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Fully charged: An empirical study into the factors that influence connection times at EV-charging stations

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Abstract: This study is the first to systematically and quantitatively explore the factors that determine the length of charging sessions at public charging stations for electric vehicles in urban areas, with particular emphasis placed on the combined parking- and charging-related determinants of connection times. We use a unique and large data set – containing information concerning 3.7 million charging sessions of 84,000 (i.e., 70% of) Dutch EV-users – in which both private users and taxi and car sharing vehicles are included; thus representing a large variation in charging duration behavior. Using multinomial logistic regression techniques, we identify key factors explaining heterogeneity in charging duration behavior across charging stations. We show how these explanatory variables can be used to predict EV-charging behavior in urban areas and we derive preliminary implications for policy-makers and planners who aim to optimize types and size of charging infrastructure.

Keywords: Electric vehicles, Charging infrastructure, Connection times

1. Introduction

Electric Vehicles (EVs) show great promise to reduce locally harmful emissions such as NO_x SO_x and PM (Razeghi et al., 2016) and greenhouse gasses such as CO_2 (Rangaraju, De Vroey, Messagie, Mertens, & Van Mierlo, 2015), triggering widespread positive attention among policy makers and researchers alike. However, three important barriers currently hamper widespread adoption, being high upfront purchase costs, limited driving range and a lack of public charging infrastructure (Coffman, Bernstein, & Wee, 2016; Egbue & Long, 2015; Liao, Molin, & Wee, 2015; Rezvani, Jansson, & Bodin, 2015). Falling battery prices (Nykvist & Nilsson, 2015) and plans for new, more affordable long range EV models suggest that the barriers of price and range can be overcome.

However, private sector investments in the roll-out of a charging infrastructure have been lagging behind these vehicle developments due to the well-known chicken-and-egg problem (e.g. Struben & Sterman, 2008). To stimulate the adoption of EVs and overcome the chicken-and-egg problem, governments at various levels are keen to help with funding charging infrastructure. Yet, in developing such charging infrastructure, policy makers face the challenge of efficiently using tax payers' money. this challenge is exacerbated by rapid technological developments such as fast charging stations (up to 350 kW) and (static and dynamic) wireless charging which further complicate decision-making. This is because such developments increase the risk of investments into potentially soon-to-be-obsolete technology rendering them worthless. In addition, new behavioural patterns, such as changing charging frequencies depending on battery size, that differ from current refuelling behaviour are not yet well understood, making it difficult to predict demand (and to optimize charging infrastructure). In the end, however, postponing the decision on how and when to roll-out which charging opportunities could increase the barrier for candidate EV drivers and thereby hamper the transition to a more sustainable transport system.

As alluded to above, efficient planning of charging infrastructure for electric vehicles (EVs) involves accurate modelling of charging demand. In predicting EV charging demand, understanding variations in the starting time and location of charging sessions is recognized to be of key importance; as such it comes as no surprise that several recent studies have been devoted to modelling demand variations (across space and time) in EV charging. While earlier work was based on the tradition of optimal planning (He, Yin, & Zhou, 2015; Nie & Ghamami, 2013), more recent studies have moved towards a more behaviorally oriented perspective (Morrissey, Weldon, & Mahony, 2016; Neaimeh et al., 2017; Sun, Yamamoto, & Morikawa, 2016).

An important aspect of demand for charging stations is missing in these studies. By nature, electric vehicle charging stations are not accessible to other users when used. When planning to meet demand it is therefore necessary to know for how long the charging station will be occupied by a given user at a given time. Yet variations in the duration of charging sessions in the public domain are not well understood. What makes predicting the duration of these sessions particularly difficult, is that it results from an interplay between *refueling* and *parking* behavior; also when fully charged, vehicle owners may wish to occupy the charging station for parking reasons (Faria, Baptista, & Farias, 2014; Gerzon, 2016; Wolbertus & van den Hoed, 2017), and this effect may be exacerbated by local policies which provide EV-owners with parking/charging locations for free (Wolbertus, Kroesen, van den Hoed, & Chorus, 2017). New refueling behaviors also comes with establishing new social norms, which can vary in different circumstances (Caperello, Kurani, & TyreeHageman, 2013). Understanding the factors that drive these behaviors is important for efficient charging infrastructure planning as it allows policy makers to optimize planning itself or to create policy measures such as pricing strategies to steer behavior into the desired direction.

This study is the first to systematically and empirically explore the factors that determine the length of charging sessions at public charging stations for EVs in urban areas. We use an unique and large data set – containing relevant information concerning 2.6 million charging sessions of 84,000 (i.e., 70% of) Dutch EV-users – in which both private users, taxi and car sharing vehicles are included; thus representing a large variation in charging duration behavior. By estimating a statistical model, we identify key factors that explain heterogeneity in charging duration behavior. We show how these explanatory variables can be used to predict EV-charging behavior in urban areas and we derive preliminary planning and policy implications regarding the optimal design of charging infrastructure (-related policies).

2. Literature review

Most currently available charging infrastructure planning studies work under the assumption that EV charging at public charging station occurs when the battery level of the car can no longer meet the travel needs of the driver and that the charging there is only done to create enough range to complete the (next) trip, leading to connection times to charging stations that are equal to charging times (Brady & O'Mahony, 2016; Brooker & Qin, 2015; Dong, Liu, & Lin, 2014). Such assumptions may hold for fast charging stations (Motoaki & Shirk, 2017; Neaimeh et al., 2017; Sun et al., 2016), however, for slower level 2 charging infrastructure in the city, charging duration is known to be a complex interplay between parking and refueling behavior by a variety of drivers, such as taxis (Asamer, Reinthaler, Ruthmair, Straub, & Puchinger, 2016; Tu et al., 2015; Zou, Wei, Sun, Hu, & Shiao, 2016) and car sharing vehicles (Van der Poel, Tensen, Van Goeverden, & van den Hoed, 2017), each with different recharging demands. As different types of drivers make use of the same infrastructure, understanding the interplay between these factors is of key importance.

Some studies do recognize that EV drivers can recharge during longer dwelling times. These studies then tend to assume that vehicles will recharge each time they are parked for a longer time or they ignore the fact that charging stations are rival goods (Paffumi, Gennaro, & Martini, 2015; Shahraki, Cai, Turkay, & Xu, 2015). In addition, these studies do not account for other intentions to charge (e.g. using a charging station mainly for the ease of parking), the effect of local parking policies such as free parking for EVs (Wolbertus et al., 2017) and particular pricing structures.

It has been recently recognized that pricing strategies form a possible solution to influence connection times. The effects of such strategies have been studied by Gerzon (2016) using a stated choice survey. He found that pricing by the hour caused a significant reduction in connection times. Motoaki & Shirk (2017) find that a fixed fee at fast charging stations increases the time connected to a charging station compared to the free charging situation, as users tend to want to get their money's worth. These results suggest that pricing strategies could possibly serve as a policy tool to influence charging behavior.

Studies that make use of real life data from EVs or charging stations do mention variations in charging and connection times. These studies mainly point at the start of the sessions as the most important factor that determines the length of the charging session (Sadeghianpourhamami, Refa, Strobbe, & Develder, 2018). Morissey et al. (2016) consider charging session length; they compare fast and slow public chargers and find that, not surprisingly, charging times are shorter at fast charging stations. Robinson, Blythe, Bell, Hübner, & Hill (2013) took a closer look by identifying different types of charging behavior based on activity type. They however only considered charging times –which barely differed across activities in their data– and not connection times. Kim, Yang, Rasouli, & Timmermans (2017) focused on factors that influence inter-charging event times; they identified two different user type groups, regular and random, and found significant differences between these groups.

In sum: while providing very valuable insights into charging behaviors, the current literature studies connection times to charging stations in a manner that does not reflect the full complexity and subtlety of real charging behavior in a city context. The wide variety in charging durations is currently only acknowledged in descriptive studies but a systematic and quantitative analysis of the factors that drive the variation in durations is missing. This research contributes to the understanding of charging infrastructure planning by modelling (variation in) the time connected to charging stations based on a large dataset of charging sessions using public charging infrastructure. This dataset provides an unique insight into charging behaviors not only because of its sheer size but also because it encompasses the entire public charging infrastructure within four cities, allowing for an analysis of different (local) policies and EV-owner types which use and compete for the same charging stations.

3. Methodology

Data were collected from public charging stations in the four major Dutch cities (Amsterdam, Rotterdam, The Hague and Utrecht) between 2014 and 2016. The data were provided by the charging point operators in these areas. Note that charging stations in these areas were accessed by swiping a RFID-card and then connecting a charging cord to the vehicle. Data were collected concerning the starting point (clock time) of the charging session, its duration, the amount of kWh charged, and the location; a unique anonymous RFID code related all relevant sessions to the RFID-card. In total 2.692.446 Sessions were recorded in this period. Sessions with a length shorter than 5 minutes and longer than 300 hours were excluded from the dataset. Additionally, sessions without any charge were not taken into account during the analysis as such data seemed unreliable. Many of these short sessions without any or little charge were considered to be most likely due to an error while connecting the car to the charging station, requiring the user to swipe the card multiple times. Also sessions with a charging speed over 50 kW were removed, as the charging stations in the dataset were not capable of offering these speeds. After this filtering process 2,531,960 (i.e., 94% of the original data points) sessions were left for the analysis.

Timing data were transformed to separate time-of-day and day-of-the-week variables. Information about charging station and user type was made available by the charging station operators. Charging station type categories were as follows: regular (2 outlets, 11kW), charging hub (at least 4 outlets clustered together) or fast charging station (50kW). User type categories were as follows: regular, car sharing vehicle or taxi. For regular users two different sub-categories were extracted, being frequent and non-frequent, on the basis of the number of observed charging sessions (20 charging sessions turned out to provide a useful cut-off point). Data on the time of day were transformed as follows: from 5AM to 9 AM was considered morning, from 10 AM until 3 PM afternoon, from 3 PM until 10 PM evening and from 10 PM until 5 AM night. This particular transformation was chosen based on the distribution of connection times as shown in *Figure 2*.

Information about the area in which the charging station was located was retrieved from The Netherlands Statistics (CBS Statline, 2016). Data about the built environment was gathered at the sub-sub-district level, which contains several buildings. In addition, information about the number of residential homes, public and social housing, and offices were gathered. We used the number of vehicles per squared kilometer as a proxy for parking pressure. Information on paid parking areas was retrieved from the four municipalities. GPS locations of the charging stations were matched with paid parking areas using the *sp* package in R (Bivand, Pebesma, & Gomez-Rubio, 2013; Pebesma & Bivand, 2005).

An obvious candidate to model the type of dependent variable in our data (note that connection times were measured at a so-called ratio-level) is linear regression. However, the distribution of connection times was found to be highly non-normal (see Figure 1; Kolmogorov-Smirnov test: $D(2531841)=0.217$, $p <0.001$), making linear regression unsuitable as an analysis technique and implying the need for a transformation of the connection time variable. Straightforward transformations such as log or square root transformations could not be applied due to the multiple peaks in the distribution. The peaks in the distribution suggest that heterogeneity in connection times results from qualitatively different types of charging behavior occurring within the dataset. To explore categories of qualitatively different charging sessions, a binning technique was used with several cut-off points. The following bins were identified: 0-1.5 hours, 1,5-7 hours, 7-11 hours, 11 to 24 hours and longer than 24 hours. The selection of the bin sizes is elaborated in the next section (4.1). Here, it is important to note that, since the bins reflect qualitatively different types of charging behavior, we decided to apply a multinomial logistic regression (rather than an ordered logistic regression), to model and explore the effects of different factors on this outcome. Data were analyzed using the Latent Gold software (Vermunt & Magidson, 2006).

4. Results

4.1 Descriptive results – identification and interpretation of bins

The distribution of connection times at charging stations binned per half hour is shown in *Figure 1.* The data is maximized at 72 hours as the distribution has a very long tail with a maximum of 298 hours. Close inspection of the figure shows that there are several segments to be recognized, including short sessions (up until 1.5 hours) which account for 15% of all sessions, representing EV-drivers that are only stopping to refill their car to be able to continue their trip; note that this segment seems to be represented in the modeling efforts described in (Brady & O'Mahony, 2016; Brooker & Qin, 2015; Dong et al., 2014). The next segment (between 1.5 and 7 hours) can mainly be attributed to visitors on the network, which park their car for a longer time at a charging station during a visit. The distribution spikes between 7 and 11 hours duration; most sessions in this segment start during the night or in the morning. A fourth segment with duration between 11 and 24 hours contains mostly overnight sessions starting at the end of the afternoon or during the evening. The tail of the distribution starts at a duration of 24 hours; we call this segment *long charge*. Although sessions in this segment only account for 6% of all sessions they do keep charging stations occupied for 29% of the total observed time, making them policy-relevant.

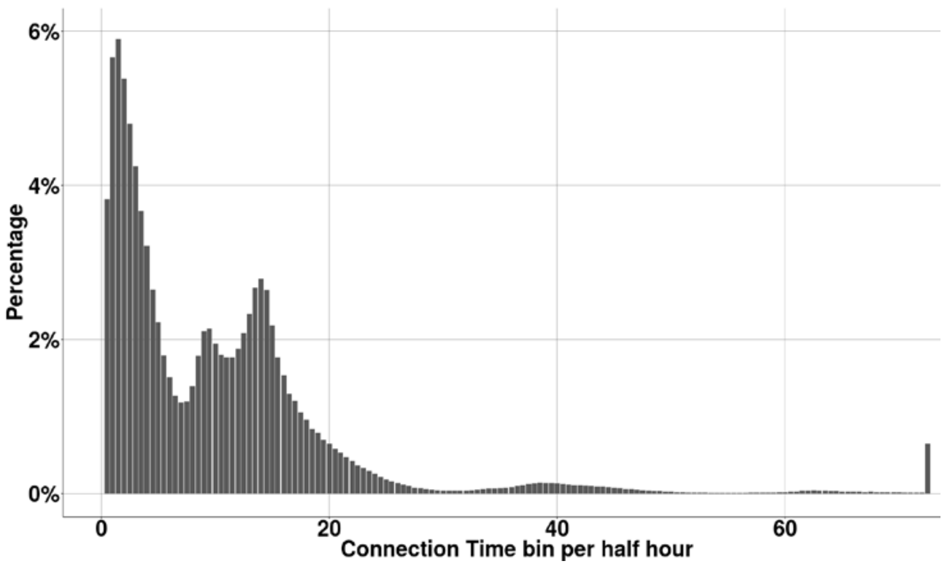

Figure 1 Distribution of connection times binned per half hour

A charging session's starting time has significant influence on the duration of the session. *Figure 2* shows the distribution of connection durations over the week for different times of day. The figure shows a clear repeating pattern for working days and a slightly shifted pattern during weekends. Short sessions up to 1.5 hours occur mainly in the afternoon (due to visitors) but the distribution also features a peak in the morning. This peak in the morning disappears in the weekends, which suggests that it is likely related to workplace charging. Nearly half of the charging sessions starting in the afternoon has a length of in between 1.5 and 7 hours. Sessions with a 7-11 hour duration mostly occur during the morning, but a significant portion also occurs late in the evening or during the night. This bin seems not only to represent workplace charging but also late overnight charging in the vicinity of one's residence. Sessions with longer durations, between 11 and 24 hours, peak in the late afternoon and early evening when drivers arrive home from work. Sessions longer than 24 hours only take a small portion of the total amount of sessions during working days but they peak significantly at Friday and Saturday night, suggesting a typical over-the-weekend parking habit.

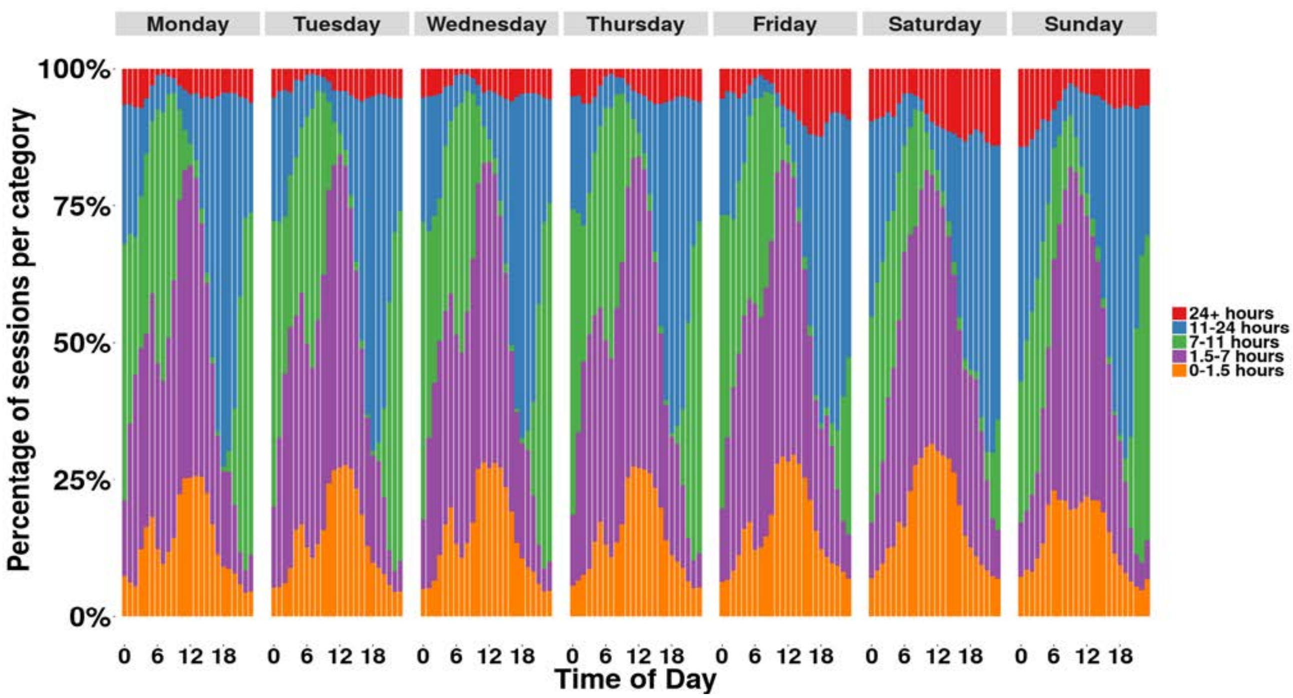

Figure 2 Distribution of connection times over the week

Based on the distributions of the durations of sessions, and their (i.e., the duration) occurrence at particular times of day, the different bins can be classified as follows: 0-1.5 hour sessions represent *stop & charge* behavior, mainly used for actual refueling of the vehicle and occurring mostly during the afternoon. *Park & charge* is the name of the bin for sessions with 1.5 to 7 hours of connection. This bin represents, although not exclusively, visitors that park their car for a longer time while leaving it to recharge. *Work & charge* behavior is attributed to 7 to 11 hour sessions which mainly occur in the morning, coinciding with morning traffic peak due to commuters; yet this bin also captures late night chargers of which sessions finish the next morning. Drivers recharging their EV in the late afternoon or early evening more often have a 11 to 24 hour connection time, representing typical overnight or *home & charge* sessions. The last category is the *long sessions* which have a higher occurrence at Friday and Saturday night, representing typical weekend parking sessions. Although the bins have been named to the behavior they most likely represent in the eyes of the authors and based on descriptive statistics, we emphasize that these names do not exclusively represent the type of behavior. The results of a more systematic and quantitative approach to evaluate the nature of connection durations at charging stations is presented in the next paragraph.

4.2 Model results

In table 1 results for model estimation are presented; note that long charge sessions (24+ hours) were used as a reference category, and that the explanatory categorical variables, time of day, day of the week and type of charger were dummy coded. Interactions between variables have been tested but did not provide a significant improvement in the model fit nor in a better interpretability of the model results. Most variables are significant and of the expected sign (see below), but note that the effects of many variables are relatively small compared to the constants. In general, the model provides a significant improvement (LL_β= -3052058) compared to the null model (LL_0=-4120764) despite that –as could be expected– a significant amount of unexplained variation in connection duration remains.

Timing

Time-of-day was dummy coded using the morning as a reference. Wednesday, a regular working day, served as reference for the day-of-the-week variable. The model results show that the timing (i.e., the starting point) of the charging sessions has the greatest impact on how long the session will last. Short sessions (*stop & charge* or *park & charge)* are more likely to occur in the morning and afternoon than during the evening or night, as suggested by parameters for the evening and night dummy variables which are significant and negative. These short sessions are equally likely to happen across working days. Significant negative parameters are obtained for weekend days, with the exception of Saturday. This result is intuitive, since during Fridays and Sundays less kilometers are driven (due to less work related traffic) whereas Saturdays generate shopping related traffic which is likely to correspond to charging behavior of the stop & charge and park & charge types. The timing parameters for *work & charge* are negative for the afternoon and evening dummies, showing that charging behavior associated with the work & charge bin (see previous section for elaboration) is most likely to occur in the morning or night. A negative parameter was also obtained for the Friday dummy. This effect for Fridays can mainly be explained by the lack of sessions which start very late in the evening but do not end during the next morning (and in that sense contrasts with a normal working day). For sessions with a duration between 11 to 24 hours (*home & charge*) we find a positive dummy for the evening, signaling that these sessions mainly start after working hours; also this result is intuitive. A negative parameter is found for the Friday dummy, indicating that this behavior is replaced by long sessions during the Friday night, as this variable is also negative for all other options. Most likely these are sessions that last throughout the entire weekend. These results show that knowing the timing of demand for charging provides important information concerning the duration of the corresponding charging sessions. The fact that the relative importance of the time-of-day factors is high, suggests that charging behavior is to a considerable extent habitual.

User types

User types were also dummy coded in which the taxi category served as reference category. Estimation results show that frequent users have tendencies for longer charging sessions, which is intuitive in light of the fact that these users are more likely to live in the area and therefore charge overnight and during the weekend. Signs of parameters for the visitor user type suggest that visitors are more likely to show *park & charge* behavior and also very short sessions up to 1.5 hours, which is in line with expectations as these represent typical visiting parking behaviors. Taxis were expected to have a large number of short sessions to refill their car in between picking up customers. Results, however, show that they are actually more likely to exhibit home charging behaviors in contrast to other user types, indicating that many EV-taxi drivers live in the city were they charge overnight, which turns out to be significant for an entire day of driving. Car sharing vehicles, as expected, have a positive and significant parameter for *stop & charge* and *park & charge* sessions. These vehicles are used more intensively and are not parked for a long amount of time as they are then picked up by another user. These results show that different user types have different distributions of connection times at charging stations.

City characteristics

Parameters associated with city characteristics show that the type of built environment is correlated with charging behavior. The betas for residential areas show that these areas are more prone to exhibit *home & charge* behavior and very long sessions, most likely referring to residents leaving their car connected over the weekend. The same holds for business areas in which the parameters suggest more *park* or *work & charge* behavior, most likely by employees or visiting costumers. The estimates for the public buildings variable show that public buildings have a stronger tendency to attract *stop & charge* and *work & charge* behavior. These could refer to visitors to e.g. the city hall who leave their car connected while there. Very long charging sessions are less likely to happen in these areas.

Charging station density has a relatively big (but still small) positive effect on 7-11 hour charging sessions and a small negative effect on 24+ hour charging sessions. A possible explanation for this result is that because areas with a high density are also more likely to have a high demand, the throughput will be higher, resulting in shorter charging sessions. Paid parking has a positive effect on very long sessions and also on *stop & charge* behavior. Such very short sessions are intuitive in light of the fact that drivers have to pay a parking fee in line with parking literature (e.g. Shoup, 2005). Very long sessions could be explained by EV owners that have a parking permit, making them more likely to leave their car parked and connected over the weekend. Parking pressure seems to have little effect on the duration of the connection to charging stations.

Charging station characteristics

As expected, charging at fast charge stations results in much shorter connection times than level 2 charging (which served as the reference category); users specifically choose this type of charging station if they are in needed of refueling their vehicle. Also note that these fast charging stations are (often) paid for by the minute, making longer connection times than necessary unnecessarily costly. Charging hubs, which are combinations of several level 2 chargers at one place, are more likely to serve *park & charge* behavior, although parameter-sizes do not indicate a large effect. The model suggests that these hubs are often used by visitors and car sharing users and serve as a recognizable point where the user is more certain to find an available charging station than at single stations. They are less likely to be used for *home* and *long charging*.

Table 1 Model estimation results

	Stop & charge 0-1.5 hours	**Park & charge** 1.5-7 hours	**Work & charge** 7-11 hours	**Home & charge** 11-24 hours	**Long charge** 24+ hours
Intercept	3.7332**	4.5281**	4.2873**	1.9417**	
Time of Day					
Morning (ref.)					
Afternoon	-0.6000**	-1.031**	-3.0471**	0.2266**	
Evening	-1.6324**	-2.0568**	-3.0804**	1.3153**	
Night	-2.5659**	-2.8021**	-0.896**	0.7492**	
Day of the week					
Monday	-0.1264**	-0.0618**	0.026*	0.072**	

Tuesday	-0.0561**	-0.0259*	0.0122	0.008	
Wednesday (ref.)					
Thursday	-0.1257**	-0.1033**	-0.164**	-0.1518**	
Friday	-0.5978**	-0.6565**	-1.2104**	-0.7621**	
Saturday	-0.1264**	-0.0618**	0.026**	0.072**	
Sunday	-0.6008**	-0.4236**	-0.654**	-0.1926**	
Use Type					
Taxi (ref.)					
Frequent	-0.9019**	-0.4641**	-0.1883**	-0.4334**	
Visitors	1.4768**	1.7733**	0.8797**	-0.2475**	
Car sharing	0.5733**	0.7677**	0.0142	-0.6115**	
City Characteristics					
% Dwellings living	-0.6603**	-0.9023**	-0.7185**	-0.1973**	
% Dwellings business	-0.7393**	0.1531**	0.172**	-0.5978**	
% Dwellings public	1.4006**	1.0906**	1.4419**	0.9271**	
% Dwellings Social	-0.3973**	-0.2263**	-0.8819**	-0.2043**	
Charging station density (charging stations/km^2)	0.2995**	0.3399**	0.4386**	0.3056**	
Paid parking	-0.4019**	-0.6106**	-0.6483**	-0.565**	
Parking pressure (cars/km^2)	-0.0025**	0.0001	-0.0003*	-0.0001	
Type of charger					
Level 2 charger (ref.)					
Fast Charger	6.4375**	2.3662**	0.8382**	0.1815	
Charge Hub	0.7111**	0.9459**	0.7042**	0.179**	
Number of observations	2531960				
Number of charging stations	2751				
Nul-Loglikelihood	-4120764				
Final loglikelihood	-3052058				
P^2	0.2593				

*****significant at 0.05 level

******significant at 0.01 level

5. Conclusion and Policy Implications

This paper is the first to systematically and empirically study the factors that influence connection times of Electric Vehicles (EVs) at charging stations. Our overview of the literature shows that many studies that try to optimize charging infrastructure roll-out strategies, treat EV charging demand as a spatial-temporal issue (i.e. they focus on the location and starting time of charging sessions). However, we argue that, due to the rival nature of charging stations, predicting the charging sessions *duration* is crucial; also in determining the right number of charging stations, such duration information is of great importance. What makes analysis of charging duration particularly difficult in an urban context, is the fact that charging stations are not solely used for refueling but for a combination of parking and refueling. An additional complication factor is that different types of users such as inhabitants, commuters, visitors, taxis and new modes such as shared electric free floating cars are all competing for the same charging stations. So far, the combined nature of parking and charging behaviors, and competing demands by different user types, have not been empirically investigated in an integral fashion. This research has filled this gap using a uniquely large dataset containing several millions of charging sessions, over a timespan of three years, at public electric charging stations in the highly urbanized Western part of The Netherlands, being one of the front-runners on electric mobility.

Estimation results show that time-of-day-related variables and the type of charging station have the most substantial effect on the duration of the connection to the charging station. More specifically, results show that –especially for level 2 charging stations (up to 11 kW)– connection duration is very much aligned with parking behavior and preferences: due to the lower charging speed at these stations, EV-drivers tend to leave their vehicle parked at a charging station for a longer time while they are (for example) at work or sleeping. Results even show that a significant proportion of the charging sessions last longer than one day, keeping charging stations occupied for almost 30% of the time in total. Especially for those drivers that do not have a private parking spot and depend on curbside parking, level 2 charging stations are vital to serve daily recharging (and parking) needs. Fast charging stations tend to serve a different purpose as behavior at such stations is more like regular refueling behavior, with short connection times aimed at the ability to complete the intended trip. Technology advancements allowing higher charging speeds are therefore also more likely to result in shorter connection times at these types of stations compared to level 2 stations, where behavior coincides with parking.

Our results also suggest that policy makers should be aware that simply providing areal coverage with charging stations will not necessarily meet charging demand in every area. That is because the type of dwelling also determines the connection duration and also the timing of the charging session. Areas with mostly one type of dwelling are expected to experience peak demand, while mixed neighborhoods could well serve different users with less charging stations due to variation in demand over time. Results also suggest that further investigation is needed into how different type of users such as car sharing vehicles, taxis and visitors can make use of charging stations by home owners. These different user types have different connection times at charging stations, implying that installing curb sides chargers could serve multiple types of users at the same time with limited interference.

Our results may assist policy makers and planners in their attempts to predict demand for charging stations and to adjust accordingly the number and type of chargers in certain neighborhoods, or implement policies to increase efficiency at charging stations such as time-based fees. Furthermore, our research shows that future research looking into combining insights from the scholarly literature into parking with insights into connection times at level 2 charging stations has the potential to offer better insights in the quite particular kinds of new parking and EV-charging behaviors at these stations. Combining the right parking policies with EV charging could prove to be difficult. Especially with the growing battery sizes of vehicles, cars may possibly not fully refill if parking times are limited. On the other hand our analyses show that a significant amount of sessions last longer than 24 hours, keeping valuable charging sports unnecessarily occupied. To design the right policies to tackle this problem, policy makers also need to combine insights from both the charging and parking literatures. In contrast, we show that fast charging stations serve a different type of demand. A promising line of research would be to explore whether technological advances would allow shorter recharging times, if fewer of these stations could serve the needs of those that depend on curbside parking, resulting in a smaller loss of public space.

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