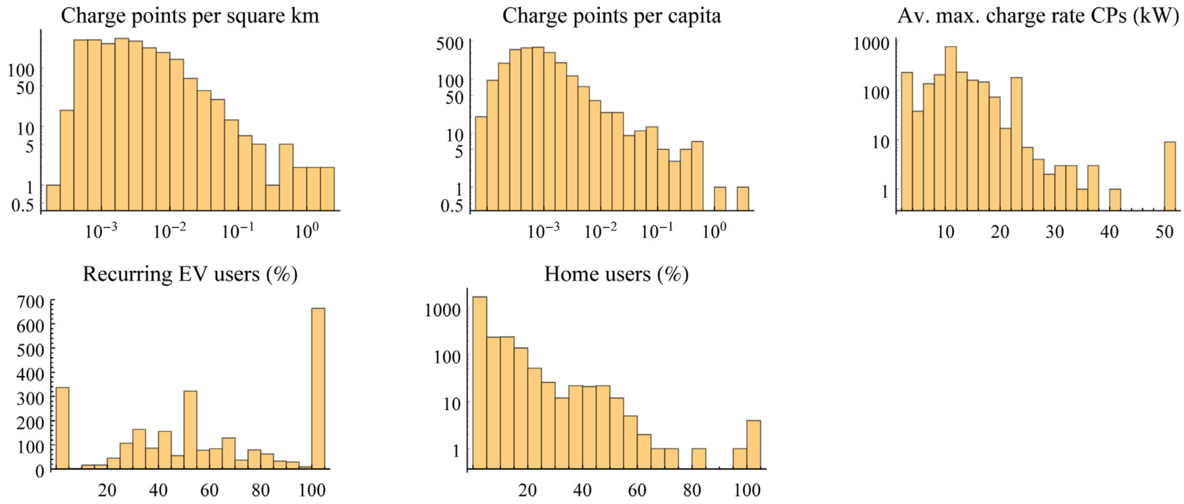

Fig. 8. Histograms of additional statistics on charging infrastructure and EV users at PC4 level. Note that the histograms of charge points per square km and charge point per capita are presented on log–log scale, and the y-axis are log scaled for the histograms of the average maximum charge rates of charge points and home users.

Fig. 8 shows the distribution of the neighborhood statistics (Supplementary Fig. A1 in Appendix A presents correlations and pairwise plots). The distributions of the charge points per km^2, charge points per inhabitant, charging sessions, charge points per session, and home users are highly skewed and presented with a logarithmic scale on the x-axis. Furthermore, there is large variation in all these variables, indicating that both charging infrastructure and the EV users that charge there differ among neighborhoods. Another noteworthy result is that most neighborhoods have charge points with an average maximum charge rate of 11 kW. Looking at the EV users, we can see that the percentage of users that return to the same charge point has peaks on the extremes (no user returns for another charging session, or every EV user charges at least twice in that area), and resembles a normal distribution in between the extremes. Also, the results show that the number of EV users that live in the area where they charge at a public charging station is generally low, and in a lot of neighborhoods only visiting EV users were charging at public charging stations.

Table 4
Results of the negative binomial regression model. The table presents the coefficients for the charging behavior indicators and model diagnostics. Standard errors in parentheses, *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. The values for theta are significant, which indicates that using a negative binomial regression model is preferred to a Poisson regression model for this data.

Variable	Connection time (15 min)	Idle connection time (15 min)	Charging time during evening peak (15 min)	Idle connection time during night (15 min)	Charging time during morning (15 min)	Idle connection time during solar hours (15 min)
Charging infra-structure						
CPs p km2	−0.025 ***	−0.0251 ***	−0.0162 *	−0.0244 **	−0.0332 ***	−0.0280 ***
	(0.006)	(0.0064)	(0.0072)	(0.0088)	(0.0068)	(0.0067)
CPs per inhabitant	−0.729	−0.842 *	−1.17 *	−2.89 ***	3.19 ***	0.073
	(0.378)	(0.402)	(0.45)	(0.61)	(0.43)	(0.424)
Av. Max. Charge Rate (kW)	−0.0325 ***	−0.0359 ***	−0.0328 ***	−0.0435 ***	0.0092	−0.0210 **
	(0.0059)	(0.0063)	(0.0071)	(0.0088)	(0.0068)	(0.0067)
EV users						
Recurring EV users (%)	0.0188 ***	0.0193 ***	0.0181 ***	0.0211 ***	0.0154 ***	0.0180 ***
	(0.0010)	(0.0011)	(0.0012)	(0.0015)	(0.0012)	(0.0012)
Home users (%)	0.0601 ***	0.0648 ***	0.0469 ***	0.0722 ***	0.0132 ***	0.0526 ***
	(0.0030)	(0.0032)	(0.0036)	0.0044)	(0.0034)	(0.0034)
Control variables						
CPs	0.109 ***	0.109 ***	0.0969 ***	0.105 ***	0.140 ***	0.119 ***
	(0.005)	(0.005)	(0.0057)	(0.007)	(0.005)	(0.005)
Constant	7.31 ***	7.08 ***	4.63 ***	6.11 ***	3.82 ***	5.49 ***
	(0.11)	(0.12)	(0.13)	(0.16)	(0.13)	(0.12)
Diagnostics						
N	2203	2203	2203	2203	2203	2203
Theta	0.458	0.406	0.318	0.211	0.354	0.365
	(0.011)	(0.010)	(0.008)	(0.006)	(0.009)	(0.009)
Log-likelihood	−21564.0	−20847.9	−14590.5	−16907.0	−13922.2	−17380.6

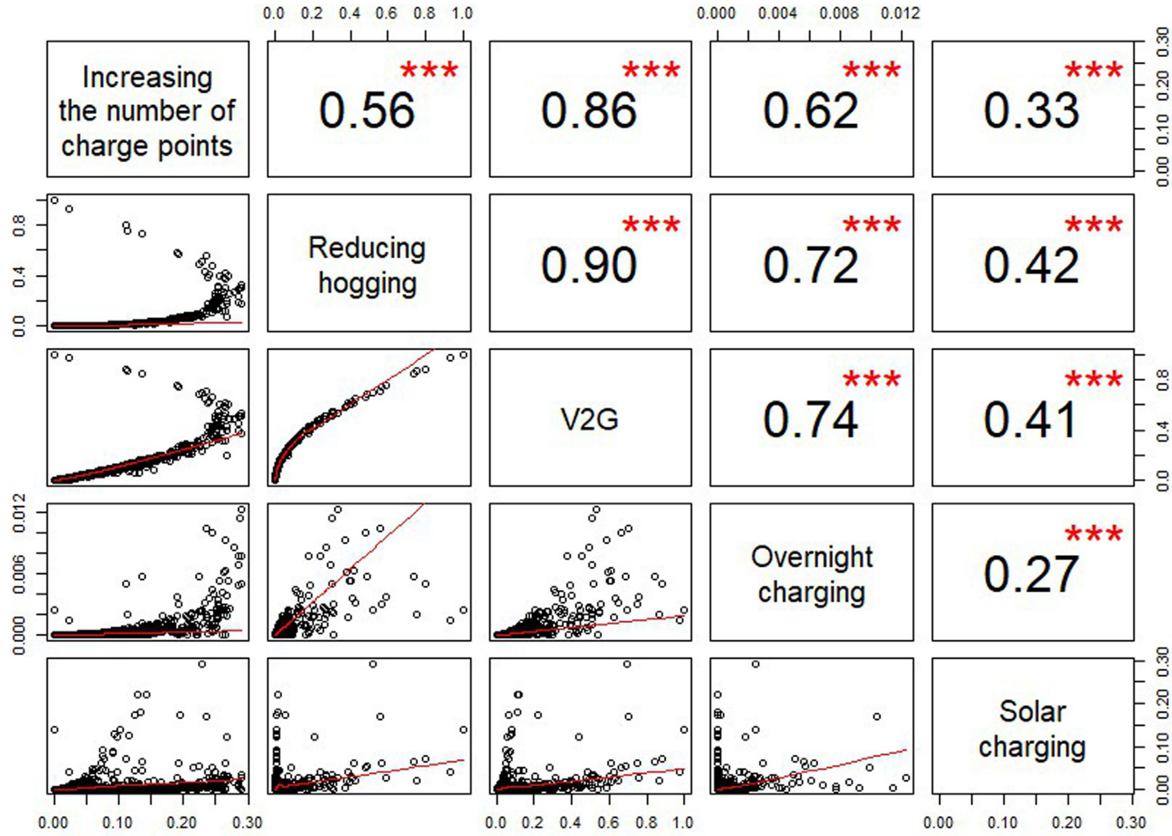

Fig. 9. Results of the MCA for PC4 areas. The lower left triangle contains pairwise plots, correlations, and the upper right triangle contains indications of p-values resulting from the ANOVA analysis, *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. The red trend line is drawn using the LOWESS smoother function (Cleveland, 1981).

5.2. Regression analysis

Table 4 presents the results of our regression model (see Supplementary Table A.2 in Appendix A for summary statistics). The results show that charge point density, as measured by area size, is negatively correlated with all charging behavior indicators. This indicates that in areas where charge points are rarer, they are used more often. The results of charge point density measured by population size are somewhat different. We find no significant correlation with *connection time* and *idle connection time* during solar hours, and a positive correlation with *charging time during the morning*. The latter effect might be because charging in the morning often takes place at the work location.

As expected, we find the maximum charge rate to have a negative correlation with *connection time*, and *charging time during the evening*. Furthermore, we find a negative correlation with *idle connection time*. Surprisingly, we do not find a significant negative correlation with *charging time during the morning*. To explain this finding, we further analyzed our data and found that EV drivers have a higher preference for charge points with high charge rates the morning than at other times of the day. Hence, the faster charging rate in these areas is compensated by more EV drivers charging in these areas, which explains the lack of a significant correlation.

Finally, we find positive correlations between recurring users and home users with all charging behavior indicators. The positive correlations of home users and the charging behavior indicators is in line with our expectations, except for *charging time in the morning* and *idle connection time during solar hours*, for which we expected a negative correlation. This indicates that also in residential neighborhoods *solar charging* has high potential.

5.3. Multi-criteria analysis

This section presents the results from the MCA. Our MCA does not allow to make absolute decisions on which policy target to pursue but enables a comparison between neighborhoods.

Fig. 9 presents the results of the MCA for neighborhoods, using pairwise plots, correlations, and p-values from ANOVA tests. A strong correlation of MCA scores for different policies indicate that these policy mixes together can form a coherent policy mix in certain neighborhoods. A correlation cannot provide a complete picture, so it is also important to look at the pairwise plots, where points representing neighborhoods for which both policy measures are good options are located the upper right side of the graphs.

The results show that many neighborhoods for which *increasing the number of charge points* is a good policy option, *vehicle-to-grid* and *overnight charging* are good options as well. There are also many neighborhoods for which both *vehicle-to-grid* and *overnight charging* are good options. Hence, these three policy measures will often be good options for same neighborhoods and present a good policy mix. The correlation between *reducing hogging* and *vehicle-to-grid* is also very strong, but *reducing hogging* aims to reduce connection time, it reduces the EV availability for ancillary services and storage. Therefore, these two policy measures do not form a coherent policy mix. Neighborhoods with high MCA scores for *solar charging* often have low MCA scores for the other policies, meaning that it will make sense to only implement this as a single policy, and not as part of a policy mix.

6. Discussion

6.1. Contributions

We distinguish three main contributions of this paper to the e-mobility literature. First, we highlight the incoherence in long-term visions of e-mobility that include EVs as a clean mode of transport, and as a stabilizing mechanism in a sustainable electricity grid, as these have different implications for charging infrastructure roll-out. Second, we develop a decision tree (Fig. 2) that explicitly links charging behavior to a set of policy measures. Third, we add to the increasing number of studies that provide empirical evidence of actual EV charging behavior.

We relate charging behavior to five policy measures for public charging infrastructure: (1) *increasing the number of charge points*, (2) *reducing hogging*, (3) *vehicle-to-grid*, (4) *overnight charging*, and (5) *solar charging*. These measures contribute to high level goals for e-mobility, either by supporting large scale adoption of EVs by increasing availability of charging infrastructure (*increasing the number of charge points*, *reducing hogging*), increasing cost-effective use of existing charging infrastructure (*reducing hogging*) or electricity infrastructure (*vehicle-to-grid*, *overnight charging*, *solar charging*), or the integration of renewable energy (*vehicle-to-grid*, *solar charging*). Crucially, these policy measures cannot all be combined in a single, coherent policy package. Furthermore, the optimal charging behavior for implementing these policy measures differs. Therefore, policy makers responsible for public charging infrastructure should take neighborhood-specific charging behavior into account in policy design.

We highlight several aspects of charging behavior relevant for policy design. A key finding is that EV charging is highly concentrated in a relatively small number of areas of the Netherlands. Also, we find a very strong correlation with *connection time* and *idle connection time,* indicating that there is a lot of potential to use the existing charging infrastructure more efficiently, or to make use of the flexibility offered by EVs for grid services and aligning charging demand with renewable energy production.

The results of the negative binomial regression analysis show that the use of charging infrastructure is higher when charge point density is lower, indicating that the charge points are unequally spread as compared to charging demand. The only exception is the correlation between charge point density and *charging time in the morning*, possibly because many EV drivers charge near their work, where municipalities and companies might have invested in public charging infrastructure more as compared to residential areas (further research could clarify this). Furthermore, we found that the *connection time*, *idle connection time*, and *charging time* in the evening is lower in areas with a higher maximum charging capacity, in line with Morrissey et al. (2016) and Wolbertus et al. (2018).

We find that the percentages of recurring EV users and EV users charging near their home (home users) are positively correlated with *connection time*, *idle connection time*, and *charging time*. High values for these indicators indicate that policy measures that require behavioral change (2–5) are good options for these neighborhoods. Hence, this finding has interesting implications for policy makers, as it might be easier for new charging behavior norms to form in these areas. Contrary to our expectations, we find the percentage of home users to be positively correlated with *charging time in the morning* and *idle connection time during solar hours*. *Solar charging* could thus also be an interesting policy measure in residential areas.

The results of the MCA show that neighborhoods for which *increasing the number of charge points* are good policy options, *vehicle-to-grid* and *overnight charging* are often good options as well. These three policy measures are not mutually exclusive, so this could be a coherent policy mix for these areas, at least from the perspective of what policies fit with charging behavior. Furthermore, we found a very strong correlation between neighborhoods for which *reducing hogging* is a good option those for which *vehicle-to-grid* is a good option. In neighborhoods for which both are good policy measures, the best choice of policy depends on factors such as parking pressure, grid conditions, and priority of policy makers. Finally, we found that neighborhoods for which *solar charging* is a good option other policy measures are not. This implies that policy makers wanting to increase the integration of EVs with PV solar power could target very specific neighborhoods to implement systems or incentives to match EV charging demand with PV solar power supply.

6.2. Limitations

Our data contains some limitations that could impact our results. There could be a selection bias in our population, since we only had data on NewMotion cardholders. We do not know whether this user group behaves differently than other EV users. Given that our estimated charging pattern followed the commonly found pattern of peaking both in the morning and the evening, see for example Helmus et al. (2018), Khoo et al. (2014), Smith et al. (2011), and Xu et al. (2018), we suspect that there is not a major difference between NewMotion customers and other EV users. NewMotion card holds could also have a membership at other EMSPs, but we suspect this to be limited, given that since 2011 the e-mobility sector in the Netherlands has allowed for members of EMSPs to charge at charge points operated by a party with whom they do not have a (direct) contract, also known as EV-roaming (Ferwerda et al., 2018). A more important selection bias is that EV users do not only use public charge points, but also charge privately. Our results thus reflect only charging behavior at public charge points, rather than all charging behavior. Furthermore, the Netherlands has a very high number of public charge points per EV as compared to other countries, which could mean that these results do not translate well to other countries.

Another limitation is that our data does not contain the power output over time or the time when the EV was fully charged. Therefore, we had to estimate the charging rate of the EV. Typically, an EV charges at a lower rate than its maximum, it is thus likely that we overestimate the charging rate in our analysis. Other research found the average charge rate of BEVs and PHEVs to be 23% lower and 14% lower than their maximum charge rate respectively (Gerritsma et al., 2019). To give some indication of how much we overestimate idle connection time, we can compare our results with Helmus et al. (2018) and Wolbertus and Van den Hoed (2017). Both studies analyzed hogging behavior in the Netherlands based on two different datasets (both of more than one million charging sessions) which both included how long the EV was charging. Helmus et al. (2018) found average idle connection times to be between 40 and 75% of the total connection time, and Wolbertus and Van den Hoed (2017) found it to be 75–85%. Based on our method, we find idle connection time to be on average 73% of the total connection duration. Hence, it is likely that we provide a reasonable estimate of idle connection times, though it certainly is possible that we overestimate it. Since we focus on the *difference* between idle connection rates across neighborhoods rather than the absolute value, we do not think our analysis is substantially affected by this potential overestimation.

Our analysis does not allow to decide which and how many different policies to implement. We compare the indicators relative to each other, and our method does not allow to determine in absolute terms which policy is the best. Rather, we recommend policy makers to use our framework as part of a larger analysis of neighborhoods which should also include information on matters such as grid conditions and expected EV adoption. While for charge point operators, city planners and grid operators it might be attractive to implement different policies and incentives throughout the Netherlands to locally optimize EV charging from their perspectives, too many variations in policies within a small region could make public charging unclear to EV users. Additional research is needed to determine to how to balance localized optimization of charging infrastructure with ease-of-use.

7. Conclusion

Summarizing, the present paper contributes to a better understanding of EV charging behavior and how it relates to the visions for the future role of EVs. A challenge for public charging infrastructure roll-out is that e-mobility is envisioned to function both as a clean mode of transportation, and as part of a sustainable electricity system, preferably at minimal costs. Translating these high-level policy goals to local policies is not trivial, as the implementations are different. Analyzing local charging behavior can provide some much-needed guidance for policy design, and we link charging behavior to specific policy measures. By applying this framework to a large dataset of charging sessions, we show that there is great variation in local charging behavior which has implications for what constitutes optimal policy mixes. While our analysis has been able to identify potentially coherent policy mixes by looking at charging behavior, we stress that policy makers need more than just behavior to inform policy design; other factors such as local grid conditions and parking pressure are also important. Ultimately, our take-home message is that policy makers should always consider local conditions in their strategies for public charging infrastructure roll-out.

Finally, we discuss our results in relation to several ongoing trends. First, there is an ongoing discussion amongst policy makers and firms working in the EV charging field on whether future charging infrastructure should consist mostly of DC fast chargers or normal AC chargers. If the future charging infrastructure will be mostly based on normal AC chargers, then charging behavior will probably not change much. However, we can expect changes in behavior if DC fast chargers become dominant. Instead of charging at home, at work, or on the street, EV users could make quick stops at DC fast chargers along the highway or at specific charge point hubs in the city. This will result in less charge point hogging, and high localized peaks in demand, with little flexibility to shift demand. While fast chargers might make e-mobility more attractive to certain consumers, it is thus likely to reduce the potential for EVs to be a stabilizing mechanism in electricity grids.

Second, an increase in EV battery capacity will reduce the number of charging sessions. This in turn, reduces the opportunities to shift demand, because the ratio of charging time to connection time will increase. However, if the number of charging sessions does not decrease with larger EV batteries, there could be more flexibility in EV charging (if connections times stay similar and average driving distances do not increase substantially).

Finally, mobility use may change considerably; examples are that car sharing may become more popular or self-driving cars may enter the market. For car sharing, it is difficult to assess how charging behavior will change, as it depends on the driving behavior of car sharers and the logistics of car sharing companies. Self-driving cars could offer grid services by automatically disconnecting from a charge point when sufficiently charged and moving to charge points at locations where additional flexibility is needed for the grid.

CRediT authorship contribution statement

Mart van der Kam: Conceptualization, Methodology, Software, Formal analysis, Data curation, Writing - original draft, Visualization. **Wilfried van Sark:** Writing - review & editing, Supervision, Funding acquisition. **Floor Alkemade:** Investigation, Writing - review & editing, Supervision, Funding acquisition.

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Appendix A. Supplementary material

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