A multi-faceted characterization of free-floating car sharing service usage

# A Multi-faceted Characterization of Free-Floating Car Sharing Service usage

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**Abstract**

During the last decade, car sharing systems appeared in many cities and gained popularity. The research community has analyzed their current utilization trends in different contexts, their growth perspectives, and their gradual shift towards more sustainable technologies. Through the large and heterogeneous amount of car sharing usage data that is now available, researchers have been able to gain new insights into these services. In this paper, we provide an extensive characterization of the Free-Floating Car Sharing (FFCS) service usage in 23 cities in Europe and North America over a 14-month period. From our data about FFCS services, we detail fleet size, operating area, and characteristics of the car bookings and rentals. We also identify temporal patterns that are peculiar to specific cities and countries. We further highlight urban zones with high attractiveness or with a high rental generation rate. Finally, we compare the systems relying on internal combustion engine cars with those based on electric vehicles in terms of various indicators, including the influence on car refueling. The results show that car utilization patterns are rather variable across cities with the highest per-car utilization rate in Madrid. The majority of the cities show negative or stable usage trends due to either the reduced appeal of the service or the presence of inefficiencies in the service provision. These data-driven insights may help system managers assess the provided services' profitability

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and sustainability from multiple perspectives.

*Keywords:* car sharing; electric cars; smart city; shared economy; data-driven analysis; clustering.

## 1. Introduction

In the last decade, car sharing has become a popular mobility solution in many cities. In the present paper, we focus on Free-Floating Car Sharing (FFCS) systems where users book a car, use it, and return it anywhere within a geo-fence area [36]. Unlike traditional car rental services, in a FFCS system car reservation, pickup, and return are all self-service. Cars are typically rented for short time periods and, at the end of the rental, they immediately become available to other users.

Since their birth in the early 2000s, FFCS services have rapidly increased in popularity. Currently, they are present in more than 40 cities [29]. Their emerging popularity has attracted the interest of the urban computing research field, which manages and analyzes mobility-related data acquired by a variety of sources such as sensors, Internet of Things devices, vehicles, buildings, and humans [35]. The increasing availability of mobility-related FFCS data has fostered research such as: (i) descriptions of the characteristics of FFCS services, (ii) identification of service usage patterns, (iii) observations of the spatial diffusion of the services, (iv) evaluations of the impact of different relocation strategies, and (v) explorations of the issues related to service profitability and sustainability. An in-depth overview of the related literature is given in Section 2.

**Current challenges.** Both academy and industry have recently expressed contrasting opinions on FFCS. On the one hand, they agree on the key role of FFCS in sustaining smart mobility in urban environments [5, 12, 26]. In particular, FFCS services that rely on electric fleets, such as those currently offered in Madrid, Stuttgart, and Amsterdam, contribute to the ongoing transition towards low-carbon emission mobility [30]. On the other hand, the recent financial losses posted by various service providers (e.g., [17]) have posed serious questions about the capability of FFCS to penetrate the market, as well as about their economic sustainability. In fact, the increasing operating costs due to service maintenance and the low daily revenue have prompted providers to shut down part of the services they offer [17]. These contrasting issues could foster further explorations of FFCS service usage and prospects of growth.

**Contributions.** This paper presents a multi-faceted analysis of FFCS service usage data aimed at supporting policymakers in shaping service provision. It analyzes real data acquired in 23 cities located in Europe and North America over a 14-month time period from December 2016 to January 2018. The aim is manifold. Firstly, we quantify the values of the key FFCS service properties (e.g., fleet size, operating area, booking types, rental duration) and evaluate their impact on service usage rate and profitability. The results show peculiar trends: for example, car density significantly varies from one city to another and the fleets in many USA cities are oversized according to their actual usage rate. Secondly, we analyze car rentals' evolution over time. In contrast with the five-year-old study presented by [28], which reported a rising trend in the adoption of car sharing solutions, the present paper shows a negative or stable usage trend in the majority of the cities analyzed. Thirdly, we compare the services that rely on internal combustion engine cars with those based on electric vehicles. In compliance with the recommendations provided by [33], our empirical evidence indicates that efficiently managing charge events is crucial for guaranteeing service sustainability and profitability.

To foster other data-driven analysis of FFCS service usage, the analyses' outcomes are made available through interactive dashboards and plots [16].

**Paper outline.** The rest of the paper is organized as follows. Section 2 overviews the related literature. Section 3 describes the data collection, whereas Section 4 presents a preliminary data characterization based on a selection of key FFCS usage descriptors. Section 5 and 6 deepen the data analysis by exploring the impact on the temporal and spatial dimensions, respectively. Section 7 compares the usage of FFCS services relying on electric and internal combustion engines. Finally, Section 8 draws conclusions and presents our future research agenda.

## 2. Related work

In recent years, the research community has paid increasing attention to FFCS services. For example, in [28] the authors have investigated the spatio-temporal factors that could influence car sharing demand. They analyzed car bookings acquired from November 2011 to September 2013 in two representative cities (i.e., Berlin and Munich) pointing out time intervals and areas with significantly higher booking rates. Our results extend their findings by characterizing the FFCS service usage in a larger number of cities (23) and in a more recent time period. A key difference is that the growing trends of FFCS observed from 2011 to 2013 have now stopped. Similarly, authors in [22] performed regression analyses on FFCS data collected in 2015 to understand the factors influencing the service growth rate. The results indicate that in specific cities, the services have already reached saturation. This trend is confirmed by the more recent evidence reported in our study.

Authors in [36] envisioned the future development of car sharing services from the perspective of policymakers and related stakeholders. The authors provided relevant insights into the future of car sharing markets in four countries (i.e., Australia, Malaysia, Indonesia, and Thailand), revealing that energy and vehicle prices have no statistically significant impact on service demand. Their empirical evidence has been partially confirmed by comparing the electric and internal combustion fleets in our work.

In [14, 24] the authors analyzed the characteristics of car sharing users and discovered different classes of users. The paths covered by FFCS vehicles have also been studied to identify the urban traffic patterns ([2, 28, 32]) and to predict the presence of available cars within a given urban area ([13, 15, 27]). Car movements appeared to be non-stationary and correlated with (i) the previous car movements within nearby areas, (ii) the weather conditions in the recent past, and (iii) the variations of the socio-demographic factors in the long run. Notably, the origin and the destination of trips have shown to be independent of the availability of public transports [2]. Unlike [13, 15, 27], this work is not aimed at predicting future service demand or FFCS flows, but rather to characterize and explain the current usage trends.

Further research works have presented case studies tailored to specific contexts. For example, in [4] the authors used spatial regression and conditional logic to analyze FFCS demand in Switzerland. Differently from [2], the research shows that in Switzerland, free-floating car sharing systems are mainly used for trips for which only substantially inferior public transportation alternatives are available. The work in [7] analyzed travel behaviour and vehicle ownership among car sharing members versus non-members in the San Francisco Bay Area. The aforesaid analysis has indicated that not only urban car sharing members are likely to own fewer vehicles than the rest of the population, but if they do, they usually own a vehicle with a smaller environmental footprint. Similarly in Europe, the authors of [19] showed how each FFCS car can replace up to 20 private cars. In our previous work [1], we analyzed the usage of three different car sharing services available in the city of Vancouver, showing how the free-floating one was used more than the others and for shorter trips.

The relevant imbalance between vehicle demand and supply has prompted the need to design vehicle relocation policies. Relocation plans typically rely on optimization models to maximize the effectiveness of the operations, considering the costs [20]. These models are commonly validated using simulation modules, which measure the differences between optimal and current vehicle positioning [34]. Vehicle relocation strategies are designed with the aim at (i) balancing vehicle fleets thus making car sharing systems manageable and profitable [21], (ii) managing vehicle reservations [23], or (iii) addressing supply-and-demand mismatches by offering incentives to move vehicle to under-supplied stations [3]. The goal of the present study is not to propose innovative vehicle relocation strategies, but rather to perform a multi-faceted, data-driven analysis of FFCS service usage.

## 3. Data collection

We collected data from Car2go[1], which is one of the most popular FFCS operators worldwide. This type of FFCS system works as follows: the system knows the position of all cars (available or not) in the fleet. A user looks for, and books, an available nearby car by using a smartphone application. The system then makes the car unavailable for the other users. With the same application, the user can autonomously unlock the vehicle and start the rental. At the end of the rental, the user parks and returns the car by notifying it via the smartphone application. The system then makes the car available at its newly recorded position.

Car2go allows developers to interact with their services through a public Application Programming Interface (API). This allows developers to retrieve the current position of all available cars in a given city. From December 2016 until the end of January 2018, Car2go granted us unlimited access to this API (which at the time was normally subject to usage restriction) in order to collect data for research purposes only.[2]

In our previous work [6] we developed a system called Urban Mobility Analysis Platform (UMAP), that we used to collect data through the Car2go API. Firstly, UMAP gets the operating area for each city served by Car2go, i.e., the area where users can start and end trips. Secondly, UMAP queries the Car2go API every minute to get the currently available cars. Along with the list of currently available cars, for each car, the Car2go API returns: the number plate, current position (i.e., the latitude and longitude coordinates), current energy level (i.e., the percentage of residual fuel or battery), car internal status, etc. Then, UMAP rebuilds the history of each car, identifying *bookings* and *parkings*. A *booking* is the time period in which a car is not available. We identify the start of a booking when the car disappears from the list of currently available cars.

[1] Currently (October 2020) merged into the ShareNow service (`https://www.share-now.com/`).

[2] The data was collected using specifically created credential provided by Car2go, i.e., the *Consumer Key* (`https://www.car2go.com/api/tou.htm`).

Table 1: Booking attributes obtained for the analysis.

| **Attribute** | **Description** |
|---|---|
| Plate | The car unique identifier |
| Initial Position | The spatial coordinates where the booking begins |
| Final Position | The spatial coordinates where the booking ends |
| Initial Time | The timestamp when the booking begins |
| Final Time | The timestamp when the booking ends |
| Initial Energy | The percentage level with respect to the total capacity of the battery/fuel tank level when the booking begins |
| Final Energy | The percentage level with respect to the total capacity of the battery/fuel tank level when the booking ends |
| Distance | The trip distance computed as haversine distance [31] between Initial and Final Coordinates |
| Duration | The booking duration computed as the difference between the Final and the Initial Time |
| Consumption | The consumption computed as the difference between the Final and the Initial Energy |

Then, we identify the end of the booking when the car reappears. Therefore, a booking is an event characterized by the plate, the initial/final position, initial/final time, and initial/final energy level (see Table 1). Conversely, a *parking* event is the time period in which a car is parked and available to users for a rental.

While we got detailed information on where users started and ended their bookings, we did not obtain any information about where and when they made the reservation nor the exact destination they wanted to reach. As such, we cannot estimate how much the user walked to reach the car, how long it took to reach the desired destination, or the path cars followed from the origin to the destination. Hence, given the lack of route information, we approximate the booking *Distance* with the haversine distance [31], and we compute the *Consumption* as the difference between the final and the initial energy level. It is also important to note that the booking *Duration*, computed as the difference between the final and the initial time, includes both the time the user used the car (paying a fee) and the possible (free of charge) *reservation time*[3]. Since

[3]Free of charge reservation time depended on the city policy.

these data do not contain any users' personal information, in this paper there is no risk to harm the users' privacy.

Not all bookings correspond to an actual trip performed by a user. For instance: (i) a user can book a car, and cancel the booking later on; (ii) the data collection may suffer from outages, thus the crawler may miss some available cars; (iii) cars may go under maintenance, disappearing and possibly returning after a long time; (iv) cars may be relocated by the provider to high demand areas of the city. As such, we define the following booking events[4]:

- *Rental*: a rental is a booking where the user performed a short duration trip with the car staying within the operating area. This describes the typical FFCS usage. Thus, we label a booking as a rental if the car has travelled in the city a $Distance \geq 100\,m$, with $2\,min \leq Duration \leq 2\,h$, and with non-negative consumption ($Consumption \geq 0$) i.e., there has been no refuel. We enforce a minimum duration of $2\,min$ to remove possible acquisition errors, and a minimum distance equal to $100\,m$ to account for possible GPS errors and distinguish one-way and round trip rentals.

- *Round Trip*: all the times a booking lasts $Duration \leq 2\,h$, the car has moved for a short distance ($Distance < 100\,m$) and had a non-zero consumption ($Consumption \neq 0$) we label it as a round trip.

- *Long*: a user could also use the car for a longer period of time with specific fares. As such, we identify all the bookings characterized by a duration $2\,h < Duration < 2\,days$ and a positive consumption ($Consumption > 0$) as long bookings. Notice that some of these bookings may be maintenance operations.

- *Cancellation*: all the times a booking lasts $Duration \leq 2\,h$, the car has not moved ($Distance < 10\,m$) and it had no consumption ($Consumption = 0$)

[4]All other booking events are discarded for the analysis.

we label it as a cancellation.

- *Refuel*: in most of the FFCS rides there is no need to refuel the car at the end of the trip. However, occasionally the users or the operator refuel the car. Internal combustion engine cars are refilled at a gas station, while electric cars are charged at a charging station. So we label all those bookings having a higher energy level at the end of the booking ($Consumption < 0$) and where the car was parked elsewhere ($Distance > 100\,m$) as refuel events. In the raw data, it is impossible to distinguish refuel events performed by users from those performed by the operator.

We collected data and computed the previously defined events in all the 23 cities in which Car2go has operated, starting from December 2016 until the end of January 2018 (see Table 2 for the list of cities).

### *3.1. Data Augmentation*

To improve the accuracy of our data, we used the Google Direction API[5] to compute a spatial and a temporal *scale factor*. The *spatial scale factor* allows us to take into account the impact of urban morphology and we use it to correct the haversine distance to get a more accurate estimate of the actual rental distance. The *temporal scale factor* allows us to evaluate how shorter (or longer) a rental last, with respect to the same trip without traffic.

We compute the scale factors as follows. Having an origin $o$ and a destination $d$, we ask the Google Direction API the *driving route* from the origin to the destination avoiding *highways* and *tolls*. As a result, we retrieve the *driving route* describing the *driving distance* and the *driving duration* to perform the trip by using a car. As in our request we do not specify any *departure time*, the Google Direction API chooses the route and the duration based on the road network and average time-independent traffic conditions. As such, we get an estimate of the average time to reach the destination from the origin.

[5] `https://developers.google.com/maps/documentation/directions/intro#DirectionsRequests`

Since our data collection is composed of millions of rentals, and the Google API have usage limitations[6], we cannot retrieve the corresponding driving route for each trip separately. We solve this issue with ingenuity. Firstly, we split each city into squared zones with side of length $500\,m$. Secondly, for each rental $i$, we map the origin (initial) $o(i)$ and destination (final) $d(i)$ coordinates with the corresponding *zone coordinates* $O(i) = zone(o(i))$ and $D(i) = zone(d(i))$, respectively. These coordinates describe the central point of each zone. Then, we ask to the Google Direction API the corresponding driving route from $O(i)$ to $D(i)$. Finally, for each rental, we compute the spatial scaling factor as the ratio between the driving distance and the haversine distance, and the temporal scaling factor as the ratio between the driving duration and the actual rental duration.

In Table 2, we summarize for each city the median spatial and temporal scale factors. We employ this spatial scale factor to scale up all haversine distances into the actual trip distances. From now on, we use this estimate as trip *distance*.

## 4. Service usage characterization

We analyze service provision in 23 cities under multiple aspects. Furthermore, we evaluate to what extent the services offered by using electric cars (in Amsterdam, Madrid, and Stuttgart) differ from those offered by using internal combustion engine cars. Firstly, we evaluate the size of the operating area and analyze the service supply in relation to the estimated fleet size. Secondly, we break-down the booking events (i.e., rentals, cancellations, long bookings, refuel events, and round trips) to evaluate their impact on service usage rate. Lastly, we analyze the duration and distance of each rental to profile user habits at different temporal granularity levels. We report in Table 2 data summarizing each analysis. Moreover, to ease plots readability and to add further details, we provide a website [16] where researchers can interact with our results.

[6]`https://cloud.google.com/maps-platform/terms`

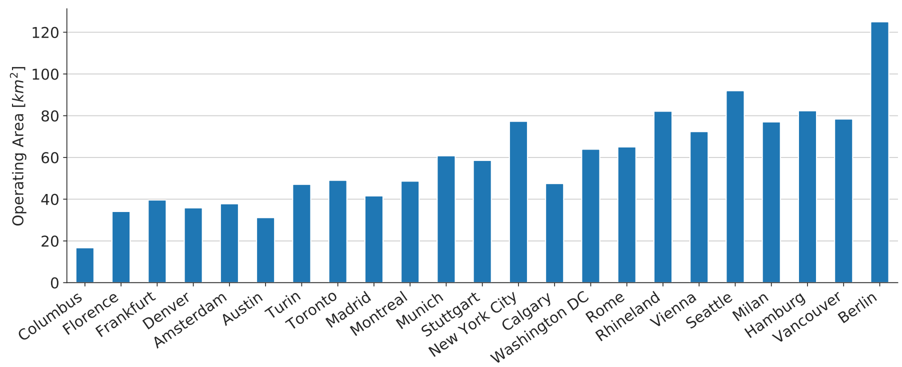



Figure 1: Surface size of the operating area of each city. Cities are ordered by increasing fleet size.

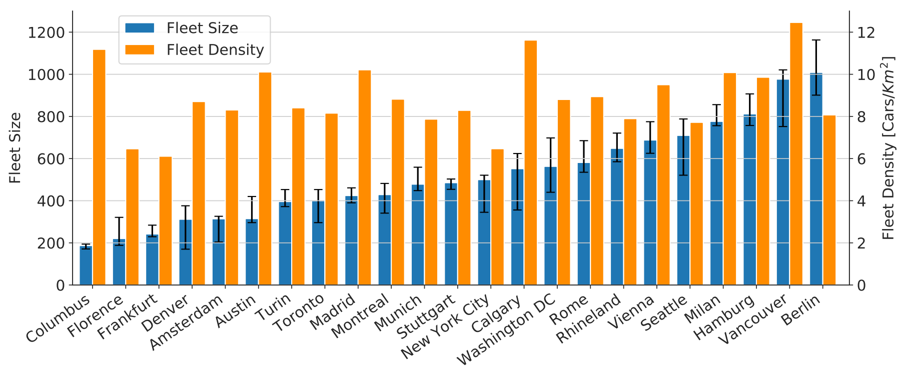



Figure 2: Fleet size and fleet density for each city. Error bars report the minimum and maximum observed fleet size in the weeks.

**Operating area and fleet size.** In Figure 1, we report, for each city, the surface of the operating area of the car sharing operator. It varies significantly, i.e., from less than $20\,km^2$ for the city of Columbus (USA) up to more than $120\,km^2$ in Berlin (Germany). Based on the aforesaid numbers, we evaluate how the fleet size and density changes in the cities. For this, Figure 2 reports the median number of vehicles seen per week, and the fleet density computed as the former value divided by the surface of the city operating area. The aforesaid number approximates the available fleet size of the operator.

In Figure 2, and in all the following ones, the cities are sorted by increasing median fleet size (ranging from 187 in Columbus up to 1 009 in Berlin). For the fleet size, in Figure 2 we also depict the variation between the minimum fleet size and the maximum fleet size in different weeks with error bars. For most of the cities, the weekly size variations are limited. The fleet size slightly changes from week to week, since the operator could increase the fleet size, or remove broken cars, or perform maintenance operations. Not shown in the picture, we check whether the difference between the minimum and maximum is due to an increase (decrease) of the fleet size over time. We want to check if the operator added (removed) cars to the fleet for increasing (reducing) the capacity. More specifically, we verify whether the minimum number of cars is recorded at the beginning of our data collection while the maximum at the end of it (or vice-versa). The results show that such temporal correlation does not hold, and the underlying patterns are quite variable. Only in four cities (Seattle, Madrid, Toronto, and Amsterdam), the number of cars seen in the first weeks is clearly lower than those seen in the last weeks. Hence, the differences between minimum and maximum weekly fleet are in most of the cases due to car maintenance/replacement.

In most cases the fleet size increases with the size of the operating area. However, some cities show peculiar situations. For example, focusing on Frankfurt and New York City, we can see that the fleet seems to be undersized with only about 6 cars per $km^2$. Conversely, in Vancouver, Calgary, and Madrid, the number of cars per $km^2$ is above average. In detail, for these three cities, we observe more than 10 cars per $km^2$, while the average is only 8.8.

**Number and types of bookings.** To start analyzing cars and fleet usage, in Figure 3 we report the total number of booking events. We classify them as *rentals*, *cancellations*, *long booking*, *refuel events*, and *round trips* according to the categorization reported in Section 3. For the majority of the cities, we observe that the larger the fleet, the more the number of bookings. Madrid (electric fleet) shows many more bookings than cities with a similar fleet size like Montreal and Toronto.

Figure 4 shows the percentage of each type of booking with respect to the

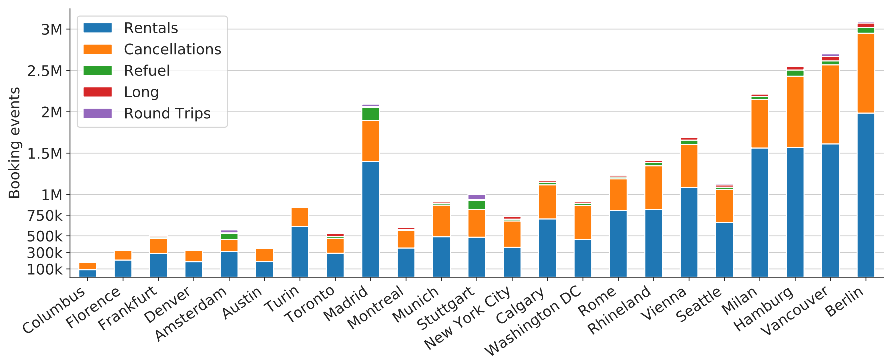



Figure 3: Break-down of the total number of booking events into event type (Rentals, Cancellations, Refuel, Long, and Round Trips).

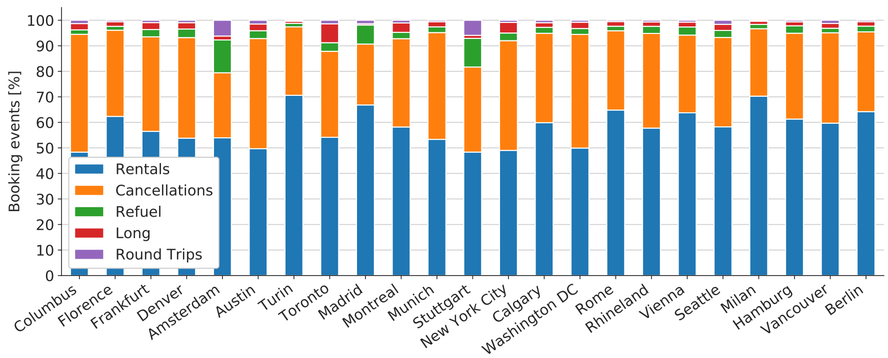



Figure 4: Percentage of booking events per type (Rentals, Cancellations, Refuel, Long, and Round Trips).

total number of bookings per city. The car sharing operator might lose money if too many cancellations occur because cars are kept busy (free of charge cancellation period lasts up to 30 minutes, depending on the region). Columbus, Austin, New York City, and Washington D.C. have the worst numbers: almost 50% of bookings are canceled. Amsterdam (electric fleet), Turin, Milan, and Madrid (electric fleet) have the best ones, i.e., less than 30% of cancellations and more than 67% of rentals. Likely linked with such a high cancellation rate, we observed that, in 2018, Car2go decreased the free of charge period from 30 minutes down to 15/20 minutes in several cities. Finally, long bookings and round trips are rare in all cities, with the maximum value of long booking reached in Toronto (7%) and the maximum value of round trips in Amsterdam (6%). This

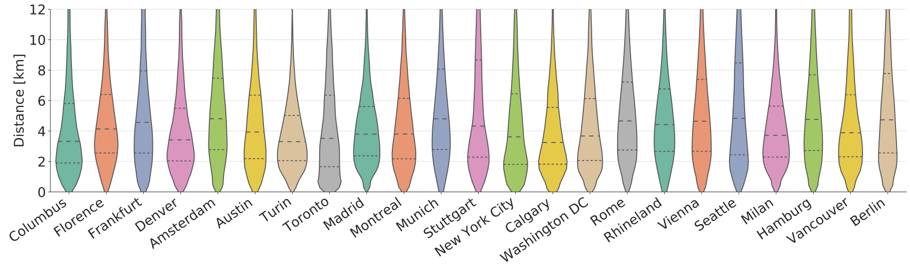



Figure 5: Rental distance (in $km$).

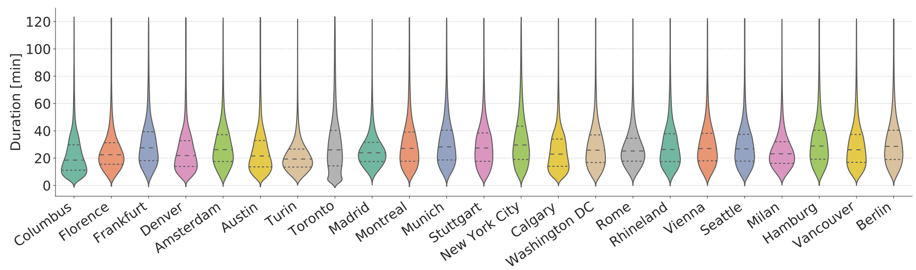



Figure 6: Rental duration (in minutes).

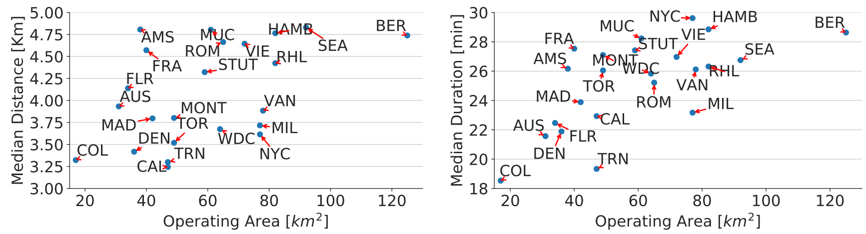
result confirms that free-floating car sharing is used mainly for short one-way rentals [21].

Regarding the refuel events, the percentages of refuel events are much higher in cities with electric fleet with respect to cities with internal combustion engine cars. As we will clarify in Section 7, this is due to the shorter autonomy of electric cars. Moreover, in Madrid, the charging process is managed by the operator in a single location (centralized infrastructure). Thus, the frequency of charge is lower than the other cities with an electric fleet as the operator charges cars only when strictly required. In Section 7, we will analyze in more detail the difference between centralized and distributed charging strategies.

**Rental distance and duration.** To analyze users' habits in the cities, Figure 5 and Figure 6 show the distribution of per rental distance and duration separately for each city, respectively. We rely on violin plots to summarize the distribution of the analyzed data. This kind of visualization shows the empirical probability density of the distribution of the data. The larger the violin shape, the more likely to get data with that particular value. Unlike other numeric data representations (e.g., box plots), violin plots combine the classical dispersion and skewness descriptors with a representation of the full data distribution. To compare rental duration and covered distance across different cities, we deem the aforesaid visual representation the most informative yet concise one. To ease the readability, in each violin plot, we report the $25^{th}$, $50^{th}$ (median), and $75^{th}$ percentiles of the distribution. Furthermore, we provide an interactive version of each plot in [16]. To keep the order consistent across plots, the cities are ordered by median fleet size.

The majority of the rentals consists in short trips, with an average distance lower than $7\,km$, and an average duration shorter than 30 minutes (see Table 2 for further details). Users in Turin and Madrid tend to use the service mainly for very short trips, as the violin plots tend to be larger in the bottom part. Conversely, Vancouver, Munich, and Berlin show rather variable usage patterns, with a mix of both short and relatively long trips. The above-mentioned results for Madrid are compatible with those reported in [2]. As expected, we observe that cities with a large operating area also show some longer trips. In cities where the operator allows the users to reach the airport, often the average and the median rental duration and distance differ a lot: for instance, in Munich, we register an average rental distance of $6\,km$, while the median is only $3.5\,km$. Regarding electric vehicles, in Amsterdam, Madrid, and Stuttgart, we observe the same usage patterns as in cities equipped with internal combustion engine cars. In Table 2, we report the average and median values of each metric.

In Figure 7, we analyze to what extent the operating area size influences the usage pattern. We compare the size of the operating area in the city with the median rental distance and the median rental duration. We rely on the median value rather than the mean as the former is more stable and less influenced by outliers. To ease the readability, city names are shortened. Table 2 reports the complete and the shortened name of each city. We can observe a weak correlation of distance and duration with the city operating area size. A bigger operating area increases the probability of having longer trips both in terms




(a) Median rental distance vs. operating area. (b) Median rental duration vs. operating area.

Figure 7: Influence of operating area size on usage.

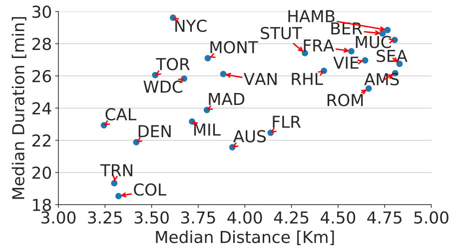



Figure 8: Correlation between rental duration and rental distance.

of distance and duration. However, there are cities like Amsterdam (AMS) characterized by a relatively small operating area ($38\,km^2$) but having a high median distance ($4.8\,km$) and duration ($26\,min$) of trips. On the contrary, cities like Milan (MIL) have a large operating area ($77\,km^2$), but a limited median distance ($3.7\,km$) and duration ($23\,min$) of the trips.

Finally, in Figure 8 we study the correlation between rental duration and distance. Here the dependence seems stronger, with few cities far from a linear relationship between duration and distance. For example, New York City (NYC) has a very high median duration ($30\,min$) but a low median distance ($3.6\,km$). This highlights the impact of traffic congestion and longer reservation time.

**Car daily usage, rental distance, and duration.** In order to evaluate daily service usage and profitability we analyze the number of rentals per car, rental duration, and rental distance, aggregated per day. We monitored car usage, identifying them through their number plates. Figures 9-11 show the corresponding distributions of daily data per car, separately for each city. The

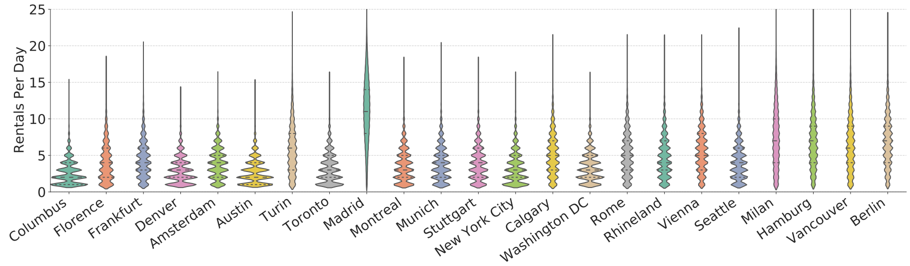



Figure 9: Daily rentals per car.

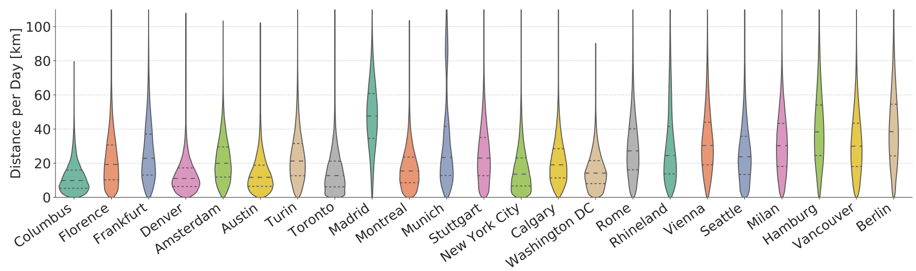



Figure 10: Daily rental distance per car (in $km$).

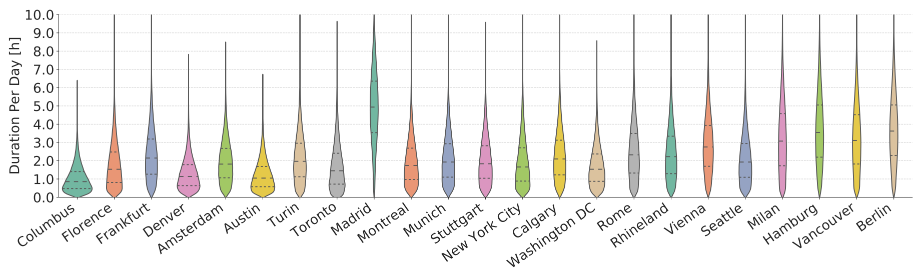



Figure 11: Daily rental duration per car (in hours).

wavy patterns in Figure 9 are due to the discrete nature of the number of rentals per car per day: the more daily rentals (and minutes rented) per car, the higher revenues the service had. Within most cities, the distribution of rental per day varied a lot: sometimes cars were rented only once in a day, e.g., because a rental ended in an unpopular zone where the car stayed parked for days before a new rental began; sometimes rented dozens of times in one day, e.g., a car which traveled only around popular zones. Notably, the city with the highest usage per car was Madrid, a city equipped with an electric fleet. On average, in Madrid, we registered 11 rentals per car per day, while, on average, only 5 rentals per car per day were observed in the other cities. The success of car sharing in Madrid is due to several factors [10]. First, in 2017 the city council of Madrid presented a plan of 544 million euros to improve air quality and counteract climate change, dedicating an entire chapter to car sharing. Among the proposed measures, electric cars park free of charge and have access to limited traffic areas. The final goal of these measures is to “impose a new culture of mobility”. As such, the measures taken by the Madrid city council are clearly beneficial for those companies that invested in electric vehicles for their car sharing fleet. Secondly, from the user’s point of view, many people have found car sharing a good opportunity to ditch the fixed cost induced by owning a car. Moreover, around 15% of the population is unemployed in Spain, with respect to only 4% in the USA. Furthermore, young workers suffer from involuntary part-time working conditions, which tend to creating insecurity and increasing the trend of not owning a private car. As such, these factors have made Madrid an environment suitable for the development and growth of car sharing and shared mobility services in general. Indeed, 5 different car sharing operators are now present in Madrid, and many electric scooter[7] and bike sharing [25] providers have emerged. Figure 9 shows how the behaviour of electric fleets in other cities is similar to that of internal combustion engine fleets. Data from Turin, Milan, Hamburg, Vancouver, and Berlin show a similar probability for a car to be used from 1 up to more than 10 times per day. In general, in some cities, especially in the USA, cars made few trips per day. In particular, in Columbus, Austin, and Denver, cars appeared to be underused, with, on average, only 3 rentals per car per day. In Table 2, we report the average and the median number of rentals per car per day.

Figure 10 shows the daily rental distance per car; the impact of Munich airport in distance is clear with many cars traveling an average distance higher than $80\,km$ per day. In general, the bigger the city, the longer the distance covered per day and the longer the rental duration, as shown in Figure 7a. Usage

[7] https://english.elpais.com/elpais/2019/04/09/inenglish/1554797032_434337.html

in Madrid again shows a clear deviation from the behaviour of the average city. As observed before, this is driven by the high amount of rentals per car per day, as observed before. Indeed, in Madrid, despite the fact that per rental distance/duration is similar with respect to that of other cities (see Figure 5 and Figure 6), each car performs many more trips than in other cities, hence the increase in daily rental distance/duration.

The daily rental distance can also be used to estimate how long a car refill/charge lasts. The gasoline Smart ForTwo car used in some fleets claims an autonomy of $560\,km$, and $159\,km$ for the electric version[8] Hence, an electric car with a full charge lasts a median of fewer than 5 days in Madrid, while this number increases to 10 and 12 days for Stuttgart and Amsterdam, respectively. The longer autonomy of gasoline cars increases the need for a refill from a median from 18 days in Berlin to more than 3 months in Columbus. More about this topic will be presented in Section 7.

The total rental duration per car per day (Figure 11) is the data that relates most to since users pay the system per minute, not per rental nor distance. The distribution of this metric describes the total amount of time each car was rented every day. Here we observe major differences. On the one hand, Madrid was the city with the highest duration per car per day. It has a median per car of 5 hours per day, resulting in an estimated income per day of 57-93 € per car.[9] This high figure reflects per car number of rentals per day in Figure 9. On the other hand, there are cities with a daily usage of about only one hour per car. For example, usage in Denver results in an estimated median income per day of 21-35 $ per car.

In our analysis, most of the cities in North America had lower utilization rates than European ones. Car sharing has proved to be less successful in North America than in Europe are manifold. Firstly, the car ownership rate is higher

[8]Autonomy is determined based on the NEDC regulation 692/2008/CE. In some cities, other gasoline cars are available in the fleets.

[9]Minimum and maximum price per minute are extracted from `https://www.car2go.com/ES/en/madrid/costs/` and `https://www.car2go.com/US/en/denver/how/`.

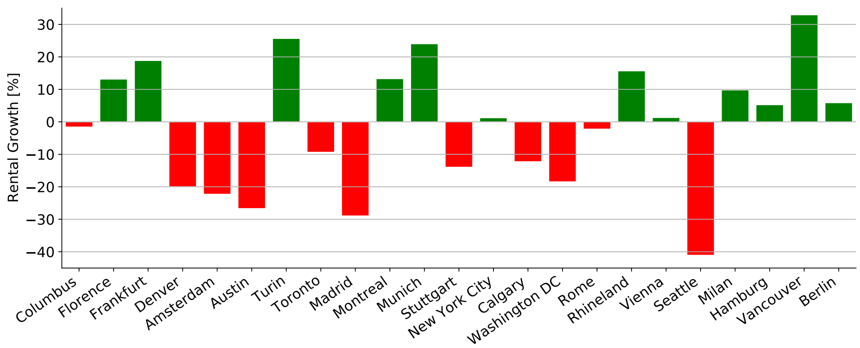



Figure 12: Rental growth for each city, computed as derivative of the daily rentals trend-line for the 14 months object of the study.

in North America than in Europe. For example, there are 838 vehicles per 1 000 inhabitants in the USA, while only 561 per 1 000 inhabitants in Germany. Secondly, in North America, most of the urban areas are less dense. For example, Milan has a population density of 7 684 per square kilometer, while Austin reaches only a density of 1 369 per square kilometer. Hence, cities are more spread out in North America, making car sharing systems ineffective. In fact, a car is more likely to be within walking distance if more people are living close to it. These evaluations and results justify the recent service shut down in different cities in North America [17].

## 5. Temporal usage analysis

To identify seasonal patterns and compare the services offered in different cities (and countries), we analyze the car rentals over time. Specifically, we study the service usage evolution over time, and we analyze the usage patterns with different timescales: from a month granularity, to days of the week, up to hours of the day.

**Evolution over 14 months.** We have collected data from December 2016 to the end of January 2018. Given the series of the daily number of rentals per city for this whole period, we approximate each series with its linear regression. This trend-line is a first coarse summary of the usage variations over time. Figure 12

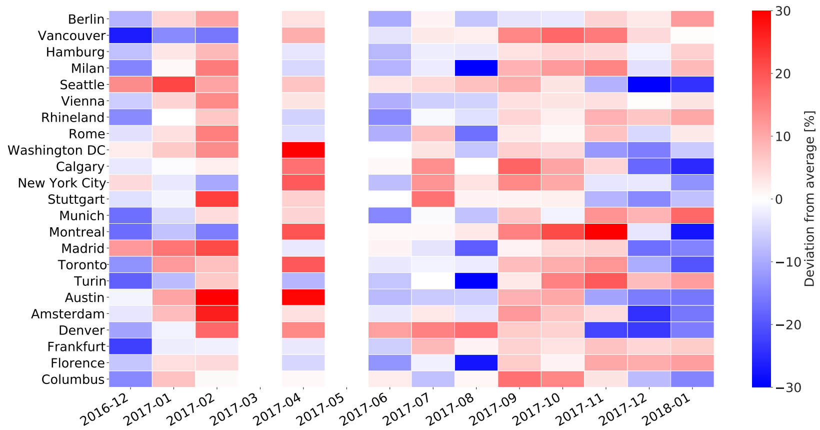



Figure 13: Deviation for the number of rentals in each month. Percentage deviation is computed from the average of each city, independently.

shows, for each city, the rental growth in the period computed as derivative of the trend-line. It indicates whether service demand is in an uptrend ($> 0$), a downtrend ($< 0$), or stationary ($\simeq 0$) over the 14 months of analysis.

Approximately half of the services show decreasing demand. The most significant drops are in Seattle (service now discontinued) and Madrid (recalling that rental demand is still very high at the end of the period). Turin, Munich, and Vancouver show the highest increasing trend in the number of rentals. Although from 2011 to 2013, Berlin had shown a significant increase in the booking frequency [28], from 2016 to 2018, the number of rentals seems to have reached a stationary state.

To give more insights, we analyze the trend in each month. Figure 13 shows, for each month, the deviations (in percentage) from the average number of rentals observed in each city. Median and average values of the number of rentals, duration, and distance per city are reported in Table 2. The months of March and May 2017 are not present due to the lack of data. The Figure shows seasonal trends for most of the considered cities, with numbers varying approximately -30% up to +30%. The number of rentals in Italian and Spanish cities (i.e., Milan, Rome, Madrid, Turin, and Florence) decreases in the summertime, especially in August, despite the high number of tourists in these cities. This

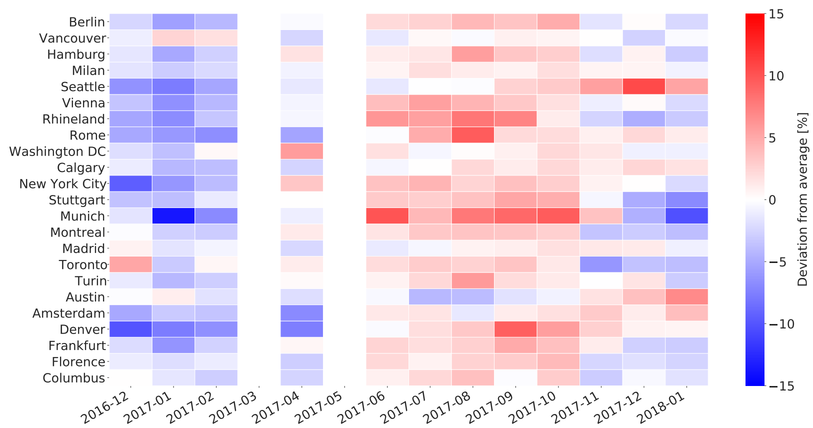



Figure 14: Deviation of the average rental distance in each month. Percentage deviation is computed from the average of each city, independently.

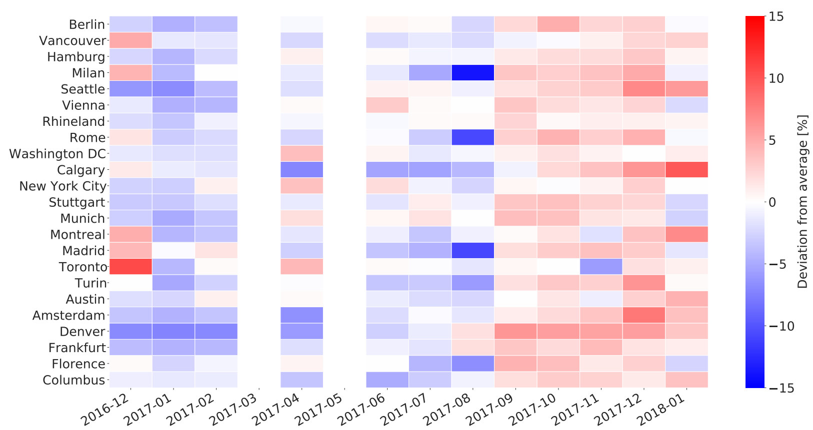



Figure 15: Deviation from the average rental duration in each month. Percentage deviation is computed from the average of each city, independently.

may be due to a change in mobility habits, e.g., less work commuting or shift toward other transportation means like bikes.

Figures 14 and 15 show the deviations of the mean rental distance and the mean rental duration per month and city with respect to the mean values of each city computed over the whole 14 months period. Most of the considered cities show non-stationary trends. On average, longer distances are covered in the summertime. During these months (June, July, and August), even if the rental distance increases, the rental duration decreases. This might be due to

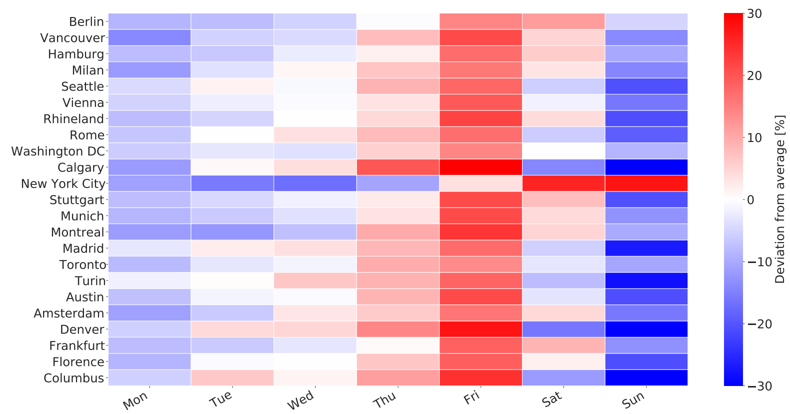



Figure 16: Deviation for the number of rentals per day of the week. Percentage deviation is computed from the average of each city, independently.

different destinations during the warmest months of the year, the adoption of other transportation means (e.g., bikes) for short trips, or less traffic leading to faster trips. Considering the rental duration, most cities show a higher rental duration from September to December 2017.

**Usage analysis of the days of the week.** After observing how the usage has changed over time, now we analyze the usage on the different days of the week. Discovering such patterns is particularly useful for planning maintenance operations and manage charging, e.g., by identifying the weekdays and hours having the lowest usage.

In Figure 16, we analyze the deviation from the average of the number of rentals per day of the week. For most of the cities, on Sundays, we observe the least usage, followed by Mondays. Hence, charging and maintenance operations should be preferably scheduled on Sundays or Mondays. A significant increase in the relative number of rentals appears on Thursdays and Fridays. Car sharing can be used for commuting to work and for leisure time, hence during Thursdays and Fridays both of these activities might be present. Berlin and Munich show the highest usage on Fridays, differently from the previous work [28], where it was recorded on Saturdays. In New York City the car sharing is mostly used on Saturdays and Sundays, with very low usage from Mondays to Thursdays. This is possibly due to the operating area limitation, not including the Manhattan district. More details will be given in Figure 17 and 18.

By aggregating service usage per day of the week, we observe small differences in average duration and distance. The corresponding plots are available at our website [16]. The relative differences in the former are within $\pm 10\%$, while in the latter are within $\pm 15\%$. Mainly on Sundays trips last less but also cover more distance. For Munich, we discover a peculiar pattern: on Mondays, the covered distance is significantly higher than those covered on all the other days. We discovered that this is due to the high number of connections on Mondays from the town to the international airport, which is located approximately $28\,km$ north-east of Munich.

We also observe the booking cancellations, here omitted for the sake of brevity. Most of the cancellations occur on the first days of the week and Sundays, especially during the night, whereas the least number of cancellations is recorded on Saturdays.

**Usage analysis of the hours of the day.** We further deepen our analysis by studying the usage in different hours of the day and week. To this end, we apply clustering techniques [31] to find similarities among the service usage patterns in different cities. We focus on the hourly service demand within each day of the week, as it synthetically describes the service usage rates across different daily time slots. More specifically, for each city $c$ and on each day of the week $d$, we define the hourly rental distribution as the percentages of recorded rentals within each hour over the total number of rentals recorded on $d$. Since service demand may significantly change on different days of the week, for each city, we consider the distributions from Monday to Sunday and generate a single time series of hourly rental usage over all days of the week. The series associated with different cities are clustered using the well-known $K$-means [18] clustering algorithm. The aim is to group into the same cluster the cities that are similar to each other in terms of service demand. The number of clusters ($K$) is estimated via grid search by finding the value that maximizes the Silhouette score [31]. In

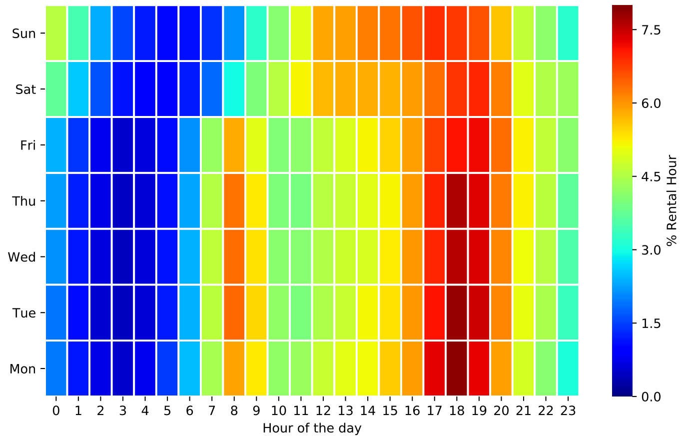



Figure 17: Distributions of the hourly rentals per day of the week averaged over the cities belonging to cluster 1 (Florence, Frankfurt, Amsterdam, Turin, Toronto, Madrid, Munich, Stuttgart, New York City, Rome, Rhineland, Vienna, Milan, Hamburg, Berlin).

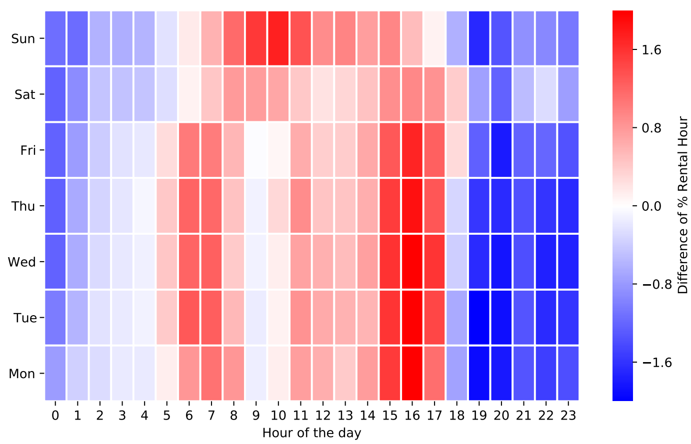



Figure 18: Differences in hourly rentals per day of the week (averaged over the cities) between the distributions in cluster 2 (Columbus, Austin, Denver, Montreal, Calgary, Washington DC, Seattle, Vancouver) and cluster 1.

our experiments, the best results are achieved by setting $K$ to 2.

Figures 17 and 18 graphically show the characteristics of the centroids of the two generated clusters.[10] To ease the visualization, in Figure 17, we depict the percentage of rentals for each hour for the centroid of cluster 1. Instead, for cluster 2, we report in Figure 18 the difference between the centroid in cluster 2 and cluster 1. We represent the characteristics of the centroids, as they are deemed as reliable descriptors of the most salient characteristics of

[10]We use in the paper the 24-hour clock notation as in ISO 8601-1.

the cities within the cluster. Intuitively, centroids are obtained by computing the pointwise average of all the cluster members. In the K-means algorithm, they are initially selected randomly and then re-assigned automatically until the algorithm converges to a local optimum.

Cities located in the same geographical area show homogeneous FFCS service demand. Indeed, the first cluster (see Figure 17) includes all the European cities, whereas the second one (see Figure 18) includes all the cities located in North America and Canada, except for Toronto and New York City. Interestingly, from a comparison between the clusters, it turns out that North American cities have a much lower evening and night utilization (19:00-01:00), where we register differences of up to 1.7%. For example, on Wednesdays around midnight, the distribution of rentals almost halves from 2.3% to 1.2%. Moreover, in North American cities, we observe an earlier afternoon commuting time than in European cities. The peak of the difference is around 15:00-17:00, where we observe distributions up to 1.6% higher.

To further evaluate the ability of the clustering algorithm to automatically assign cities of the same continent to the same cluster, we use the Rand Index [31]. It measures the ability of the clustering algorithm to well separate points belonging to preassigned categories. In our case, we assign the continent as label of each city record, and we empirically verify the hypothesis that service usage patterns are strongly correlated with the geographical area in which the city is located (Rand Index equal to 67%).

Additional results related to temporal analyses are given in [16]. Specifically, for each city, we have analyzed the service usage in terms of percentage of rentals, average duration, and average distance for each hour of the week. Results show that rental duration early in the morning tends to be higher, probably due to the lack of alternative transportation means.

**Impact of Traffic Congestion.** We study the impact of traffic congestion on the users' rentals behaviour, using the temporal scalar factor described in Section 3.1. For each city, we evaluate for each hour of the day the median

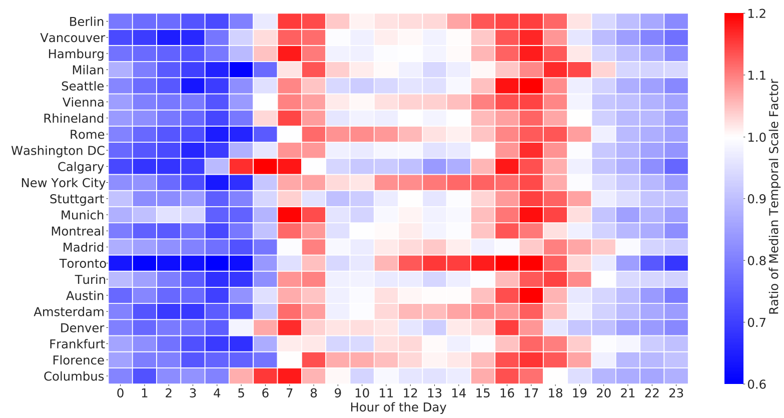



Figure 19: Ratio between the hour median temporal scale factor and the median temporal scale factor for each city.

*temporal scalar factor* considering all the rentals performed during weekdays. We recall that it is computed as the ratio between the estimated driving duration and the duration of the actual rental. A large temporal scalar factor is likely due to the presence of congestion. Finally, for each city, we compute the ratio between the hour median temporal scale factor and the median temporal scale factor of the city (reported in Table 2). In this case, we use the city median temporal scale factor as a reference of what is the usual rentals behaviour in the city. As a result, we get a ratio greater/smaller than 1 when the rentals tend to last longer/shorter than the usual city behaviour. Figure 19 reports this ratio for all the cities during the 24 hours. As expected, during night hours this ratio tends to be smaller than 1 in all the cities, with the smallest value in Toronto, where we get a ratio of 0.57. On the opposite, during commuting times in all cities, we observe an increase in time up to 20% longer than the usual city behaviour.

## 6. Spatial usage analysis

Complementary to the temporal analysis, here we explore the spatial characteristics of the rentals.

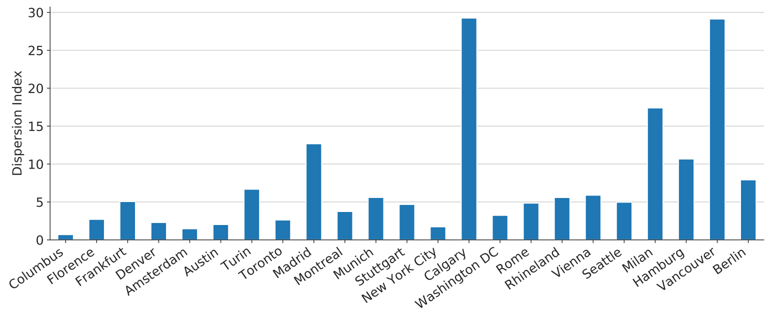


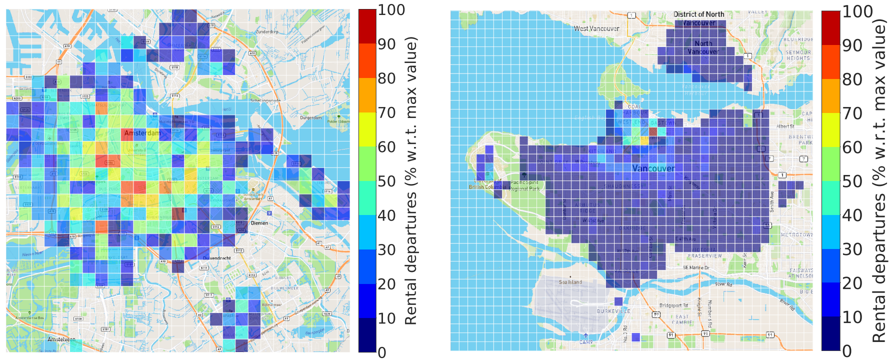

Figure 20: Spatial dispersion index of the rentals. A high dispersion index implies dishomogeneity in the usage of car sharing over the city.

**Dispersion of rentals.** We analyze how the rentals are distributed in space. For each city, we split the operating area into square zones with side length $500\,m$. Then, we compute the average number of rentals starting from each zone in a day. Finally, we only consider active zones, filtering out zones where, on average, there is less than one rental per week.

Our goal is to study if rentals start homogeneously or not in the different zones of each city. In Table 2, we report the mean and the variance of the distribution of the average number of rentals per day over the zones of the cities. To evaluate the homogeneity of rental departure positions within a city, we employ the dispersion index [11] on this distribution. The dispersion index is defined as the ratio between the variance and the mean of the distribution, and it measures the dispersion of a probability distribution. To exemplify, we take the two extreme situations: on the one hand, a completely homogeneous situation results in a dispersion index equal to 0, meaning that the rentals start equally in all the zones of the city. On the other hand, the dispersion index will be maximum if all the rentals start from a single zone.[11]. As we evaluate the dispersion index only on active zones, it is not changing if there are large parts of the cities where the car sharing is not present or never used.

In Figure 20 we report the dispersion index for each city. Cities are ordered

[11]The maximum value depends on the number of zones and rentals.




(a) Amsterdam

(b) Vancouver

Figure 21: Rentals departures in the operating area of two cities. Amsterdam has low dispersion index (left plot) and Vancouver has high dispersion (right plot).

by increasing fleet, as previously in the paper. We observe how the dispersion index is low in cities like Columbus, New York City, and Amsterdam. In these cities, most of the rentals start homogeneously in all the zones. From the operator point of view, relocation strategies will be harder to implement in a homogeneous situation. On the opposite side, in cities like Milan, Vancouver, and Calgary, we have a high dispersion index, hence rentals and parking events occur much more likely in a few zones.

In Figure 21, we show the rental departures in the operating area of two cities. We selected a low dispersion index city (Amsterdam) and a high dispersion city (Vancouver). The number of rentals departing from each zone of the city is normalized with respect to the maximum in the city, i.e., the zone with the most rental departures. In Amsterdam many rental departures are spread through the whole operating area of the city. Instead, a limited number of zones of Vancouver have many rental departures. For the sake of brevity, the distribution of the other cities are omitted, but they are available at our website [16].

In Figure 22, we evaluate the median distance among the top 10% zones in terms of rental departures. This measure shows not only how non-homogeneous the zones are, but also their mutual distance. Farther median distance implies

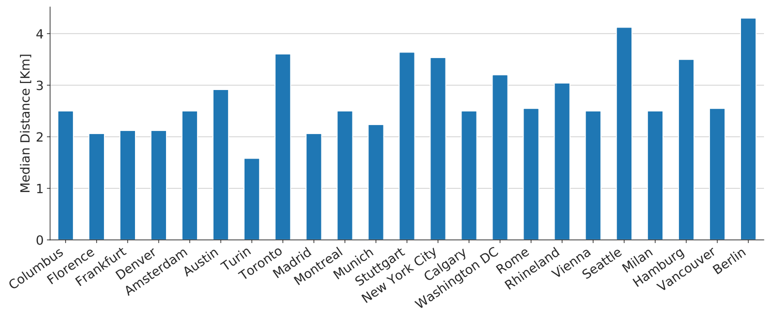
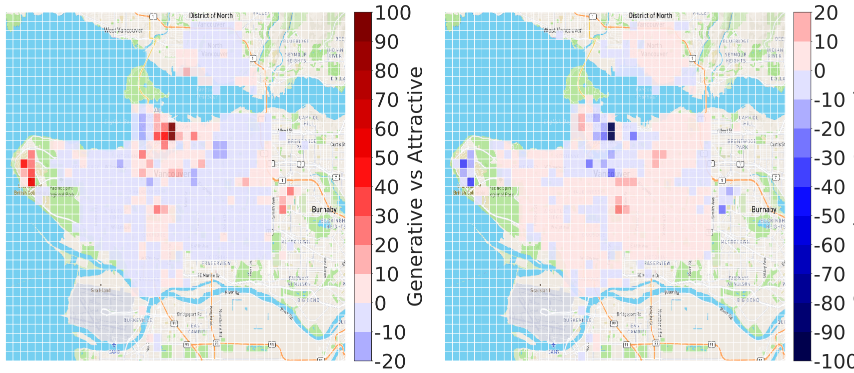



Figure 22: Median distance among the top 10% of zones for number of rentals.

that popular zones are in different parts of the city. If the operator manages the car relocation, it will need to cover more distance to move the cars among these popular zones. These distances vary from less than $2\,km$ for Turin to more than $4\,km$ for Berlin. Notice that, even if the operating area of Berlin is more than 6 times larger than Columbus one (Figure 1), the median distance of popular zones only increases from $2\,km$ to $4.3\,km$. Vancouver and Amsterdam have very similar median distance ($2\,km$ vs. $2.5\,km$) between their popular zones, even if the operating area of Vancouver is two times the one in Amsterdam. This happens because the dispersion index of Vancouver is much higher than Amsterdam, and the popular zones are located close to each other (Figure 21).

**Rental generation and attraction.** To better understand the spatial usage of FFCS, we analyze the situation in different moments of the day. For each zone, we compute the net flow of rentals (number of arrivals minus number of departures) in specific time slots of the day. We consider the following 5 time slots: 00:00-05:59, 06:00-09:59, 10:00-15:59, 16:00-19:59, and 20:00-23:59. Then, we analyze how many zones in a time slot are generative and how many are attractive. In generative zones there are more rentals starting from them, while in attractive zones there are more rentals ending there. Interestingly, for all the cities we observe a prevalence of generative zones compared to attractive ones in the mornings, whereas in the late afternoons and evenings we find the opposite trend. For the sake of brevity, the corresponding plot is available at




(a) Time slot 06:00-09:59

(b) Time slot 16:00-19:59

Figure 23: Rental flow in Vancouver for two time slots. The heatmap shows attractive zones in red while generative ones are in blue.

our website [16].

In Figure 23, we show an example of a daily pattern for the case of Vancouver. Zones of 500 x 500 $m$ are shown. The two commuting time slots are shown, i.e., from 06:00 to 09:59, and from 16:00 to 19:59. The Figure shows the rental flow (arrivals minus departures) for each zone with respect to the maximum flow (in absolute value). Attractive zones are shown in red, while generative ones are shown in blue. Two big attractive zones are visible in the morning, i.e., the city center and the University of British Columbia. The same zones become generative in the afternoon. Notice how there are many zones being weakly attractive or generative, likely related with the high dispersion index.

## 7. Electric car charge analysis

We now analyze the differences in the refuel events, focusing on cities having electric fleets. Electric cars are moved to a charging station and they are connected to an electric pole. In the case of Madrid, the refuel is performed only by the operator, with the aid of a centralized charging hub. Instead, in Stuttgart and Amsterdam, cars are charged in a distributed charging infrastructure where both the users and the operator can perform the charging operation. In an internal combustion engine car, the car tank is refilled by a user or by the

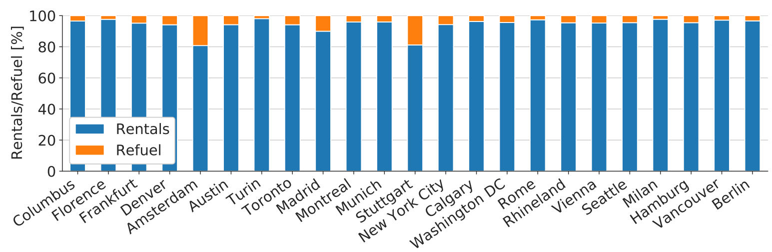



Figure 24: Percentage of rentals and refuel events for each city.

operator. After a refuel event, the car is made available for further bookings. From our data we cannot differentiate refuel events performed by users from those performed by the operator.

In Figure 4, we showed how many bookings were refuel events. In Figure 24, we further detail this analysis by only including rentals and refuel events. On the one hand, results show that for internal combustion engine cars the refuel events are rare, ranging from 2% (in some Italian cities) up to 6% (in some North American cities). On the other hand, this number increases to 10% in Madrid and up to 18-19% in Amsterdam and Stuttgart. These numbers show how electric cars, and in particular in the case of the distributed infrastructure, need more refuel events than the internal combustion engine fleets. This is expected given that the Smart ForTwo autonomy is 159 $km$ for the electric version and 560 $km$ for the gasoline one. In the case of distributed charging infrastructure, the user might be willing to leave and plug the car in a reserved parking spot, especially in congested zones where finding a parking spot for private cars is difficult.

Since from now on we focus on electric cars, we use the term *charge events* to refer to the *refuel events*. First of all, we compute the time gap between two charge events as the time between the end of a charge event and the start of a new one. In Figure 25, we report the Empirical Cumulative Distribution Function (ECDF) of this time gap, while in Table 2 we report the mean and the median for all the cities. The distributions of the time gap clearly show the difference between the centralized and the distributed infrastructures. In

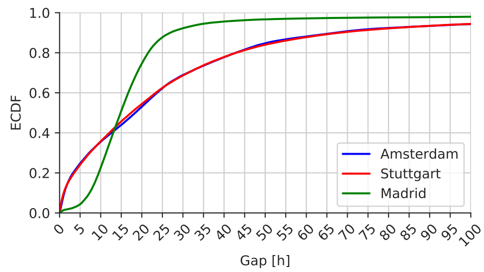



Figure 25: Distribution of time gap (in hours) between the end of a charge event and the start of a new one.

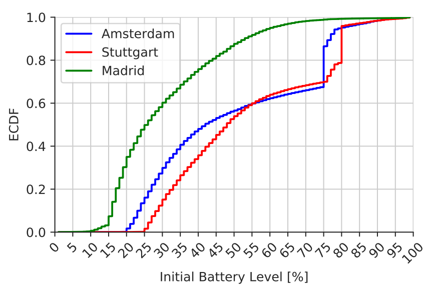



Figure 26: Distribution of battery level at the beginning of a charge event.

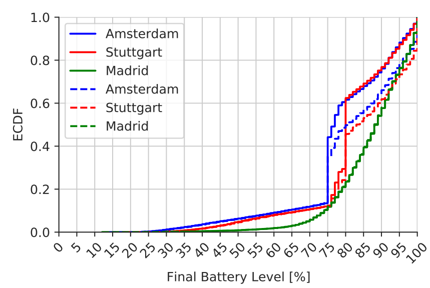



Figure 27: Distribution of battery level at the end of a charge event (solid line) and at the beginning of a new rental after the charging process (dashed line).

Madrid, the cars are charged regularly, with 60% of the charge events occurring between 10 and 22 hours apart from each other. Instead, in the other two cities, we also observe short gaps (20% of the times below 3 hours) and long gaps (40% of the times above 24 hours). Notice how these gaps are much shorter than the estimate based on the median car usage (in Section 4). This fact suggests that most of the cars are charged even if they still have a high battery level. This is confirmed in Figure 26, where we report the distribution of the battery level at the beginning of a charge event. On the one hand, in Madrid, a car is rarely charged when the battery level is high. Indeed, only 20% of the time, the car is charged if the battery level is above 43%. On the other hand, in Amsterdam and Stuttgart, we observe many charge events, although the high battery level. Interestingly, many times the charge events start exactly when the battery level

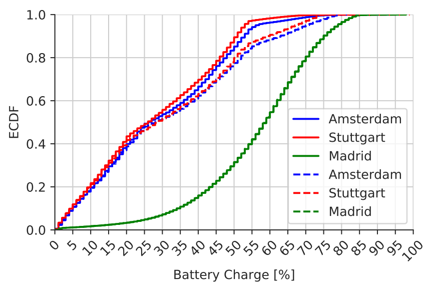



Figure 28: Distribution of battery charge at the end of a charge event (solid line) and at the beginning of a new rental after the charging process (dashed line).

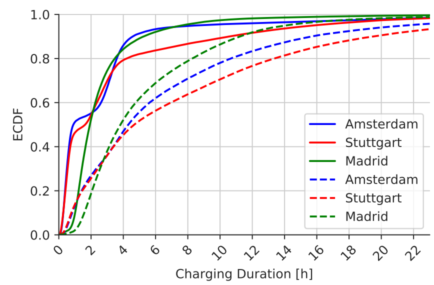



Figure 29: Distribution of the charging duration (in hours) at the end of a charge event (solid line) and at the beginning of a new rental after the charging process (dashed line).

is 75% and 80% in Amsterdam and Stuttgart, respectively. Indeed, these are the thresholds above which a charging car becomes available for further rentals or, sometimes, its charge is even stopped.

The distribution of the battery level after charging is shown in Figure 27. Here we depict two different estimations. The first one reports the battery level when the car is made available (solid line) at the end of the charge event. This represents a lower bound since a car may keep charging after it is made available. The second one reports the battery level when a new rental starts (dashed line). This level is more representative than the first one as it accounts for the full charging period. In Madrid, the two lines overlap since the cars are charged in the hub and they must be relocated before being available. We can distinguish Amsterdam and Stuttgart thresholds after which a charging car is available for rental. We further analyzed at which battery level the car becomes available for rentals. The results, here not reported for brevity, show that the operator employs different policies according to the hour of the day and the zone of the city. Reverse engineering of the policies adopted by the operator is out of the scope of this research.

Figure 28 depicts the distribution of battery charge during a charge event. This is computed as the difference between the battery level at the end of the charging process and its initial level. Again, we consider both the battery level at the end of the charge event (solid line) and the one when the car is rented again (dashed line). We can see that for Madrid, the cars are charged most of the time at least for 55% of their capacity. Instead, in the other two cities, the distributions are very similar and most of the time the cars are only charged for less than 25% of their capacity. We report the mean and median charge percentages when the car is rented after a charge in Table 2, also for combustion engine fleets.

Next, in Figure 29, we report the charging duration. Again, we can compute two different estimations. The first one is the time between the initial and final time of the charge event (solid line), and the second one is the time between the start of the charge event and the start of the following rental (dashed line). Here the differences between the two metrics are higher. This is because we do not have the exact information about when the car stopped charging after it is made available.

Results show that for the distributed infrastructure (Amsterdam and Stuttgart), most of the time the cars are released in less than 1 hour after their charging processes start. This is likely due to a policy of the operator that makes the cars available as soon as possible in certain zones and time slots. After this short time, we observe a plateau that lasts till 2-3 hours of charge. This means that if the car is not released in the first hour, then it stays in charge for longer than 2-3 hours. Instead, in Madrid, all charge events last more than 1 hour, and we do not observe any plateau. In Madrid the charging process is managed by the operator, who does not have any advantage by relocating the car to the charging hub for a short period of time.

We observe that for all the cities, 80% of the time, the car returns available within 4 hours. Instead, the time before the next rental is more than 4 hours 50% of the time. The gap between the time the car is made available (solid) and the time the car is rented again (dashed) is smaller in Madrid (green curves). This means that the time lost for the whole charging procedure is reduced in Madrid.

To conclude, in Figure 30, we report when charge events begin. The re-

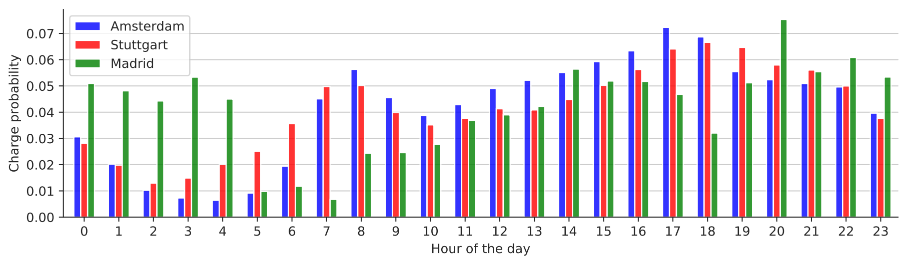



Figure 30: Daily pattern of the beginning of charge events.

sults highlight further differences between the centralized and the distributed infrastructures. In Madrid, many charge events occur in the night (20:00-04:59). Again, since the charging operation is managed, the operator optimizes it by charging the cars in time periods when the demand is low (see Figures 17 and 18) without compromising the possibility to satisfy demand and make revenues. On the contrary, the two distributed infrastructures show comparable patterns with many charge events also during pick hours.

## 8. Discussion and conclusions

The present study investigated the characteristics of FFCS services in 23 cities from December 2016 to January 2018. In terms of fleet size, it was found that many services appeared to be oversized compared to their actual level of usage. It also became clear that the growth trend observed in previous years [28] had stopped. In the period studied, service demand was either stationary or in a downtrend, which caused a service shutdown in many cities. As previous studies have shown, strong incentives towards sustainable shared mobility put in place by governments, municipalities, and policymakers can foster positive changes [5, 12, 26]. A prominent example is the municipality of Madrid. Our results demonstrate how the efforts made in Madrid to “impose a new culture of mobility” quickly achieved positive results; among all the cities considered, Madrid had the highest daily service usage rate, i.e., more than 10 rentals per car and a daily travel distance of up to 100 $km$ per car. These outcomes are even more impressive considering that the Madrid fleet is composed solely of electric cars. Amsterdam and Stuttgart also have electric fleets which achieved car utilization levels comparable to most of the cities equipped with combustion engine fleets. Our results therefore confirm that the range anxiety affecting electric vehicle users does not significantly limit actual service demand.

For all the cities, Thursdays and Fridays were found to be the days of the week with the maximal number of rentals, showing that FFCS is used both for commuting and leisure activities. Furthermore, daily usage was clearly different for North American and European cities: North American cities had a higher utilization early in the afternoon and much lower utilization in the evening and at nighttime. Italian and Spanish cities showed seasonal patterns, e.g., a decrease in the number of rentals in the summertime. These data-driven analyses can help operators to shape service provision according to the usage patterns and to schedule refuel and maintenance operations.

Considering the spatial usage of FFCS, results show that in some cities like New York City and Amsterdam rentals were homogeneously spread, whereas in cities like Milan and Vancouver rentals were concentrated in only a few zones. For instance, in many cities, we noted that a small number of zones were strongly attractive in the morning, and further noted that these zones were likely to become generative in the afternoon. In order to improve the utilization level of the vehicles, operators should therefore consider the hourly rental distribution to decide on relocation strategies.

Due to their reduced autonomy, electric cars need to be refueled more often than internal engine cars: they also need longer refueling operations. In Madrid, cars are charged by the operator through a centralized infrastructure, whereas in Amsterdam and Stuttgart users can charge the cars for themselves in the parking spots distributed around the cities. Our study shows that, in the latter case, cars are often charged multiple times in a day, for just a fraction of their capacity. Instead, in Madrid, the operator fully charges the cars, often at nighttime, when utilization is lower. Both the solutions seem to succeed in providing a sufficiently high car availability, but Madrid likely has higher management costs due to its centralized nature.

To summarize, results demonstrate the importance of data-driven analyses to understand current system usage and possible future directions. We believe that such a large-scale analysis over many cities in two continents paves the way for scientists, car sharing operators, and policymakers that want to design mobility solutions for future cities where electric vehicles will likely play a key role. To support further data explorations, we encourage readers to play with the interactive plots available at [16].

In our future works, we plan to integrate and analyze data acquired from different shared mobility systems and to develop an economic analysis to support the design of more efficient, integrated mobility services. We are also interested in helping service providers and urban planners to design and optimize the infrastructure needed to support electric mobility [8, 9]. Furthermore, we plan to use data mining techniques such as clustering techniques to group cities based on their characteristics and to forecast FFCS future usage.

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Table 2: Statistics summary for each city.

| City | Short Name | Fleet Size [-] | City Size [$km^2$] | Rentals [-] | Round Trip [-] | Cancel-lations [-] | Long [-] | Refuel [-] | Scale Factor Spatial [-] | Scale Factor Temporal [-] | Rental Duration [$min:sec$] | | Rental Distance [$km$] | | Daily Rentals per City [-] | | Daily Rentals per Car [-] | | Daily Rentals per Zone [-] | | Charge Gap [day-hour] | | Refuel/ Charge [%] | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | | Med | Med | Avg | Med | Avg | Med | Avg | Med | Avg | Med | Avg | Std | Avg | Med | Avg | Med |
| Columbus | COL | 187 | 17 | 90k | 2k | 86k | 5k | 3k | 1.35 | 1.98 | 22:47 | 18:32 | 4.4 | 3.3 | 301 | 315 | 2.7 | 2 | 2.3 | 1.2 | 24d-02h | 17d-19h | 59 | 63 |
| Florence | FLR | 220 | 34 | 208k | 2k | 112k | 6k | 5k | 1.71 | 1.73 | 25:35 | 22:27 | 5.3 | 4.1 | 692 | 715 | 4.1 | 4 | 3.0 | 2.8 | 17d-13h | 12d-04h | 65 | 75 |
| Frankfurt | FRA | 242 | 40 | 285k | 5k | 187k | 14k | 14k | 1.50 | 1.88 | 31:14 | 27:32 | 5.9 | 4.6 | 948 | 975 | 4.5 | 4 | 3.8 | 4.3 | 06d-23h | 03d-17h | 42 | 50 |
| Denver | DEN | 312 | 36 | 187k | 3k | 137k | 9k | 12k | 1.34 | 2.24 | 25:35 | 21:52 | 4.2 | 3.4 | 626 | 648 | 3.1 | 3 | 2.5 | 2.5 | 10d-17h | 04d-22h | 28 | 82 |
| Amsterdam | AMS | 314 | 38 | 309k | 35k | 146k | 9k | 74k | 1.51 | 1.85 | 29:19 | 26:10 | 5.4 | 4.8 | 1028 | 1054 | 4.0 | 4 | 4.0 | 2.2 | 01d-16h | 00d-18h | 31 | 28 |
| Austin | AUS | 315 | 31 | 187k | 6k | 162k | 10k | 12k | 1.34 | 2.06 | 25:44 | 21:33 | 4.9 | 3.9 | 629 | 652 | 2.9 | 2 | 2.4 | 2.2 | 11d-04h | 05d-05h | 33 | 76 |
| Turin | TRN | 396 | 47 | 613k | 3k | 233k | 7k | 12k | 1.41 | 1.71 | 21:43 | 19:19 | 4.0 | 3.3 | 2041 | 2181 | 5.9 | 6 | 7.9 | 7.1 | 13d-13h | 09d-02h | 71 | 82 |
| Toronto | TOR | 400 | 49 | 290k | 7k | 181k | 40k | 18k | 1.36 | 1.96 | 30:31 | 26:03 | 4.5 | 3.5 | 974 | 1039 | 3.3 | 3 | 3.0 | 2.8 | 09d-03h | 05d-06h | 56 | 63 |
| Madrid | MAD | 424 | 42 | 1398k | 28k | 499k | 11k | 156k | 1.46 | 1.83 | 26:17 | 23:52 | 4.2 | 3.8 | 4660 | 4866 | 11.3 | 11 | 20.2 | 14.5 | 01d-02h | 00d-14h | 56 | 59 |
| Montreal | MONT | 429 | 49 | 353k | 6k | 210k | 22k | 15k | 1.40 | 2.05 | 31:05 | 27:06 | 4.6 | 3.8 | 1185 | 1236 | 3.8 | 3 | 3.5 | 3.6 | 09d-16h | 07d-07h | 55 | 65 |
| Munich | MUC | 478 | 61 | 489k | 5k | 383k | 18k | 21k | 1.39 | 1.92 | 31:56 | 28:14 | 8.4 | 4.8 | 1629 | 1682 | 4.0 | 4 | 4.2 | 4.8 | 09d-16h | 06d-06h | 49 | 70 |
| Stuttgart | STUT | 486 | 59 | 484k | 59k | 334k | 12k | 112k | 1.58 | 2.24 | 30:04 | 27:25 | 6.2 | 4.3 | 1614 | 1648 | 4.1 | 4 | 3.1 | 3.8 | 01d-15h | 00d-17h | 30 | 29 |
| New York City | NYC | 500 | 77 | 362k | 6k | 318k | 31k | 22k | 1.36 | 2.02 | 33:56 | 29:37 | 4.8 | 3.6 | 1216 | 1165 | 3.4 | 3 | 3.0 | 2.2 | 07d-23h | 05d-16h | 54 | 60 |
| Calgary | CAL | 552 | 47 | 705k | 11k | 412k | 21k | 27k | 1.40 | 2.43 | 26:05 | 22:56 | 4.0 | 3.2 | 2365 | 2527 | 5.2 | 5 | 6.8 | 14.2 | 08d-08h | 04d-01h | 37 | 31 |
| Washington DC | WDC | 563 | 64 | 459k | 7k | 409k | 23k | 21k | 1.31 | 2.11 | 29:06 | 25:49 | 4.4 | 3.7 | 1539 | 1586 | 3.6 | 3 | 3.3 | 3.3 | 10d-15h | 07d-12h | 53 | 63 |
| Rome | ROM | 582 | 65 | 804k | 6k | 385k | 23k | 22k | 1.59 | 1.78 | 28:18 | 25:12 | 5.6 | 4.7 | 2680 | 2835 | 5.3 | 5 | 6.4 | 5.3 | 10d-22h | 07d-05h | 68 | 82 |
| Rhineland | RHL | 648 | 82 | 820k | 10k | 527k | 24k | 40k | 1.43 | 2.01 | 29:55 | 26:18 | 6.4 | 4.4 | 2734 | 2832 | 4.9 | 4 | 4.9 | 5.2 | 06d-14h | 03d-12h | 38 | 37 |
| Vienna | VIE | 688 | 72 | 1085k | 13k | 518k | 32k | 54k | 1.44 | 1.94 | 30:15 | 26:57 | 5.8 | 4.6 | 3617 | 3807 | 5.8 | 5 | 8.0 | 6.5 | 04d-17h | 02d-12h | 36 | 32 |
| Seattle | SEA | 710 | 92 | 661k | 18k | 397k | 27k | 31k | 1.30 | 2.16 | 29:41 | 26:45 | 6.1 | 4.8 | 2217 | 2396 | 4.3 | 4 | 3.3 | 4.1 | 09d-04h | 03d-19h | 24 | 79 |
| Milan | MIL | 776 | 77 | 1562k | 8k | 587k | 28k | 38k | 1.47 | 1.85 | 26:10 | 23:10 | 4.2 | 3.7 | 5207 | 5555 | 7.5 | 7 | 11.0 | 13.3 | 08d-15h | 05d-19h | 59 | 66 |
| Hamburg | HAMB | 812 | 82 | 1570k | 16k | 861k | 40k | 74k | 1.36 | 2.18 | 32:09 | 28:51 | 5.8 | 4.8 | 5232 | 5427 | 7.0 | 7 | 9.9 | 10.0 | 04d-09h | 02d-02h | 36 | 79 |
| Vancouver | VAN | 977 | 78 | 1612k | 34k | 956k | 51k | 48k | 1.33 | 2.39 | 29:30 | 26:07 | 4.8 | 3.9 | 5409 | 5600 | 6.7 | 6 | 11.3 | 17.9 | 08d-03h | 04d-17h | 42 | 38 |
| Berlin | BER | 1009 | 125 | 1985k | 17k | 966k | 54k | 69k | 1.32 | 2.08 | 32:02 | 28:37 | 5.8 | 4.7 | 6615 | 6826 | 7.0 | 7 | 9.4 | 8.3 | 05d-23h | 04d-00h | 49 | 66 |