Characterizing Usage Patterns and Service Demand of a Two-Way Car-Sharing System

Characterizing usage patterns and service demand of a two-way car-sharing system

Felipe Rooke[1][0000-0001-5625-2694], Victor Aquiles[1][0000-0002-9670-076X], Alex Borges Vieira[1][0000-0003-0821-126X], Jussara M. Almeida[2][0000-0001-9142-2919], and Idilio Drago[3][0000-0003-1932-1261]

[1] Departamento de Ciência da Computação, Universidade Federal de Juiz de Fora, Juiz de Fora, MG, Brazil
felipe.rooke@ufjf.edu.br,victoraquiles@ice.ufjf.br, alex.borges@ufjf.edu.br

[2] Departamento de Ciência da Computação, Universidade Federal de Minas Gerais, Belo Horizonte, MG, Brazil
jussara@dcc.ufmg.br

[3] Department of Electronics and Telecommunications, Politecnico di Torino, Italy
idilio.drago@polito.it

Abstract. Urban mobility is directly linked to the demand for communication resources and, clearly, its understanding is useful for better planning of urban and communication systems. However, getting data about urban mobility is still a challenge. In many cases, only a few companies have access to accurate and updated data. In most cases, these data are also privacy sensitive. It is thus important to generate models that can help to understand mobility patterns. We here characterize the demands of a two-way car-sharing system. We explore data of the public API of Modo, a car-sharing system that operates in Vancouver (Canada) and nearby regions. Our study uncovers patterns of users' habits and demands in the service, which can be explored for urban and communication planning.

Keywords: car-sharing · two-way · characterizing · urban mobility · patterns.

1 Introduction

The comprehension of urban mobility has been a target of studies and investments. Urban mobility is a key research area, attracting several academic studies and private investments. It is intrinsically connected to a wide number of urban activities, such as the demand for communication resources. Indeed, the massification of mobile devices turned the network access ubiquitous and user-centered. The actual network infrastructure is each day less rigid, and users demand communication while moving across the city. Understanding the urban mobility, specifically the traffic-related mobility, is important for a series of tasks, ranging from road mesh planning to communication resources allocation [Herrera et al. 2010,Ma et al. 2013].

The first step in understanding urban mobility patterns is the proper acquisition of data. Data related to this problem domain can be obtained by several ways, e.g., by observing vehicles passing through sensors or fixed/mobile radars, by acquiring traffic data from cameras, or even by the active participation of users (*crowdsourcing*). However, the data acquisition is still a challenge. Only a few companies have access to accurate data, and most of the time these data are privacy sensitive [Ciociola et al. 2017]. Therefore, it is important to generate models that can help to understand the urban mobility and the social interactions of people in the urban environment.

Many alternative transport modes contribute to urban mobility. Among them, car-sharing systems have received an increased attention from the academic community [Boldrini et al. 2016,Ciociola et al. 2017,Becker et al. 2017]. In a car-sharing sharing system, people can schedule the use of a vehicle, without worrying about maintenance and parking fees. These systems have already a large volume of users and thus can be representative of an important type of urban mobility pattern. In fact, by 2015, more than 1.5 million users and more than 22,000 shared vehicles have been counted in the Americas, and growth in usage is still expected [Shaheen 2016].

There are different business models for operating car-sharing services [Nourinejad 2014]: (i) *one-way* services, which rely on base stations scattered in one region, with users renting and returning vehicles at arbitrary stations; (ii) *two-way* services, in which users must return the vehicles always at the same station where the rent started; and (iii) *free-floating* services, where there is no base stations, and users are free to rent and return vehicles at any position inside the operating area of the service [Boldrini et al. 2016].

Recent studies have addressed one-way services, showing spatial-temporal usage characteristics [Boldrini et al. 2016]. Similarly, user characteristics and usage patterns in free-floating services have been addressed [Kopp et al. 2015,Ciociola et al. 2017,Cocca et al. 2018]. However, there is no study that characterizes and models two-way services.

In this work, we characterize usage patterns and the demands of a two-way car-sharing system. More precisely, we explore the data offered by the public API of *Mode*,[4] a car-sharing service that operates in Vancouver (Canada) and nearby regions. Our contributions are the following:

(i) the characterization of demands in a large two-way car-sharing service;
(ii) the study of the system workloads, which can be exploited, e.g., for planning urban and communication systems.

We believe our study is an important step towards understanding all types of car-sharing usage. It can help uncover particular situations where such services are attractive and, together with data from other transport modes, help to uncover trends and mobility patterns. In fact, the data and its characterization can support decision-making related to urban mobility planning.

[4] http://www.modo.coop/

The paper is organized as follows: Section 2 describes the operation of existing car-sharing services and introduces details of the two-way model, the focus of this work; Section 3 discusses the data collection methodology and describes the acquired dataset; Section 4 presents results obtained from the characterization and analysis of the dataset; Section 5 describes related work, whereas Section 6 concludes the paper.

2 Car-sharing system basic model

The first concepts of car-sharing systems date back to 1948. Although, the basic principles of such service were consolidated during the 1970's [Harms and Truffer 1998]. At a glance, the key idea behind car-sharing systems is that a fleet of cars can be shared by several users. They drive a car whenever they need without owning the car.

During the 1990's, along with emerging problems of large urban centers, high fuel prices, traffic congestion, high emission of pollutants, the idea of sharing came back again [Becker et al. 2017]. Since then, car sharing has been the subject of academy studies [Millard-Ball 2005]. Understanding the dynamics of these services provides valuable insights into how people move in urban centers. This information can give support to precise and efficient urban planning, ranging from traffic planning or the design of communication infrastructures.

There are two major car-sharing models: station-based and free-floating. Moreover, station-based may be divided into *one-way services* and two-way services. Station-based models require that a user pick up the vehicle she/he will use at a given base station. The user, in turn, may leave the vehicle at any of the base stations scattered throughout the service coverage region (i.e., one-way car-sharing service), or she/he may be obliged to return the vehicle to the station of origin (i.e., two-way car-sharing service). Clearly, the two-way model requires simpler logistics and infrastructure compared to other models. Its implementation can be performed at a lower cost and higher speed.

Note that, car-sharing, in special the two-way model, differs from classical car rental in many ways. Indeed, car-sharing is a self-service based service, where vehicles can be allocated in fractions of times, as well as by the day, as traditional car rental. Moreover, the one-way model may be more flexible and cost-efficient to users than classical rental. For example, in case there is a base station near to the final user destination, she/he may leave the car at the station while she/he perform other tasks. The time the vehicle is parked is not charged, incurring to lower costs to users. However, users may not be able to make a new reservation, in case the same vehicle is reserved by another user.

The free-floating model does not require any fixed station. In other words, users reserve the nearest car, parked into city streets. By the end of the use, users may leave vehicles at any location in a predefined area. Notably, free-floating model eliminates the limitations that station-based models hold, making the experience more flexible and closer personal vehicles [Ciari et al. 2014]. However, there are some problems, such as the uncertainty of finding nearby cars.

We are aware of works that characterize and model one-way services [Ciari et al. 2014,Stillwater et al. 2009,Burkhardt and Millard-Ball 2006]. These works achieve a consensus about some questions as: (i) the most accepted markets for these services are in dense urban areas with good public transport [Stillwater et al. 2009]; (ii) the profile of the users of these systems is composed of young people with high income and good schooling [Burkhardt and Millard-Ball 2006]. A number of researchers also confirm positive impacts on the actual transport system, such as the reducing on traffic and emission of pollutants [Cervero and Tsai 2004,Martin and Shaheen 2011], the reducing on parking areas and the increase in the use of public transport [Shaheen et al. 2010]. However, to the best of our knowledge, there are no characterization studies or models for two-way car-sharing services and so there is a gap to be explored.

Figure 1 presents an abstract model that describes the operation of a car-sharing system. This simple model can be applied to three types of services. Note that there are four possible states for a vehicle: available, partially available, rented, and unavailable. These states define when a vehicle is busy or idle. A vehicle, when reserved, passes from the available state to the partially available state (1). The reservation can also occur as an immediate rent, in that case passing from the state available to rent (2). From the partially available state, when the reserved time arrives and the rental starts, the vehicle moves to the rented state (3). In the case of cancellation of a reservation, the vehicle returns to the available state (4). Starting from the rented state, a vehicle may return to the partially available state, when a rental is finalized and there is a reservation scheduled in the interval (5) or it may return to the available state when there is no more reserve for it (6). The vehicle enters the unavailable state when it is in maintenance or out of service (7), and it returns to the system when issues have been resolved (8).

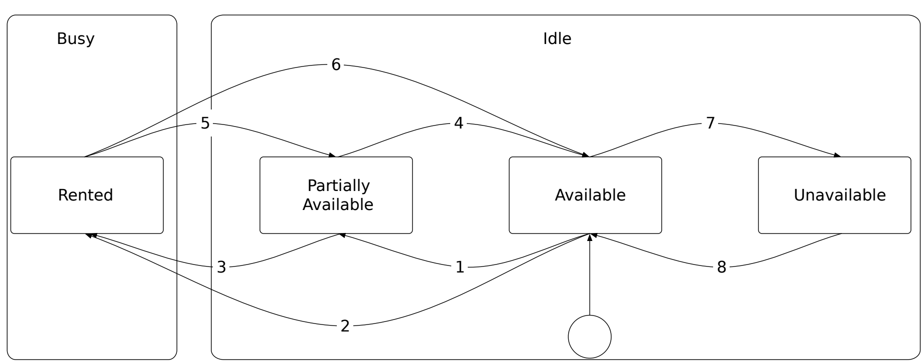


Fig. 1. States of a vehicle in a car-sharing system.

3 Dataset and methodology

Our study relies on data crawled from the public API of Modo, a car-sharing service operating in Vancouver (Canada) and nearby regions. Modo, in 2017, featured about 600 vehicles, distributed among conventional, electric and hybrid cars. In addition, this system covers about 18000 users, over an area of approximately 133 km^2.

The data collection process was conducted using a crawler which uses the API provided by the Modo[5] platform. The crawling process allows us to gather data about vehicles available on the platform. These data enable to study the distribution of supply and demand for vehicles in time and space.

The first step was to request the API a list of all vehicles of the platform. We perform a request per minute, for every available vehicle, and each request to the Modo API returns the period a specific vehicle will be available, during the next 24-hour interval. In addition, the responses include the vehicle location and its station identification. We discarded data from unavailable vehicles, i.e., in maintenance or out of service.

Note that Modo API does not return specific vehicle status, nor any information that could be used to identify users of the system. We uncover if a vehicle is busy or idle based on its reservation period and the current observation time. For example, Figure 2 illustrates the process of collecting data for a given vehicle.

As we previous stated, each API request tells us the period a given vehicle is booked in the next 24-hours. According to Figure 2, we leverage three possible situations:

- First, as shown in Figure 2-a, at $t = 1$, we perform a request to the Modo API and note that a given vehicle is booked between $t = [1; 5]$. At $t = 2$, the new request to the Modo API still returning the previously booking period. Each following request to the API confirms the booking period. In this case, at time $t = 6$, we perform a request to the API and the vehicle is no longer booked. In sum, we are able to judge that someone booked the vehicle between $t = [1; 5]$, used the car and, disposed of it after the original booking period.
- Second, as shown in Figure 2-b, at $t = 1$, we perform a request to the Modo API and note that a given vehicle is booked between $t = [1; 6]$. The request at $t = 2$ still confirms the previously booking period. However, in this case, a request at $t = 3$ shows no booking period at this moment. In this case, we judge that user canceled the [future] booking [period] between the moment $t = 6$ and the final previous booking period $t = 5$.
- Finally, as shown in Figure 2-c, the user extends its booking period, and the car is used for a longer period than the first booking. Note that, in this case, we accounts for the total observed period.

We perform this interactive process to register the states of all vehicles during the whole data capture period.

[5] http://modo.coop/api/

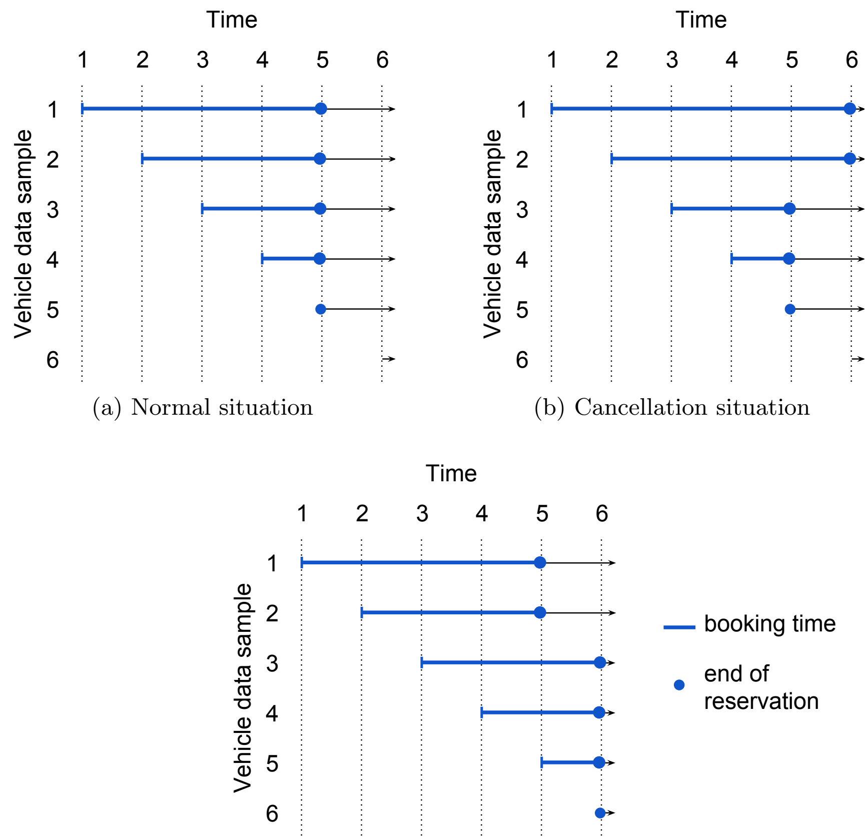


Fig. 2. Possible vehicle situations during a measurement. In (a) a normal booking and usage situation until the time t = 5; (b) a cancellation situation can be observed from the data sample 3; (c) a consecutive booking situation can be observed from sample 3.

In addition to vehicles availability information, we also collect base stations location, vehicle models, accessories and whether the vehicle is electric or hybrid. Researchers interested in the data can contact the authors.

Table 1 summarizes the volume of data collected/analyzed in this work. We have collected more than 82 k records, corresponding to 3 months of data —21 October 2017 to 21 November 2017; 01 March 2018 to 27 April 2018 —, from a fleet of 592 vehicles, distributed in 471 stations, each of them with one or more cars, in the territory of Vancouver (Canada) and regions in its surroundings. We were able to analyze about 97 k booking records and more than 66 k travels.

Description		Amount
# of Collected Records		82.275.495
# of Booking Records		97.865
# of Travels Records		66.371
# of Stations		471
	- Common	475
# of Vehicles	- Hybrids	114
	- Electrical	3

Table 1. Summary of the data collection.

4 Characterizing the car-sharing usage

In this section, we present the characterization about the car-sharing system service. First, we present the service temporal analysis. Then, we present the service spatial-temporal characteristics. Finally, we present service user behavior characteristics.

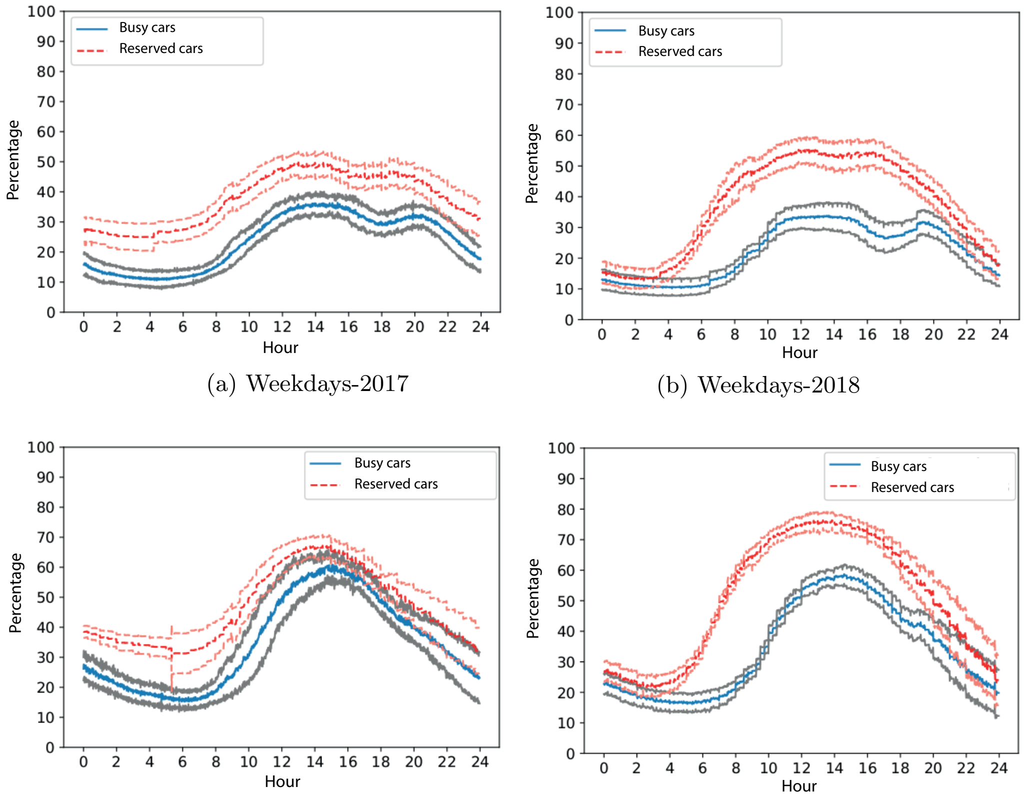
4.1 Service temporal characteristics

We now present the car-sharing service characterization. First, we present — in Figure 3— the service daily demand pattern. Figures 3-a and b present the demand pattern during labor days and Figures 3-c and d present the demand for weekends. All figures present a minute-by-minute mean value, and standard deviation, for the percentage of busy (blue curve) and reserved cars (red curve). In this case, we compute mean values and standard deviation taking into account the same one-minute period, for all days in our dataset[6].

Note that, according to Figures 3-a to d, there is a considerable difference between the number of reserved and effectively used cars, which occurs due to service cancellations. During labor days, the number of cancellations is more prominent during peak load periods, as during the middle day lunchtime and the end of the labor day. During weekends, we observe only a modal pattern, which occupies all the day.

More precisely, during labor days (Figures 3-a and b), we observe two load peaks, occurring between 11 AM–4 PM and 7 PM–8 PM. The first peak initial growth starts at 8 AM and extends until almost 6 PM. The nocturne peak may occur during after-work happy hours. For both periods, we notice a larger amount of reservation, when compared to the number of used cars, between 10 AM and 9 PM. The difference between reserved cars and actually used cars is smaller between 10 PM and 4 AM, especially noticed for the 2018 dataset. During this period, we also observe a lower demand for the service which can contribute to this behavior. Finally, we notice a negligible difference between the two datasets. In this case, the only notable difference occurs by the beginning and the ending of the day, which are slightly higher for the 2017 dataset.

[6] The standard deviation of idle and busy curves are the light red and gray curves, respectively



(a) Weekdays-2017

(b) Weekdays-2018

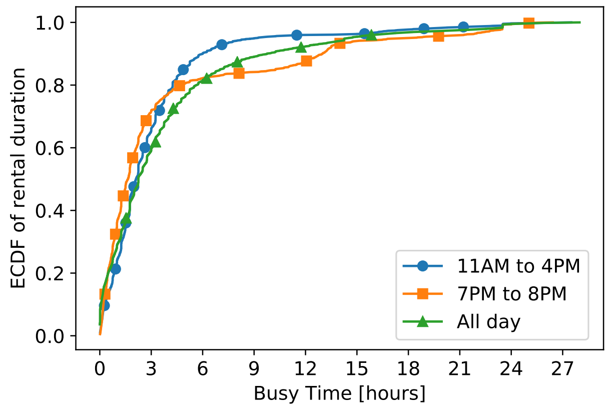
(c) Weekends-2017

(d) Weekends-2018

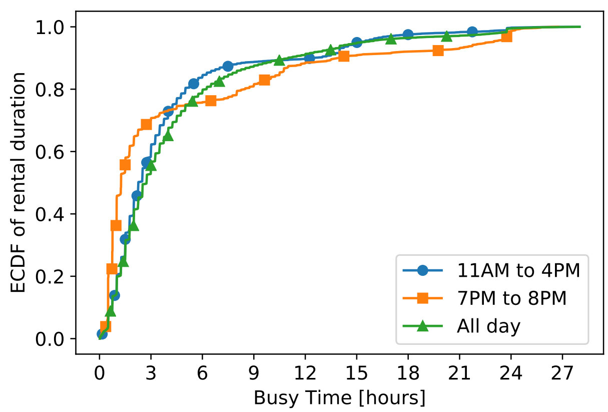
Fig. 3. Average percentage of vehicles busy/reserved at a given time for weekdays and weekends.

To analyze the characteristics of the load peaks during the working days we present in Figure 4-a and b the Empirical Cumulative Distribution Function (ECDF) of rental durations. In this case, we evaluate the load periods of a day (i.e., starts at 11 AM to 4 PM and 7 PM to 8 PM) and also, all day data. According to these figures, about 70% of vehicles rentals presents no more than 5 hours of occupation. This usage time value indicates the relationship between car-sharing demand and daily work routines, suggesting that the car remains rented during the daily work times.

At weekends (Figures 3-c and d), there is a notable behavioral difference from the presented for weekdays. On weekends, there is an occupation peak between 11 AM and 6 PM, with a maximum occupancy of about 60%, near 3 PM. The reserve peak occurs between 10 AM and 6 PM, and up to 70% of available cars are booked (around 2 PM). The increased use of cars at peak times when compared to weekdays can be explained by the fact that these are times



(a) 2017



(b) 2018

Fig. 4. ECDF of vehicle busy time in weekly load peak times.

of movement for consumption in shopping and leisure centers, characteristic of weekends.

In general, it is notable that the number of reservations, for the most part, is higher than that of occupancy, given that on weekends there is a greater chance of activities not having fixed time, so we conjecture that it is common for reservations to be for long periods even if they come not be fully utilized.

In summary, from Figures 3-a and b, it is observed that vehicle utilization follows usual patterns during the day, with peaks at work schedules and at night exits on weekdays, and peak in the afternoon on weekends. There was also a great variation in the number of reservations at these times, which can be explained by the great movement and availability of other means of transportation, especially in a large center such as Vancouver.

4.2 Service spacial-temporal characteristics

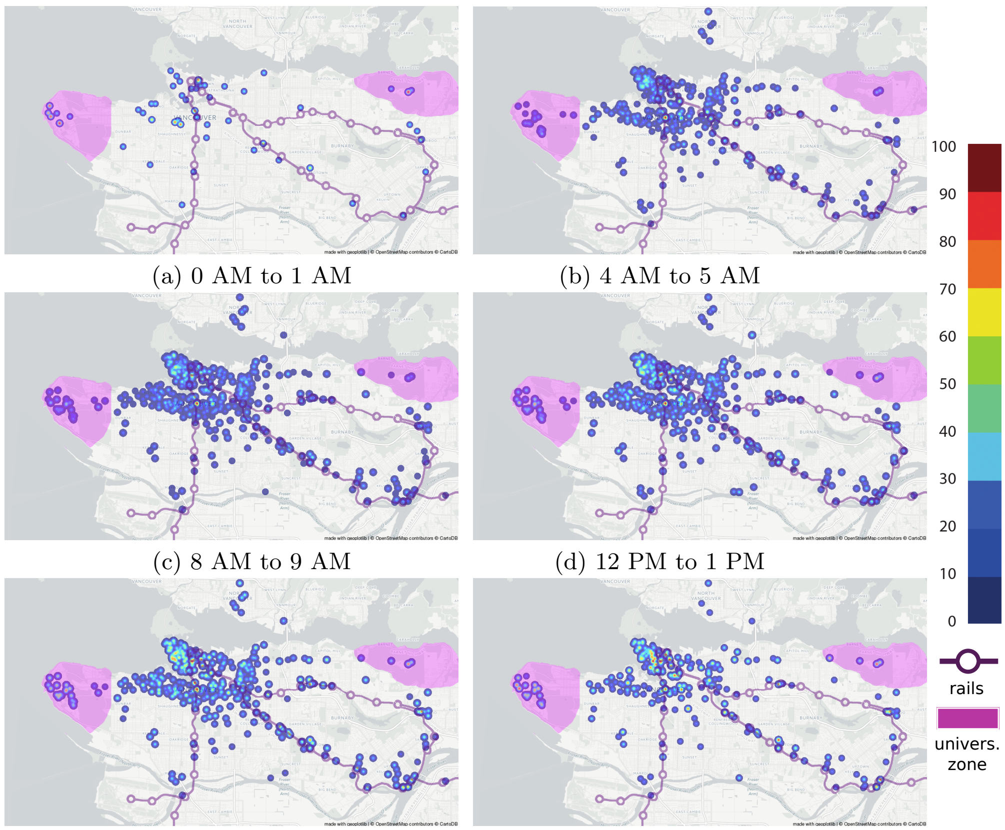
We have also analyzed the spatial-temporal car-sharing service demand. In this sense, as shown in Figure 5, we present heat-maps which show the hourly mean demand (occupation of vehicles) in a given base station for all data period we have analyzed. We have normalized the number of occupied vehicles to a 0-100 interval. In other words, the closer to 0, the lower the number of occupied vehicles in a given region.

Each subfigure —Figures 5-a to f— represents a 1-hour interval we sampled every 4 hours. We have also evaluated a distinct number of intervals, and qualitative results are similar. In this figure, we have omitted the base stations that do not present any used vehicle within the 1-hour we sample.

Note that, during the first intervals (Figure 5-a and b), the demand is notable in central zones, university areas and along the rail lines, specially Expo Line and Millennium Line. In this case, we note a strong relationship between the existing public transport system and the car-sharing system demand. Indeed, during the morning period (Figure 5-c), most of the existing stations are active and we note an increasing demand for car-sharing in central regions (in special, during the period around 12 PM). During the afternoon, we note demands peaks in all regions, especially between 2 PM and 4 PM. After 6 PM, the demand on map borders starts to decrease, and the demanding focus turns back to specific points in the center, as Vancouver as well neighboring cities, universities and train stations where there are possible connections. Again, this characteristic indicates that the car-sharing users make use of public transport too. We also highlight the remarkable participation of the university public in this service. The average concentration of occupied vehicles per hour in university zones are between 50% to 100%.

4.3 User behavior characterization

In order to characterize the two-way car-sharing service usage, we analyze the busy and idle time of a vehicle. For this analysis, we present two cumulative distribution functions, as shown in Figure 6, we filtered the data with less than 90 hours of duration to make the curves comparable and to avoid analyze outliers. In this figure, we plot the busy and idle vehicle time, both for common, hybrid and electric cars. We have also identified the statistical distribution that best fits the actual data. For this purpose, we tested distributions widely used in the literature: normal, lognormal, exponential, Gamma, Logistics, Beta, Uniform, Weibull and Pareto for continuous variables; Poisson, Binomial, Negative, Geometric and Hypergeometric Binomial for discrete variables. For each component of the model, the parameters of the distribution that most closely approximate the data are determined using the maximum likelihood estimation method. After defining the parameters of each component of the model, the distribution



(a) 0 AM to 1 AM (b) 4 AM to 5 AM

(c) 8 AM to 9 AM (d) 12 PM to 1 PM

(e) 4 PM to 5 PM (f) 8 PM to 9 PM

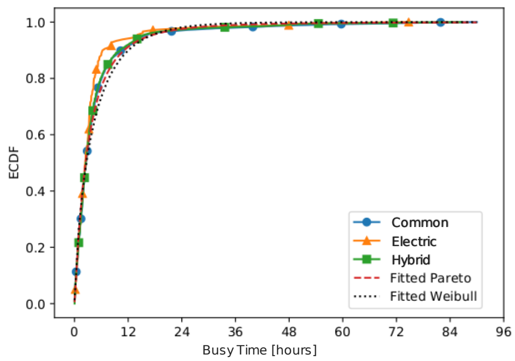
Fig. 5. Percent of hourly busy vehicles in Vancouver and their environments.

with shorter Kolmogorov-Smirnov distance (continuous distributions) or lower least square error (discrete distributions) in relation to the data was chosen. This choice is also validated with a visual assessment of the curve fitting.

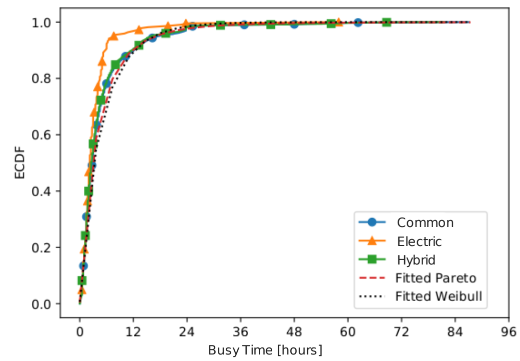
Figure 6-a shows the CDF of vehicle busy time, for the 2017 dataset. Note that Weibull[7] (with parameters $\alpha = 0.7074744$ and $\beta = 503.1711$) and Pareto[8] (with parameters $\alpha = 2.97408$ and $\beta = 1275.347$) distributions, present adequate adjustments to the measured data. Both distributions have similar MLEs and visually fit well into data curves. Figure 6-b shows equivalent CDF, for the 2018 dataset. As occurred to the 2017 data, the Weibull and Pareto CDF distributions best adjusted the actual data, differentiating only by their parameters: Pareto - $\alpha = 0.88077$ and $\beta = 284.551$ and Weibull - $\alpha = 3.69557$ and $\beta = 812.152$. The

[7] Cumulative distribution function (CDF) of the Weibull distribution: $F(x; \alpha, \beta) = 1 - e^{-(x/\beta)^{\alpha}}$.

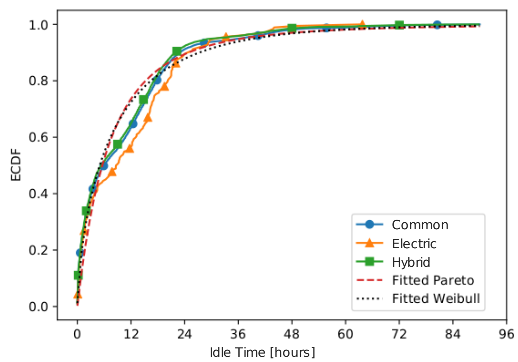
[8] Cumulative distribution function (CDF) of the Pareto distribution: $F(x) = 1-(\frac{\beta}{x})^{\alpha}$.



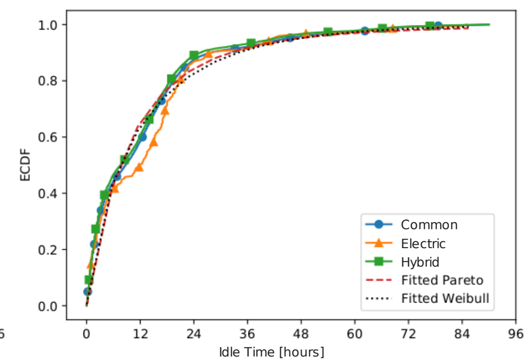
(a) Busy-2017



(b) Busy-2018



(c) Idle-2017



(d) Idle-2018

Fig. 6. Busy and idle times distribution.

changes in the parameters can be attributed to seasonal changes, which will be further investigated in future work.

According to Figures 6-a and b, we note that at least half of the vehicles, independent of its type, are used for more than 3 hours, demonstrating that the service is used for medium to long duration travels. In addition, common and hybrid vehicles have similar characteristics however, about 40% of the electric vehicles remain busy 1 hour less than the others. There is an indication that the lower electric vehicles busy time occurs due its intrinsic characteristics: these cars need frequent recharges, which turn them not so favorable for long-term use, but more assertive conclusions demands more electric vehicle samples.

Finally, Figures 6-c and d, presents vehicle idle periods distribution. In other words, these figures show for how long a car will be idle in its base station. It is possible to note that vehicles remain for a considerable time in their stations. Most of 60% of the cars stay for periods longer than 3 hours idle. Again, common and hybrid vehicles have similar characteristics, while electric vehicles have 45% of their vehicles remaining 1 hour more idle than the others. For example, at least

20% of ordinary cars get more than 18 hours stationary while electric cars, in the same proportion, stay for 19 hours. As we previously stated, electric vehicle intrinsic characteristic imposes hard constraints to their use, in special, forcing vehicles to be idle for long periods while they are recharging.

Weibull and Pareto distributions best fit actual data, for both datasets. In this case, both distributions favor the curves heads an tails, which comprises more than 60% of actual data. For the 2017 dataset, distribution parameters are: Weibull - $\alpha = 0.7074744$ and $\beta = 503.1711$; and Pareto - $\alpha = 2.97408$ and $\beta = 1275.347$. For the 2018 dataset, distribution parameters are: Weibull - $\alpha = 0.7940277$ and $\beta = 709.7194$) and Pareto - $\alpha = 3.34977$ and $\beta = 1944.027$).

In sum, our analysis shows that the two-way car-sharing system is mostly used for medium and long-term travels, most likely for the round trip of a work routine, or visits to cities around Vancouver. In addition, we have observed that ordinary and hybrid cars do not have notable differences in their idle and busy times, while the electric vehicle presents at least one hour difference in both cases (1 hour less busy time and 1 hour more idle time), probably because the need for constant recharges. Again, more assertive conclusions about electric cars demand more samples and analysis.

5 Related work

The characterization of the usage and demands of car-sharing systems have so far been focused on one-way and free-float models. Some authors generalize one-way and two-way models as station-based models [Becker et al. 2017] [Ciari et al. 2014] [Rooke et al. 2018] [Boldrini et al. 2016]. This paper explores the two-way model due to its specific characteristics, and the fact that this model has been little approached in the literature.

Most of the recent research [Becker et al. 2017] [Ciari et al. 2014] [Martin and Shaheen 2011] [Boldrini et al. 2016] addressed one-way car-sharing services, revealing some important characteristics of these services. In special, these works characterize user behavior, revealing that the services are mostly used for long journeys and for shopping [Ciari et al. 2014]. In most cases, the car is used by 2 or more passengers [Becker et al. 2017]. These works also reveal interesting features about the fleet of electric cars: e.g., vehicles remain parked in central regions much less than in suburban regions, directly interfering with the autonomy of the vehicle [Boldrini et al. 2016]. Finally, it is important to emphasize that these works indicate a close interaction between the use of the services and the use of public transport, in particular, the rail transport system [Stillwater et al. 2009].

The free-floating model clearly presents different usage patterns from the one-way model. Indeed, the free-floating vehicles are often used for shorter journeys, presenting pendular movements and a considerable number of trips to airports [Ciari et al. 2014,Becker et al. 2017,Ciociola et al. 2017]. Typically, free-floating vehicles carry a single user [Becker et al. 2017]. The free-floating model also presents a remarkable seasonal usage. For instance, during the mornings, central areas of the city are the main destination. During the evening, suburban areas turn the main targets [Ciociola et al. 2017].

Despite the flexibility of the free-floating model, previous works have not observed a clear difference in users' preferences between services [Ciari et al. 2014], which may be a signal that the services complement each other. Some works have identified that the services attract different user classes, exposing the fact that free-floating models and station-based models must be treated separately [Becker et al. 2017].

6 Conclusions and Future Work

In this paper, we have studied the usage pattern and service demand of a large two-way car-sharing system. Our work relies on real datasets from Modo, a car-sharing service that operates in Vancouver (Canada) and nearby regions. Our work reveals important two-way car-sharing properties, as its demand seasonality, vehicles occupation duration, travels cancellation and the waste of productivity while vehicles are idle. At a glance, our work shows that this service presents load peaks during the day. In special, during labor days, these peaks occur around the lunch time. At weekends, peaks occur during the afternoons. Most travels are rest for about 3 hours and, electric vehicles stays occupied about 1 hour less than other vehicles, and also present a longer maintenance period. Moreover, the car-sharing system usage presents a strong relation with public transport system, as well as with regions nearby points of interests, such as public universities and commercial centers. Finally, we believe the characterization we provide may be used as a substrate for urban centers planning.

As future work, we intend to analyze the car-sharing system regardless its type. We also plan to include additional parameters to the analysis, such as socioeconomic and environmental data.

References

[Becker et al. 2017] Becker, H., Ciari, F., and Axhausen, K. W. (2017). Comparing car-sharing schemes in switzerland: User groups and usage patterns. *Transportation Research Part A: Policy and Practice*, 97:17–29.

[Boldrini et al. 2016] Boldrini, C., Bruno, R., and Conti, M. (2016). Characterising demand and usage patterns in a large station-based car sharing system. In *Computer Communications Workshops (INFOCOM WKSHPS), 2016 IEEE Conference on*, pages 572–577. IEEE.

[Burkhardt and Millard-Ball 2006] Burkhardt, J. and Millard-Ball, A. (2006). Who is attracted to carsharing? *Transportation Research Record: Journal of the Transportation Research Board*, (1986):98–105.

[Cervero and Tsai 2004] Cervero, R. and Tsai, Y. (2004). City carshare in san francisco, california: second-year travel demand and car ownership impacts. *Transportation Research Record: Journal of the Transportation Research Board*, (1887):117–127.

[Ciari et al. 2014] Ciari, F., Bock, B., and Balmer, M. (2014). Modeling station-based and free-floating carsharing demand: test case study for berlin. *Transportation Research Record: Journal of the Transportation Research Board*, (2416):37–47.

[Ciociola et al. 2017] Ciociola, A., Cocca, M., Giordano, D., Mellia, M., Morichetta, A., Putina, A., and Salutari, F. (2017). Umap: Urban mobility analysis platform to harvest car sharing data.

[Cocca et al. 2018] Cocca, M., Giordano, D., Vassio, L., and Mellia, M. (2018). Free floating electric car sharing in smart cities: Data driven system dimensioning.

[Harms and Truffer 1998] Harms, S. and Truffer, B. (1998). The emergence of a nationwide carsharing co-operative in switzerland. *A case-study for the EC-supported rsearch project "Strategic Niche Management as a tool for transition to a sustainable transport system", EAWAG: Zürich.*

[Herrera et al. 2010] Herrera, J. C., Work, D. B., Herring, R., Ban, X. J., Jacobson, Q., and Bayen, A. M. (2010). Evaluation of traffic data obtained via gps-enabled mobile phones: The mobile century field experiment. *Transportation Research Part C: Emerging Technologies*, 18(4):568 – 583.

[Kopp et al. 2015] Kopp, J., Gerike, R., and Axhausen, K. W. (2015). Do sharing people behave differently? an empirical evaluation of the distinctive mobility patterns of free-floating car-sharing members. *Transportation*, 42(3):449–469.

[Ma et al. 2013] Ma, S., Zheng, Y., and Wolfson, O. (2013). T-share: A large-scale dynamic taxi ridesharing service. In *Data Engineering (ICDE), 2013 IEEE 29th International Conference on*, pages 410–421.

[Martin and Shaheen 2011] Martin, E. and Shaheen, S. (2011). The impact of carsharing on public transit and non-motorized travel: an exploration of north american carsharing survey data. *Energies*, 4(11):2094–2114.

[Millard-Ball 2005] Millard-Ball, A. (2005). *Car-sharing: Where and how it succeeds*, volume 108. Transportation Research Board.

[Nourinejad 2014] Nourinejad, M. (2014). Dynamic optimization models for ridesharing and carsharing. Master's thesis, University of Toronto.

[Rooke et al. 2018] Rooke, F., Aquiles, V., Vieira, A. B., do Couto Teixeira, D., Almeida, J. M., and Drago, I. (2018). Caracterização de padrões de demanda e uso de um sistema de compartilhamento de veículos de duas vias. In *Simpósio Brasileiro de Redes de Computadores (SBRC)*, volume 36.

[Shaheen 2016] Shaheen, S. A. (2016). Mobility and the sharing economy. *Transport Policy*, 51(Supplement C):141 – 142.

[Shaheen et al. 2010] Shaheen, S. A., Rodier, C., Murray, G., Cohen, A., and Martin, E. (2010). Carsharing and public parking policies: assessing benefits, costs, and best practices in north america. Technical report.

[Stillwater et al. 2009] Stillwater, T., Mokhtarian, P., and Shaheen, S. (2009). Carsharing and the built environment: Geographic information system-based study of one us operator. *Transportation Research Record: Journal of the Transportation Research Board*, (2110):27–34.