Free Floating Electric Car Sharing in Smart Cities: Data Driven System Dimensioning

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***Abstract*—Car sharing is a popular means of transport in smart cities. The free floating paradigm lets the customers autonomously pick and drop available cars freely, within city limits. In this work we study the different policies when designing an electric Free Floating Car Sharing (FFCS) system. This system has the need to guarantee battery charge, a time-consuming operation, for which charging stations availability becomes a key factor for the sustainability of the whole system.**

We harvest the data of an already operative FFCS provider, and extract information about actual users' driving patterns. We implement a trace driven simulator to replay collected users' trips and simulate car batteries consumption for different design parameters. In this work, we limit the study to a single city, Turin (Italy), where we leverage actual trips registered over 2 months. We analyse and discuss several system design alternatives: the number of charging stations, their placement, and when to force users to return cars for charge. We identify regimes where cars never discharge and users can freely drop cars anywhere, albeit they are rarely rerouted to a charging station, possibly located in a nearby area to their original destination. Surprisingly, our data shows that even few charging stations (15 or more, i.e., 6% of city areas) guarantees the system to work almost autonomously, making thus possible free floating car sharing a feasible solution with electric cars.

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

I. Introduction

Due to fast growth of urbanization, nowadays mobility and pollution are very important challenges for our society. Regulators and policy makers try to push the usage of more eco-sustainable solutions for transportation in cities. Hybrid or electric cars are considered among the best options to replace combustion engine cars. Along with the usage of public transport, the sharing mobility such as bike sharing, car pooling and car sharing, is seen as an important means to reduce traffic and pollution. In this work, we focus on the design of an electric car sharing system, where customers rent a car for moving within the city for a short period of time, usually for less than one hour. Among the possible car sharing solutions, a very interesting one is the so called Free Floating Car Sharing (FFCS) system. The peculiarity of this system is that customers are free to pick and return the car wherever they like, inside a geo-fenced area.

The design of a system based on electric cars is more challenging compared to an internal combustion based one. Indeed, the time needed to perform a complete charge is not comparable to refuelling time, and can grow up to several hours [1]. As such, electric car sharing systems require to setup an infrastructure of charging stations, whose design requires [2], [3], [4]. Two are the main problems that need to be faced: i) the charging station placement problem and ii) the return policy the users have to follow at the end of the rental, i.e., in which cases forcing the user to return the car to a charging station.

In this paper we face both the above problems. In the past some works have proposed solutions for the adoption of electric FFCS [5], [6] and for a smart placement of charging stations [2]–[4], [7]. Here we are the first to take a data driven approach for dimensioning an electric FFCS system and analysing customer experience. We collect real data from the actual usage pattern of the FFCS system currently in use in the city of Turin (Italy), which is based on traditional combustion engines [8]. By observing the actual rentals and parking durations, and the origin and destination of hundred thousands trips, we study and compare the performance of a hypothetical equivalent car sharing system based on electric vehicles. We first compare different charging station placement policies, including simple random solutions and more advanced algorithms that exploit the knowledge of parking areas and duration. Results show that placing the charging stations in those areas where cars stay parked for long periods performs similarly to a random placement. Instead, placing charging station in those areas where cars are frequently parked even for short times guarantees much better performance.

Second, we compare three different return policies and we observe how they impact on the system cost, in term of number of charging stations, and on the user satisfaction, in term of number of times users are forced to drive to a charging station and the cost for additional distance. Opportunistic free floating solutions, i.e., charge only when there is an available nearby charging pole, requires more than twice as much charging stations compared to policies that force to charge when the battery level gets below a threshold.

We run extensive simulations using data of real rentals we collected over 2 months. Results show that it is sufficient to cover at least 6% of zones with charging stations provided smart return policies are adopted. This corresponds to install only 15 charging stations in the whole city of Turin, which has 1 million inhabitants, to sustain a free floating electric car

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sharing system like the one currently in use with 300 vehicles.

We believe that our data driven approach offers novel opportunities to guide the design of electric car sharing system, where the realistic figures provided by data allow finding solutions that meet both user requirements and limit system costs.

II. Related work

The diffusion of the free floating approach to car sharing leaded to an increasing attention by many researchers, with analyses of these systems and their extension to electrical vehicles. The studies performed in 2011 by Finkorn and Müller [9], [10] are the first attempts to analyse benefits of FFCS for the population. Their results on users' behaviour, like travelled distances, are similar to ours. Later works [11]–[13] also collected data and analysed the mobility pattern of users and differences among cities.

The introduction of electrical vehicles for private and public transportation brought the problem of placing the electric charging stations. Authors in [7] show the benefits of placing charging stations with different capacity according to the user parking duration. Few data driven studies address the charging station placement, either by respectively minimizing cost of installation, power loss and maintenance [2], [4], or by minimizing the users' walked distances necessary to reach a charging pole [3].

After a survey among FFCS users in Ulm (Germany), authors of [5] investigated the positive influence and feasibility of an electric FFCS systems. Lastly, authors of [6] studied the relocation of electric cars in FFCS, since few charging stations may be blocked by fully charged vehicles.

In our work we are the first to take a data driven approach for dimensioning the electric FFCS system by analysing and optimizing different metrics impacting customer experience.

III. Data collection and characterization

Our goal is to solve the design of an electric FFCS system, and to run accurate performance evaluation. For this, we rely on actual data that we collect by harvesting available information on the web. Here we first describe how we collect data and then how we characterize the system utilization. We focus on those metrics that impact the design of an equivalent system based on electric cars, i.e., driving distance and parking habits.

A. Data collection and filtering

FFCS systems like Car2Go, DriveNow or GoGet, consist of a web backend which allows users to rent a car using, e.g., a web interface, or a smartphone. These backends expose information, which can be harvested to extract indicators about system usage, and user habits. For instance, Car2Go offers APIs for downloading data of the system status.[1] We use these APIs to obtain and collect data. First, we get the service operative area limits, i.e., the perimeters of the parking areas in the city we are studying, that remains constant over several months. Second, we track locations of the cars that are currently available by taking a snapshot every minute. In each snapshot, we get those cars that are parked in the operative limits and without any ongoing booking. For each car, we collect (i) the plates, used as car identifiers, (ii) the geo-positions, obtained from in-car GPS device, and (iii) the fuel levels, obtained from the car electronic unit, with precision of 1% of tank capacity.

We developed a software, called UMAP [8], capable to reconstruct, for each car, *parking* and *booking* periods. A parking event is characterized by the time interval (i.e., all consecutive snapshots) during which a car is available on the online system. A booking event is characterized by the time between two parking periods during which a customer is possibly using the car to move from one point to another.

We started collecting data with UMAP in December 2016, and we have collected more than a year of data in all the 22 cities Car2Go offers service. In this work, we focus on 8 weeks between September and November 2017, and consider the city of Turin only. We collected about 190 000 bookings from the 300 cars of the Car2Go fleet.

Next, we filter this data to obtain actual rentals. Recall that, the Car2Go system allows users to reserve a car. In case the user cancels the reservation, the car becomes available again, showing up as a booking in our dataset. In addiction, some bookings last for several days or weeks. These may be due to a car going offline, or under repair. At last, the backend system may sometimes fail, generating spurious bookings. UMAP filters these artefacts to obtain actual *rentals*: starting and ending position must be at least 700 m far apart, booking duration must be greater than 3 minutes, and shorter than 1 hour. After filtering, our dataset contains than 125 000 actual rentals.

Given that we only know the starting and ending position of a rental, we need to estimate the possible driving path and length. Euclidean distance between starting and ending coordinates of the trip represents a lower bound of the real driven distance, since cars have to follow the topology of the city and traffic laws. To estimate the real driving distance, we apply a corrective factor, that we obtain again from data. In more details, given a rental, we use Google Maps APIs[2] to get driving directions. Then, we compute the ratio between the returned driving distance, and the euclidean distance. We repeated this for about 10 000 trips, observing the distribution of the ratio which ranges between 1 and 2, with a median value of 1.4. We use this value as corrective factor to obtain the driving distance from the euclidean distance. We further verify this results by analysing the data about fuel consumption. We estimate an average consumption of 11.7 litres every 100 kilometres, which is clearly an overestimate in city driving. By multiplying by 1.4, we have a consumption pretty closer

[1] car2goAPI, https://www.car2go.com/api/tou.htm, service subject to approval by Car2Go. Approval granted in September 2016, service disconnected at January 2018.

[2] https://developers.google.com/maps/documentation/distance-matrix/, freely available for a limited number of queries.

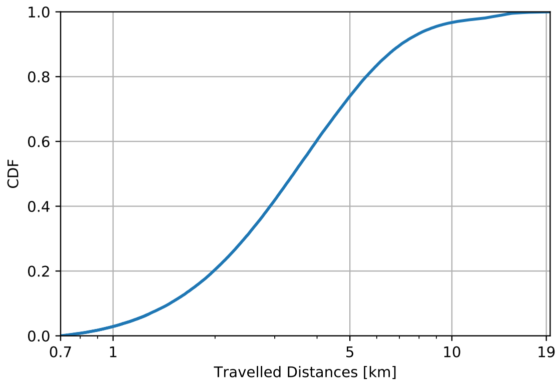


Fig. 1. CDF of travelled distances. X-axis is logarithmic.

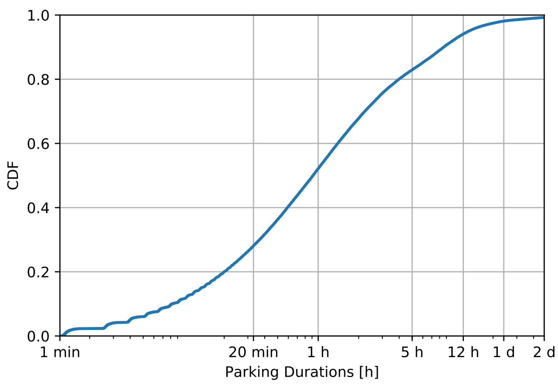


Fig. 2. CDF of parking durations. X-axis is logarithmic, and limited to 2 days.

to the one typically observed in the city (7.4 l every 100 km).[3] In the following we 1.4 as the corrective factor for all driven distances.

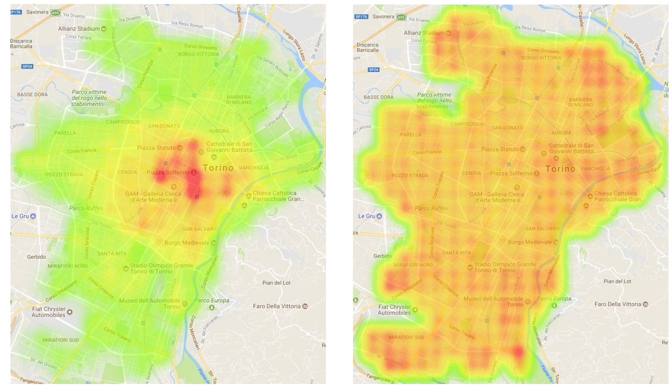
At last, Car2Go allows users to reach the Turin airport, that is about 15 km far away from the city centre. Distances for trips to the airport, reached by a straight highway, are not corrected.

B. Data characterization

Here we briefly characterize the actual usage of the FFCS system in Turin. This is instrumental to guide the design of the charging station placement algorithms.

Let us focus on the characterization of the (estimated) distance travelled during rentals. This figure is interesting since it is directly related to the minimum amount of charge an electric car shall have to complete a trip. Fig. 1 shows the empirical Cumulative Density Function (CDF) of the distances covered over all rentals. Trips of less than 700 meters were pre-filtered. Notice how 97% of the trips covers less than 10 km, roughly corresponding to the operative area diameter in Turin. Trips to and from the airport are the longest one, up to 19 km.

[3]https://www.alvolante.it/prova/smart-fortwo-coupe-twinamic.



(a) (b)

Fig. 3. Heatmaps showing (a) number of parkings per zone and (b) average parking time per zone. Darker areas have larger values. Zones are interpolated for better visualization.

Next, we investigate the parking duration. This figure is interesting since it is related to the amount of charge a parked car obtains when attached to a charging station. Fig. 2 illustrates the empirical CDF of parking duration. Interestingly, more than half of the parkings lasts less than 1 hour. This is due to the high utilization of cars in FFCS, especially during business hours. Conversely, 10% of the parkings lasts more than 8 hours, with some cars that are left parked for days. The former are probably due to overnight parkings, while the latter hint for some cars parked in areas with few customers.

Next, we analyse how parking habits are different in the city area. For this, we divide the service operative area limits into a grid of squared zones of 500x500 meters, obtaining 261 zones covering the operative area in Turin. For each zone, we compute statistics about parkings: the total number, the sum of all the parking duration, and the average parking time (i.e., parking duration divided by number of parkings).

Fig. 3(a) shows the heatmap of the total number of parkings in the city zones. The more a zone is red, the more frequently cars are parked here. The red area correspond to the city centre which hosts the highest number of parkings, implying that users rely on car sharing for travelling downtown, a working area full of shops and restaurants. On the contrary, few parkings are observed in the suburbs, where people live and likely return home in the evening [8]. Interestingly, the sum of the cumulative parking times inside each zone brings to similar results (not shown here for brevity).

Fig. 3(b) instead shows the heatmap of the average parking time for each zone. In this case, the metric is quite homogeneous, with peaks on some borders of the operative area. This means that few cars reach these border zones and they stay unused for long time (see also rightmost part of Fig. 2).

The large spread of parking density and duration challenges the decision on where to place charging stations. Indeed, if placed in areas where cars are frequently parked but for short time (e.g., city centre), batteries would get little charge. If placed in areas were few cars stay parked for long time (e.g., suburbs), cars will be fully charged cars but occupying the station for long time.

IV. Electric car sharing simulator

Our goal is to study different design choices for electric car sharing systems, based on collected data. For this, we developed a flexible event-based simulator that allows us to compare different algorithms and tune parameters while collecting metrics of interests.

We simulate a fleet of electric cars, which move in the city according to events recorded in a trace. Each car is characterized by its parking location, and the current status of battery charge. The simulator takes as input a pre-recorded trace of rentals characterized by the start and end time, and initial and final geographic coordinates. For simplicity, space is divided into 261 zones of 500 x 500 m each (as in Section III).

Our simulator, written in Python, takes less then 5 seconds to complete a single simulation on the full trace. Due to the large number of simulations we run, we use PySpark to analyse the simulation results by using a Big Data cluster of 30 nodes[4]. We made the simulator source code publicly available.[5]

A. Parking station placement

Z zones (with $Z \leq 261$) are equipped with recharging stations, each with 4 poles. The simulator implements different charging station placement algorithms. Each zone i is assigned a likelihood l_i. We greedily choose the top Z zones, according to four likelihood definitions:

- *random placement*: l_i is an independent and identical distributed random uniform variable, so that recharging stations result placed at random;
- *average parking time*: l_i is the average parking duration in i as recorded in the trace;
- *total number of parkings*: l_i is the total number of parkings recorded in i in the trace;
- *total parking time*: l_i is the total parking time accumulated in i by all cars recorded in the trace.

The last three heuristics are driven by the intuition that placing recharging stations in those zones where cars are likely to be parked could improve system performance.

B. Trace event processing

Each recorded rental reflects a mobility interest of user, i.e., a desired trip. The simulator process events in order of time. When a car rental start event is processed, the user looks for a car in the initial position zone. If a car is present, the user rents the most charged car. If no car is present, the user walks to the closest zone containing an available car, mimicking the normal behaviour of FFCS users that use their smartphone to rent the closest car from their position. A car rental end event is then scheduled using the trace final time and location. When a car rental end event is processed, the user returns the car. After returning it, the simulator updates the battery charge status by consuming an amount of power proportional to the trip distance. In case the battery level drops below 0, the trip is declared *infeasible*. The discharged car still performs further trips, all marked as infeasible, until it reaches a charging station.

Depending from the return policy, the user may connect the car to a charging station. We investigate the following return policies:

- *Free Floating*: the user opportunistically connects the car to a charging station if and only if it is available in the final zone of the rental;
- *Needed*: cars are connected to a pole when the battery charge at the end of the rental is below a certain threshold α. This implies the user may be rerouted to a different zone than the desired one, if no available pole exists in the desired zone;
- *Hybrid*: the car must be connected to a charging pole, if available in the ending zone; if the battery charge is below a given threshold α, cars must be returned to the closest charging zone.

The *Free Floating* policy never obliges the user to bring the car far from the desired ending location, even in case battery charge is close to exhaustion. *Needed* mandates to connect cars to a charge station only if energy runs low, thus trying to protect from battery exhaustion. *Hybrid* mixes the two policies.

C. Performance metrics and parameters

We measure the following metrics, that we identify having influence in the quality of experience of the users:

- percentage of infeasible trips due to completely discharged battery;
- percentage of trips users have to connect the car to a charging pole, implying the burden to plug the car;
- percentage of trips users are rerouted to a zone different from their original destination because they are forced to charge the car;
- average walked distance from the desired location when the car is charged or rerouted.

Infeasible trips are critical, and the system shall be engineered so that they never happen. Other performance metrics shall be minimised. In addition to the above metrics, the simulator collects statistics about car battery charge level, and fraction of time a battery stays under charge.

The key design parameters that we focus on, other than station placement and return policy, are:

- number of zones Z which are equipped with a charging station;
- battery threshold α for *Needed* or *Hybrid* charge policies.

We consider the following scenario: the fleet has a constant number of cars equal to 300 (the same as observed in the trace). Electric cars have the same nominal characteristics as the Smart ForTwo Electric Drive, i.e., $17.6\,kWh$ battery, for

[4] http://spark.apache.org/docs/latest/api/python/#

[5] https://github.com/michelelt/sim3.0.

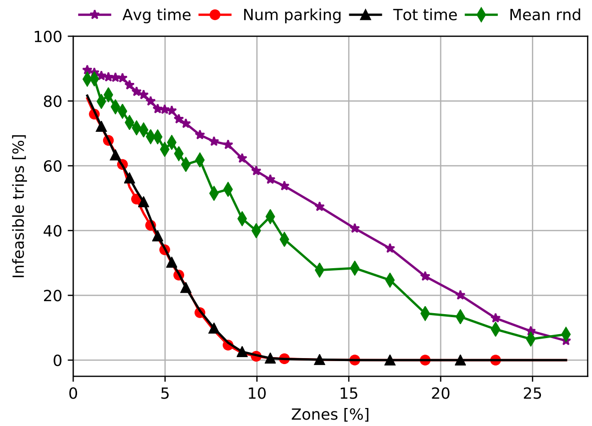


Fig. 4. Percentage of unfeasible trips as function of charging stations (percentage coverage of city zones), for the different placement algorithms.

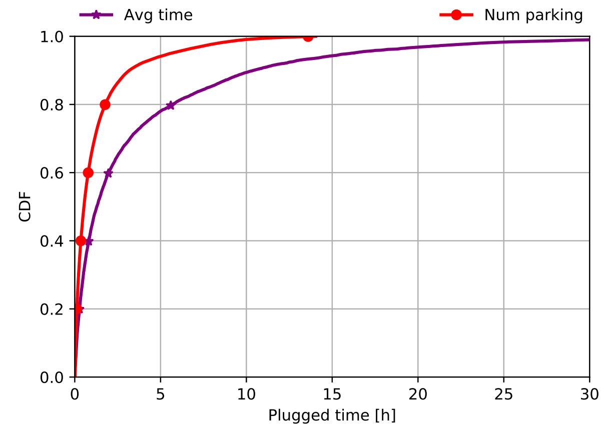


Fig. 5. CDF of the time spent by a car at a charging station (Z=40), for total number of parking and average parking time placement algorithms.

$135\,km$ of range, with a discharge curve that is proportional to the travelled distance ($12.9\,kWh/100\,km$). [6]

Charging stations have 4 low power ($2\,kW$) poles each. These are cheap to install and they are a good compromise between costs, power requested, and occupied road section. We model a simple linear charge profile (complete charge in 8 hours and 50 minutes in our case). At last, the initial position of the cars, only affecting the initial transitory, is chosen randomly.

V. IMPACT OF CHARGING STATION PLACEMENT

In this first set of experiments, we consider the simple opportunistic *Free Floating* car return policy, i.e., users always return the car in the desired zone, and connect it to a charging pole if available. The goal is to check if this simple mechanism is sustainable with electric cars, and the impact of the different charging station placement policies.

Fig. 4 shows the performance of the different placement algorithms in terms of infeasible trips percentage with respect to the percentage of charging zones, ranging from 1% to 27%. In Turin, this corresponds to install from 2 to 70 charging stations. We observe notably different performances. First, the average parking time placement policy (*Avg time*) performs the worst, with still 6% of infeasible trips even when more than 25% of zones are equipped with charging stations. Even a simple random choice performs better (*Mean rnd*, obtained as the average of 10 random instances). The total parking time (*Tot time*) and total number of parkings (*Num parking*) perform very similarly. They permit to reach about 2% of infeasible trips at 10% coverage, reaching 0 infeasible trips when more than 20% of zones are equipped.

The intuition of why such a striking difference is given by the different city areas they place charging stations. *Avg time* placement favours peripheral zones where few trips ends, and where cars stay parked for long time (see Fig. 3(b)). On the contrary, *Num parking* and *Tot time* favour city centre areas, where cars frequently are parked for short time (see Fig. 3(a)). Indeed, in the whole simulation, for $Z = 40$, only 7 430 charges have been recorded for *Avg time*, compared with 47 628 charges of the *Num parking*. Moreover, as shown in Fig. 5 the average parking time placement generates much longer plugged times, often much longer than the time needed for a full charge. Therefore, many cars occupy the charging poles when they are already charged, preventing other cars to use the pole and increasing the number of infeasible trips. Even if plugged time is shorter, the *Num parking* policy allows the cars to charge the (little) energy consumed in the (short) trips.

In a nutshell the best approach is to choose charging station zones that favours the central areas, in which the parkings last less and are more frequent. 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, i.e., we quantify the implications of forcing users to return the car to a different zone than the desired one, when the battery is below a critical level.

A. Infeasible trips

Considering Fig. 1, we already saw that the maximum travel distance is 19 km. This consumes about 14% of the total battery capacity for the considered car model. In the following, we take a precautionary approach to set the minimum battery charge threshold, α, equal to 25%, unless differently specified.

We first focus on the infeasible trips percentage with respect to the charging station coverage. Fig. 6 shows results for the different return policies. *Forced* and *Hybrid* policies perform much better than the original opportunistic *Free Floating*. In details, *Hybrid* and *Needed* guarantee to successfully conclude al trips with just 11 and 15 charging zones, respectively (see the insert if the Figure), while *Free Floating* reaches this goal only at 23% of charging zones (60 zones). In a nutshell, adopting a policy which mandates users to charge the cars

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

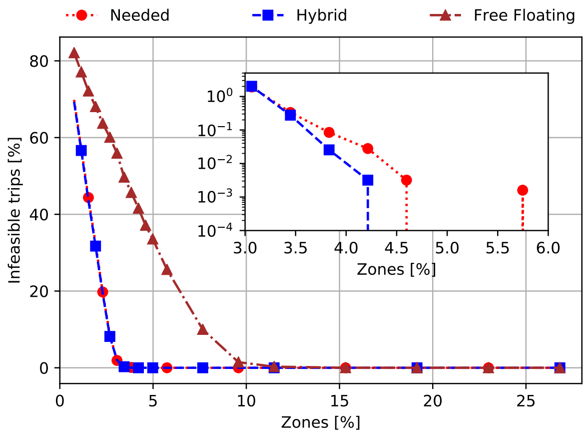


Fig. 6. Percentage of infeasible trips for different zone coverage percentage analysing the charging policies. The zoom highlights where the lines go to 0.

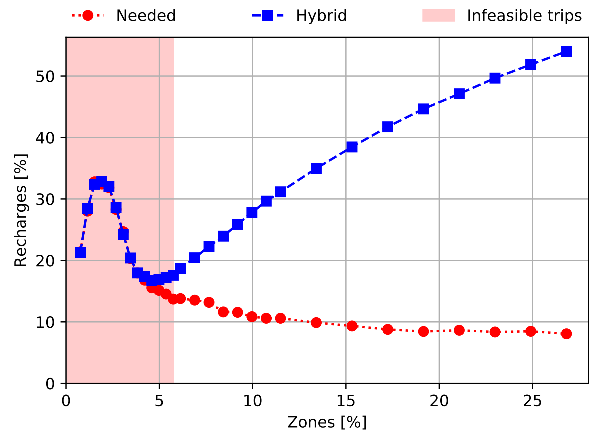


Fig. 7. Percentage of trips that end in a charging station, as function of the zones for the two return policies.

when battery charge gets below a threshold drastically reduces the number of infeasible trips, even with a handful of charging stations. We focus on *Hybrid* and *Needed* policy from now on, with at least 6% of coverage. We mark as *Infeasible* the region below this threshold.

B. Rerouting and charge percentage

Forcing a user to park in a charging station can be annoying, because the customer has to reach the charging station, and lose time to plug and unplug the car to the pole. Even worse, rerouting users to the closest zones for charging increases the distances they have to walk. In the following, we show indexes that involve users' figures. In particular, we analyse the percentage of trips that require the user to plug to a charging pole (charge percentage for short), and percentage of rerouting events (charge events that occur in another zone) over all trips.

Fig. 7 shows the charge percentage for the two returning policies, as a function of charging stations coverage. Shaded area highlights the infeasible region, where the lack of charging zones create artefacts. Focusing on the feasible region instead, the two curves start with similar values, but then they diverge. Interestingly, the percentage of charges decreases for the *Needed* policy, getting as low as 8%. This happens since, when few stations are present and all of them can be occupied, hence some cars will not be charged despite they would need to. Conversely, the *Hybrid* policy increases almost linearly the fraction of trips where users have to plug to a pole. *Free Floating* policy shows similar trend to *Hybrid*, not shown here for the sake of brevity.

Let us now investigate the average state of charge measured at the end of each trip. Fig. 8 shows results versus percentage of charging zones. In the infeasible area, performances are comparable, since the lack of charging stations does not generate enough charging opportunities. In the feasible range, the *Hybrid* policy keeps increasing to almost 90% of average charge, since users opportunistically plug the car every time they encounter a free pole (see again Fig. 7). Instead, for

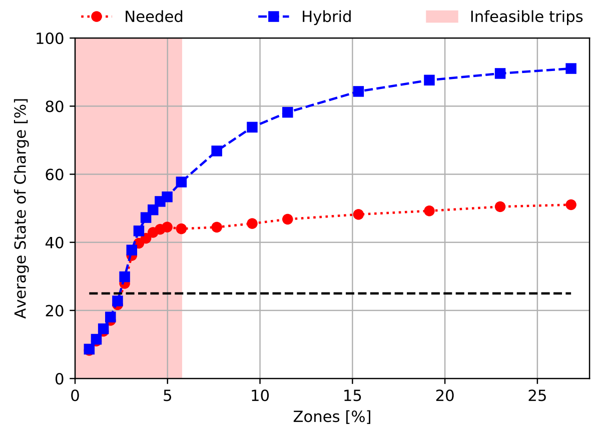


Fig. 8. Average state of charge percentage in function of the charging zones.

Needed policy, the level increases much slower, staying above the 25% threshold, that is the sole condition for charging.

Focusing on the trips that ends with charge events that occur in a zone different from the desired destination, Fig. 9 represents the rerouting percentage in function of charging stations coverage. Rerouting probability decreases as expected: the more the stations are, the more likely users find a charging station at their desired final zone. Yet, the two policies have different performance. The *Hybrid* policy is less likely to reroute the user. In fact, by opportunistically connecting the car to a charging pole if available, the average battery charge is higher, thus decreasing the rerouting probability. With more than 7% of charging zones, the percentage of rerouting is already lower than 1% for *Hybrid* policy.

In a nutshell, *Hybrid* policy significantly reduces the number of times the user has to drive to a charging station in a different zone than the desired one. However, it increases the number of times the user 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 the final users. Next, we check how this charges and

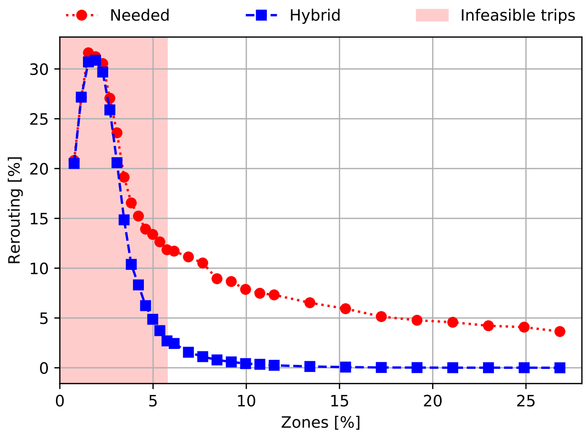


Fig. 9. Reroute percentage as function of the zones for the two returning policies.

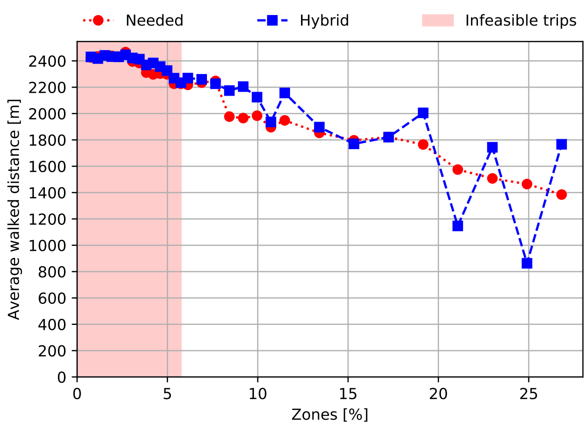


Fig. 10. Average walked distance covered by users to reach their final destination after a reroute

reroutes impact the users in terms of distance to the desired final position.

C. Walked distance

When the system forces a user to drive and park the car in a charging station that is not in their desired zone, it means that the customer has walked by at least 500 m to reach her destination. Fig. 10 shows the average walked distance from the actual parking zone to the original desired one, given the user has been rerouted. Intuitively, the average walked distance decreases as the charging zone percentage increases, since the likelihood of finding a nearby charging zone increases. In general, the average of users' walked distance (*Needed* case) goes from about 2.5 km to about 1.4 km, still a sizeable amount. Recall that the charging station placement algorithm is likely placing stations mainly in the city centre. Therefore, the charging stations are concentrated in a small area, so that rerouting from the suburbs significantly affect the average walked distance. The two policies perform similar here, given that the distance mainly depends on the charging station

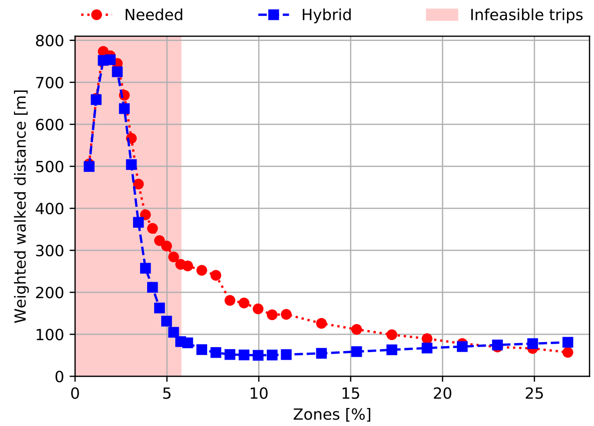


Fig. 11. Overall average distance covered by users to reach their desired destination, calculated over all trips. Trips ending with charging but not rerouting weight $150\,m$

placement. Moreover, this result must be checked in light of rerouting probability (see Fig. 9). Rerouting events are extremely rare for the *Hybrid* policy for high number of charging zones, hence the extreme variability of its mean walked distance. Given the very few rerouting of the *Hybrid* policy, one can envision a system that directly takes care of those very few cars that need a battery charge, i.e. by relocating vehicles. For instance less than 3 cars per day would need to be relocated with coverage 14% or higher.

At last, we focus on the overall distance the users have to walk to reach their actual final destination. Three are the cases: i) they suffer rerouting, ii) they end in a charging zone, or iii) they end in a zone with no charging station. For the first case, we already have shown results. For the second case, we need to compute the average in-zone distance from the charging stations (placed at the centre) and all possible destinations within the same zone. Assuming a square of $500\,m$ side, the average distance from the centre is about $150\,m$. This is the average walked distance when charging the car in the zone of the desired destination. For the third case, we assume users arrived at their final destination directly.

The results are shown in Fig. 11. Consider the feasible region first. The *Needed* policy exhibits a decreasing trend (from $280\,m$ to $60\,m$). On the contrary, the *Hybrid* policy first exhibits a decrease (minimum of $50\,m$ at 8% of charging zones), but then it slowly increases till it overtakes the *Needed* policy. This is due to the fact that with few charging stations (6-12%) the number of charges is limited ($< 30\%$, see Fig. 7) by the availability of charging stations. Instead, when this number grow, the opportunistic policy that mandates to attach the car to a charging pole if it exists forces the user to walk more (within the ending zone). To this extend, the *Needed* policy is better giving users have to charge only when actually needed.

In summary, about 10% of zones guarantees all feasible trips, reduces the walked distance and obtains few reroutings and not too many charges.

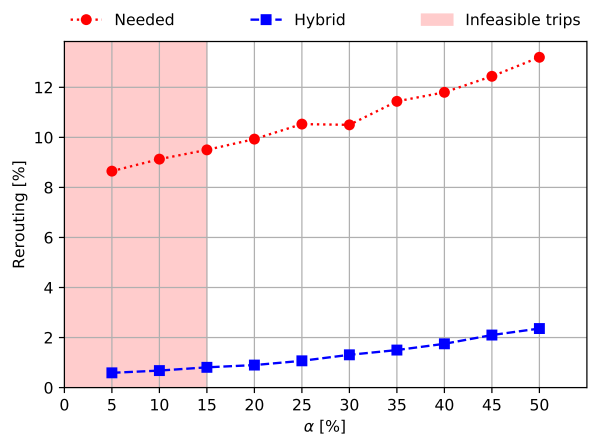


Fig. 12. Reroute percentage in function of α, with 8% of charging zones.

D. Impact of minimum battery threshold

At last, we check the impact of α. Fig. 12 focuses on the rerouting percentage, considering a coverage of 8% (i.e., $Z = 20$). Both policies slightly increase rerouting when α increases: a higher threshold is crossed more frequently, increasing the reroute probability. This however brings little or no benefits to system performance. Values of α equal or lower than 15% generates infeasible trips, then we cannot clearly get below this threshold. Thus setting $\alpha = 25\%$ is a safe choice.

VII. Conclusion and Future Work

Designing an electric free floating car sharing systems leads to many interesting problems and trade-off. In this work, we built on actual rental traces to study via accurate simulations the impact of i) the charging station placement, and ii) return policies. We considered Turin as a case study, using 2 months of rentals recorded from a currently operational FFCS that we use to run trace driven simulations. Considering charging station placement, we have seen that it is better to place charging stations within popular parking area (e.g., downtown), where parking duration is short but enough to top-up the battery.

We have shown that a FFCS solution with electric vehicles can auto-sustain itself, even with very few charging stations (6% of zones, i.e., 15 in total in Turin, with 300 cars and 1 million inhabitants). These results are obtained also thanks to the users collaboration by returning the car to a nearby charging station, and whenever the battery level drops below a target threshold.

Car sharing providers shall take into account the trade-off between usability, costs and benefits for the users. For instance our results hint for possible alternative design solution, i.e., the adoption of some simple relocation policies that would move cars that need a charge, a promising solution to limit discomfort for users due to rerouting enforcement. The same could be achieved by considering incentives to users.

We leave for future work: (i) the optimization of the poles distribution in space, (ii) a thoughtful study of a electric FFCS systems in different cities, (iii) the simulations of future scenarios with new technologies (charging pole and battery), (iv) scalability in terms of users and cars. We believe that our approach, based on data and accurate simulation results is very promising to design electric FFCS systems in near future smart cities.

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