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Original
Characterizing client usage patterns and service demand for car-sharing systems / Alencar, Victor A.; Rooke, Felipe; Cocca, Michele; Vassio, Luca; Almeida, Jussara; Vieira, Alex Borges. - In: INFORMATION SYSTEMS. - ISSN 0306-4379. - ELETTRONICO. - 98:(2021), p. 101448. [10.1016/j.is.2019.101448]

Availability:
This version is available at: 11583/2843628 since: 2021-03-22T13:27:04Z

Publisher:
Elsevier

Published
DOI:10.1016/j.is.2019.101448

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17 October 2022

Characterizing Client Usage Patterns and Service Demand for Car-Sharing Systems

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Abstract

The understanding of the mobility on urban spaces is useful for the creation of smarter and sustainable cities. However, getting data about urban mobility is challenging, since only a few companies have access to accurate and updated data, that is also privacy-sensitive.

In this work, we characterize three distinct car-sharing systems which operate in Vancouver (Canada) and nearby regions, gathering data for more than one year. Our study uncovers patterns of users' habits and demands for these services. We highlight the common characteristics and the main differences among car-sharing systems. Finally, we believe our study and data is useful for generating realistic synthetic workloads.

Keywords:
Urban mobility, car-sharing, characterizing, two-way, one-way, free-floating

1. Introduction

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. Understanding the urban mobility, specifically the traffic-related mobility with motorized vehicles, is important for a series of tasks, ranging from road mesh planning to communication resources allocation [1, 2].

The first step in understanding urban mobility patterns is the proper acquisition of data. Data can be obtained in several ways, e.g., by observing vehicles passing through sensors or fixed/mobile radars, by acquiring traffic data from cameras, or by the active participation of users (*crowdsourcing*). However, large

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data acquisition is still a challenge, only a few companies have access to them and, usually, these data are also highly privacy-sensitive [3]. Therefore, it is important to collect data and 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, the car-sharing paradigm is quickly growing [4, 3, 5]. In a car-sharing system, people can drive a vehicle, without worrying about buying it and paying for maintenance, fuel and parking fees. By 2015, more than 1.5 million users and 22 000 shared vehicles have been counted in the Americas, and growth in usage is still expected [6]. Overall, car-sharing services are classified into three categories: (i) the one-way services, where the vehicles are available in specific stations and the user can move a car from a station to another; (ii) the two-way services, where the user must return the vehicle to the same station she/he picked up the vehicle and; (iii) the free-floating service where vehicles are not tied to stations. In this case, the users are able to start and finish their trips everywhere within an operative area and in public parking spots [4].

In this work, we consider the three car-sharing categories, which are all present in Vancouver (Canada) and nearby urban area. Our characterization relies on data we gathered for more than a year from Modo, Evo and Car2Go car-sharing services —a two-way, a one-way and a free-floating service, respectively—. We explore the demand and usage patterns of vehicles from these services and, at a glance, our contributions are twofold: first, we provide a characterization of three important car-sharing paradigms and, second, we model the demand for their vehicles, providing statistical distributions which describe their busy and idle periods. We believe our study is important to highlight particular situations where car-sharing services are attractive and, together with data from other transport modes, to uncover trends and mobility patterns. Moreover, we also believe the data we collected and the models we develop can be used to generate accurate synthetic workload. As a consequence, these can contribute to the development of better capacity planning models to car-sharing systems and also to a better plan of public transport systems. To best of our knowledge, we are the first to jointly consider all these three types of services, leveraging their common characteristics and highlighting their peculiarities.

The remainder of the work is structured as follows: Section 2 describes related work; Section 3 describes details of the three car-sharing paradigms; Section 4 discusses the data collection and analysis methodology for all services; Section 5 presents the results of the characterization for each model and the comparison of them, whereas Section 6 concludes the article.

2. Related Work

Prior works on one-way car-sharing services revealed some important characteristics of these services as its usage patterns and their impact on the urban centers [5, 7, 8, 4]. For example, one-way car-sharing systems are mostly used in dense urban areas with good public transportation system [9]. Young people with a higher education level are more attracted to use this service [10].

Moreover, several works also confirm positive impacts on the actual transport system, such as the reduction on traffic and emission of pollutants [11, 8], the increase of free parking spots and in the use of public transport [12]. These prior works also reveal that one-way car-sharing services are used for long journeys and shopping [7]. In most cases, at least two passengers use the vehicle [5]. Finally, these works also reveal interesting features about the fleet of electric cars. For instance, vehicles remain parked in central regions for lower periods than in suburban regions, directly impacting the autonomy of the vehicles [4].

Previous works also point out the differences between the free-floating and the one-way model services. Indeed, the free-floating vehicles are often used for shorter periods, presenting commuting trips and a considerable number of trips to airports [7, 5, 13]. Typically, free-floating vehicles carry a single user [5] and this user presents fast driving habits [3]. Finally, the free-floating model also presents a periodical usage: during the mornings, central areas of the city are the main destination, while during the evening, suburban areas are reached more [3]. Despite the flexibility of the free-floating and one-way model, previous works have not observed a clear difference in users preferences between them [7]. On the other hand, some works have identified that these services attract different users classes, exposing the fact that free-floating models and station-based models must be treated separately [5].

To the best of our knowledge, only our prior works characterize the two-way car-sharing service model [14, 15]. More precisely, in [14] we first characterize the usage patterns and the demands of *Modo*,[1] a car-sharing service that operates in Vancouver (Canada) and nearby regions. We present a simple model that represents the demand for vehicles in this car-sharing system, presenting statistical analysis to parametrize this model. Then, in [15], we further explore this two-way car-sharing service model, by evaluating two distinct periods and also present a spatial analysis of the vehicle demands. Our results evidence long travel duration, and many cancellations which produce a low utilization factor of the system. Moreover, the two-way system usage presents a strong relationship with the public transport system, as well as with regions nearby points of interests, such as public universities and commercial centers [15]. In [16, 13] we analyzed free-floating car-sharing data in different cities and propose models and optimization methods in order to efficiently use electric cars. We are not aware of studies that jointly study the three types of services in the same city, leveraging their common characteristics and highlighting its particularities as we are doing in the present work.

3. Car-sharing systems

The first concepts of car-sharing systems date back to 1948, although the basic principles of such service were consolidated during the 1970s [17]. The key idea behind car-sharing systems is that a fleet of cars is shared by several users

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

that drive the cars whenever they need without owning it. Car-sharing differs from classic car rental because it is a self-service based service, and vehicles can be rented for shorter fractions of times (usually minutes). At the beginning of the 1990s, along with the emerging problems of large urban centers, high fuel prices, traffic congestion, high emission of pollutants, the idea of sharing vehicles started to become popular [5]. Since then, car sharing has been the subject of academy studies [18]. 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.

The car-sharing can be either station-based or the free-floating. The station-based can 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). On one hand, the two-way model requires simpler logistics and infrastructure compared to other models. Its implementation can be performed faster and at a lower cost. On the other hand, the one-way model may be more flexible and cost-efficient to users than a 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 performing other tasks. The time the vehicle is parked is not charged, incurring to lower costs to users. However, a parked vehicle may be reserved by another user. The free-floating model does not require any fixed station. In other words, users reserve a car, parked into non-reserved spots in the 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 to private-owned vehicles [7].

Figure 1 presents an abstract model that describes the possible states of a vehicle in any of the three car-sharing systems. Intuitively, a car can be in use (i.e., *busy*) or *idle*. A *busy* vehicle is *rented*, meaning that someone is paying for it during this period. On the other hand, *idle* vehicles may be *unavailable* (i.e., during a maintenance process), *available*, which means someone can reserve or it, or *reserved*. The state in which the car is ready for a customer is *available*. In this situation, the user can reserve the car and subsequently begins the ride or start to drive the vehicle instantaneously. In the first case the state changes from *reserved* and then *rented* while in the second case the state switches into *rented* directly. When the customer concludes the rent the vehicle state moves from *rented* to *available* returning ready for another rent. Notice that if a user reserves the car and then cancels the reservation the vehicle state moves from *reserved* to *available* without assuming the state *rented*. If a vehicle is not in one of the previous three states, then it is *unavailable*, e.g., it is out of service. As we will see in the next Section, not always the data contains plain information about which of the four states the vehicle is. We will need to infer it by making some assumptions deducing the car state by filtering the rentals according to the duration and the possible driven distance.

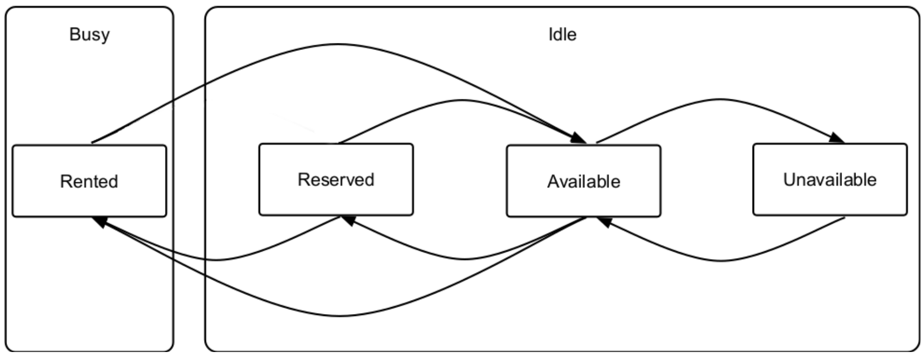


Figure 1: Possible states of a vehicle in a car-sharing system.

4. Datasets and crawling methodology

Our work relies on usage data from three car-sharing services: Modo, Car2Go, and Evo. These services operate in several cities and countries. We focus on data from the Vancouver area, where all these three services operate. Modo fleet is composed of combustion, electric and hybrid cars; Car2go offers combustion cars and finally, Evo supplies only hybrid vehicles. For each service, we collected both users' trips and fleets composition. In total, we observed more than 680 cars for Modo, 1 200 for Car2go, and 1 000 for Evo.

For all the three services, we collected vehicle status minute-by-minute, through public Application Programming Interfaces (APIs) or, directing accessing their service information web-page. We can get some values like vehicle ID and position. In short, through the Modo API[2] we can obtain the station of a vehicle and the period it is available, reserved or running. The data we get from Evo[3] information page allow us to check the remaining fuel (in percentage) of a vehicle and its location. Finally, Car2go APIs[4] output is similar to the Evo's one. Data from Evo and Modo comprises five months, ranging from March 1st, 2018 to July 16th, 2018. Car2Go data comprises thirteen months, ranging from December 31st, 2016 to January 31st, 2018. It is important to notice that, to not violate the users' privacy, the providers do not expose any users' personal information. Moreover, the companies do not track the cars during a trip so we do not know exactly the travel path, but only the start/end positions and the duration of travel.

[2]Modo API, `http://modo.coop/api/`
[3]Evo public portal, `https://www.evo.ca/api/Cars.aspx`
[4]Car2go API, `https://www.car2go.com/api/tou.htm`

All measurements used in our analyses are publicly available the following trace repository: `http://netlab.ice.ufjf.br/index.php/carsharingdata/`

4.1. Modo crawling methodology and data summary

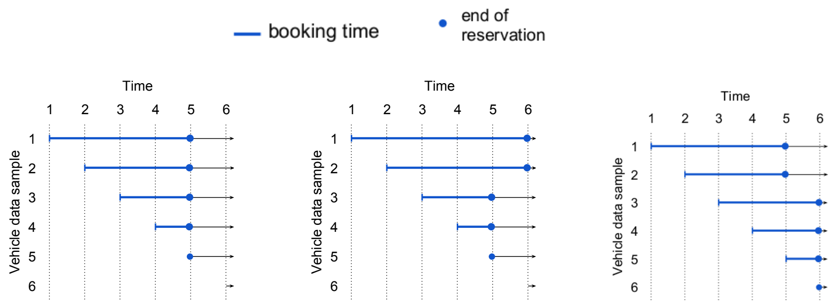
The Modo data collection process was conducted with a crawler that uses its public API. First, we request to the Modo API the list of all vehicles of the service. Then, minute by minute, we request the status of each of these vehicles. Each request returns the schedule of a vehicle, informing the periods it will be available for the next 24-hours. Moreover, it returns the vehicle location, i.e., the station with its identifier. 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. In other words, we collect several vehicle schedules and compare each other. Figure 2 illustrates the process of collecting data for a given vehicle. Each data sample corresponds to a request to the API in the order they occur. Data sample #1 is the result of the API request at minute 1 ($t = 1$), data sample #2 is the result of the API request at minute 2 ($t = 2$), etc. At each data sample, the blue dot represents the time a vehicle will be available. We highlight three possible situations:

- First, as shown in Figure 2(a), at $t = 1$ a given vehicle is shown reserved up to $t = 5$. At $t = 2$, the new request to the Modo API still show us that the vehicle will be available only at $t = 5$. Each of the following requests to the API confirms the booking period. At the time $t = 6$, we perform a request to the API and the vehicle is no longer booked. In sum, we are able to infer that someone booked the vehicle before or at $t = 1$, and returned it to the station at $t = 5$.

- Second, as shown in Figure 2(b), at $t = 1$ the Modo API returns that a given vehicle is reserved up to $t = 6$. However, in this case, a request at $t = 5$ shows the vehicle is no longer reserved. In this case, we can infer that the user returned the vehicle earlier to the station which means she/he used the vehicle only up to $t = 5$.

- Finally, as shown in Figure 2(c), the user may extend the booking period. More precisely, at $t = 1$ the given vehicle is reserved up to $t = 5$. At the third request, we note that the vehicle will no longer be available at $t = 5$ but $t = 6$. The following API requests confirm the use of the car until $t = 6$.

Besides, we also collect base stations location, vehicle models and whether the vehicle is electric or hybrid. Table 1 summarizes the data we have collected from Modo. We stored 134 millions of records in 5 months, from a fleet of 682 vehicles distributed in 528 stations, each of them with one or more cars. The



(a) Normal situation

(b) Anticipated vehicle return

(c) Extended travel situation

Figure 2: Possible vehicle status during the Modo crawling. In (a) a normal booking and usage situation; (b) a cancellation situation; (c) a consecutive booking situation.

stations are located in Vancouver, Canada, and its neighbor cities. This data allows us to analyze more than 98 000 travels.[5]

# of Collected Records		≈ 134 000 000
# of Booking Records		149 732
# of Travels Records		98 915
# of Stations		528
	- Common	530
# of Vehicles	- Hybrids	148
	- Electrical	4

Table 1: Summary of the Modo dataset.

4.2. Evo crawling methodology and data summary

Evo does not offer a public API to researchers. For this reason, we collect data which is publicly available at its web portal. Minute by minute, we retrieve a list of all system vehicles. Moreover, we request service snapshots, describing which vehicles are parked, where they are parked and if they are available to travel. We process all snapshots of the system to infer the moments a vehicle is busy (rented) or idle (parked at a station). During a snapshot, if a vehicle is listed among the system vehicles but it is not parked at any station, we infer it is in use. Then, we set-up the travel starting point as the last station the vehicle was parked. Analogously, the travel ending point will be the next station the vehicle appears in a future snapshot. The total travel time is accounted for as the difference between these snapshots times. For each travel we identify, we also record the end-to-end path, according to the Google Maps API. In this way, we are also able to calculate the estimated travel, taking into account the local traffic conditions. Clearly, this estimation does not take into account the car-sharing client behavior and, as a consequence, differ from the real travel time

[5]Data are available on http://netlab.ice.ufjf.br/index.php/carsharingdata/

we also store. One may reserve a car in Evo and cancel this reservation, within a thirty minutes range, without any charges. Thus, we infer the number of cancellation in Evo by filtering short travels (i.e., < 30 minutes) where the start and end points are the same. To accommodate GPS imprecision, we consider a 3 meters threshold. Table 2 summarizes the data we collect from Evo. Note that this service does not need a large number of stations because the user can park the car in some public park spots in the service area, that is called home zone (Vancouver and its neighbor cities).

# of Collected Records	142 853 500
# of Travels Records	644 887
# of Stations	130
# of Vehicles	1 237

Table 2: Summary of the Evo data collection.

4.3. Car2Go crawling methodology and data summary

Car2Go offers APIs providing information about available cars at the moment of the request. Each API request returns, among other information, the car unique ID, its position and other fields which specifically describe the car status. Therefore the API response is semantically equivalent to the Evo's one. In this way, we applied the same methodology to gather and store the Car2go data too.

There are two main events, which changes the car status, clearly observable from the data. Considering the current time instant t_i:

- if in t_i the car is present in the API response and at time t_{i+1} it is not, that car passes from available to rented.
- if in t_i the car is *not* present and at time t_{i+1} it reappears in the API reply, that car passes from rented to available. It represents a booking finish and a parking beginning. Indeed, for privacy constraints, the position of the car during a booking is not available.

Notice that from a single rented status is impossible to estimate the traveled distance: by computing the Euclidean or Haversine distance we obtain only a lower bound of the real travel distance which is practically too optimistic to be used as a primary travel estimation. To improve this estimation we attach to each entry the distance provided by the Google Maps API. As in Evo's methodology, we infer the number of cancellations by filtering short travels where the start and end points are very close. Table 3 summarizes Car2go dataset. We have more than one million travels in our thirteen months of data. As a free-floating service, Car2Go does not have stations but it has an operation zone, that covers a large area of Vancouver city and North-Vancouver.

# of Travels Records	1 095 577
# of Vehicles	1 077

Table 3: Summary of the Car2Go data collection.

5. Car-sharing services characterization

In this section, we first present temporal characterization of the three services (Section 5.1). Then, we describe the services spatial-temporal characteristics (Section 5.2). Finally, we present users' behavior (Section 5.3).

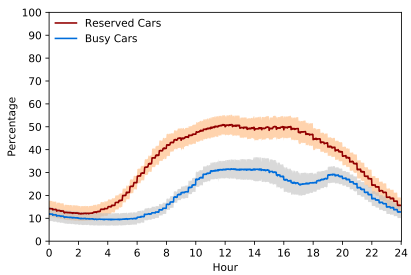
5.1. Temporal characteristics

We present in Figure 3 the service daily demand pattern. The blue and red solid lines refer to a minute-by-minute mean value over the studied period for the percentage of busy and reserved cars, respectively, for each service. We also show the standard deviation from the mean as the smoothed gray and orange background areas around the mean. The left column of Figure 3 (Figures 3-a, c, and e) present the demand pattern during working days, while the right column (Figures 3-b, d, and f) present the demand for weekends (Saturdays, Sundays, and festivities).

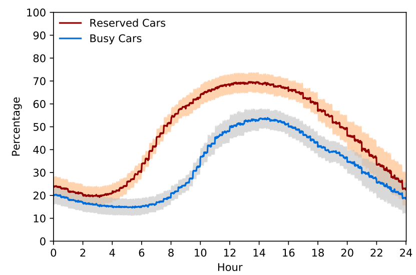
All three services present two peaks of demand during weekdays and only one during the weekends. During weekdays, for Evo and Car2Go, the one-way and free-floating services, the peaks of demand occur about 8 AM and 6 PM whereas for Modo, the two-way service, these peaks occur around 2 PM and 7 PM. Moreover, note that for Evo and Car2Go, weekdays demand is higher than during weekends. On the other hand, for Modo, we observe just the opposite. Mostly, Modo users are regulars and present weekly/daily/hourly subscription. In this sense, they tend to reserve cars at the same hour, for regular periods, which explains Modo lower variation. For a given moment, we consider the relative difference between the reserved and busy cars as the cancellations of the system. Modo presents up to 60% of cancellations, while the other two services present no more than 5%.

Figure 4 presents the Empirical Cumulative Distribution Function (ECDF) of vehicles busy time, i.e., the rental duration, during load peaks of the day. In this case, we evaluate the load periods from 7 AM to 10 AM and from 4 PM to 8 PM for free-floating and one-way, from 11 AM to 4 PM and 7 PM to 8 PM for two-way, and also all-day data for the three services.

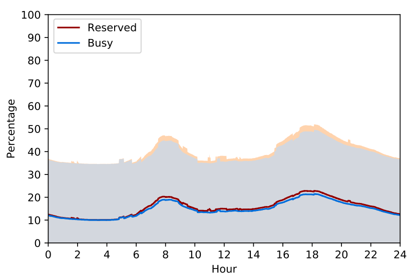
As for the demand, Evo and Car2Go present similar behavior, which is different from Modo. For Modo we observe at least 80% of vehicles rentals presents more than 1 hour of occupation, with more than 10% of rentals that last for more than 15 hours. On the other hand, Evo and Car2Go usually present shorter rentals, with no more than 10% of vehicles busy for more than one hour. In sum, we believe the most notable differences between these services occur due to their business model. Indeed, Modo presents a strict policy, where users must pick-up a car and leave it at the same station. However, Modo presents a flexible policy regarding cancellations. The other two services, only allow users to cancel the rent of a vehicle up to 30 minutes after its booking.



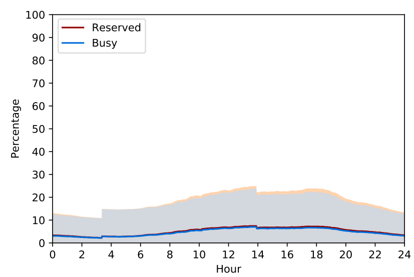
(a) Two-way Modo Weekdays



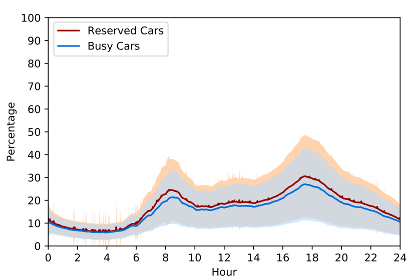
(b) Two-way Modo Weekends



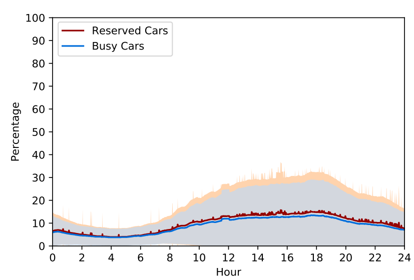
(c) One-way Evo Weekdays



(d) One-way Evo Weekends

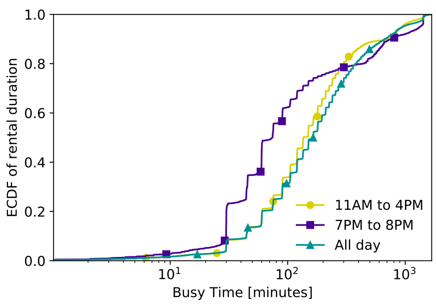


(e) Free floating Car2Go Weekdays

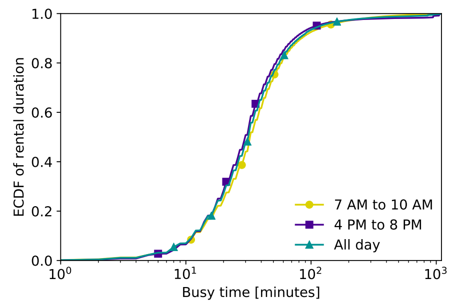


(f) Free floating Car2Go Weekends

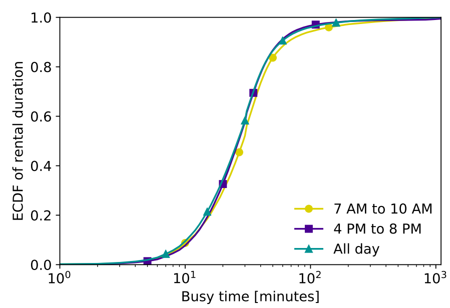
Figure 3: Minute-by-minute mean value (plus/minus standard deviation) for the percentage of busy (blue curve) and reserved cars (red curve), for weekdays and weekends.



(a) Two-way Modo



(b) One-way Evo



(c) Free floating Car2Go

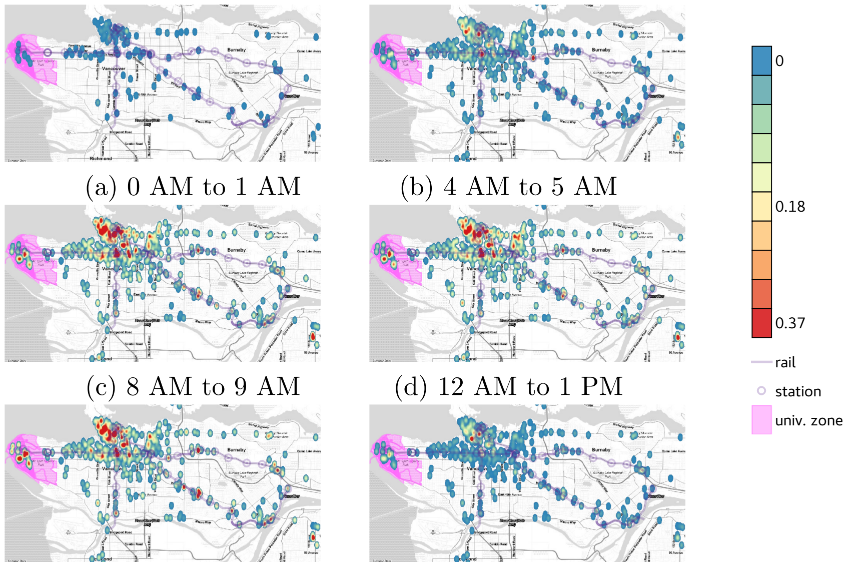
Figure 4: Cumulative distribution function of vehicle busy time during a weekday.

5.2. Spatial-temporal characteristics

Figures 5, 6 and 7 present heat-maps of the hourly[6] mean number of busy vehicles in a given location, considering analyzed period. In the case of Modo, a location refers to a fixed station. In the case of the other two services, we have clustered all travel records where users pick-up or leave a vehicle. To cluster these points we use a 400 m radius as a reference, forming a region close to a neighborhood. We have also experimented values from 100 m to 1000 m, obtaining similar results.

First, all three services present a large demand in the downtown area and the university zone. Note that the demand in downtown for all three services is low during the night, starts increasing at 4-5 AM, reaches its peak during office working hours and reduces by the end of the day. In this case, users usually pick-up cars to their daily tasks, as go to work and shopping. During the night, usage increases in the surroundings of the city, the university zone, and neighborhoods with leisure facilities (such as bars). Modo presents a distinct demand pattern.

[6]Due to space constraints, we only show one-hour period every four hour.

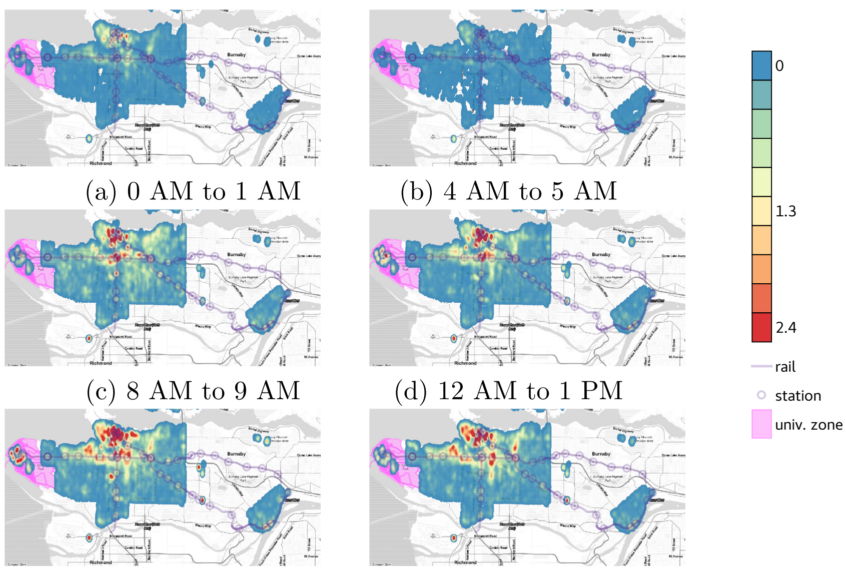


(a) 0 AM to 1 AM (b) 4 AM to 5 AM

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

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

Figure 5: Spatial-temporal service demand for two-way service Modo.



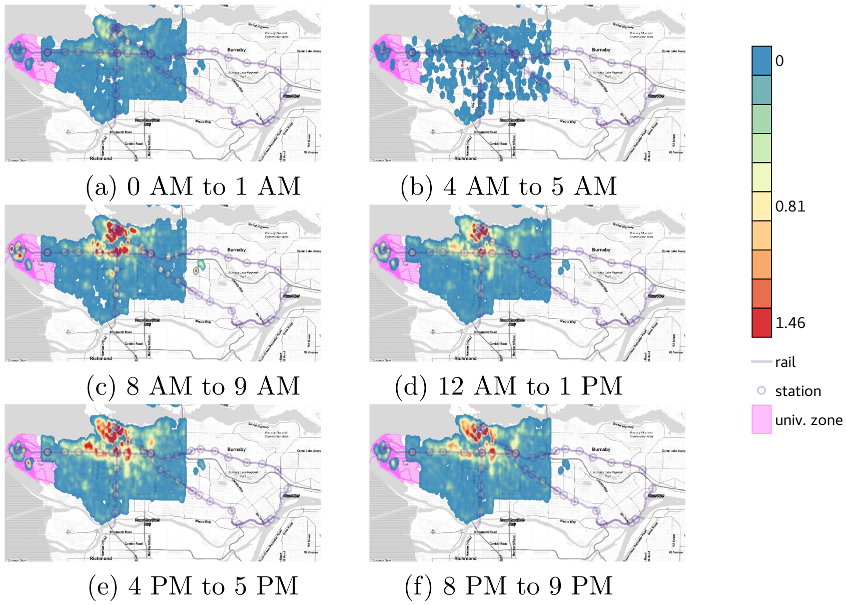
(a) 0 AM to 1 AM (b) 4 AM to 5 AM

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

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

Figure 6: Spatial-temporal service demand for one-way service Evo.

Indeed, Modo has fixed stations located along with the existing public transport system, especially the Expo Line and Millennium Line. For this reason, we note



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

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

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

Figure 7: Spatial-temporal service demand for free-floating service Car2Go.

a strong relationship between the existing public transport system and the car-sharing system demand. On the other hand, the other two services are more flexible. Users can rent a car almost anywhere. In this sense, despite the major demand in downtown, we note a widespread demand all over the city.

Figures 8 and 9 detail the spatial-temporal demand for Evo and Car2Go by presenting their origin-destination matrix. We use the 31 city areas as defined by the metropolitan city of Vancouver. To enhance the visual effects, we normalized the previous heat-maps values to a scale between 0-1, using the min-max method. Moreover, due to space constraint, we only show the origin-destination matrix at a specific hour, i.e., at 4 PM. We note that users tend to start and end a trip at the same location. It appears that during working days, users tend to use a shared car returning it to the same region where they start (likely where they are working or living). However, for both services, we note a non-negligible probability to spread services along all city area. Moreover, we also note that some regions serve as hubs. This is more notable for Evo service. As shown in Figure 8, the downtown area serves as a hub to start trips to almost all other regions. We do not observe the opposite (a high tendency to start a trip ending at downtown). As a consequence, service may become unbalanced and, from time to time, service maintenance should relocate vehicles from a region to another, to accommodate the daily demand.

5.3. User behavior characteristics

Vehicles busy and idle periods direct impacts service revenue. Indeed, the longer the busy period is and the lower the idle period of a vehicle is, the more

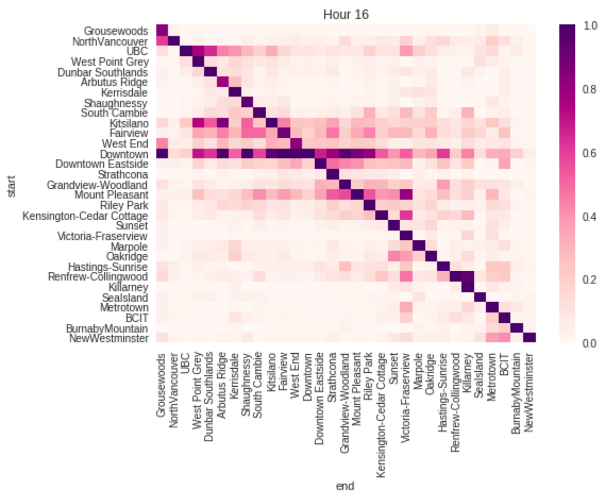


Figure 8: Origin-destination matrix for one-way service Evo (from 4 PM to 5 PM).

profitable the car will be. Therefore, we characterize the busy and idle periods of vehicles for all three services. In our analysis, we have considered all vehicles and we filtered out travels longer than 90 hours, which corresponds to less than 0.5% records. For each service, we identified the statistical distribution that best fits the actual data (busy and idle period). For this purpose, we tested more than 40 well-known statistical distributions. More in-depth, for each component of the model, the parameters of the distribution that most closely approximate the data are determined using the Maximum Likelihood Estimation (MLE) method. After defining the parameters of each component of the model, the ten distributions with shorter Kolmogorov-Smirnov distance (continuous distributions) or lower least square error (discrete distributions) concerning the data are chosen. Finally, we chose the top three common distributions to each car-sharing service. These choices are also validated with a visual assessment of the curve fitting.

Figure 10 shows the Cumulative Distribution Function of vehicle busy time. Modo, Evo and Car2Go busy time and their best statistical distribution fitting are shown in blue, red and yellow, respectively. For all three services, the Inverse Gamma[7], the Burr[8], and Mielke's Beta-Kappa[9] distributions present a

[7] Cumulative distribution function (CDF) of the Inverse Gamma distribution: $F(x, a, \beta, \delta) = \frac{1}{\Gamma(a)} \int_{1/((x-\beta)/\delta)}^{\infty} t^{a-1} e^{-t} dt$

[8] Cumulative distribution function (CDF) of the Burr distribution: $F(x, c, d, \beta, \delta) = \left(1 + ((x-\beta)/\delta)^{-c}\right)^{-d}$

[9] Cumulative distribution function (CDF) of the Mielke's Beta-Kappa distribution: $F(x, k, s, \beta, \delta) = \frac{((x-\beta)/\delta)^k}{(1+((x-\beta)/\delta)^s)^{(k*\frac{1}{s})}}$

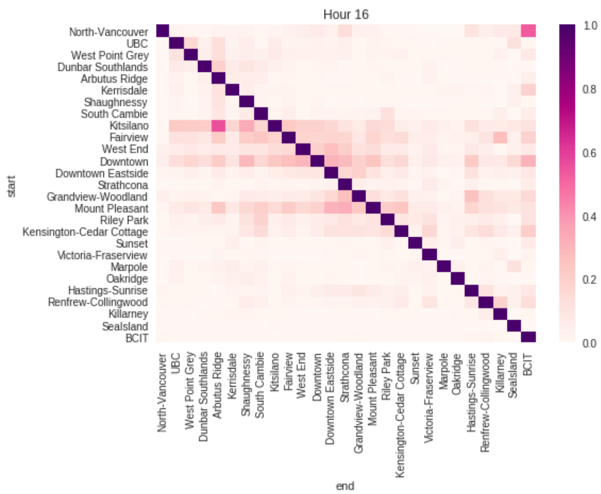


Figure 9: Origin-destination matrix for free-floating service Car2Go (from 4 PM to 5 PM).

good fitting to the empirical data, with similar MLEs. Table 4 summarizes the parameters of the distributions of the busy time for each statistical distribution. Despite all three services present the same statistical distribution fitting, the two-way service (i.e., Modo), presents a clear shift to right on its curve when compared to the other two services, as shown in Figure 10. As we previously discussed, the median busy time on Modo is more than one hour longer than the median busy time for the other services. Users in Modo must return cars to the same station they originated travels. As a consequence, they tend to perform longer tasks. On the other hand, with the other two services users tend to do a longer number of shorter travels.

Finally, Figure 11, presents vehicle idle periods distribution. Power log normal[10], Burr and Mielke's Beta−Kappa distributions best fit the idle data, for all three datasets. Table 5 presents the distribution parameters. Again, Modo presents a distinct behavior from the other two services. The longer idle period for Modo vehicles corroborates to our previous observations. Indeed, the demand for car-sharing varies over the city during a day. While users in Evo and Car2Go can park anywhere, they contribute to spreading cars over the city. For example, at least 75% of cars in Modo remains idle for periods longer than 2 hours. For the other two services, no more than 20% of vehicles remains idle for the same period.

In sum, our analysis shows that the free-floating and one-way car-sharing systems have similar characteristics. They are mostly used for short/medium

[10] Cumulative distribution function (CDF) of the Power log normal distribution: $F(x, c, s, \beta, \delta) = 1 - \left(\frac{1}{\sqrt{2\pi}} \int_{-\infty}^{-log((x-\beta)/\delta)/s} e^{-t^2/2} dt \right)^c$

	Inv.Gamma	a = 1.7032, β = -38.5120, δ = 278.8487
Modo	Burr	c = 1.5651, d = 1.0327, β = -1.8893, δ = 163.0525
	Mielke	k = 1.59745, s = 1.5687, β = -1.6713, δ = 164.9877
	Inv.Gamma	a = 2.0674, β = -4.7928, δ = 63.4382
Evo	Burr	c = 1.8332, d = 1.5078, β = -0.1855, δ = 23.5794
	Mielke	k = 2.7305, s = 1.8336, β = -0.1125, δ = 23.7291
	Inv.Gamma	a = 2.7688, β = -4.9702, δ = 75.2494
Car2Go	Burr	c = 2.3869, d = 64.2072, β = -12.5240, δ = 5.7419
	Mielke	k = 37.8163, s = 2.3450, β = -10.9187, δ = 9.6407

Table 4: Distributions parameters of the busy time fit curves. The β and δ are key parameters to adjust the location and scale of the distributions.

	PLogNorm	c = 118.7142, s=3.6088, β=0.7191, δ=3780209.5149
Modo	Burr	c = 1.9865, d = 0.3860, β = -7.7229, δ = 1105.5853
	Mielke	k = 0.8898, s = 1.5390, β = -1.4862, δ = 860.6790
	PLogNorm	c = 0.0723, s = 0.7003, β = -0.6723, δ = 1.8246
Evo	Burr	c = 0.6931, d = 3.7574, β = -0.4881, δ = 2.3713
	Mielke	k = 2.7161, s = 0.5882, β = -0.2800, δ = 0.9725
	PLogNorm	c = 4.8747, s = 3.3741, β = 0.7134, δ = 1334.7243
Car2Go	Burr	c = 0.7714, d = 0.7337, β = 0.7166, δ = 53.9727
	Mielke	k = 0.5743, s = 0.8826, β = 0.7166, δ = 68.1029

Table 5: Distributions parameters of the idle time fit curves. The β and δ are keyword parameters to adjust the location and scale of the distributions.

period travels, while the two-way system is mostly used for medium to long travels. Moreover, Evo and Car2Go dynamically spread car over the city, turning the car's idle periods shorter. The longer number of shorter travels, associated with the shorter idle periods, may indicate a more profitable service.

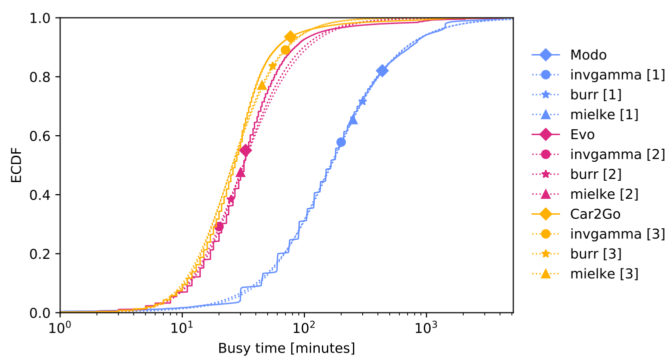


Figure 10: Cumulative distribution function of vehicle busy time.

6. Conclusions

In this article, we characterized three distinct car-sharing systems which operate in Vancouver (Canada) and nearby regions. Our study, using data of more than one year of real trips, uncovers patterns of users' habits. We provided a characterization of the different car-sharing services, including spatial-temporal

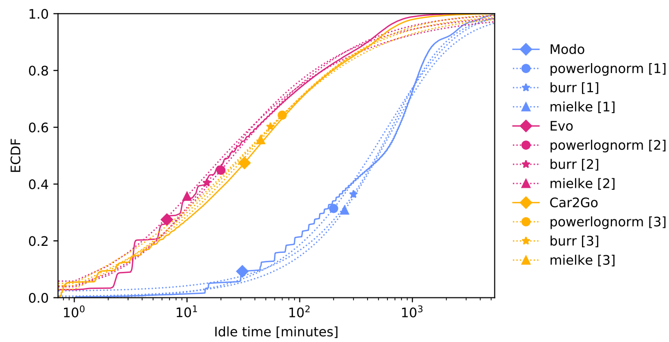


Figure 11: Cumulative distribution function of vehicle idle time

usage. Finally, we highlighted the main differences and the common characteristics of these services.

We showed that in Vancouver in 2017 the one-way and free-floating services were used similarly. They present shorter travels when compared to the two-way service. All three services present peaks of demand during the day. During working days, these peaks occur at around 8 AM and 6 PM, while in weekends, peaks are distributed in the afternoon. The two-way service we analyze presents a considerable number of booking cancellations and a higher vehicle idle time. This indicates a low utilization of the vehicles, likely due to their business model. Indeed, one-way and free-floating services allow users to pick-up a car and leave it anywhere in the city, dynamically satisfying the floating demand. We also highlight the strong relationship with the public transportation system, as well as with 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.

Acknowledgements

The authors would like to thank CAPES, CNPq, FAPEMIG for their financial support in this research.

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