Free Floating Electric Car Sharing: A Data Driven Approach for System Design

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***Abstract*—In this paper, we study the design of a free floating car sharing system based on electric vehicles. We rely on data about millions of rentals of a free floating car sharing operator based on internal combustion engine cars that we recorded in four cities. We characterize the nature of rentals, highlighting the non-stationary, and highly dynamic nature of usage patterns. Building on this data, we develop a discrete-event trace-driven simulator to study the usage of a hypothetical electric car sharing system. We use it to study the charging station placement problem, modeling different return policies, car battery charge and discharge due to trips, and the stochastic behavior of customers for plugging a car to a pole. Our data-driven approach helps car sharing providers to gauge the impact of different design solutions. Our simulations show that it is preferred to place charging stations within popular parking areas where cars are parked for short time (e.g., downtown). By smartly placing charging stations in just 8% of city zones, no trip ends with a discharged battery, i.e., all trips are feasible. Customers shall collaborate by bringing the car to a charging station when the battery level goes below a minimum threshold. This may reroute the customer to a different destination zone than the desired one; however, this happens in less than 10% of all trips.**

***Index Terms*—Car sharing, electric vehicle, data driven optimization, charging station, free floating.**

I. Introduction

MOBILITY is a very important challenge for our society, with strong implications on pollution in large cities. More eco-sustainable solutions are seen as a means to improve the current situation. Along with the usage of public transport, the sharing mobility such as bike sharing, carpooling and car sharing, help to address this problem. In this work, we focus on the design of an electric car sharing system where customers rent a car for moving within the city limits for short periods of time. We focus on the so called Free Floating Car Sharing (FFCS) system where customers are free to pick and return the car wherever they like inside a geo-fenced area

Electric car sharing systems need an infrastructure of charging stations, whose design requires ingenuity. Two are the main problems that need to be faced: i) the charging station placement problem, i.e., how many and where to install charging stations; and ii) the return policy the customer has to follow at the end of the rental, i.e., in which cases the customer shall return the car to a charging station.

Data is fundamental to answer these questions. In this work, we base our study on millions of actual rentals we collected from FFCS systems based on internal combustion engine cars. We leverage real FFCS data related to the city of Vancouver (Canada), Berlin (Germany), Milan, and Turin (Italy) that we selected as good representative of different habits and scenarios. Our data naturally factors the non-stationarity of FFCS systems. We study and compare the performance of a hypothetical car sharing system which is based on electric vehicles. We develop a discrete-event simulator which replicates previously recorded traces of trips in each of the 4 cities. The simulator considers different design parameters: the charging station placement, the return policy, the car battery charge and discharge process, and stochastic behaviors of the customers. Compared to previous works (see Section II), we are among the firsts to take an approach based on actual trips performed by FFCS users for the design and the validation of electric FFCS systems. We rely on the data we collected to compare different charging stations placements, and analyze the system performance through trace-driven simulations, without the need of an artificial transport demand model.

We first consider an opportunistic free floating policy where customers return the car in a charging station only if it is very close to their actual destination. Results show that placing the charging stations in those areas where cars stay parked for long time performs badly. Instead, placing charging station in those areas where cars are frequently parked and rented, e.g., near train stations and working areas, guarantees much better performance. This is consistent in all cities.

Next, we study different return policies, where customers are asked to return the car to a charging station in case the battery level decreases below a minimum threshold. This collaborative policy reduces the size of the charging infrastructure by a factor of 2 or more with respect to an opportunistic free floating solution. Equipping just 8% of zones with 4 poles of $2\,kW$ would support almost all trips (>99.9% of trips ending without discharged battery) in an electric car FFCS equivalent to the combustion engine FFCS currently in use.

At last, we compare system design alternatives to check whether it is better to place a lot of charging poles in very

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few areas, or rather to spread a lot charging stations with few poles in many areas. Results demonstrate that both extreme solutions perform badly, with best performance obtained when installing charging stations with 5 to 20 poles in popular areas.

We believe that the results presented in this paper, are very important for regulators and policy makers, as well as for researchers working in this area. We make both dataset and simulator publicly available.[1]

After discussing related work in Section II, we present and characterize data in Section III, and the simulation and tool in Section IV. Section V discusses the impact of charging stations placement policies, while Section VI compares return policies. Section VII discusses the model limits, providing a lower bound estimation. Section VIII presents the impact of concentrating or spreading charging stations in the city. Finally Section IX concludes the paper.

II. Related work

The diffusion of the free floating approach to car sharing led to an increasing attention by many researchers, with the analysis of these systems and their extension to electric vehicles. For instance, the ESPIRIT project [1] tries to reduce traffic congestion in urban areas by developing light-weight electric vehicles that can be stacked together to gain space.

The studies performed in 2011 by Finkorn and Müller [2], [3] are the first attempts to analyze benefits of FFCS for the population. Their measurements on customers' behavior, are similar to ours [4]. Later works [5]–[7] collect data and analyze the mobility patterns of customers in different cities. More in details, authors of [5] characterize Car2go service in 22 cities in Europe and North America; authors in [6] perform the same analysis adding correlations with socio-economic data. Finally authors of [7], after a brief characterization, propose a linear regression able to predict the demand in short and long-term in Berlin and Frankfurt. Their study shows how the short-term demand prediction is strongly influenced by time, while the long-term is more correlated with the neighborhoods demography.

The introduction of electric vehicles for private and public transportation raises the problem of placing the charging stations. Authors of [8] present a simulation study similar to ours, but using random models to generate trips rather than actual traces. Their algorithms tend to place charging stations along frequently used streets to let drivers recharge the car with 10 minutes or more waiting time. Authors of [9] solve the charging station optimization problem, again using synthetic data and adopting a genetic programming approach.

Few data driven studies address the charging station placement, either by minimizing installation cost, power loss and maintenance of the power grid [10], [11], or by minimizing the customers' walked distances required to reach a charging pole [12]. Here we focus on the minimization of charging infrastructure cost and on the impact of different car return policies.

Authors of [13] study the relocation of electric cars in FFCS, since few charging stations may be blocked by already charged vehicles. Lastly, after a survey among FFCS customers in Ulm (Germany), authors of [14] investigate the positive effect over pollution of an electric FFCS systems.

Previously in [15] and [16], we performed several analyses for designing an electric FFCS in the city of Turin and Milan. In [17] we optimized the charging stations placement for Turin. In this work, we extend and complement these papers by generalizing the study to 4 cities, and by studying new return policies to observe the impact of the willingness of customers to contribute to the system by returning the cars to charging stations. We further extend our works by discussing the benefits of using charging hubs.

Most of the previous works use either synthetic data or analytic models to design the charging station placement or generate the trips. Instead, we are among the first to use directly the collected data both to study different design solutions and to validate them using realistic trips.

III. Data collection and characterization

We describe the methodology we follow to harvest data from already operative FFCS systems. We first describe the data collection mechanisms. Then we characterize system usage, focusing on those metrics that are instrumental for the design of FFCS systems based on electric vehicles.

A. Data collection and filtering

Modern FFCS providers like Car2go, DriveNow or GoGet use information systems to expose the position of the available cars through web services. Customers access these to check which cars are available for a rental by using a smartphone app. Car2go offers a public Application Programming Interface (API) to access the information about the system status.[2] We use this API to collect data about rentals occurred over time. First, we get the service area for each city, i.e., the area where cars can be rented and returned. Next, we collect a snapshot reporting the positions of cars available for a rental. We take the snapshots every minute. From each snapshot we save the car plates, used as car identifiers, and their geographic coordinates.

We developed UMAP [4], a software able to process these snapshots and rebuild, for each car, the history in terms of *bookings* and *parkings*.[1] A booking is an event describing a possible car rental, characterized by the start/final position, and start/end time. A parking describes a period of time when the car was parked and available for rentals; it is characterized by the location, start and final time. In a nutshell, we process the snapshots of the available cars and derive booking and parking periods. When a car "disappears" from a snapshot, it means that someone has booked it – so that the car is not available for other customers. A new booking is started. When the same car "reappears" back later on, it means someone has returned it. The booking is then ended, and a new parking starts.

Not all bookings correspond to actual rentals: (i) a customer can book a car, and cancel the booking later on; (ii) the data

[1] https://smartdata.polito.it/car-sharing-and-electric-charging-station-placement-from-data/

[2] car2goAPI, https://www.car2go.com/api/tou.htm service subject to approval by Car2go. Approval granted in September 2016 and discontinued in January 2018.

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collection may suffer from outages, so that some snapshots may miss some available cars; (iii) cars may go in maintenance, so that they disappear and never come back (or return after a long time); (iv) cars may be relocated by the provider to zones with high demand. We develop data cleaning and filtering procedures to extract actual *rentals* from bookings. A booking is considered a valid rental if: (i) it lasts at least 3 minutes; (ii) the ending position is at least 700 m far from the staring position, with both positions inside the city service area[3]; (iii) its duration is smaller than 1 h. These thresholds have been selected by domain knowledge – see [4] for more details. Bookings that do not correspond to rentals are then merged with parking events (since the car did not move). We cannot distinguish between rentals done by the users, and relocations done by the system. However, to the best of our knowledge, relocation of vehicles in the city we considered is not massively used by Car2go, and likely limited to a very small fraction of all trips.

While we obtain precise information on where the users begin and end the ride, we have no information about where they accessed the system to enter the reservation and where they want to go (we know where they parked). As such, we cannot estimate how much the user has to walk to reach the car nor to reach the real destination. Moreover, we do not have any kind of users' personal information, we do not know how many people were in the car during the ride and which path they drove.

We started to collect data in December 2016 in all the 22 cities in which Car2go was operating, and stopped our collection in January 2018. Fig. 1 reports the number of rentals recorded for each day from June 2017 to January 2018 in four cities: Turin, Milan, Berlin and Vancouver. Notice that in some intervals of time data is missing due to failures in the data collection, (see central weeks of August and the second week of November). Despite the fact that rentals are non-stationary, especially during periods like Christmas, notice how the usage tend to be similar over the year without any particular seasonal pattern. For example, the usage level in July looks similar to the one in October. Here we focus our analysis on a 2 months long period from September to November 2017 in these four cities. We select this period because it is the longest one without data collection failures and it is representative of the customers' behavior. Overall, we collected more than 1 million rental events. In the following we make the simplifying assumption that the typical usage patterns of FFCS customers are independent from the type of engine employed in the car (internal combustion or electric).

In our previous works [15], [17], we considered only the city of Turin. Here, we extend our analysis to other three cities that we selected because they are the cities with the largest Car2go fleet in Europe and North America.

B. Temporal characterization

Firstly we provide a characterization of usage patterns by current FFCS customers in each city. We focus on temporal characteristics.

[3]This to account for possible errors in the GPS fixing, and to remove rentals started and ended in different cities.

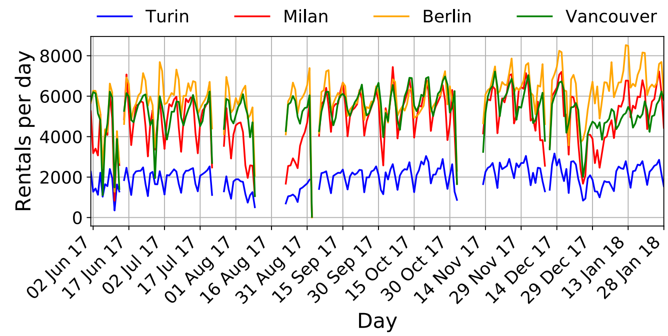


Fig. 1. Number of rentals per day, from June 2017 to January 2018. Some data is missing.

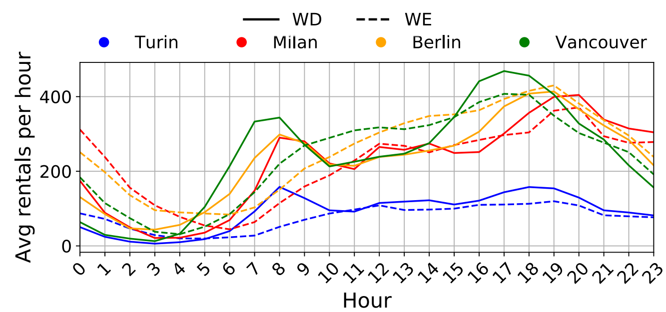


Fig. 2. Average number of rentals per hour.

TABLE I
MAIN CHARACTERISTICS OF OUR DATASET, RECORDED FROM SEPTEMBER TO NOVEMBER 2017

City	Rentals	Fleet Size	Rental Time [min]		Rental Dist. [km]		Parking Time [h:min]		Zones
			Avg	Med	Avg	Med	Avg	Med	
Turin	125k	377	21	20	3.96	3.36	3:17	0:42	261
Milan	320k	739	25	24	4.15	3.66	2:21	0:24	549
Berlin	342k	900	29	28	6.22	5.24	2:23	0:22	833
Vancouver	317k	941	26	24	4.70	3.98	2:54	0:22	532

Fig. 1 shows the number of recorded rentals for each day. Usage similarity is striking, with Milan, Berlin and Vancouver that have a larger number of rentals per day than Turin. This intense usage justifies the difference in fleet size among the cities, with the former three cities having twice as much cars with respect to Turin (see Table I). This highlights the importance of extending our previous work to other cities than Turin. A second interesting aspect is the presence of a weekly pattern: in correspondence of the weekends the number of rentals drops of about 30%. This is justified by the fact that during the working days cars are used for commuting. Moreover, non-stationary events due to holidays or strikes are visible, e.g., October 6^{th} in Milan due to a public transport strike, and Christmas holiday during which the usage decreased.[4]

To deeply analyze customers' habits, we detail the average number of rentals per hour in Fig. 2, separately per working-days (WD, solid line) and per weekends (WE, dashed

[4]The sudden fall around the October 2^{th} is due to a system outage that caused a lack of data.

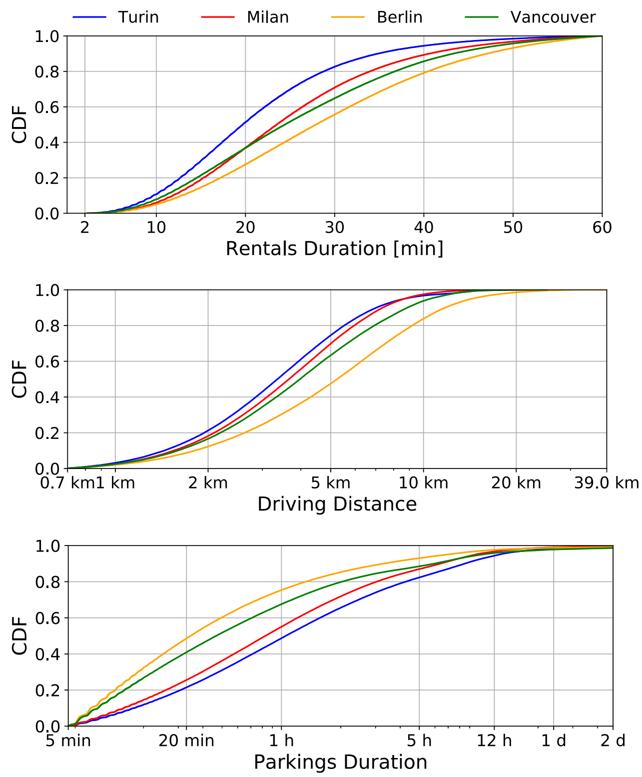


Fig. 3. Car sharing usage characterization.

line). Each curve reports the average number of rentals considering the same hour in the dataset. Firstly, notice the usage peaks during commuting times. These happen at different times for different cities, e.g., 8 am for Turin, Milan and Berlin vs 7 am for Vancouver, following local commuting habits. Secondly, notice how the evening and night usage tend to be larger during weekends than working days. This reflects the different usage at night, when cars are used to reach areas dense of pubs and nightlife. At last, observe again the different patterns in different cities. For instance, the average number of rentals in Vancouver and Berlin during weekend mornings is higher than during working days. This does not happen in Italian cities. Thus the charging station placement design must weight these different needs and non-stationary patterns.

Given our goals of deriving guidelines for charging station placement policies, we focus now on the characterization of three important metrics: (i) rental duration, (ii) driving distance, and (iii) parking duration. The former two metrics guide the battery discharging properties, while the latter metric is fundamental to understand battery charging opportunities. Given that we have no information on car path during a rental, we compute the driving distance by assuming the customer went directly from the origin to the destination. This is indeed compatible with the typical short rental duration. We use Google Map service to compute a correcting factor to be applied on the euclidean distance [4].

Fig. 3 reports the empirical Cumulative Distribution Function (CDF) of the rentals duration (top), driving distance (middle) and parking duration (bottom). The size of the city has a clear impact, with Turin that has the shortest trips, and Berlin the longest. Rental duration is in general very short, leading to the intuition that drivers tend to minimize the rental time (and cost). Driving distance is fundamental to understand the battery consumption: Assuming energy consumption is proportional to the traveled distance (more on this later), the trip with the maximum driving distance sets the minimum battery charge to sustain such trip, i.e., the minimum battery residual capacity that allows to perform the trip. Looking at the middle plot in Fig. 3, we observe that in Berlin the longest trips are twice as long as the longest trips in other cities. Therefore, the same battery constraints would not fit for all cities. Overall, the limited driving distance and rental duration suggest that people use the car just for the time strictly needed to reach their destinations.

At last, the bottom plot of Fig. 3 details the duration of the parking events. Interestingly, 50% of parking events lasts less than 22 minutes in Berlin, testifying a very high system utilization. In Turin, the median grows to 42 minutes, still showing that most of the cars are parked for short time. Yet, the long tail of the CDF (note the log scale on x-axis) suggests that there is a sizable fraction of parkings that last for 5 or more hours. These are cars usually parked in the periphery or at night, where the demand is lower.

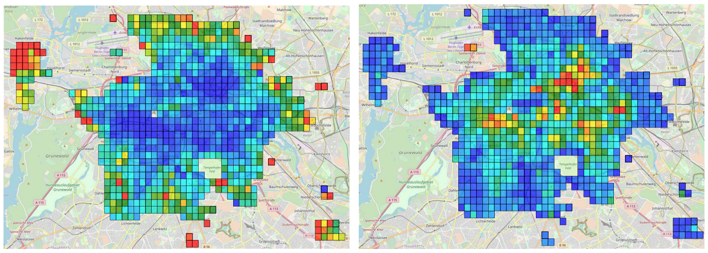
Takeaway: car sharing usage is time heterogeneous and non stationary. However, many patterns can be identified. FFCS customers tend to use the system mostly during commuting time and for short trips.

C. Spatial characterization

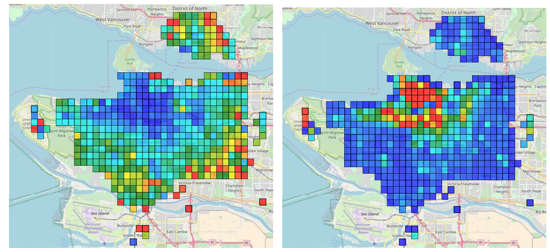
The charging station placement depends on the opportunity of charging cars. Intuitively there are two possibilities: place the charging stations (i) where cars stay parked for long time – so to maximize the charging time for a charging event; or (ii) where cars are frequently parked and rented – so to maximize the number of charging events. For this, knowing the zones within the city where cars are left parked is fundamental.

We divide the service area of each city into squared zones by a grid of 500 m of side. For each zone, we compute the average parking time and the total number of parking events. Fig. 4 shows the above metrics for Berlin and Vancouver using a heat map – with blue and red colors corresponding to the minimum and maximum values, respectively. Focus on Berlin first - Fig. 4a. Left plots show the average parking time. Results show that cars stay parked for very short time in busy downtown areas with an average of 74 minutes. On the contrary, cars stay parked for long time in the periphery i.e., up to an average of 2 days. Conversely, right plot depicts the total number of recorded parking events in each zone. In the downtown areas the majority of rentals/parkings occurs, and we observe up to 45 rentals per day. In the periphery we observe the least number of rentals/parkings, with some zones where we observed only a single parking event in two months.

In a nutshell, in busy areas, the average parking time is short, and the number of rentals and parkings is high. This reflects the specific usage of FFCS according to which cars go to downtown areas in the morning, then are rented to move within central areas, and finally go back to the periphery at the



(a) Berlin: average parking time (left) and total number of parkings (right).



(b) Vancouver: average parking time (left) and total number of parkings (right).

Fig. 4. Heat map of average parking time and total number of parking. The warmer the color, the higher the value.

end of the day. Similar results apply to all cities – see Fig. 4b which details Vancouver.

Takeaway: Periphery zones are characterized by a long parking time, while central areas are characterized by many parkings which last for short time.

IV. Electric Car Sharing Simulator

Our goal is to study different design choices for electric car sharing systems. For this, we develop a flexible event-based simulator to compare different algorithms and tune their parameters while collecting metrics of interest. Simulations are based on the traces of actual rentals previously explained, simply called trace from now on. This allows us to factor all spatial and temporal characteristics of actual FFCS systems.

A. Simulation model

We simulate a fleet of electric cars that move in the city. Each car is characterized by its location, and the current level of battery charge. The simulator takes as input the pre-recorded trace of rentals.

In more details, each trip $i \in \mathcal{I}$ in the trace is characterized by its start and end time, $t_s(i)$ and $t_e(i)$, and origin and destination coordinates, $o(i)$ and $d(i)$. For simplicity, we divide the city area into squared zones, of side 500 m as before. We associate each position to the zone $O(i) = zone(o(i))$ and $D(i) = zone(d(i))$. We assume a charging station cs, composed of k poles, can be placed at the center of a given zone $z \in \mathcal{Z}$, so either $cs(z) = 1$ if the station is present, or $cs(z) = 0$ otherwise. $N = \sum_{z \in \mathcal{Z}} cs(z)$ is the total number of zones equipped with charging stations, with $K = N \cdot k$ the total number of poles.

We have a set $\mathcal{A}$ of cars, with its cardinality $|\mathcal{A}|$ obtained by the trace. Each car $a \in \mathcal{A}$ at time t is characterized by its position $p(a, t)$, its zone $P(a, t) = zone(p(a, t))$, and the residual battery capacity $c(a, t) \in [0, C]$, with C being the maximum nominal battery capacity.

The simulator processes each rental event i in temporal order. When a *rental-start* event i is processed at time $t = t_s(i)$, we choose the most charged available car in the closest zones to the initial position zone $O(i)$. In formulas, we get a car $\bar{a} \in \mathcal{A}$ such that:

$$c(\bar{a}, t) \geq c(\hat{a}, t)\ \forall \hat{a} \in \operatorname*{argmin}_{a \in A} dist(O(i), P(a, t)).$$

Intuitively, we mimic the normal behavior of FFCS customers that use their smartphone to rent the closest car from their position and are worried about vehicle range [18]. Notice that this behavior is independent from whether the car is at a pole being charged or not. The simulator schedules a *rental-end* event using the trace final time $t_e(i)$ and desired destination location $d(i)$.

When car a *rental-end* event is processed at time $t_e(i)$, we return the car in $P(a, t_e(i))$, chosen according to the behavior described in Section IV-B. The simulator updates the battery charge status by consuming an amount of energy proportional to the trip distance:

$$c(a, t_e(i)) = \max(c(a, t_s(i)) \\ - Energy(p(a, t_s(i)), p(a, t_e(i))))$$

with $Energy(\cdot)$ that models the energy necessary to go from the car origin $p(a, t_s(i))$ to the car destination $p(a, t_e(i))$. We make the simplifying assumption that the consumption is linearly proportional to the estimated trip distance. This rough linear correlation between the energy consumed and the driving distance, regardless the orography of the city, can be accepted since we are not interested on a fine estimation the energy consumed of a single trip. In some trips the consumption will be overestimated (e.g., applying the corrective factor on a straight road), while in other cases underestimated (e.g., driving in a circular road). Therefore the consumption error on average will be balanced.

Whenever $c(a, t_e(i)) = 0$, the trip i is declared *infeasible*. The discharged car a still performs further trips, all marked as infeasible, until it reaches a charging station.[5]

B. Car charging policies

When returning the car, the customer may connect it to a pole in a station, hence charging the battery and possibly deviating from the desired destination.

We define different policies that the electric FFCS may enforce, and different probabilistic behaviors of customers. We investigate the following policies:

- *Free Floating*: the customer must connect the car to a charging pole if and only if it is available in the desired final zone $D(i)$;

[5] This is instrumental to give an exhausted car the chance to recover energy.

- *Needed*: cars must be connected to a pole when the fraction of battery charge at the end of the rental i would go below a certain threshold α, i.e., $(c(a, t_s(i)) - Energy(p(a, t_s(i)), d(i)))/C \leq \alpha$. This implies the customer can be *rerouted* to the closest zone equipped with a charging station, if no free pole exists in the desired final destination zone;
- *Hybrid*: the customers follow the needed policy; they may also voluntarily connect to a charging pole - if available - in the desired ending zone $D(i)$ with probability w, whatever car charge status is.

The *Free Floating* policy never obliges the customer to bring the car far from the desired ending location, even in case battery is close to exhaustion. *Needed* mandates to connect cars to a charging station only when battery runs low, thus trying to protect from battery exhaustion. *Hybrid* mixes the two policies, with w that measures the level of customers willingness to collaborate. $w = 0$ is equivalent to the Needed policy, while $w = 1$ adds to the Needed policy the Free Floating policy, thus always connecting the car to a charging pole if available in their final position zone.

C. Charging stations placement

Given a number of charging station N, our first objective is to place them to make all rentals feasible, i.e., to find a charging stations placement so that

$$c(a, t_e(i)) > 0 \ \forall a \in \mathcal{A}, \quad \forall i \in \mathcal{I}$$

Since we do not make any assumption on the set of trips $\mathcal{I}$, we cannot know a-priori if a solution exists. The number of candidate solutions increases as the binomial coefficient $\binom{|\mathcal{Z}|}{N}$, making ineffective to numerically compute all possibilities. Here we provide a class of greedy algorithms and analyze the performance. In details, each zone $z \in \mathcal{Z}$ is assigned a likelihood $l_z \geq 0$. We then solve the problem of finding the subset of N zones that maximizes the total likelihood. In formulas,

$$\max \sum_{z \in \mathcal{Z}} cs(z) l_z$$

subject to:

$$\sum_{z \in \mathcal{Z}} cs(z) = N; \ \ cs(z) \in \{0, 1\}, \forall z \in \mathcal{Z}$$

The above optimization problem can be solved by choosing the top N zones, ordered in decreasing likelihood. We compare the performance of different placement algorithms based on different definition of the likelihood.

- *Random placement* (Random): l_z is an independent and identically distributed uniform random variable, so that charging stations result placed at random;
- *Average parking time* (Avg time): l_z is the average parking duration in z as recorded in the trace;
- *Total number of parkings* (Num parking): l_z is the total number of parking events recorded in z in the trace;
- *Total parking time* (Tot time): l_z is the sum of all the parking duration events recorded in z.

As discussed in Section III-C, the last three heuristics are driven by the intuition that placing charging stations in those zones where cars are parked for long time (average parking time) or frequently parked (total number of parkings) could improve system performance. The total parking time combines these two metrics: it measures the average parking time multiplied by the total number of parkings. Indeed, considering this parameter, the value of l_z increases both when the car stays parked a lot of time or when a lot of cars stay parked in the same zone. From our analysis, the *Total number of parkings* and the *Total parking time* tend to place charging stations in the same areas since the variance in number of parking events is larger than the variance in parking time.

D. Performance metrics and parameters

The simulator measures the following key performance indicators to assess the quality of experience of customers:

- *Infeasible trips*: measures if a trip i performed by a car a ends with a completely discharged battery, i.e., when $c(a, t_e(i)) \leq 0$;
- *Charge event*: indicates if a trip ends with putting in charge the car, implying the burden to drive to the pole position, and plug the car;
- *Reroute event*: a trip where the customer is rerouted to a zone different from the desired destination in order to charge the car, i.e., $P(a, t_e(i)) \neq D(i)$;
- *Walk distance*: distance between the desired final location $d(i)$ and the actual final position $p(a, t_e(i))$.

The number of infeasible trips is critical and the system must be engineered so that they never happen. In this way, all trips can be performed and end with a still charged battery. For this reason, in our analysis we focus on the feasible region where all trips are possible. Other performance metrics shall be minimized. In addition to the above metrics, the simulator collects statistics about car battery charge level $c(a, t)$, and amount of time a battery stays under charge.

E. Simulation scenario

We focus on key design parameters, i.e., the charging station placement and return policies. We study the impact on the number of zones that are equipped with charging stations N, and the number of poles k of each charging station.

Table I summarizes the dataset main characteristics. For our study, we consider all rentals observed in September and October 2017. We consider in each city a fleet that has a number of cars equal to the one observed in the trace. Electric cars have the same nominal characteristics as the Smart ForTwo Electric Drive, i.e., 17.6 kWh battery, for 135 km of range, with a discharge curve $Energy()$ that is proportional to the traveled distance (12.9 $kWh/100\,km$). [6] Different works [19]–[21] show that many parameters may affect the battery consumption, with road inclination which is one of the key parameter that affect the energy consumption. Unfortunately our data granularity does not allow us to know the users' route. We study the impact of variation in the energy

[6] https://www.smart.com/uk/en/index/smart-electric-drive.html

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consumption in Section VII to observe the impact of extra energy consumption due to car auxiliaries and orography. Our simplifying assumption could be considered a valid approximation for our goals since:

- The cities under study do not present big road gradients. The difference between the maximum and minimum elevation within the city limits are: $45\,m$ for Milan, $86\,m$ for Berlin, $152\,m$ for Vancouver, and $511\,m$ for Turin (due to Superga hill, which is outside the Car2go service area).[7]
- On average, the battery capacity supports many car-sharing trips. Therefore the underestimation introduced due to the missing gradient on a single trip is compensated by the overestimation on an other trip.
- Authors in [21] shows that the error introduced by do not consider different parameters (altitude gradient, wind, etc.) is only about 16% of the trip consumption. This number is less than the possible errors we analyze in Section VII.

Considering charging stations, we assume each is equipped with $k = 4$ low power ($2\,kW$) poles. These are cheap to install and a good compromise between costs, power requested, and occupied road section. Li-ion batteries are normally designed for being charged first with constant current (and slightly increasing voltage) up to a fraction of their capacity (see [22] and [23]). In this region the SOC increase almost linearly, absorbing the maximum power of the pole. We approximate that the whole charge is performed at this power (complete charge in 8 hours and 50 minutes for our electric car). Finally, the initial car position, only affecting the simulation transient, is chosen randomly.

Our simulator, written in Python, takes less then 5 seconds to complete a single simulation for a given city and parameter set. Due to the large number of simulations, we run them in batches of 128 processes in parallel. Each simulation produces 100 MB of detailed logs, that we process on a Big Data cluster using Apache PySpark to extract the desired performance metrics.[8]

F. Lower bound on charging station number

To understand whether our methodology produces good results we compute a lower bound to the number of charging stations required to complete all the trips. This lower bound evaluates the minimum number of charging stations required to supply the energy consumed by all the cars in the considered period. We compute the energy needed for trips in the whole trace and then, independently of the actual trips, we assume all the poles are used in the best way to provide energy. Hence, the poles are delivering energy all the time to an ideal not-fully charged cars, so no charge opportunity is wasted.

To compute the lower bound, we evaluate the total distance covered by all cars. Knowing the consumption per km ($12.9\,kWh/100\,km$), we compute the total energy consumption. Then, given the power of each pole ($2.0\,kW$), we compute the amount of hours required to provide all the consumed energy. Finally, knowing the number of days in the trace (58 days), we compute the minimum number of poles and the percentage of charging zones. Table II reports the lower bound for each city. The minimum value ranges from 22 poles in Turin to 94 in Vancouver. Assuming $k = 4$ poles per charging station the minimum percentage of equipped zones goes from 1.9% to 4.4%.

TABLE II
LOWER BOUND OF NUMBER OF POLES AND CHARGING STATIONS

City	Total distance [km]	Consumption [kWh]	Charging time [h]	# of poles	Zones %
Turin	509 492	66 234	29 799	22	2.3
Milan	1 328 538	172 710	79 852	58	2.6
Berlin	1 491 200	193 856	89 008	64	1.9
Vancouver	2 128 192	276 665	130 052	94	4.4

V. IMPACT OF CHARGING STATION PLACEMENT

We consider first the Free Floating return policy and study the impact of different charging station placement policies. Our aim is to check what would be the minimum number of charging stations to install to sustain a FFCS system based on electric vehicles that is equivalent to the one currently in use.

Fig. 5 shows the performance of the different placement algorithms in terms of percentage of infeasible trips with respect to the percentage of zones equipped with charging stations for each city. Bottom x-axis reports the percentage of equipped zones with respect to the total, while top x-axis reports the actual number, different for each city.

We observe dramatically different performance for different placement algorithms. First, the average parking time placement policy (*Avg time* - purple line) has very poor performance in all the cities. Even a simple random choice sometimes performs better (*Mean Random* - green line, obtained as the average of 10 random instances). In Milan – Fig. 5b – and Berlin – Fig. 5c, the random placement results the worst. This is due to the larger number of zones, which makes the space of available solutions much larger.

Second, the total parking time (*Tot time* - black line) and total number of parkings (*Num parking* - red line) perform similarly and consistently better than other policies. In all the cities except for Berlin we can reach a negligible percentage of infeasible trips with just 15-18% of charging zones (still 5-10 times higher than the lower bound). In Berlin we still observe some infeasible trips with 30% of charging zones. Recall that the nominal car battery guarantees to travel $135\,km$. The presence of infeasible trips is explained by looking the rental distance presented in Fig. 3. Trips in Berlin can be as long as $39\,km$. Therefore, with few long-trips which do not end in a charging station area, the battery could run out the energy.

The overall trends confirm the intuition of why the charging stations placement algorithm is of primary importance. *Avg time* placement favors peripheral zones where few trips end, and where cars stay parked for long time, sometime longer than the time required for a complete charge, (see left heat

[7] Data obtained from http://www.comuni-italiani.it and https://en.wikipedia.org/

[8] https://smartdata.polito.it/computing-facilities/

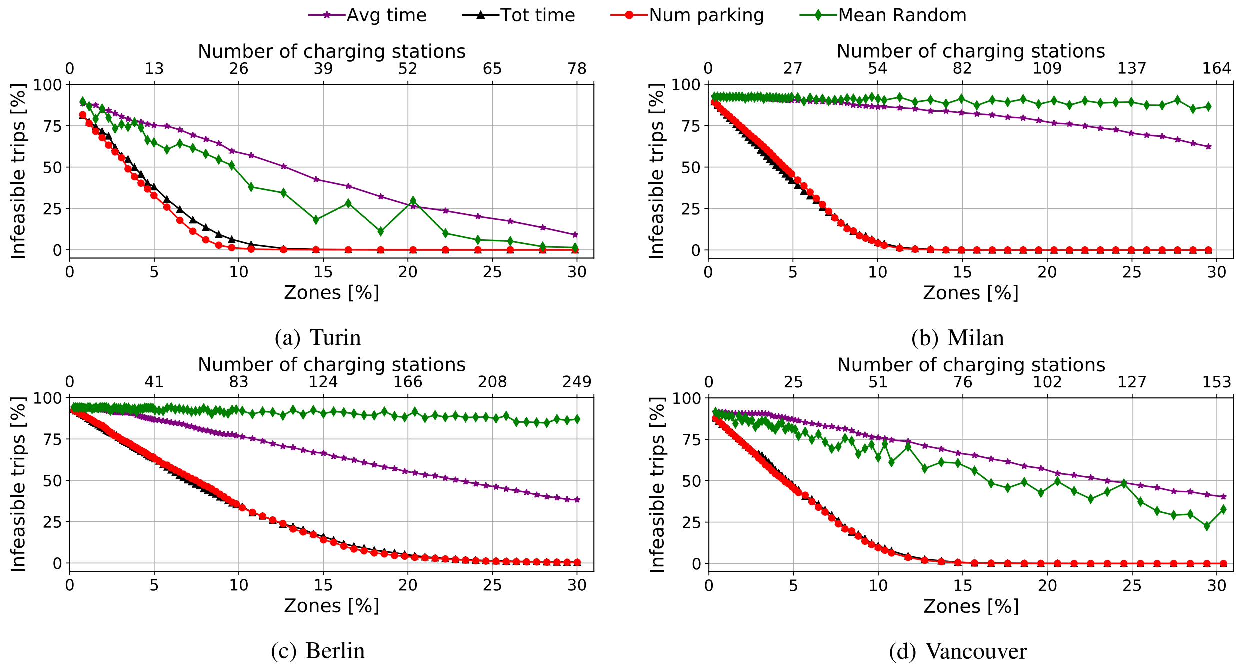

Fig. 5. Percentage of infeasible trips as function of charging station number for the Free Floating return policy. Placing charging stations where cars are frequently parked (Tot time and Num parking) is much better than where cars stay parked for long time (Avg time).

maps Fig. 4a and Fig. 4b). On the contrary, *Num parking* and *Tot time* favor city center areas, where cars are frequently parked for short time (see right heat maps in Fig. 4a and Fig. 4b).

Takeaway: Placing charging stations in areas where cars stay parked for long time is not convenient. Placing charging stations in areas where cars are frequently parked allow many cars to recover the (little) energy consumed in the (short) trips. This results in a much better policy.

Given this, we will use the total number of parking placement algorithm for the rest of the paper.

VI. Impact of Return Policy

We now investigate the impact of the different return policies. In particular, we quantify the implications of asking customers to return the car to a different zone than the desired one when the battery goes below a critical level.

A. Impact on infeasible trips

In Fig. 3 we already noticed that trips are typically short. This is instrumental to choose a proper minimum charging threshold α. Given the maximum trip distance, we obtain the corresponding maximum energy being consumed. For instance, a maximum distance of $20\,km$ correspond to about 15% of battery capacity for the considered car model. In the following, we take a conservative approach and set the minimum battery charge threshold $\alpha = 0.25$, i.e., 25% of the battery capacity. To make results comparable, we keep the same threshold also for Berlin, where the maximum traveled distance grows to $39\,km$, i.e., suggesting $\alpha > 0.3$. Here our choice is not conservative.

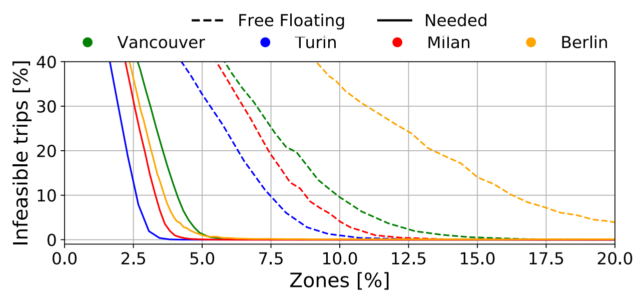

Fig. 6. Infeasible trips when comparing the Free Floating vs Needed return policies. Forcing customer to charge when $c < \alpha$ drastically improves performance.

As before, we focus on the infeasible trip percentage with respect to N. We compare results for the Free Floating and the Needed policies. Fig. 6 shows the results. The Needed policy (solid lines) performs much better with respect to the original Free Floating policy (dashed lines). In a nutshell, adopting a policy which mandates customers to charge the car when battery level goes below a threshold drastically reduces the number of infeasible trips, even with a handful of charging stations. Indeed, in all cities we have a negligible percentage of infeasible trips ($< 0.1\%$) with 6-8% of zones equipped with charging stations. This is just twice as much the (very optimistic) lower bound.

We now focus on the impact of the willingness w in the Hybrid policy. We want to understand if the more altruistic are the customers, the higher are the benefits for the system. Fig. 7 details the percentage of infeasible trips with a different willingness probability for Vancouver and Berlin. Turin and Milan are similar and not reported for the sake of brevity. Results show that increasing w has very little impact on the

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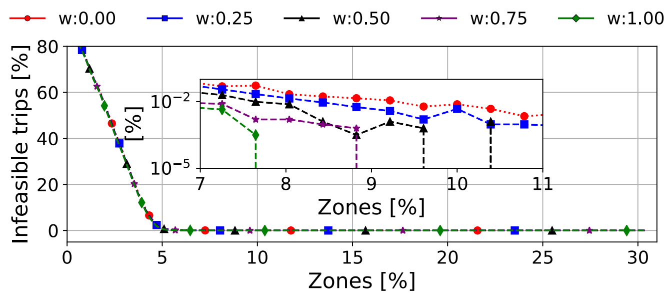
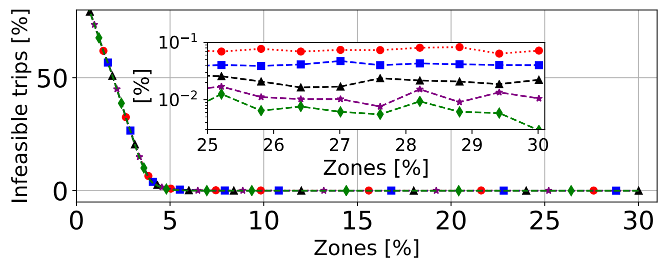


(a) Vancouver



(b) Berlin

Fig. 7. Impact of customer willingness to cooperate w. Albeit the small impact, the higher w is, the better it is.

percentage of infeasible trips. Only by looking at the insets that offer a zoom in log-scale, we observe that an increasing willingness reduces the infeasible trips, which are however already a marginal percentage of trips. This is due to the higher average battery level, obtained by imposing the Free Floating policy on the top of the Needed one. In Berlin, we can still observe some infeasible trips even when 30% of zones are equipped with charging stations. This is due to the maximum length of the trips, confirming the need to increase the threshold α.

Takeaway: Asking customers to return the car to a charging station when the battery level goes below a minimum level drastically improves system efficiency. Just 6%-8% of zones covered by charging stations guarantees to always have the needed battery capacity to complete all trips. Recalling that up to 4.4% of zone are required as lower bound, this confirms the goodness of this solution.

B. Impact on customer experience

As there is no strong impact of w on the infeasible trips percentage, here we check benefits on the customer's experience. Forcing customers to park in a charging station can be annoying, because they have to reach the charging station, and spend time to plug and unplug the car to and from the pole. Even worse, rerouting customers for charging increases the distances they have to walk to reach their desired destination.

Fig. 8 reports, the percentage of charge events (left plots), the percentage of reroute events (middle plots), and the average walk distance when rerouted (right plots). In all graphs the shaded area highlights the infeasible region, i.e., when infeasible trips are higher than 0.1% in at least a case. The lack of charging zones creates artifacts here.

Focus first on the percentage of charge events - leftmost plots. When the number of charging stations is close to the minimum, most poles are occupied by cars that must be charged. This leaves little room for opportunistic charges, and there is little impact of w. For increasing number of charging stations, the opportunity to find a free pole increases. Thus, the higher is w, the higher are the charging events. Correspondingly, the average battery charge increases – detailed in Fig. 9 for Vancouver. Interestingly, the percentage of charge events decreases for selfish customers ($w = 0$), reaching about 5-8% for sufficiently large number of charging stations. This corresponds to the average number of charges per car that guarantees minimum battery charge of 25%. Indeed, given the average rental distance of $5\,km$ (Table I), the car considered in our scenario could perform on average 20 trips before needing to charge.

Move now to the percentage of rerouting events - middle plots in Fig. 8. Two important effects are visible. First, rerouting probability decreases as expected: the more the stations are, the more likely customers find a charging station at their desired final zone. With selfish behavior ($w = 0$), the fraction of rerouting events remains large even for large N. Second, the more collaborative are customers, the better it is for the entire system. With 50% of chance that customers return voluntarily the car to charging station, the reroutings are less than 1% with 18% of charging zones for Milan, Turin and Vancouver. These can be handled by a relocation policy, i.e., the system could take care to charge those 1% of cars whose battery level is smaller than α. Note that this corresponds to about 50 relocation events per day. For Berlin the number of rerouting remains larger than 3%, mainly due to the larger size of the city.

At last focus on the average walk distance when the car is rerouted – rightmost plots in Fig. 8. When forced to charge to a different zone than the desired one, customers would be asked to drive farther than 1-2$\,km$, a likely unacceptable penalty unless mitigated by offering incentives to customers, e.g., offering a free rental when rerouted.[9] Notice that by increasing the number of charging stations, the walked distance slowly reduces. This is due to the fact that charging stations are not placed uniformly in space, following the number of parking heuristic, which places most of them in the downtown area.

In summary, we would like to have $w = 1$ to reduce reroutings and infeasible trips, and $w = 0$ to reduce charging events. Moreover, we would like to have as few charging stations as possible to minimize installation costs, but as many charging stations as possible to minimize reroutings and walking distance when rerouted. Given this multi-objective optimization problem, there is not a single optimal solution, but we could extract all the optimal Pareto solutions useful for the decision process of a car sharing operator.

In an attempt to weight the different effects of changing w, we compute the (global) walk distance averaged over all trips. This considers the penalty due to (i) the rerouting events, and (ii) the walk distance when charging in a pole of the desired final destination (pole distance would be $150\,m$, on average). Fig. 10 reports results for Vancouver. For more than 10% of zones with charging stations, customers have

[9]The noise for large N is due to the very small number of rerouting events.

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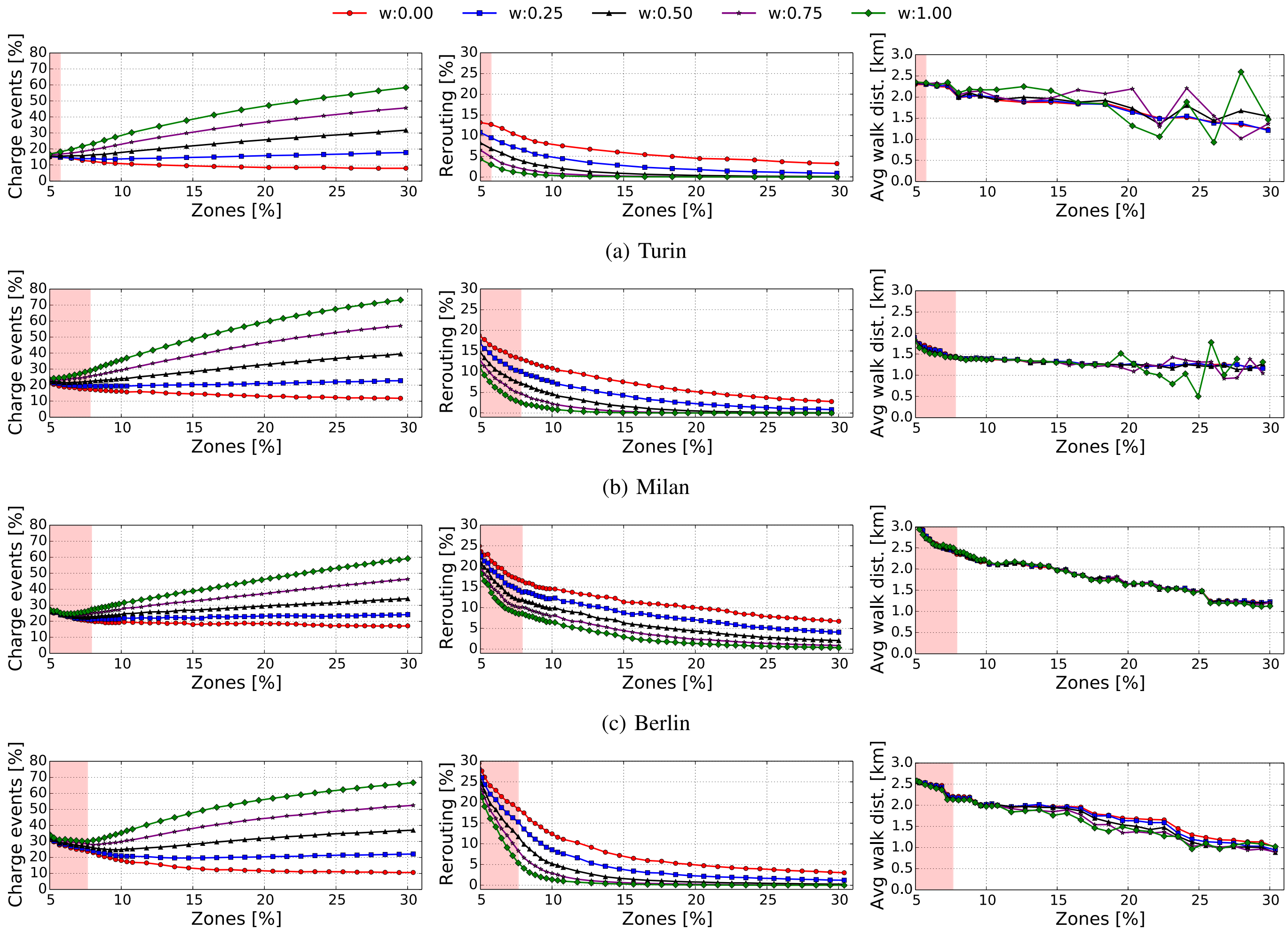


(a) Turin

(b) Milan

(c) Berlin

(d) Vancouver

Fig. 8. Charge events percentage (left), reroute events percentage (middle) and walk distance averaged over rerouted trips (right), per city. Increasing w benefits the customers' experience by reducing the rerouting events significantly, but increasing the charging events.

to walk on average less than $300\,m$. When the number of charging stations is low, increasing w reduces the average walking distance, since opportunistic charges reduce rerouting events. However, further increasing the number of charging zones slightly increases the average walk distance since the customer has higher probability of finding a pole in the desired zone. After about 20% of zones, the best policy switches from $w = 1$ to $w = 0$. Therefore, the policy to use may be different according to the number of charging stations. Overall, for all the cities and 10% of zones, customers on average walk less than $200\,m$ to reach their desired destination with $w = 1$.

Takeaway: Hybrid policy significantly reduces the number of times the customer has to drive to a charging station in a different zone than the desired one. However, it increases the number of times the customer parks at a charging station and has to plug the car to the pole. Therefore, one must be cautious when weighting these results and designing the return policies which impact customers' experience.

VII. Sensitivity to Battery Discharge Rate

In this section we explore the scenario in which the consumption for a trip $Energy$ is higher than the nominal one

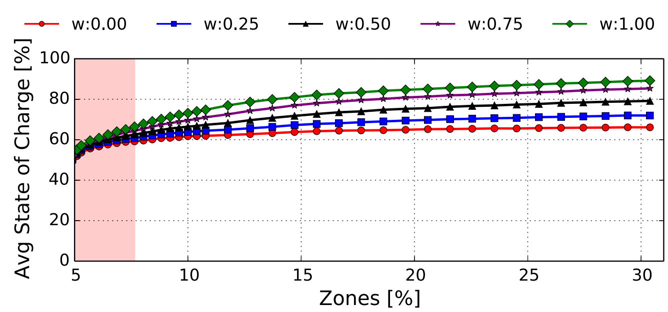


Fig. 9. Details of the average battery charge status for Vancouver - the higher the better. Other cities have similar results.

we studied so far. As pointed out by different studies [21], the linear consumption rate proportional to the travel distance is an approximation. In this section we rely on the findings of authors in [24] to evaluate the impact of an higher consumption per km due to: (i) different driving style, (ii) the utilization of auxiliaries e.g., Air Conditioning system, (iii) traffic congestion, and (iv) different morphology of the city. It is important to recall that these factors have a limited impact on electric

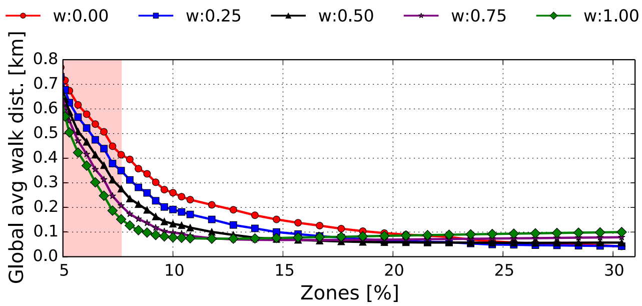
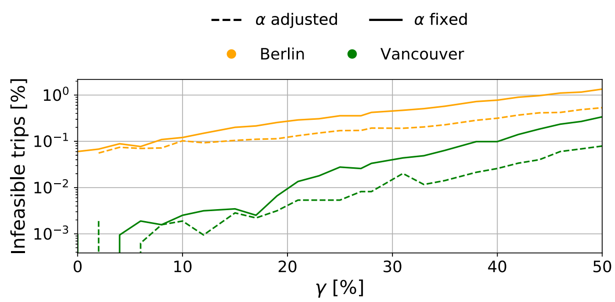
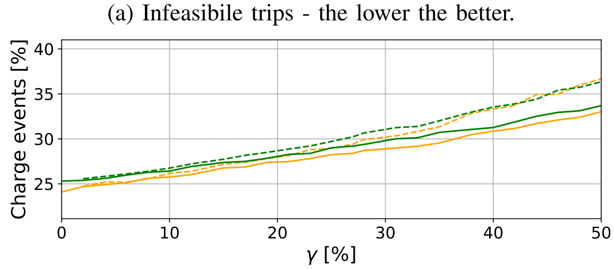


Fig. 10. Details of the global average walk distance for Vancouver. Other cities have similar results.



(a) Infeasibile trips - the lower the better.



(b) Charge events percentage - the lower the better.

Fig. 11. Impact of higher consumption. Increasing consumption by up to 50% has limited impact on the ability of completing the trips.

cars due to high efficiency of electric engines, including the energy recovery while breaking, and very limited consumption while idle.

Based on [24], we multiply the consumption rate by a factor $(1 + \gamma)$. The factor γ models the relative increase of consumed energy. We perform different simulations for Berlin and Vancouver, with γ in [0, 0.5]. We use 10% of zones equipped with charging stations (53 zones for Vancouver and 83 for Berlin), $k = 4$ poles per charging station, and user's willingness $w = 0.5$.

We also adopt different values of the battery threshold α:

- α *fixed*: $\alpha = 0.25$
- α *adjusted*: $\alpha = 0.25 \cdot (1 + \gamma)$

Fig. 11a depicts the infeasible trips percentage with respect to different γ (notice the log scale on y-axis). The results are quite intuitive: the higher γ is, the more the infeasible trips are. When the energy consumption increases by 50% the percentage of infeasible trips increases by 1 order of magnitude in the case of Berlin, and by 2 orders of magnitude in the case of Vancouver. However, in both cases the percentage of infeasible trips stays below 2%. Adjusting the charging threshold level α helps limiting the impact of unforeseen energy consumption.

Fig. 11b details the frequency of charge events for different values of γ. As expected, the higher consumption requires for more charge events. The user's discomfort increases since the percentage of charge events raises. However, the difference between α *fixed* and α *adjusted* is little with similar curves in both cities.

Takeaway: A consumption 50% higher than the nominal one, that could account for the approximation introduced by our assumptions, still allows the percentage of infeasible trips to stay below 2%. These could be handled with a handful of extra charging stations.

VIII. How to Distribute Poles in Stations

In the previous sections, we have assumed charging stations with $k = 4$ poles each. Here, we study the impact of installing charging stations with a different number of poles each. We keep the total number of charging poles $K = kN$ constant, and equally distribute them in a varying number of charging stations N. In other words, we check if it is better to have (i) few charging hubs with many poles (one single hub corresponds to $N = 1$, with K poles), or (ii) a very large number of charging stations each with few poles. We call *pole spread percentage* the percentage of zones in which poles are distributed among, i.e., $100 \cdot N/K = 100 \cdot \frac{1}{k}$. For example, pole spread percentage 5 corresponds to 20 poles per zone ($k = 20$), spread percentage 10 corresponds to 10 poles per zones, etc. up to spread 100 that corresponds to a single pole per each charging zone ($N = K$ and $k = 1$).

For our study we pick a constant number of charging poles K corresponding to a 7% of charging zones when $k = 4$.[10] Then, we distribute poles evenly among different zones, chosen according to the number of parkings policy (as in the previous Sections). We consider the Hybrid policy with $w = 0.5$ and simulate the resulting system.

From top to bottom, Fig. 12 reports percentage of infeasible trips, the average time cars are plugged to a charging pole (even if they are completely charged), the percentage of rerouted trips, and the average walk distance for rerouted trips. Colors refer to different cities and the x-axis reports the spread. Note that with $k = 4$, as in the previous experiments, we have a spread percentage of 25% for all the cities.

Focus first on Fig. 12a. With spread percentage going below 5%, hence concentrating poles in very few hubs, the number of infeasible trips quickly grows to non negligible values. Even Turin and Milan suddenly suffer of a sizable percentage of infeasible trips. The lowest values are obtained with spread between 5 and 20, meaning that increasing the number of poles per charging station in the $[5 - 20]$ range helps the system to sustain. Conversely, spreading a lot of charging stations, each equipped with few poles is not optimal. In this case poles are spread also in areas where (few) cars stay parked for long time, keeping poles busy (see rightmost part of Fig. 12b).

[10]Each city has a different K, producing a different number of infeasible trips.

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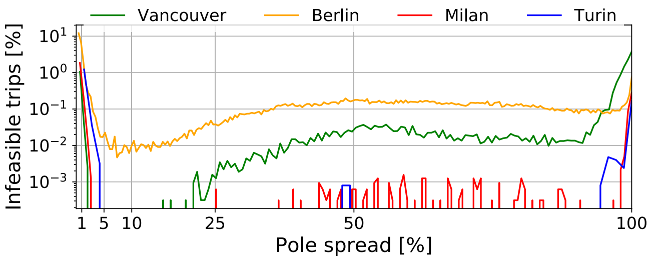
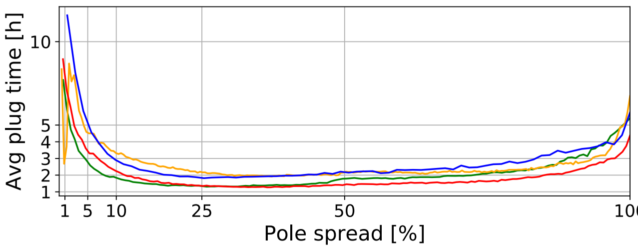
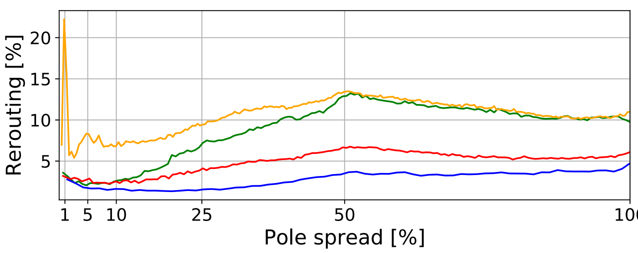


(a) Infeasible trips - the lower the better.



(b) Average time spent plugged to a pole.



(c) Reroute events percentage - the lower the better.

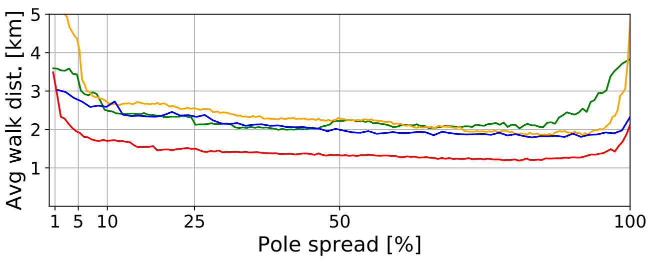


Fig. 12. Impact of pole distribution among zones. Concentrating all poles in few hubs (low pole spread) performs poorly, as well as placing single pole charging stations (pole spread 100%).

Fig. 12c shows the percentage of reroutings. Here we also observe that it is better to have a low spread percentage. For the region where we have negligible infeasible trips (spread between 5 and 20), the percentage of reroutings increases because poles start to be located in less popular destination, and because cars are charged for less time (see Fig. 12b).

Lastly, we show walk distance for rerouted trips in Fig. 12d. As expected, the walk distance decreases with spread percentage. Indeed, when customers are rerouted, they can return the cars in more areas, likely closer to their desired destination. Only when single pole stations are used, the walk distance increases again. This is justified again by cars that stay connected to poles for too long time, reducing the availability of free poles and forcing customers to drive further away.

Since there is not a single value of pole spread that optimize all the metrics, a trade-off among them should be chosen, and this can change from city to city. In general, it looks better to concentrate poles only in those zones where cars are frequently rented and returned, so to increase the chance to find a free pole, and let the battery quickly charge before the next rental makes the pole free again. In a real scenario of a design of a charging infrastructure, it is appropriate to optimize the number of charging poles for each different charging station.

Note that both extreme solutions of pole spread percentage would cause the highest installation and operating expenditures. The single hub solution would require to have a huge amount of power at disposal in a single location. While the single pole solution would largely increase the installation cost.

Takeaway: Concentrating all charging poles in very few hubs, or spreading them among all city areas performs badly. The intermediate solutions look beneficial, and must be carefully weighted also considering the cost of installing charging stations.

IX. Conclusion

Designing an electric vehicle free floating car sharing system leads to many interesting problems and trade-offs. In this work, we built on actual rental traces to study via simulations the impact of the charging station placement, and car return policies. Differently from previous works, we followed a data driven approach to simulate realistic scenarios.

While our results confirm many expectations, our data-driven simulations let us exactly quantify the requirements for a FFCS system based on electric vehicles. Considering the car return policies, we showed that a FFCS based on electric vehicles results feasible especially if customers return the car to a nearby charging station whenever the battery level drops below a minimum threshold. Considering charging station placement, we proposed heuristic algorithms and showed that it is better to place charging stations in popular areas (e.g., downtown) rather than in areas where cars stay parked for long time. Our simulations showed that equipping just 6-8% of zones is enough to complete all trips without discharging the battery. We further optimized the placement in [17], while also validating on data from different months.

Our results hint for possible alternative design solution where the system itself takes care of charging cars to limit discomfort for customers. Suitable relocation policies could be a possible solution or considering incentives to customers, e.g., via price differentiation as recently introduced by Car2go and UBER. We plan to study this in our future work.

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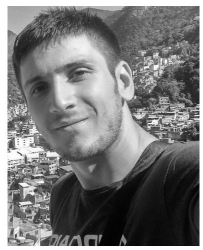

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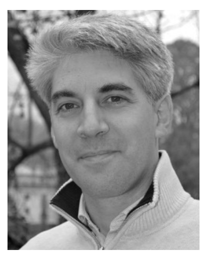

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