Revealing hidden patterns in transactional charging data: new insights from public charging stations in Brussels and San Francisco

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SHORT SUMMARY

The transition towards Electric Vehicles (EVs) has led many cities to develop networks of public charging stations. As a result, the observed charging data at these stations constitutes a valuable input to model charging demand. However, existing research that utilizes this data often relies on simple descriptive statistics (e.g. energy consumption or charging duration) that fail to capture the complex charging behaviour of EV drivers. In this study, we analyse two real-world charging datasets from Brussels and San Francisco and show how hidden behavioural patterns can be found. Our results indicate that groups of stations exist that are frequently visited by the same EV drivers. Furthermore, we are also able to reveal where these EV drivers divert when a preferred station is unavailable. Practitioners can use our methods to gain a better insight in how their infrastructure is used, and to more accurately determine where additional infrastructure is needed.

Keywords: Electric vehicles, Charging infrastructure, Location modelling, Data Analytics

1. INTRODUCTION

Electric Vehicles (EVs) have a great protentional to improve local air quality and reduce the pollution of greenhouse gases (Van Mierlo, Messagie, & Rangaraju, 2017). This has led many cities to set targets on the emission standards of passenger cars and to restrict access for combustion engine vehicles. In addition, both the European Parliament and California have voted on new legislation to fully ban the sale of gas-powered cars by 2035. The resulting transition to EVs will require significant investments in Charging Infrastructure in the coming decade. Having sufficient chargers available in the public domain is of considerable importance, especially to convince car owners without access to private home charging to adopt EVs (Hardman et al., 2018). Policymakers and urban planners should thus carefully consider how to optimally manage their network of public chargers, and how this network should be upgraded over time.

In this sense, transactional charging data on the existing network of public chargers can constitute a valuable input. However, determining how this data can be used to model charging demand is not straightforward. First, observed charging data is inherently biased due to the limited supply capacity of each charging station (Hüttel, Rodrigues, & Pereira, 2023). A charging station that is for instance equipped with two plugs is limited to observe at most two vehicles charging simultaneously, while the true demand might be higher. Based on GPS trajectories from gas-powered cars in Copenhagen, Hüttel et al. (2023) found that this type of censorship occurs up to 61% of the time in some areas. Second, existing research that uses observed charging data has modelled charging demand based on descriptives that relate to *when* (Wolbertus, Kroesen, van den Hoed, & Chorus, 2018) and/ or *where* (Straka et al., 2020) the charging occurred. However, few studies have also looked at *who* conducted the charging. Comparing charging transactions stemming from the same EV driver could result in new insights into how the charging network is currently used.

The goal of this study is to demonstrate how charging demand can be accurately modelled from transactional charging data. To achieve this, we utilize the concepts of *charging zones* (i.e., groups of stations that are all visited by the same EV drivers) and *overflow dynamics* (i.e., where EV drivers divert when a preferred station is unavailable) and apply them on to two real-world datasets from Brussels and San Francisco. By comparing the results between two cities with a different charging location policy, we furthermore discuss the transferability of our methods.

2. METHODOLOGY

This study uses two real-world datasets of charging transactions measured at public charging stations in Brussels (BRU) and San Francisco (SFO). Besides the start time, end time, and energy consumption, each session also has the unique ID of the charging station and the EV driver (based on the card that was used for payment) available. We suggest two methods that practitioners can use to analyse transactional charging data: (1) finding charging zones, and (2) finding overflow dynamics. These have been initially proposed by Weekx, Tal, and Vanhaverbeke (2023), and are briefly summarized here below. We refer the reader to this work for more details on their methodology.

Charging zones

Charging zones are groups of one or more charging stations that are located near each other and are used by a common group of EV drivers. The search procedure of finding charging zones consists of two steps as shown in Figure 1. In step one, the charging network is represented as a graph, with the nodes indicating the charging stations and the edges indicating whether the two stations are within $t_{\max}$ walking time of each other. Within this graph, we find all maximal cliques (i.e., largest groups of stations that are all pairwise connected with edges), which are the candidate zones. In step two, we iterate over each candidate zone and search in the charging data whether at least $EV_{\min}$ EV drivers can be found that visited all stations in the zone (= Support). If this is the case, the candidate zone is a charging zone. If not, the process is repeated for all subzones of the candidate zone.

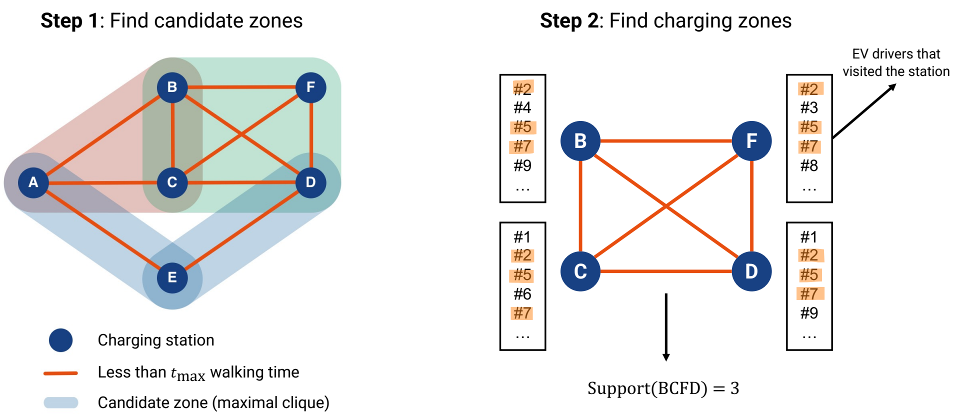

Figure 1: Method to find charging zones.

Overflow dynamics

Overflow dynamics indicate to which charging station(s) EV drivers divert when a preferred station is not available. They are found by analysing the dataset of charging transactions in 5 steps. First, all unique charging stations in the dataset are listed. Second, for each charging station, we identify all EV drivers that have this station as their favourite (i.e., most visited) from the total set of stations in any of the charging zones that this station belongs to. Third, for each EV driver, we list out all the charging sessions that this driver conducted at any of the stations in the same charging zone other than the favourite. Fourth, we determine whether two minutes before the start time of these sessions, the favourite station was occupied. If so, this might be evidence that the EV driver used another station than the favourite *because* the favourite was unavailable. Finally, in the fifth step, we verify this statistically by calculating the probability of observing this proportion of sessions where the favourite station is occupied due to random chance, given the utilization rates of each station (which can be calculated from the charging data). If this probability is less than 5%, we label the sessions as overflow.

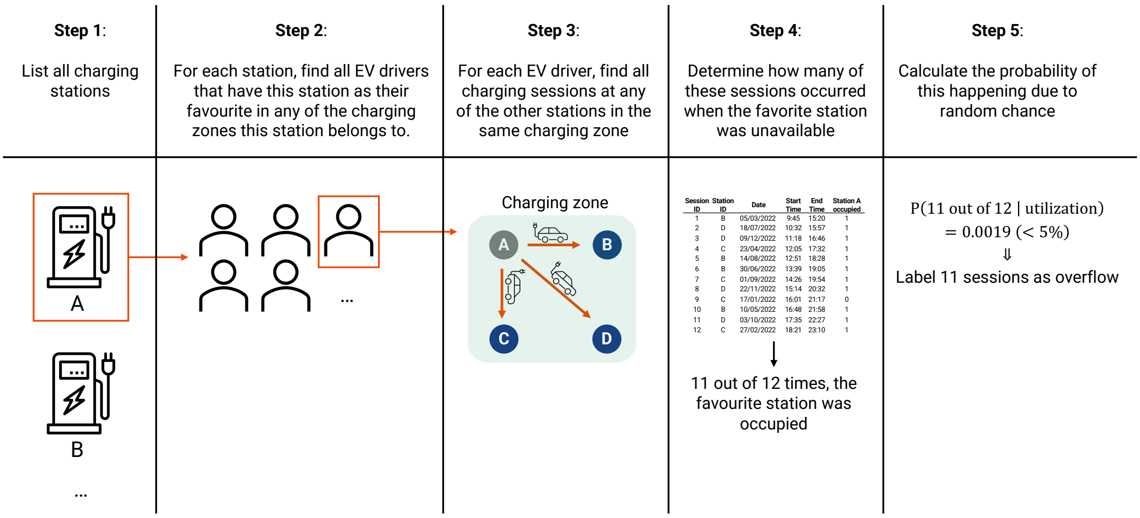

Figure 2: Steps for identifying overflow sessions.

3. RESULTS AND DISCUSSION

Dataset

The BRU dataset contains 197 level-2 charging stations, each equipped with 2 plugs. Each station is located on-street (see Figure 3) and at a unique location. The SFO dataset contains 53 charging stations (out of which 3 are level-1, and the others level-2), equipped with either 1 or 2 plugs. Each station is located in a parking garage (see Figure 4) owned by the San Francisco Municipal Transportation Agency (SFMTA, 2024). The dataset includes 16 garages in total, with each garage hosting between 1 and 9 charging stations. Both datasets include one full year of charging session. After data cleaning the most recent period available for BRU is Dec. 1st, 2021 – Nov. 30th, 2022, while for SFO this is from Jan. 1st – Dec. 31st, 2021.

Figure 3: Example of a public charging station in BRU (source: Belga).

Figure 4: Example of a public charging station in SFO (source: PlugShare).

Charging zones

Table 1: Summary statistics on charging zones.

	BRU	SFO
Number of zones	413	14
1-station	2.1%	21.4%
2-stations	40.0%	42.9%
3-stations	49.2%	35.7%
4-stations	8.5%	0%
5-stations	0.2%	0%

Figure 5 and Figure 6 show the charging zones found in BRU and SFO respectively, and summary statistics can be found Table 1. All stations within a zone are located within at most 15 minutes of walking time ($= t_{\max}$) of each other and have at least 4 EV drivers ($= EV_{\min}$) in common that visited all the stations. Charging stations located in the same zone serve the same group of EV drivers, and as such could be considered as one large station from the EV driver's point of view. This can provide new insights to practitioners complementary to commonly used statistics of popularity such as the utilization rate or consumed energy (Straka et al., 2020). When determining which stations require additional capacity (based on e.g. popularity indices), the charging zones allow us to have a more detailed view of which other stations are also visited by the same EV drivers and whether alternative stations to divert exist.

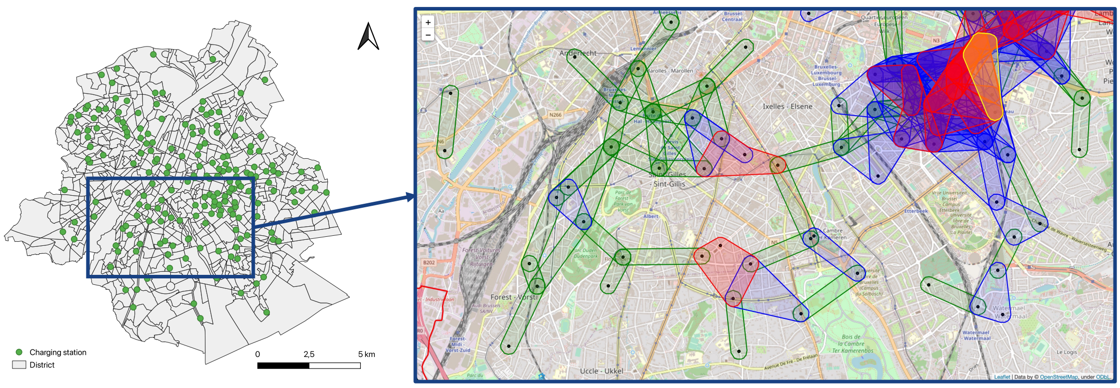

Figure 5: Charging zones in Brussels.

Within BRU, 413 charging zones are found of sizes between one and five stations. We furthermore find that in areas with a high density of charging stations (such as in the upper right corner of Figure 5), many partially overlapping zones occur. This reflects the many combinations of charging stations that are used by partially overlapping groups of EV drivers. Within the SFO charging network, only 14 charging zones between one and three stations large are found. However, it should be noted that the charging stations in SFO are grouped within a discrete set of parking garages, which is completely different to the on-street policy in BRU. As a result, zones can only be found when the parking garages are located close enough to each other.

Figure 6: Charging zones in San Francisco.

Overflow dynamics

Identifying overflow sessions allows for a more detailed understanding of the relationship between stations that belong to the same charging zone. Figure 7 to Figure 10 below show the overflow plots for different charging zones in BRU and SFO. The nodes represent charging stations (with the size proportional to the station's charging activity) and the arcs the number of overflow sessions found between them. Overflow always originates at the node with the same colour. For instance, in Figure 7, 134 charging sessions were identified that took place at charging station D because station C (i.e., the preferred station for these sessions) was occupied.

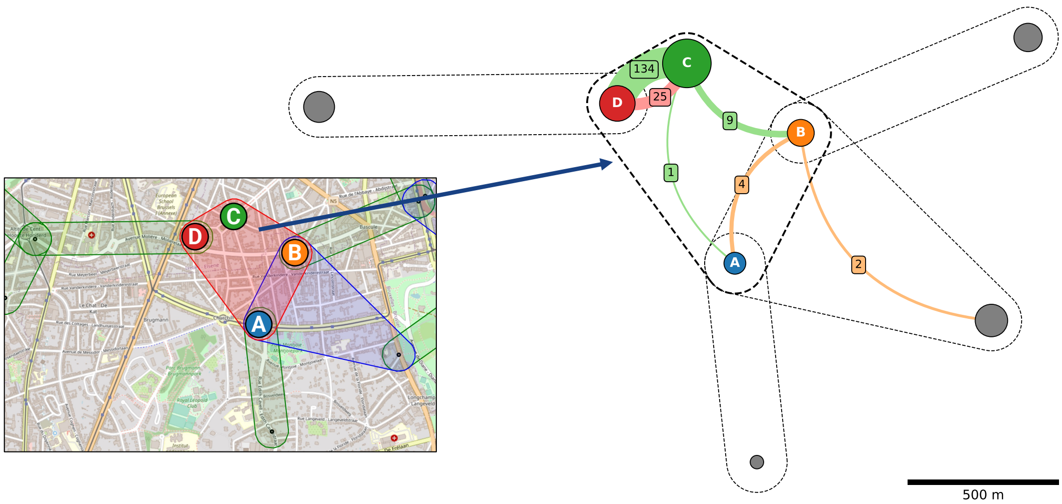

Figure 7: Overflow plot in BRU for a charging zone in a low-density area.

Figure 7 and Figure 8 demonstrate the overflow plots in BRU in a low- and high-density area respectively. In the high-density area, EV drivers have more options to divert when a preferred station is occupied, and more overflow sessions are found. The plots can also provide more detail on where the actual demand is most likely to occur. In Figure 8 for instance, considerably more overflow occurs on the Eastern side of the station compared to the North-Western side. EV drivers may prefer the Eastern side as it may be located closer to their intended destination. Further analysis that considers the points of interest nearby could shed more light on this.

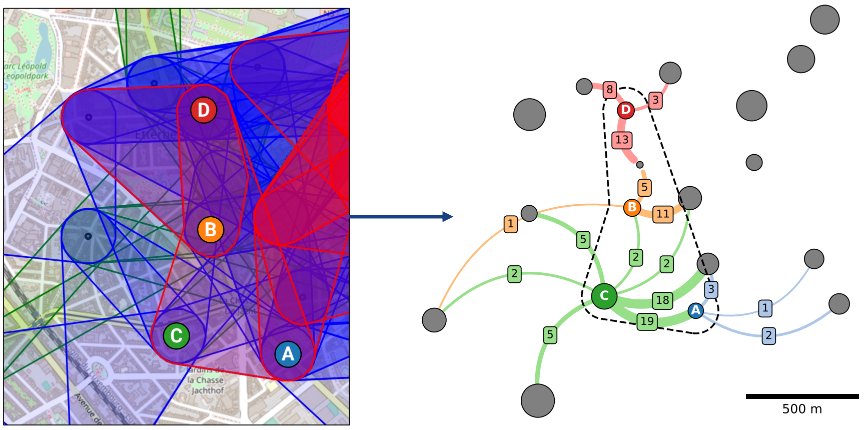

Figure 8: Overflow plot in BRU for a charging zone in a high-density area.

Figure 9 and Figure 10 demonstrate the overflow plots for one of the charging zones in SFO. Interestingly, given the garage configuration of the public charging network, overflow can be analysed both between different parking garages, as well as within the same garage. When looking at the between garage scenario (Figure 9), overflow was only found between stations A, B and C. It is also apparent that the overflow stemming from garage B and C is directed to garage A, while garage D is closer located. A possible explanation might be that garage D only has one plug available in its garage, while A has 16 plugs available, meaning that an EV driver is more likely to find an available plug in the further located garage A compared to D.

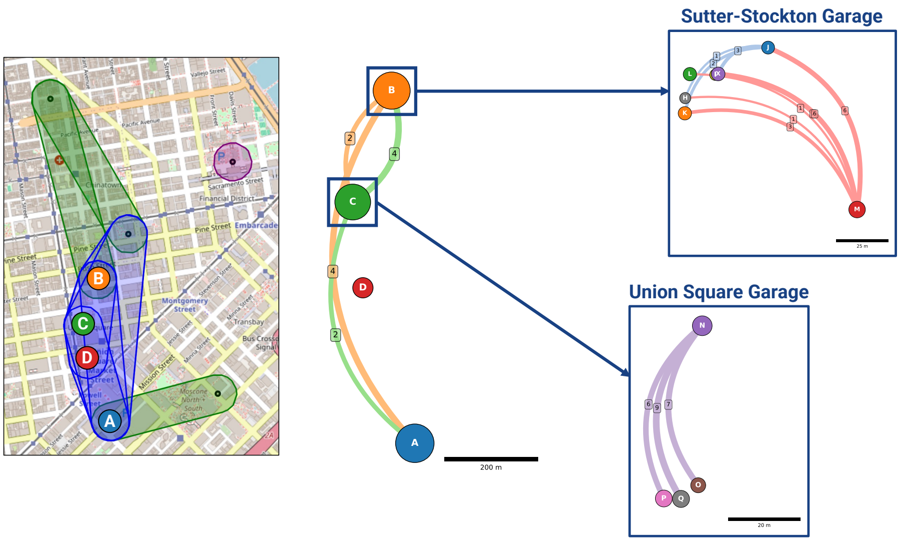

Figure 9: Overflow plot between and within parking garages in SFO.

The overflow dynamics within the same parking garage provide a more micro-level view of how the different stations are used (shown in Figure 10 and Figure 9). The same pattern is observed in all four garages with internal overflow: one or two ‘primary’ charging stations are found where EV drivers tend to charge most often. When this preferred station is occupied, overflow occurs to a ‘secondary’ station, with some being used more than others to capture overflow. Although it is difficult to determine from the dataset why certain stations are preferred over others, we found that in all four garages, the primary stations were always the newest charging stations installed. For instance, in the Sutter-Stockton Garage (Figure 9), two primary stations are found (M and J) which were both installed in 2020 and 2019, while all the secondary stations were installed between 2012 and 2013. The same applies to the San Francisco General Hospital Garage and the Union Square Garage. For the Civic Center Garage (Figure 10), 5 out of 9 stations were installed in 2019, out of which one was identified as a primary station. Potential reasons why the newer station is preferred might be their higher reliability.

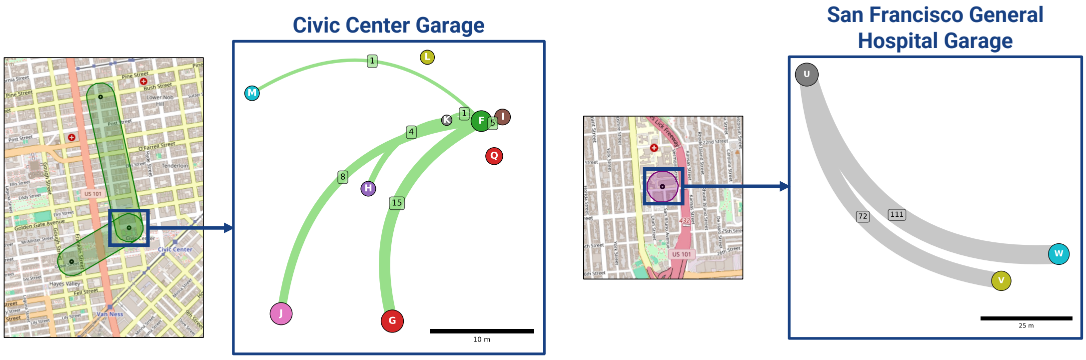

Figure 10: Overflow plot in SFO within two parking garages.

Comparing the overflow in BRU and SFO, it is apparent that considerably less overflow is found in SFO, as shown in Table 2. This can be explained by the garage configuration of SFO, which results in fewer unique locations where charging stations are located and thus less potential for interaction between locations. Besides, less charging activity was observed in the SFO dataset, which might be explained by the COVID-19 restrictions that were still in place in 2021. Table 2 also shows that, both for BRU and SFO, overflow sessions occur more often overnight compared to in the total dataset (65% more in BRU and 120% more in SFO). This might indicate that EV drivers who charge overnight are more willing to search for alternative stations nearby. The table also shows that the mean energy consumption of an overflow session is 30% higher compared to the total dataset in BRU, while it is 39% lower in SFO. For BRU, this might indicate that EV drivers who are willing to travel to the next available station do this because of a higher need for charging. For SFO, overflow often occurs between charging stations located in the same parking garage, and as shown above, this often means that the EV driver needs to use older infrastructure, which may be less reliable and as such result in less energy consumption. Further analysis on the reliability of the chargers could shed more light on this.

Table 2: Summary statistics on overflow dynamics.

	BRU	**SFO**
Number of overflow sessions	2,966	276
Factor change in share of overnight sessions	1.65	2.20
Factor change in mean energy consumption	1.30	0.61

Besides on the relationship between stations, overflow dynamics give insight in “censorship bias” as identified by Hüttel et al. (2023). When overflow sessions are found at a station, this is also evidence that the true demand for that station is higher than was observed in the transactional charging data. Inversely, this also means that the observed charging demand at some stations might be higher because of the presence of a more popular station nearby. Our work is the first explore these dynamics empirically from analysing charging transactions. Future work that uses charging data could use our method to measure the true demand for charging more accurately.

4. CONCLUSIONS

In this study, we demonstrate how transactional charging data can be analysed to find charging zones and overflow dynamics. We use two real-world datasets of charging transactions from public charging stations in Brussels and San Francisco. Although the charging location policy in both cities is completely different (only on-street stations in BRU vs. public parking garages in SFO), we find that charging zones and overflow dynamics are present in both. These give a more detailed view of which charging stations EV drivers prefer over others, where EV drivers divert to when a certain charger is occupied, and how the observed demand at a charging station may differ from its true underlying demand. Practitioners can use the concepts of charging zones and overflow when deciding where to install additional chargers, complementary to existing charging infrastructure popularity indices such as utilization and energy consumption.

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