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One charging station is not the other: spatial-temporal analysis of public charging stations

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Executive Summary

The lack of public charging infrastructure still remains an important barrier for many potential EV drivers. With more people driving EVs, data on their charging transactions can help urban planners to improve the future charging infrastructure. In this paper we demonstrate how this data can be used to understand the temporal charging behavior at existing charging points (CPs), as well as to explain where to expect which type of charging behavior. Based on real-world charging session data from 392 public charging points (CPs) in the Brussels Capital Region, we find that CPs can be classified into four behavioral clusters based on their connection profile. Furthermore, we find that spatial variables describing the land-use, socio-economic and mobility related factors of the CP's location significantly correlate to its temporal behavior. These results can be used for urban planners that seek a data-driven expansion of their public charging infrastructure.

Keywords: charging, infrastructure, clustering, user behavior

1 Introduction

To improve local air quality and reduce the impact of climate change, many regions have implemented policies to ban the sale of petrol and diesel vehicles over the coming decade(s) [1]. The feasibility of achieving these goals will largely depend on the mass adoption of Electric Vehicles (EVs). However, three main barriers have been identified that hinder the transition from Internal Combustion Engine Vehicles (ICEVs) to EVs, being the limited driving range, the high purchase price and the lack of Charging Infrastructure (CI). While technological advancements and the decreasing cost of battery packs are mitigating the former two barriers [2, 3], the general lack of CI still remains an important hurdle for the transition towards EVs. Installing sufficient public CI is of significant importance, especially in densely populated urban areas, where many people are living in multi-dwelling houses and have no access to private home charging [4].

As installing public CI requires significant resources [5], it is of utmost importance that urban planners carefully consider where to install which type of charging infrastructure. In this paper, we demonstrate how historical charging data can be used to help urban planners answer these questions. First, based on a real-world charging dataset from 392 public charging points (CPs) in the Brussels Capital Region, we use clustering analysis to cluster CPs according to their temporal charging behavior. Second, these clusters are explained in a regression model using spatial variables that describe the land-use, socio-economic and mobility related factors of the CP's location. Descriptive statistics on the first-stage clustering results reveal the underlying behavior, while the results from the second-stage regression model inform planners on where to expect which type of charging behavior.

The remaining of the paper is organized as follows. Section 2 discusses what research has already been done on this topic and how our work relates to this. In section 3 and 4, the data and methodology of this study are respectively described. Finally, the results together with a discussion are presented section 5, followed by the conclusions in section 6.

2 Literature review

Existing research has focused on charging behavior in various ways. One line of research that utilizes survey data has revealed the charging preference for different charger locations and -types [6, 7]. Lee, et al. [6] conduct a survey on EV drivers in California to reveal their choice of charging location, after which they use regression modelling to explain the location choice. Their results show that most EV drivers rely solely on home charging, and that the choice of charging location is furthermore influenced by a range of factors, including socio-demographics, vehicle attributes, travel behavior, electricity cost at home, and the accessibility of workplace and home charging. Anderson, et al. [7] analyze charging behavior based on a survey of German EV drivers. Similar as in [6], the authors found home charging to be the most occurring type of charging, and that in general insufficient public charging infrastructure is found near the end destination of the EV driver.

Another line of research studies charging behavior from historical charging session data. These datasets typically originate from one specific type of infrastructure, with the majority being public AC charging stations. Two research directions in the literature can be identified. On the one hand, studies that focus on supervised methods and use the charging data as a labeled dataset to predict EV charging demand [8-11]. This is done by relating the observed charging demand (measured either in kWh or connection time) with variables that describe the near surrounding of the charging station. These studies have shown that charging demand is related to a multitude of surrounding factors, including: EV adoption [8], socio-demographics (with income and housing type as main drivers) [9], parking behavior [10] and Points-of-Interest (POI) [11].

On the other hand, research has used unsupervised methods combined with historical charging data to identify patterns of charging behavior. The strategy of clustering is used to group together CPs with similar charging behavior into groups called 'clusters'. Xydas, et al. [12] have used K-means to cluster CPs based on their 24 one-hour power intervals, and find (depending on the use case) 3-6 clusters. Related to this, Friese, et al. [13] use agglomerative clustering based on each CP's 144 ten-minute connection intervals. This results in four clusters of charging stations have been found, labeled as *nighttime*, *daytime*, *evening*, and *late morning*.

Based on the existing literature it is clear that charging behavior has already been analyzed from different perspectives, based on either surveys or charging session data. However, less is known on the spatial factors that explain why certain behavior is observed at certain locations. A limited analysis is given only by Friese, et al. [13] who use a random forest classification model to predict charging behavior from socio-demographic predictors. However, no statistical analysis is given on the significance of the variables included, and they furthermore neglect other relevant factors such land-use and mobility variables. In this study, we bridge this gap in the literature by first clustering CPs based on their observed temporal charging behavior, after which we identify the land-use, socio-economic and mobility related factors explaining this behavior.

3 Data

The charging dataset used for clustering CPs is described in section 3.1, followed by a description of the predictor dataset used in the regression model in section 3.2.

3.1 Charging dataset

This study uses a dataset of charging sessions at level 2 public CPs located in the Brussels Capital Region (referred to as Brussels). Only data from the last 12 months (Dec. 2021 – Nov. 2022), and recorded on weekdays is used. This because charging behavior can change significantly between weekdays and weekends [14]. After removing charging sessions with missing or illegal values, and all CPs that were installed after December 1st, 2021 (so as to only include only CPs that were active during the full period of observation), the dataset includes a total of 392 charging points, distributed over 197 charging stations[1]. We study the temporal charging behavior of CPs by analyzing their mean half-hour connection bins over the period of observation (referred to as their *usage*- or *connection profile*). The connection profile of each CP is calculated in two main steps, as is illustrated in Figure 1. First, based on each charging session's start- and end datetime, the dataset is converted into half hour connection bins. For each bin, the connection time is calculated as the proportion of time that the session was active within this bin (which is ≤ 1 for the bin in which the session started and/or ended, and $= 1$ for all bins in between). For all time bins where the CP was not in use, the connection is set equal to 0. Second, for each CP and for each time bin, the overall mean connection is calculated. This results in a final dataset that has 392 observations (i.e., CPs) and 48 features (i.e., half hour time bins).

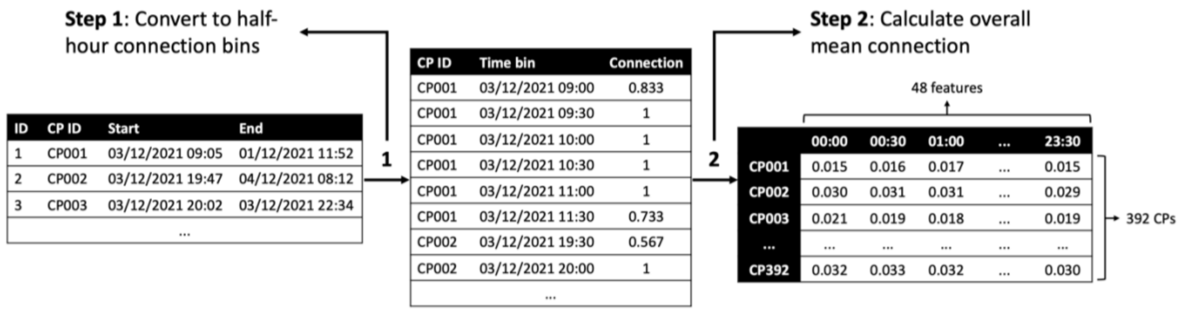


Figure 1: Overview of data manipulations.

As the purpose of this study is to classify CPs based on their temporal charging behavior, all connection bins are furthermore normalized so that all bins from the same CP sum up to one. This means that the connection profiles only reflects the CP's relative temporal usage, and not its absolute 'popularity' (i.e., high vs. low utilization). Before entering the clustering model, the connection profiles of all CPs are smoothed with a Gaussian filter of 1 standard deviation, which is recommended when clustering usage profiles [15].

3.2 Predictor dataset

In the second stage, explanatory variables are collected that measure the near surrounding of each CP in terms of its land-use, socio-economics, and mobility characteristics. An overview of these variables is given in Table 1. The spatial level of detail at which the variables are gathered is given in the column 'spatial granularity'. As each CP has a specific location, the explanatory variables need to be spatially mapped with the CPs coordinates. The columns 'geometry' and 'CP mapping' respectively indicate the geometry type and associated mapping strategy of each variable. The '*buffer zone'* strategy means that a circular buffer zone of radius r is constructed around each CP, and that the values of variables are calculated based on the intersection of the variable's geometry with the buffer polygon (see Figure 2 for an example). A radius of $r = 300$ meters is chosen based on previous research [8]. The '*exact mapping*' strategy means that the values of variables are determined by a one-to-one match between the CP's coordinates and the variable's geometry. For instance, to determine the parking demand per CP, the parking demand at the exact location where the CP is located is taken. All spatial mapping is implemented in Python using the *GeoPandas* package. Finally, in order to mitigate the impact of outliers and skewed distributions, transformations are applied to some variables as indicated by the 'Transformations' column. This is done based on a visual inspection of the variable's distribution. Before entering the regression model, all variables are furthermore standardized to improve comparability across coefficients.

[1] Every charging station has two charging points, however, two stations were found where sufficient data was only available for one CP.

Table 1: Overview of the second stage predictor variables.

Variable	Description	Spatial granularity[+]	Geometry	CP mapping	Transformation[*]	Source
Land-use						
Population density	The number of residents per km^2.	Statistical sector	Polygon	Buffer zone	-	Statbel, 2020
On-street parking demand at night	The occupancy rate of the on-street parking places between 5-7am and 8-10pm.	Street side	Line	Exact mapping	Truncate outliers, Log transform	Brussels mobility, 2018
On-street parking demand at day	The occupancy rate of the on-street parking places between 10am-12pm and 3-5pm.	Street segment	Line	Exact mapping	Truncate outliers, Log transform	Brussels mobility, 2018
Off-street parking	The number of off-street parking places used for housing.	Building block	Polygon	Buffer zone	Log transform	Brussels mobility, n.d.
Residential area	The percentage of area that is classified as '(highly-) residential' according to the administrative land-use plan.	Building block	Polygon	Buffer zone	-	Brussels perspective, 2018
CBD area	The percentage of area that is classified as 'central business district' according to the administrative land-use plan.	Building block	Polygon	Buffer zone	Log transform	Brussels perspective, 2018
POI count	The count of Points-of-Interest.	Exact	Point	Buffer zone	Log transform	Open Street Maps, 2023
Socio-economic						
Income	The median income in euro of the residents.	Statistical sector	Polygon	Buffer zone	-	Statbel, 2019
Education	The percentage of residents with a higher education.	Statistical sector	Polygon	Buffer zone	-	Statbel, 2017
House owners	The percentage of residents living in owned dwellings.	Statistical sector	Polygon	Buffer zone	-	Statbel, 2017
Household size	The number of persons per household.	Statistical sector	Polygon	Buffer zone	-	Statbel, 2016
Males	The percentage of male residents.	Statistical sector	Polygon	Buffer zone	-	Statbel, 2020
Foreigners	The percentage of non-Belgian nationality residents.	Statistical sector	Polygon	Buffer zone	-	Statbel, 2020
Age	The median age of the residents.	Statistical sector	Polygon	Buffer zone	-	Statbel, 2020
Mobility						
Salary cars	The number of salary registered to the residents.	Statistical sector	Polygon	Buffer zone	-	Statbel, 2020
Incoming commuters	The number of incoming commuters from the Census survey.	Statistical sector	Polygon	Buffer zone	Log transform	Statbel, 2011
Incoming movements	The total sum of all trips that end in a region, based on cell phone data.	Traffic analysis zones	Polygon	Buffer zone	Log transform	Proximus, 2019

[*] *If the variable contains at least one zero value, the log transform was applied as* $\log(x+1)$.
[+] *Brussels has an area of 161.38 km^2. The mean spatial level of details are as follows: Statistical sector: +/- 0.22 km^2; Building block: 0.03 km^2; Traffic analysis zone: 0.18 km^2*

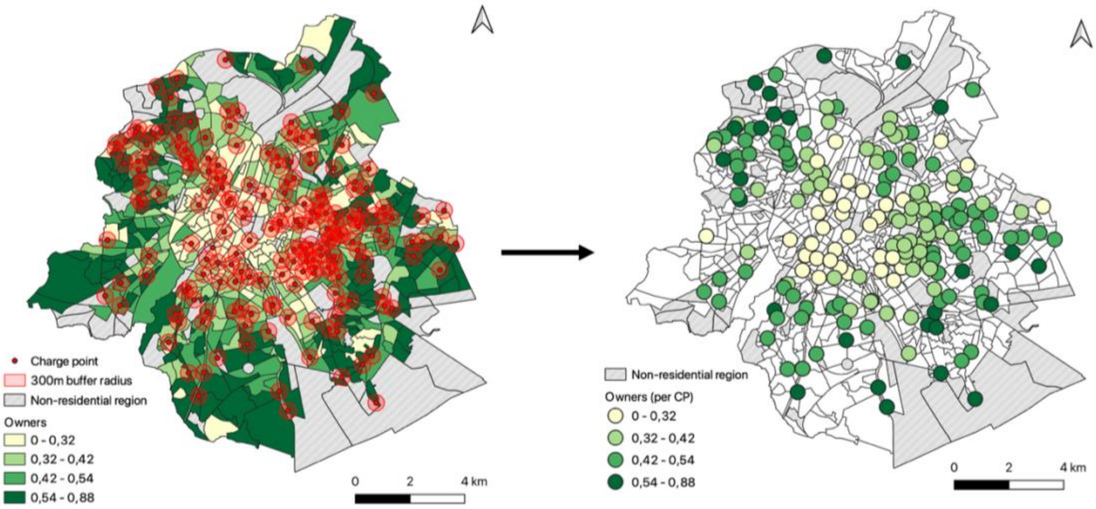


Figure 2: Example of 'buffer zone' strategy for the variable 'House owners'.

4 Methodology

First, the temporal analysis to cluster the connection profiles is described in section 4.1, followed by the spatial analysis to identify the factors explaining the connection profile in section 4.2.

4.1 Temporal: Clustering connection profiles

In this paper we use K-means clustering to identify clusters of CPs that have a similar connection profile. K-means clustering is an unsupervised learning method that iteratively groups together observations by minimizing the distance between observations of the same cluster [16]. That is, observations are assigned to clusters by minimizing the total within-cluster sum of squared distances (WSS):

$$WSS = \sum_{k \in K} \sum_{\boldsymbol{x}_i \in C_k} (\boldsymbol{x}_i - \boldsymbol{\mu}_k)^2 \tag{1}$$

where K is the number clusters, $\boldsymbol{x}_i$ is the ith observation belonging to cluster C_k, and $\boldsymbol{\mu}_k$ is the mean of C_k, defined as the centroid of cluster k. One difficulty of K-means clustering is that the number of clusters K needs to be chosen a priori. Different methods are available to help determining its optimal value, such as the Elbow plot and Davies-Bouldin score. More information on these techniques can be found in [17, 18]. The clustering model is implemented in Python using *scikit-learn* package.

4.2 Spatial: Multinominal regression

Next, after all CPs are assigned to clusters based on their connection profile, a Multinominal Logit Model (MLM) is fitted to identify the factors driving the observed profile. This model is useful when the dependent variable is nominal and has more than two categories. MLM estimates the probability that a charging point i belongs to cluster k as:

$$\mathrm{p}_{ik} = \Pr(y_i = k | \boldsymbol{z}_i) = \frac{\exp{(\boldsymbol{z}_i' \boldsymbol{\beta}_k)}}{\sum_{k \in K} \exp{(\boldsymbol{z}_i' \boldsymbol{\beta}_k)}} \tag{2}$$

where $\boldsymbol{z}_i$ is the vector of land-use, socio-economic and mobility variables that explain the observed connection profile, y_i is the outcome variable that contains the cluster number, and $\boldsymbol{\beta}_k$ is the coefficient vector. However, equation (2) specifies one equation for each $k \in K$, of which only $K - 1$ can be determined [19]. This means that before running the MLM, a reference cluster has to be chosen for which $\boldsymbol{\beta}_k$ is set to 0. The estimated coefficients for the other clusters are expressed relative to the reference cluster. The Stata package *mlogit* is used to perform the regression analysis.

5 Results & discussion

5.1 Identifying usage patterns

Before running the K-means clustering model, the number of clusters needs to be chosen. The elbow plot (Figure 3) does not show an obvious sharp drop, although it seems that the inertia starts leveling off around 4 clusters. Looking at the Davies-Bouldin plot (Figure 4), it shows that the scores have a sharp increase after cluster 4, after which they become relatively constant. Based on these plots and the results from previous studies (between 3-6 clusters are found in [12, 13]), the number of clusters is chosen as $K = 4$.

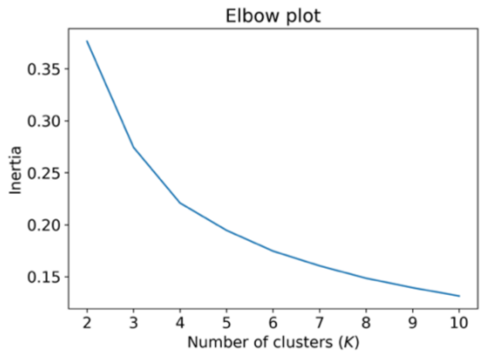


Figure 3: Elbow plot.

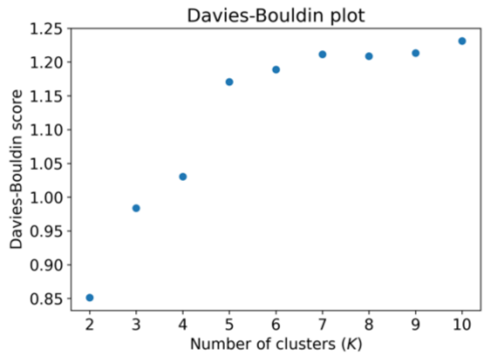


Figure 4: Davies-Bouldin plot.

The results of the K-means algorithm are given in Figure 5 to Figure 8 below. The thin lines on the figures show the individual connection profiles of the CPs belonging to that cluster, while the thick bold line shows the average of all individual profiles (referred to as the *usage*- or *connection pattern*). CPs in cluster 1 are mostly used during the daytime, with a first peak in the late morning and a second peak in the evening. Cluster 2 contains CPs that are used mostly during the nighttime, and less during the day. The CPs in cluster 3 are found to have a 'flat' connection profile, with a slight decrease during the morning and the late afternoon. This most likely reflects the time when most people start their trips. Finally, cluster 4 contains CPs that are used almost solely during business hours.

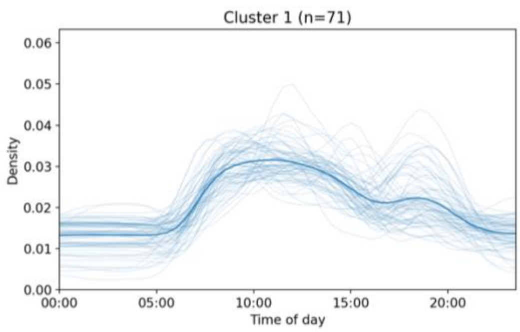


Figure 5: Business hours- and evening usage.

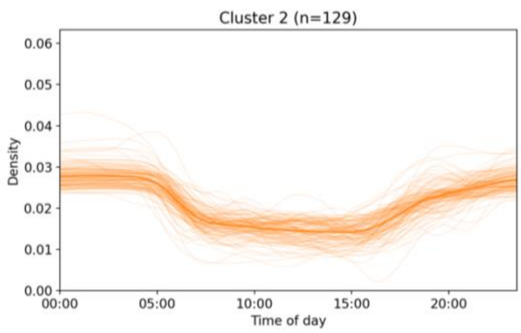


Figure 6: Night usage.

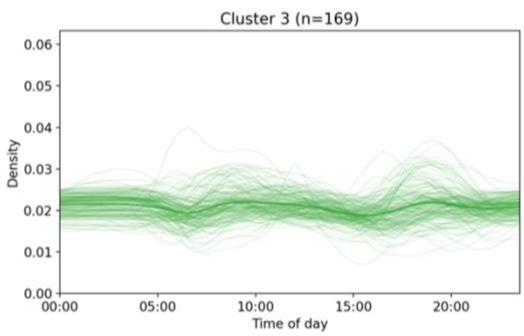


Figure 7: Equal day- and night usage.

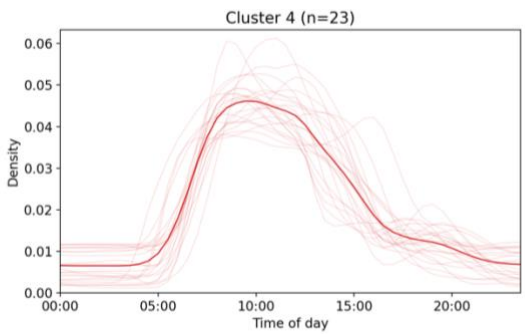


Figure 8: Business hours usage.

Descriptive statistics on the duration, volume, start hour and unique users are respectively given in Figure 9 to Figure 12. It is apparent that besides the different connection patterns observed between the clusters, the consumed energy volume per session is strikingly similar across all clusters. This lack of relationship between connection times and consumed energy has also been found by previous studies [10, 14] and indicates the mixed purpose of CPs to serve both a mobility demand as well as parking demand. In terms of duration and start hour, cluster 2 and cluster 4 are found as two 'extremes'. Cluster 2 is used most often for longer sessions that start in the evening, while cluster 4 is used for shorter sessions starting in the morning. From a user behavior perspective, this means that low-power CPs would most likely be able to suit the needs of EV drivers at cluster 2, while high-power CPs might better suit EV drivers at cluster 4. Clusters 1 and 3 are found to be hybrids of these extremes. Finally, looking at the unique users observed per CP, cluster 2 clearly stands out as having less unique visitors compared to the others. This might be explained by the fact that CPs in this cluster are typically used by the same set of EV drivers, that most likely live nearby the CP and use it to charge their vehicle overnight [10].

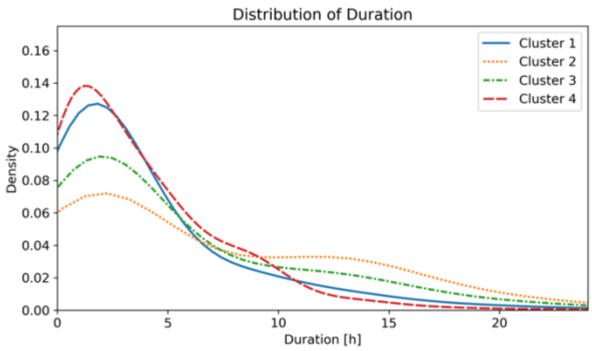


Figure 9: Distribution of duration per session.

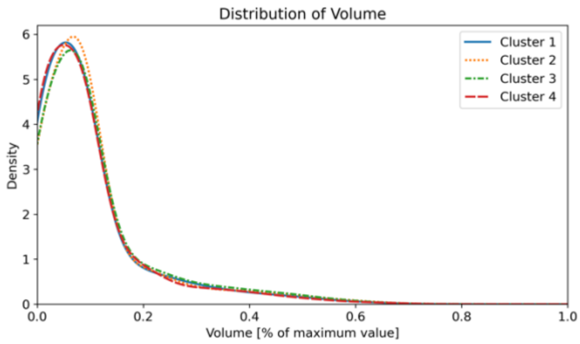


Figure 10: Distribution of volume per session.[2]

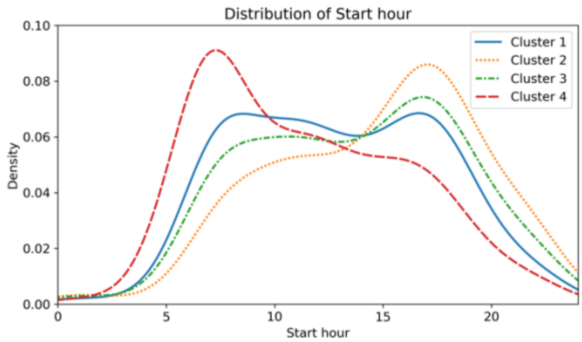


Figure 11: Distribution of start hour per session.

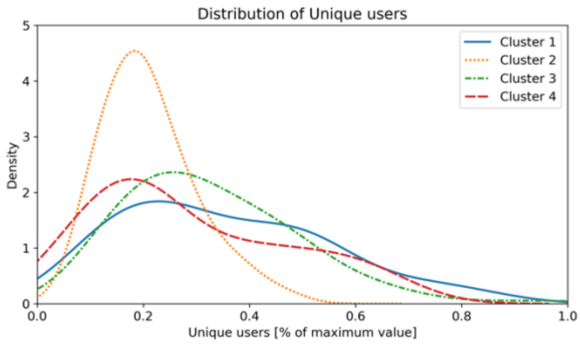


Figure 12: Distribution of unique users per CP.[2]

5.2 Explaining usage patterns

Regression results are given in Table 2. Since cluster 3 (equal usage over day and night) has an overall flat connection pattern, it is used as the reference category, and thus no estimates are given for this cluster. The coefficient estimates of the other clusters reflect the likelihood of belonging to this cluster relative to the reference cluster. To ensure that multicollinearity does not affect the outcome, the variance influence factor (VIF) of each predictor has been calculated. This resulted in omitting the variables income and education as their VIF score was larger than 5.

Regarding cluster 1 (higher usage during business hours and evening), it are mostly the population density and socio-economic variables that explain the presence of this behavior type. This connection pattern is more likely to occur in areas with a lower proportion of home owners, a higher mean household size and a higher proportion of foreigners. Interestingly, all these factors have been found to be negatively associated with EV

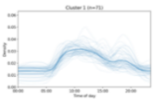
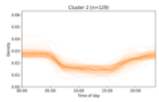
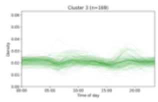
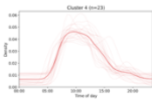
[2] To preserve the confidentiality of the data, the x-axis is rescaled between 0 and 1.

adoption by previous studies [20, 21]. This may indicate that a higher CP usage during business hours and evening is more likely to occur in regions with less EV adoption. Population density has a significant negative effect on the likelihood of this cluster.

Looking at cluster 2 (higher usage during the night), its presence can be explained by all mobility variables and some land-use variables. Estimations show that a higher number of salary cars, lower number of incoming commuters and lower number of incoming movements are associated with nighttime CP usage. This seems to characterize mostly residential areas with higher levels of EV adoption, as salary vehicles are more likely to be electric given their tax deductibility [22]. Areas with a higher population density and less off-street parking places also have a significant positive impact on a nighttime connection pattern. This characterizes areas where people are less likely to have home charging available.

Finally, cluster 4 (higher usage during business hours) is mostly explained by land-use characteristics of the surrounding area. The parking behavior observed at the location of the CP seems to be an important indicator, with higher on-street parking demand during the day and lower demand during the night being positively associated with this pattern. This makes sense as the CPs in this cluster are almost solely being used during the day. The presence of a Central Business District (CBD) nearby, a lower population density, and, surprisingly, a lower POI count increase the likelihood of observing this cluster. While the former two factors indicate that this pattern occurs more in business areas with less residents, the negative effect of the POI variable is unexpected. One may expect that more POIs to visit nearby, would result in a higher likelihood of cluster 4 since this cluster mainly includes shorter sessions during the day. A potential reason for the negative coefficient could be the large variety of categories included in the POI variable, ranging from categories that relate to short-term visits (i.e., shopping) and long-term visits (i.e., accommodation). Finally, higher household sizes, a higher proportion of males and less salary cars have increase the probability of this cluster.

Table 2: Multinominal Logit Model results.

	 Cluster 1 Business hours- and evening usage	 Cluster 2 Night usage	 Cluster 3 Equal day- and night usage	 Cluster 4 Business hours usage
Land-use				
Population density	**-0.599***	**0.867***		-1.047
On-street parking demand at night	-0.069	0.459		**-3.275***
On-street parking demand at day	-0.283	-0.362		**2.578***
Off-street parking	-0.151	**-0.487***		-0.223
Residential area	-0.108	0.210		-0.311
CBD area	0.228	-0.043		**1.901***
POI count	-0.303	-0.298		**-1.929***
Socio-economic				
House owners	**-0.710***	0.492		0.104
Household size	**1.087***	-0.261		**2.314***
Males	0.200	-0.281		**3.174***
Foreigners	**0.804***	0.253		0.837
Age	0.321	-0.236		1.309
Mobility				
Salary cars	-0.107	**0.425***		**-3.026***
Incoming commuters	0.030	**-0.973***		-0.369
Incoming movements	-0.007	**-0.620***		-0.615
Intercept	**-1.158***	**-0.934***		**-9.396***
Observations	392			
Chi2-test	280.74			
Pseudo R^2	0.30			

*Note: coefficients in bold and marked with * are found significant at the 0.05 level.*

6 Conclusion

In this study we demonstrated how analyzing charging session data can guide urban planners in the development of new charging infrastructure. First, K-means clustering was used to identify distinct connection patterns. Four clusters of CPs were identified, which range from the one extreme of being used almost solely at night for longer sessions to the other extreme of being used during the day for shorter sessions. While the clusters have different start time and duration distributions, the consumed volume is surprisingly similar across all clusters. This might indicate the intertwined usage of CPs for both parking and mobility, and the need for different types of charging infrastructure. CPs in cluster 2 (night usage) could meet user needs with lower power levels compared to CPs in cluster 4 (business-hour usage).

Second, in a Multinominal Logistic regression model, the cluster of each CP is explained based on the CPs location as characterized by its land-use, socio-economic and mobility variables. The model shows that all categories of variables possess explanatory power on the connection pattern of the CP. Nighttime usage was mainly explained by mobility related variables, business-hour usage by land-use variables and the hybrid cluster (business-hours and evening usage) by the socio-economic variables. When deciding on where to install new chargers, urban planners should consider all these variables to predict which connection pattern is most likely to occur, and thereupon which type of charger is most suitable for this location.

Finally, this research has some limitations. First, we used K-means clustering as it is a powerful and straightforward method, often used for unsupervised modelling. However, it might be that other more advanced clustering methods are better suited, possibly resulting in a different number of optimal clusters. Second, our study limits to analyzing the weekday connection patterns of CPs. An interesting approach for future research would be to also analyze how weekend behavior is different from weekdays.

Acknowledgments

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Presenter Biography

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