On Scalability of Electric Car Sharing in Smart Cities

(Article begins on next page)

On Scalability of Electric Car Sharing in Smart Cities

Michelangelo Barulli[a], Alessandro Ciociola[b], Michele Cocca[b], Luca Vassio[b], Danilo Giordano[c], and Marco Mellia[b]

[a]Department of Industrial Engineering and Management, Politecnico di Torino, `first.last@studenti.polito.it`

[b]Department of Electronics and Telecommunications, Politecnico di Torino, `first.last@polito.it`

[c]Department of Control and Computer Engineering, Politecnico di Torino, `first.last@polito.it`

***Abstract*—In this paper we analyze which are the design options that would impact a free floating electric car sharing system performance and costs, studying how the system would scale with an increase in the intensity of the demand. We consider the case study of the city of Turin, for which we leverage hundred of thousands of actual rentals from a (combustion-based) car sharing system to derive an accurate demand model. Armed with this, we consider the transition to electric cars and the need to deploy a charging station infrastructure.**

Using a realistic simulator, we present the impact of system design options, like the number of charging poles, their allotment, and the number of cars. We first consider performance indicators, like fraction of satisfied demand and working hours system has to spend to bring to charge vehicles. Then we map these figures into revenues and costs, projecting economical indicators. At last, we investigate the scalability of the whole system, i.e., how performance and costs scale when the demand increases. Our results show that concentrating the charging stations in key places is instrumental to optimize car distribution in the city to better intercept the demand. Considering system scalability, the charging infrastructure must intuitively grow proportionally with the mobility demand. Interestingly instead, the fleet size can grow much slower, showing some nice economy of scale gains.

***Index Terms*—car sharing; scalability; charging infrastructure**

I. Introduction

Today, around 55% of the world's population lives in urban areas, a proportion that is expected to increase to 68% by 2050 [1]. Cities face important challenges to manage mobility, with a mixture of public and private transportation means. The widespread usage of private cars led to land consume, increase of air pollution and higher health risk [2]. Private cars are often chosen by citizens for their flexibility and comfort, with the burden of higher fixed and variable costs. Recently, the sharing economy has brought regulators and policy makers to invest on free floating car sharing (FFCS) systems, car rental models where the customers can freely pick and drop a car within an operative area through a mobile app. They pay only for the time spent driving, usually with minute-based fares which include all costs. Thus, this combines some of the benefits of public transport and private cars [3]. Sharing the same car among different people helps reducing the number of vehicles and brings benefits for the whole community like increase of parking availability and reduction of pollution [4]. Moreover, since there are no fixed costs for users, usually FFCS is economically convenient for users who travel few thousand kilometers per year [5].

To make another step towards sustainable mobility, the challenge is to convert FFCS fleet from internal combustion engine vehicles (ICE) to electric ones (EVs), maintaining the same service flexibility. This change would further reduce the noise and pollutant emissions in congested areas [6], but calls for the creation of a charging infrastructure, and the management of the additional costs to handle battery charging operations.

In this work we analyze the feasibility and scalability of FFCS with electric vehicles. Our goal is to find an economically sustainable solution that brings benefits to both citizens (i.e., high availability) and operators (i.e., high profit), with the economic sustainability being a crucial aspect. For instance in Italy, the main FFCS operator had revenues around 48 million euros in 2016, but still losing around 27 millions euros, with each car burning 4700 € on average [7]. Despite that, car sharing is estimated to increase from 20% to 40% from 2019 to 2021 [8].

However, the shift to EVs implies not trivial decisions due to the additional need of deploying and managing the charging infrastructure. What are its impacts on system performance and profit?

As a case study, we focus on the city of Turin in Italy. We leverage hundred of thousands of real FFCS trips [9] to extract the geo-temporal mobility demand. We use Kernel Density Estimation (KDE) to catch the demand spatial variability, and modulated Poisson models for the temporal demand [10]. We use it to feed a trace-driven flexible simulator that allows us to study how the design choices and system parameters impact on performance. We first consider an electric-car sharing system that has the same number of cars and faces same demand of the current one in Turin. We observe the impact of different charging infrastructure design, i.e., the number of poles and how to spread these are over the city area.

Next, we consider when the intensity of the mobility demand grows. How would the charging infrastructure need to grow correspondingly? And what is the impact of the fleet size? Summarizing our contributions, this paper proposes an answer to these questions making use of the demand model to project future or different scenarios and the cost-revenue model to evaluate the profitability of each configuration. We focus on performance indicators like the fraction of demand the system can satisfy and the total working hours it has to spend for the battery charging operations. Then, we project these into economical figures, observing how the design options impact on profitability.

Our results show that the charging station placement is fundamental if poles are placed in areas with high demand, as cars get located where customers need them. This allows the system to naturally intercept the customers demand, thus to maximize the satisfied demand, and revenues. Considering system scalability, as expected the charging infrastructure must grow proportionally to the mobility demand. Interestingly instead, the number of vehicles can grow much slower, showing economy of scale savings which make the system likely profitable if well designed.

The paper is organized as follows: In Section II we discuss our work in light of past literature for FFCSs and their economical aspects. After reporting the details about the dataset and demand model in Section II, and our simulator in Section IV, we present results in Section V before drawing conclusions in Section VI.

II. Related Work

While first FFCS are operative since 2008 in Europe [11], the research on this topic has only recently flourished, especially for EVs. A common problem in transportation is to define models to optimize the fleet management and system design in general. For example, the authors of [12] proposed a Mixed Integer Problem (MIP) to maintain and organize fleet distribution in short term considering a stochastic demand. In the recent work [13] authors showed how to analytically model customers' probability to use car sharing. Other studies include more complex phenomena in their works, like [14] where the authors consider a non-linear charging function and detailed power lines constraints to optimally design *one-way* car sharing system (using a MIP).

Another strategy to study FFCS is to *simulate* how users interact with it. For example, the authors of [15] proposed (but did not implement) an agent simulator approach to measure how FFCS can be scaled on the entire Swiss traffic. The authors of [4] present a study of two-ways car sharing growth, with the help of an event-based simulator that measures if and how charging stations produce profits. Similarly, [16] proposes an open-source multi-agent simulator able to replicate travelling people's habits. In particular, it focuses on the realistic replication of users' behavioral model relying on multinomial distribution of modal choice.

Recently, the availability and abundance of data helped shaping FFCS users' behaviour. Considering this, some works like [17] and [9] scraped data from real ICE FFCS, characterized their services and proposed model generalizations. Big Data approaches helped researchers to improve the simulation fidelity. In particular, authors of [18] used data to predict the shareability of an urban ride, finding that this a property city-invariant. On the same optic, the authors of [19] use data from several American cities to optimize the position of the charging stations of a one-way car sharing, finding that the optimal results place the stations in high-demand areas. We confirmed this result in [20] and [21] where we used a simulation based approach to measure the impact of different design options of an EVs FFCS system. Here use big data to derive realistic demand models to feed accurate simulations. We move one step forward - showing that this is beneficial also as a proxy of relocation, i.e., cars get naturally relocated to high demand zones.

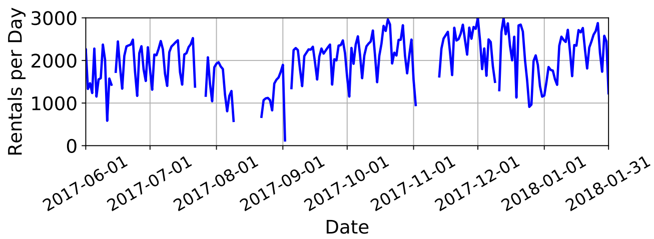


Fig. 1: Number of rentals per day in Turin, from June 2017 to January 2018. Some data is missing.

The economic sustainability is another key aspect of car sharing - especially with EVs. Authors of [22] studied the economic sustainability of one way electric car sharing systems finding out that charging station should have an amortization period of at least 5 years to produce profits. The authors of [23] compared how FFCS with EVs and ICE can produce profits, observing the best compromises with ICE fuelled with cheap and cleaner fuel like ethanol. Another study [24] concerning the city of Lisbon found out that switching to EVs would cost more than ICE and would lead to a negative profit of about one million per year. This is largely due to the higher cost of electric cars and of the charging infrastructure. In our work we explore which are the most efficient and economically sustainable combinations of fleet size, charging infrastructure design, also in light of demand growth.

To the best of our knowledge, our work is among the first to study the scalability of a FFCS system with electric vehicles, exploring key parameters like number of poles, fleet size and increase in demand can affects economic and performance of the system.

III. Dataset and demand model

In this work we leverage the data collected in our previous work [9] capturing real trips performed by car2go users. These data let us model the users' mobility demand in time and in space. From this, we derive a demand model that generalize the users' demand observed in the real data. We use it to generate realistic traces describing possible user trips and feed them to our event-based simulator to derive performance figures.

TABLE I: Main characteristics of our dataset, recorded in Turin from October to December 2017. Rental time and rental distance report both median (Med) and average (Avg) values.

Rentals	Fleet Size	Rental Time [min]		Rental Dist. [km]		Zones
		Avg	Med	Avg	Med	
180k	400	21	20	3.96	3.36	279

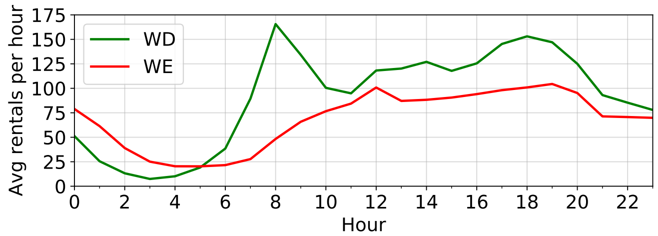


Fig. 2: Average number of rentals per hour during weekdays (WD) and weekends (WE).

A. Dataset

Our data consist in actual rentals performed by car2go users in Turin. Each observed rental has precise geo-spatial coordinates for trip origin and destination, and accurate timestamps. In Figure 1 we summarize the number of daily rentals from June 2017 to January 2018 in Turin, our reference dataset[1]. Despite the fact that rentals are non-stationary, especially during periods like August and Christmas holidays, the service usage follows a hourly and weekly pattern, not showing any particular growth. From this data, we select three months - from October 1st to December 31st. Table I outlines the main characteristics of this data. 400 cars were available, traveling on average less than 4 km in each trip, for an average rental time of 21 minutes.

To catch customers' habits, in Figure 2 we detail the average number of rentals per hour, separately per working-days (Monday to Friday) and per weekends. The weekdays hourly profile reflects the commuting pattern, with two clear peaks in the morning and evening rush hours. Conversely, during the weekends the number of night rentals is higher, likely due to more nightlife, while the morning peak is drastically smoothed. Not shown here for lack of space, our data allow us to observe the spatial diversity, with different origin and destination areas over the city. This shows how fundamental is to use actual data to build realistic scenarios for accurate system analysis.

B. Demand Model

While we could directly use the original trace to observe system performance, we need a model to observe what-if scenarios, e.g., to observe the impact of a growth in the demand. For this, we use the data at our disposal to create a generalized demand model. We follow the approach we presented in [10].

[1]For some periods we did not record data due to server failures.

In a nutshell we model the demand in time by using modulated Poisson processes - a common accepted model for independent service requests of a very large population [25]. To capture the spatial heterogeneity, we generalize the traces using Kernel Density Estimation (KDE) [26]. KDE gives us the possibility to smooth the real data over a multi-dimensional space while maintaining the origin/destination correlation. In more details, for the request arrival time process we assume that the inter-arrival time of trips follows an exponential distribution with rate depending on the type (weekend or working day) and hour of the day. We consider 24 time bins of 1 h each - 48 periods in total. In each time/day bin, the Poisson arrival rate matches the average rate of requests in that time bin in the original dataset as shown in Figure 2. This temporal model allows to scale the overall demand by introducing a global scaling factor λ as a multiplier of the request rate of each time bin.

To model the spatial diversity of the demand, we divide the city in a set Z of contiguous 500 m x 500 m zones, obtaining in total 279 zones. Each couple of spatial coordinates in the city area (x, y) maps to one and only one zone. Since each trip i departs from a certain zone (origin O_i, described by two coordinates) and arrives to another zone (destination D_j, described by two coordinates), it is therefore characterized by two couples of coordinates, that can be represented as 4 scalars. For each time bin, we derive an origin and destination matrix counting how many trips were originated from a given zone O and destined to a given zone D. Thus, in order to model the OD matrix in each temporal slot, we fit a 4-dimensional KDE based on the aforesaid coordinates. For each of these matrices, we compute a KDE model, using Gaussian kernels, with bandwidth equal to 1. Not reported here for the sake of brevity, we compare the number of trips generated from the model and the ones presented in the original trace. As expected, there is a very good match with low residuals. We refer the reader to [10] for details.

Notice that we employ a single global scaling factor λ directly the temporal model to keep the spatial distribution of trips unchanged while increasing the request rate.

IV. Simulator and System Parameters

Armed with the generalized demand model, we design and implement an event driven simulator to study the EVs FFCS system. Here we detail the simulation model, the simulator assumptions, the performance metrics, and the cost model used to project system performance into economic figures.

A. Simulator and assumptions

We consider a fleet F of electric cars. As before, we divide the city into a set Z of zones of 500 m x 500 m each, where cars can be parked, rented, charged and returned. Car characteristics are the same as MY2018 electric Smart ForTwo, namely $B = 17.6$ kWh battery capacity and 15.9 kWh/100 km energy efficiency. Each car is characterized by its location, status (i.e., available, rented, under charge) and battery State of Charge (SoC). At simulation startup, cars are randomly placed in zones, with initial SoC uniformly distributed in $[0.5B, B]$, and marked as available.

The charging infrastructure considers n_p Level-2 chargers, with 3.7 kW nominal power and 92% charging efficiency. Charging stations are spread around the city zones. We place poles in those zones having the highest probability of being destination zones. This results in a good strategy to maximize system performance [20], [21]. In details, we sort zones $z \in Z$ by the total number of parkings $tot\_park(z)$ observed in the original trace. We then consider the top z_p fraction of zones, and place a number of poles in each proportionally to $n_p \cdot tot\_park(z) / \sum_z tot\_park(z)$.

At $t = 0$, the simulator generates the first *rental request* event, extracting origin and destination coordinates according to the KDE model of the current hour/day slot, and schedules the next rental request event according to the modulated Poisson process. Events are then processed as follows:

Car request event. When a *rental requests* fires, a customer looks for a car within the origin zone and in 1-hop neighbouring zones. If at least one car with enough SoC to reach the desired destination exists, the car gets rented, and a *car release* event is scheduled after the time to reach the destination that is proportional to the distance, considering both orography and road network shape [21]. If more than one such cars exists we choose the closest one, and, if need be, we choose the one with highest SoC. If no car is suitable for this ride, the trip does not occur and the request is marked as *unsatisfied*.

Car release. When a *car release* event fires, the simulator updates the car SoC decreasing it proportionally to the travelled distance. If the updated SoC is above a threshold α, the car is parked in the user's arrival zone, and marked available for other rentals.

If instead the SoC is below α, the car battery needs to be charged. The system handles the charging event by moving the car to the nearest-free charging pole. The simulator schedules a *charge complete* event which accounts for both the time to reach the pole and the time to bring the SoC to 100%[2].

Charge complete. When a *charge complete* event fires, the car is marked as available, and customers can rent it again. The charging pole is released as well. Notice that we assume the car is released in the same zone where it was being charged, i.e., the system does not implement any relocation policy after charging.

B. Performance metrics

In this work, we focus on the following performance metrics to compare different design options:

Unsatisfied Demand: it is the fraction of requests that are not satisfied because there is no car with enough SoC in the origin and neighbouring zones. It is an indicator of the quality of the service in terms of car availability for user requests, and shall be minimised.

[2]For simplicity, we assume there are infinite workers to handle the battery charge events so that a car gets serviced immediately. In case all poles are busy, the car gets placed in a queue of the closest charging station, and gets serviced when the first pole is freed.

TABLE II: Summary of parameters and economic cost assumed for Turin.

Parameters used for the simulations		
Param	Description	Range
$\|F\|$	Fleet size	[80, 2000]
$\|Z\|$	Number of 500 m x 500 m zones	279
B	Battery capacity - Electric Smart ForTwo	17.6 kWh
n_p	Number of charging poles - 3,7kW each	$[8, 300]$
z_p	Fraction of zones with charging poles	$[0.003, 0.20]$
α	SoC charging threshold	0.25
λ	Rental demand rate scaling factor	$[1, 5]$

Cost and revenue parameters with values for Turin		
C_{lease}	Yearly electric Smart ForTwo vehicle lease cost	4000 €/yr/vehicle [27]
C_{pole}	Material cost of a level-2 charging pole	1700 €/pole [28]
C_{labor}	Labor cost to install a charging pole	2200 €/pole [28]
C_{setup}	Make-ready infrastructure cost per charging station	1500 €/station [28]
p_{life}	Charging station and pole lifetime - amortization period for C_{pole}, C_{labor} and C_{setup}	10 yr [24]
C_{maint}	Yearly pole maintenance cost	500 €/yr/pole [28]
C_{ground}	Yearly ground occupation tax	355 €/yr/pole [29]
C_{energy}	Energy cost for kWh	0.19 €/kWh [30]
$C_{drivers}$	Hourly labour cost to bring the cars to charge	23 €/h [31]
C_{disinf}	Disinfection and interior cleaning cost	15 €/charge [32]
C_{wash}	Cost to wash the car	8 €/100 rentals [32]
R_{rental}	Average revenue per rental minute (exl. VAT)	0.20 €/min [33]

Total charging handling time: it measures the monthly time spent by the system to bring cars to the charging stations. It is the sum of the driving time spent by workers to drive the cars to the nearest-free pole. It gives an indication of the goodness of the charging infrastructure. Being it a cost, it shall be minimized (see the operating costs described below).

C. Cost model

While performance indexes are useful to explore design options, the FFCS operator is ultimately interested in the economic sustainability of a solution. For this, we derive a cost model based on yearly projections. We then consider revenues by projecting the number of rental and their duration. Armed with both, we estimate profit. Here we consider:

Vehicle cost. We assume cars are leased to include all costs, namely registration, tax, insurance, ordinary and extraordinary maintenance, and roadside assistance. We assume electric cars do not pay for parking on street and for accessing limited traffic areas. Given the yearly car lease C_{lease} and the number of vehicles, we easily derive the total yearly fleet cost.

Charging infrastructure cost. Here we refer to actual use cases as defined in [28]. Pole installation costs account for material and labor cost. Material cost C_{pole} includes hardware cost for Level II chargers. Labor cost C_{labor} is highly dependent on the city, region and country. We need also to consider the make-ready infrastructure cost C_{setup} that represents the cost for a charging station setup. It does not depend on the number of charging poles per station, but depends only on the number of charging zones $z_p \cdot |Z|$. It represents a highly variable cost since it depends on the location and the electric distribution infrastructure already in place. In fact, the expenses of trenching and laying conduit can add thousands of Euros to costs. All these costs are one-time costs. We assume these costs have an amortization period equal to the average charging station and pole lifetime p_{life}.

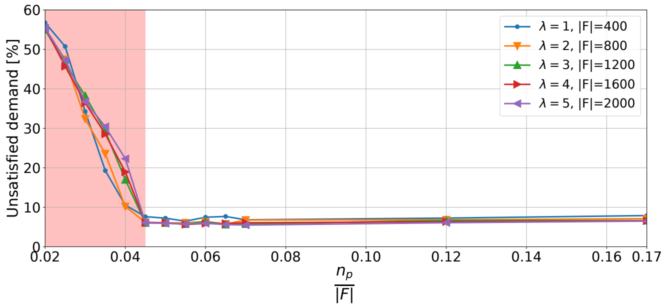


Fig. 3: Unsatisfied demand with respect to different number of poles per vehicle. Curves show performance with different demand factor λ and fleet size $|F|$, with z_p = 0.05.

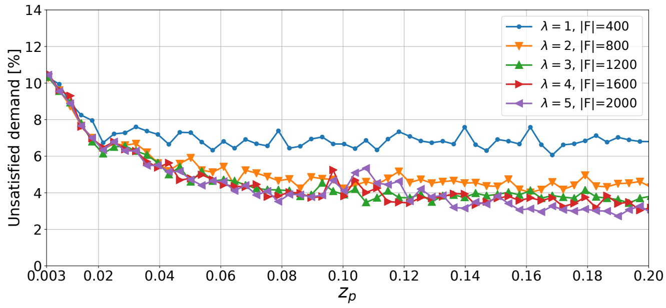


Fig. 4: Unsatisfied demand with respect to the fraction of zones with charging poles z_p. Curves show performance with different demand factor λ and fleet size $|F|$, with $n_p/|F|$ = 0.06.

Next, we consider pole maintenance costs C_{maint}, which we derive from variable site-specific parameters. In some cities, we need also to consider the per vehicle ground occupation tax C_{ground}, that usually depends on the surface for dedicated charging spot. Due to the small size of Smart ForTwo, charging spots are assumed to be 4,50 m x 2,30 m, for each pole.

Operating costs. For this we take into account the C_{energy} cost for the energy to charge the vehicles; the hourly cost for workers $C_{drivers}$ who have to handle the charge events; a cost C_{disinf} to clean and disinfect the car any time the worker brings it to charge. Finally, we assume exterior car washing every 100 rentals, each costing C_{wash}.

Rental Revenue We consider a simple average cost-per-minute R_{rental}. This allows us to transform the total rental minutes into the total revenues.

Top part of Table II summarizes the parameters that define the scenarios used in the simulations. Bottom part shows the cost we consider for the Turin use case. Given a scenario, we run a simulation to collect performance indexes. We next post-process the simulation results to derive the monthly cost and revenue figures. The custom simulator used is written in Python and based on SimPy library.[3] The cost-revenue model is implemented in Python too and it is available online. The cost model allows one to interactively observe what happens by changing the cost values.[4]

V. Results

Given the multiple system design parameters, here we proceed by steps. First we analyse the impact on performance in order to select good design options. We then project the results through the cost figures to gauge the economic implications of these choices.

We consider as starting parameters the ones referring to the current FFCS running in Turin based on ICE cars, i.e., a fleet size $|F| = 400$ and demand scaling factor $\lambda = 1$. We explore the charging infrastructure design options, namely its size n_p and extensiveness z_p. We fix $\alpha = 0.25$ corresponding to the minimum energy needed to perform the longest trip in Turin [20]. We also check the impact of increasing the demand up to $\lambda = 5$. Correspondingly, we increase the fleet size $|F(\lambda)| = 400 \cdot \lambda$ by the same factor. Each simulation considers three months of virtual time, corresponding to more than 200 000 rental requests for $\lambda = 1$.

A. Impact of infrastructure design options

Focus first on the impact of the number of poles per vehicles $n_p/|F|$ on the unsatisfied demand - reported in Figure 3. Consider $\lambda = 1$ first. Here $z_p = 0.05$ (14 charging zones). We observe two working regions: on the right - the charging infrastructure has enough capacity to supply the energy to support all customers' trips - resulting in a constant unsatisfied demand. On the left, system charging capacity goes below a minimum threshold (highlighted by the red area). Here the charging infrastructure cannot supply enough energy and unfeasible trips grow linearly with the lack of energy. Consider now a demand factor that doubles ($\lambda = 2$, and $|F| = 2 \cdot 400$). The energy supply must grow by a factor of 2 to supply twice the number of trips. As such the minimum threshold in terms of number of poles per vehicles remains the same. The same holds for higher λ. Interestingly, the number of poles to supply the energy to cope with the mobility demand is quite small: a pole every 20 cars results enough.

There is still a 5-7% of unsatisfied demand which results from the mismatch between zones with available cars, and zones with demand. We now check the impact of z_p on this. Figure 4 fixes $n_p/|F| = 0.06$, and shows the impact of concentrating or spreading them on few or more zones. On the leftmost case, we have the "charging hub" scenario, meaning that all poles are located in a single zone where all cars must be brought for charging. This solution creates a surplus of cars in the zone where the hub is, and a lack of cars in other zones. Unsatisfied demand then grows, calling for relocation policies. Increasing z_p has the benefit of spreading cars in the city[5]. Having opted to place poles in *top_park* zones, cars get

[3] SimPy is a discrete-event simulation library. Documentation is available at: https://simpy.readthedocs.io/en/latest/contents.html.

[4] The code and data for cost and profit evaluation are available at: https://smartdata.polito.it/on-scalability-of-electric-car-sharing-in-smart-cities/.

[5] For $\lambda = 1$ we can equip $n_p = 24$ zone maximum ($z_p = 0.09$), after which results do not change. Differences are due to simulation randomness.

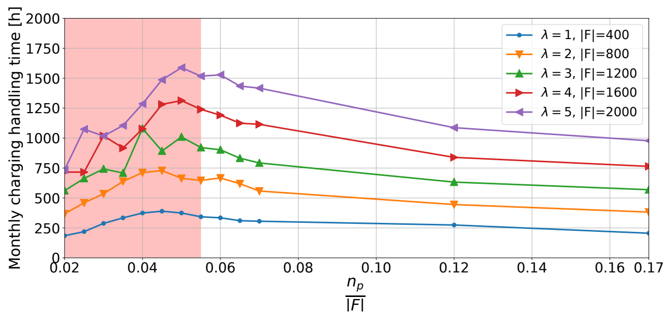


Fig. 5: Monthly charging handling time drivers have to spend to bring cars to charging poles. Curves show performance with different values of demand factor λ and fleet size $|F|$, with $z_p = 0.20$.

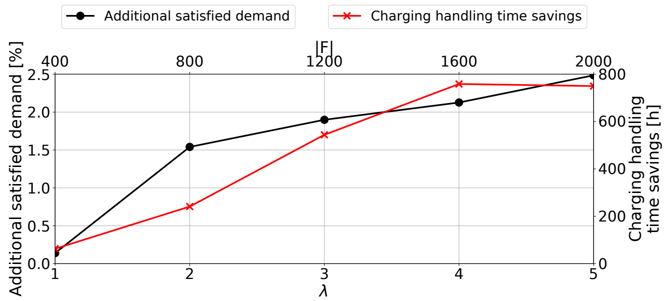


Fig. 6: Gain in terms of satisfied demand and charging handling time of a more spread infrastructure ($z_p = 0.20$) with respect to a more centralized infrastructure ($z_p = 0.05$). Gain is showed for increasing demand factor λ and fleet size $|F|$. Here $n_p/|F|$ = 0.06.

naturally located there, facilitating customers that look for a car in those high-demand zones. This reduces the percentage of unsatisfied demand significantly, questioning the need of costly relocation policies. Performance-wise, the higher the fraction of zones with poles, the better.

Focus now on the time the system has to spend to bring cars to the closest charging pole, reported in Figure 5 for $z_p = 0.20$. Notice that if the system cannot supply enough energy to satisfy the demand ($n_p/|F| < 0.055$ in this case), the charging handling cost decreases. Likely not a good design choice being this due to loss of satisfied demand. Consider the region $n_p/|F| \geq 0.055$, where the system has enough charging capacity. If there are just enough poles, most of them results busy, and the workers need to drive cars to far away free poles. This results in an increase of handling time up to 1600 h for $\lambda = 5$. By increasing $n_p/|F|$, we increase the probability of finding a nearby free pole, shortening handling time down to 1000 h per month for $\lambda = 5$. As expected, the higher λ, the higher the time to handle charging events – with an almost perfect linear increase.

This highlights a trade-off between infrastructure costs and management costs. To better gauge this, Figure 6 compares

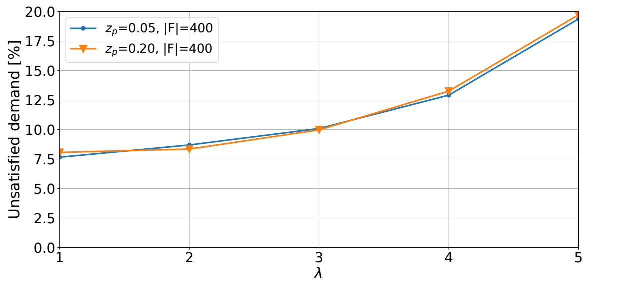


Fig. 7: Unsatisfied demand for increasing values of λ but same number of vehicles $|F| = 400$, and large enough charging infrastructure ($n_p = 120$).

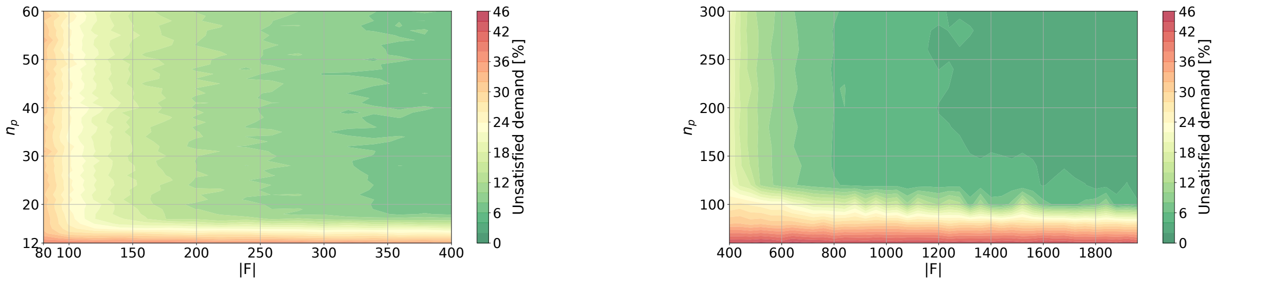
a more concentrated system with $z_p = 0.05$ with a more distributed system with $z_p = 0.20$. We plot the "additional satisfied demand" (black curve) and the saving in charging handling time (red curve) for increasing demand factor λ and fleet size $|F|$ (fixing $n_p/|F|$ = 0.06). In all cases, $z_p = 0.20$ results in higher satisfied demand and lower cost than $z_p = 0.05$, with benefits that increase with increasing demand. In a nutshell, distributing the same number of poles among more zones improves system performance and reduces charging handling time. Clearly this needs to be weighted by the additional cost of installing a more distributed charging infrastructure.

B. Impact of fleet size

We now explore the impact of the number of cars when the demand increases. For this, we scale λ, but keep the fleet size constant to $|F| = 400$. For simplicity, we consider a charging infrastructure capacity that can cope with the highest demand, i.e., $n_p = 120$. We consider two cases, $z_p = 0.05$ and $z_p = 0.20$. We plot results in Figure 7. Interestingly, the same number of vehicles can sustain a sizeable increase in λ without a significant impact the unsatisfied demand. For instance, $|F| = 400$ vehicles can cope with a factor $\lambda = 3$ increase in the demand, just losing 2.5% of customer requests. This would result in a significant saving in the cost of vehicles. Given there are no differences in concentrating or spreading the charging poles in few or more zones, we fix $z_p = 0.20$ from now on.

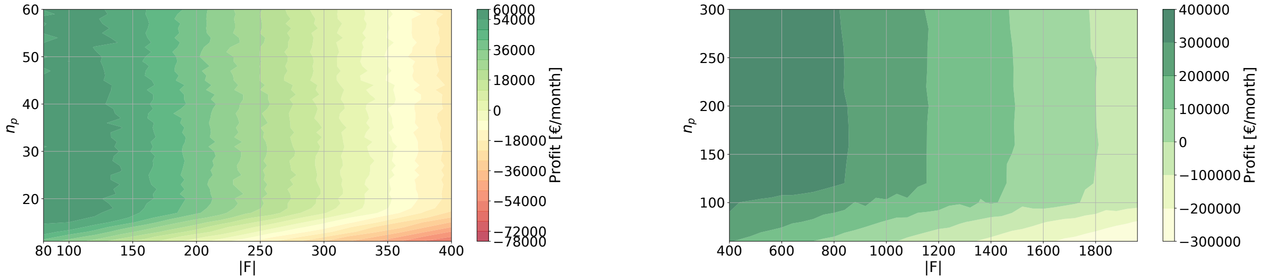
To observe how the unsatisfied demand would be impaired by further reducing the number of cars and/or the number of poles, we present contour maps in Figures 8(a) and Figure 8(b), for $\lambda = 1$ and $\lambda = 5$, respectively. Interestingly, the two design parameters seem to affect unsatisfied demand in almost independent manner. On the one hand, reducing the number of cars has limited impact until we reach very small values. For instance, halving the fleet size down to $|F| = 200$ would increase the unsatisfied demand by 6-8% only. On the other hand, increasing n_p brings no benefit - provided there are enough poles (cfr. Figure 3).

The same considerations hold when $\lambda = 5$, with a slightly higher interaction between n_p and $|F|$ when approaching small



(a) Demand factor $\lambda = 1$ (b) Demand factor $\lambda = 5$

Fig. 8: Unsatisfied demand varying number of poles n_p and fleet size $|F|$ with $z_p = 0.20$.



(a) Demand factor $\lambda = 1$ (b) Demand factor $\lambda = 5$

Fig. 9: Monthly estimated profits varying number of poles n_p and fleet size $|F|$ with $z_p = 0.20$.

values for both. Observe also a large region with unsatisfied demand lower than 6% (dark green). The high number of vehicles allows a high multiplexing gain so that fewer cars can offer the same service level. For instance, $|F| = 800$ cars guarantee about 10% of unsatisfied demand if $n_p > 120$. In a nutshell, the system needs less cars to satisfy the same percentage of demand when the demand increases, with significant economy of scale gain.

C. Impact of costs

To have a clear and complete picture, we now project the performance indexes into economic figures. Here we compare the monthly profit an EVs FFCS provider would reach for different combinations of the number of vehicles and the number of poles, i.e., its investment in the fleet and charging infrastructure. All costs included in Table II are considered.

Figure 9(a) shows the results for $\lambda = 1$. Green shades reflect positive profit, while yellow and red shades highlight loss-making configurations. Interestingly, the zones with the highest profits tend to be in the leftmost part of the figure, i.e., for small number of cars. While this causes a higher unsatisfied demand - see Figure 8(a) - it looks the only way to reduce the cost of the fleet so to have a profitable system. The impact of the charging infrastructure is quite negligible unless when n_p becomes too small (i.e., when not enough charging capacity is present). This is due to the low cost of buying and installing a charging pole when amortized on $p_{life} = 10$ years. Recall that we have seen that the charging infrastructure design calls for a charging pole every 20 vehicles. As such, the overall economic impact of the charging infrastructure results quite negligible compared to the fleet size costs.

The picture improves drastically when $\lambda = 5$, shown in Figure 9(b). Here, we explore scenarios with a 5-fold increase in both the number of poles ($n_p \in [50, 300]$), and in the number of vehicles ($|F| \in [400, 2000]$) with respect to the $\lambda = 1$ scenario. Here, all configurations result in positive profit. Even more interestingly, by reducing the number of cars we observe a marginal decrease in the profit, with the best scenarios being in $|F| \in [1400, 2000]$. This is due to large multiplexing effect we already observed in Figure 7. Even when reducing the number of cars to 800, we observe sizeable profits.

Considering the number of poles, as expected, when $n_p < 120$ (the minimum threshold for constant unsatisfied demand when $|F| = 2000$, showed in Figure 3) the insufficient system charging capacity impairs cars availability, increasing the unsatisfied demand. As seen already, increasing n_p above the minimum threshold brings little benefit, but it also has little impact on the profits (due to the relatively low cost of pole installation).

In summary, we can conclude that the FFCS provider needs to carefully evaluate the minimum number of poles when designing and implementing the charging infrastructure. The limited cost of pole installation, and the long amortization time make overprovisioning the charging infrastructure a viable option to make the system robust to demand increase. Considering the fleet size, when the demand is low, the high cost of vehicles suggests limiting the number of vehicles.

When instead the demand grows, an economy of scale gain is possible, making the system even profitable with large fleet size.

VI. Conclusions

In this paper we presented a simulation study of free floating car sharing systems. Armed with a realistic demand, we studied the performance implications of moving from ICE FFCS to a EV based solution.

Our study offers several take-away messages: first, the charging infrastructure must be able to provide enough energy to cope with the mobility demand. Interestingly, it results to be quite limited, with just 20 poles able to sustain a system of 400 vehicles. Second, distributing the charging poles in zones where cars get frequently parked and rented is instrumental to maximize the demand the system can satisfy, while also limiting the time workers have to spend to bring cars for charging. Third, the system exhibits useful economy of scale, so that the fleet size shall increase sublinearly with respect to the mobility demand intensity.

At last, when projected into economic figures, the fleet setup and management represent the main cost factors. Choosing the right number of vehicles results more fundamental than optimizing the charging infrastructure costs. For instance, for the current demand intensity in Turin, the switch to EVs must be carefully designed to be profitable. Interestingly, when the demand grows, the margins are much higher, allowing some nice economy of scale opportunities.

As future direction, we are studying different cities as new use cases, looking at opportunities of involving users in the charging process in order to decrease management costs.

References

[1] United Nations. (2018) Revision of World Urbanization Prospectsa. https://www.un.org/development/desa/publications/2018-revision-of-world-urbanization-prospects.html. Accessed: 2020-07-09.

[2] J. L. Kent, "Carsharing as active transport: What are the potential health benefits?" *Journal of Transport & Health*, vol. 1, no. 1, pp. 54–62, 2014.

[3] U. Huwer, "Public transport and csar-sharing—benefits and effects of combined services," *Transport Policy*, vol. 11, no. 1, pp. 77–87, 2004.

[4] E. W. Martin and S. A. Shaheen, "Greenhouse gas emission impacts of carsharing in north america," *IEEE Transactions on intelligent transportation systems*, vol. 12, no. 4, pp. 1074–1086, 2011.

[5] T. Litman, "Evaluating carsharing benefits," *Transportation Research Record*, vol. 1702, no. 1, pp. 31–35, 2000.

[6] C. Green. (2009) Car-Sharing – Good for the Environment and the Budget. http://www.blueplanetgreenliving.com/2009/09/16/car-sharing-good-for-the-environment-and-the-budget/. Accessed: 2020-07-09.

[7] M. Rossi, "Mobilità alternativa crack sharing," *Quattroruote*, vol. 746, 2017. [Online]. Available: http://shoped.it/shop/prodotto/quattroruote-ottobre-2017/

[8] P. L. del Viscovo. (2019) Car sharing, in crescita +30% all'anno fino al 2021. https://www.ilsole24ore.com/art/car-sharing-crescita-30percento-all-anno-fino-2021-ACkAQgP. Accessed: 2020-07-09.

[9] A. Ciociola, M. Cocca, D. Giordano, M. Mellia, A. Morichetta, A. Putina, and F. Salutari, "UMAP: Urban mobility analysis platform to harvest car sharing data," in *Proceedings of the IEEE Smart City Innovations*. IEEE, 2017.

[10] A. Ciociola, D. Markudova, L. Vassio, D. Giordano, M. Mellia, and M. Meo, "Impact of charging infrastructure and policies on electric car sharing systems," in *Proceedings of the 23rd IEEE International Conference on Intelligent Transportation Systems*. IEEE, 2020.

[11] K. Kortum, R. Schönduwe, B. Stolte, and B. Bock, "Free-floating carsharing: City-specific growth rates and success factors," *Transportation Research Procedia*, vol. 19, pp. 328–340, 2016.

[12] R. Nair and E. Miller-Hooks, "Fleet management for vehicle sharing operations," *Transportation Science*, vol. 45, no. 4, pp. 524–540, 2011.

[13] L. He, H.-Y. Mak, Y. Rong, and Z.-J. M. Shen, "Service region design for urban electric vehicle sharing systems," *Manufacturing & Service Operations Management*, vol. 19, no. 2, pp. 309–327, 2017.

[14] M. Xu and Q. Meng, "Fleet sizing for one-way electric carsharing services considering dynamic vehicle relocation and nonlinear charging profile," *Transportation Research Part B: Methodological*, vol. 128, pp. 23–49, 2019.

[15] F. Ciari, M. Balmer, and K. W. Axhausen, "Concepts for a large scale car-sharing system: Modelling and evaluation with an agent-based approach," *Working Paper/IVT*, vol. 517, 2008.

[16] F. Ciari, M. Balac, and K. W. Axhausen, "Modeling carsharing with the agent-based simulation matsim: State of the art, applications, and future developments," *Transportation Research Record*, vol. 2564, no. 1, pp. 14–20, 2016.

[17] S. Habibi, F. Sprei, C. Englund, S. Pettersson, A. Voronov, J. Wedlin, and H. Engdahl, "Comparison of free-floating car sharing services in cities," in *Proceedings of the ECEEE Summer Study*, 2017.

[18] R. Tachet, O. Sagarra, P. Santi, G. Resta, M. Szell, S. Strogatz, and C. Ratti, "Scaling law of urban ride sharing," *Scientific reports*, vol. 7, p. 42868, 2017.

[19] X. Li, J. Ma, J. Cui, A. Ghiasi, and F. Zhou, "Design framework of large-scale one-way electric vehicle sharing systems: A continuum approximation model," *Transportation Research Part B: Methodological*, vol. 88, pp. 21–45, 2016.

[20] M. Cocca, D. Giordano, M. Mellia, and L. Vassio, "Free floating electric car sharing design: Data driven optimisation," *Pervasive and Mobile Computing*, vol. 55, pp. 59–75, 2019.

[21] ——, "Free floating electric car sharing: A data driven approach for system design," *IEEE Transactions on Intelligent Transportation Systems*, vol. 20, no. 12, pp. 4691–4703, 2019.

[22] Y. Hua, D. Zhao, X. Wang, and X. Li, "Joint infrastructure planning and fleet management for one-way electric car sharing under time-varying uncertain demand," *Transportation Research Part B: Methodological*, vol. 128, pp. 185–206, 2019.

[23] R. F. Lemme, E. F. Arruda, and L. Bahiense, "Optimization model to assess electric vehicles as an alternative for fleet composition in station-based car sharing systems," *Transportation Research Part D: Transport and Environment*, vol. 67, pp. 173–196, 2019.

[24] M. Vasconcelos, G. Correia, and Farias, "Environmental and financial impacts of adopting alternative vehicle technologies and relocation strategies in station-based one-way carsharing: An application in the city of Lisbon, Portugal," *Transportation Research Part D: Transport and Environment*, vol. 57, pp. 350 – 362, 2017.

[25] A. K. Menon and Y. Lee, "Predicting short-term public transport demand via inhomogeneous poisson processes," in *Proceedings of the 2017 ACM on Conference on Information and Knowledge Management*, 2017, pp. 2207–2210.

[26] R. T. García, M. F. Lopez, J. C. Pérez Sánchez, and R. Pérez Sánchez, "The kernel density estimation for the visualization of spatial patterns in urban studies," in *15th International Multidisciplinary Scientific GeoConference SGEM 2015*, 2015, pp. 867–874.

[27] Mercedes-Benz. (2020) Leasing cost. https://mymobilitypass.mercedes-benz.it/offerte-noleggio-lungo-termine/smart-fortwo-eq-passion. Accessed: 2020-07-09.

[28] C. Nelder and E. Rogers. (2019) Reducing EV charging infrastructure costs. https://rmi.org/ev-charging-costs. Accessed: 2020-07-09.

[29] Comune di Torino. (2020) Ground occupation tax for the city of Turin. http://www.comune.torino.it/cosap/. Accessed: 2020-07-09.

[30] Eurostat. (2019) Electricity price statistics. https://ec.europa.eu/eurostat/statistics-explained/index.php/Electricity_price_statistics. Accessed: 2020-07-09.

[31] Infodata. (2019) Il costo del lavoro divide in due l'Europa. https://www.infodata.ilsole24ore.com/2019/08/19/39139/. Accessed: 2020-07-09.

[32] (2020) Doctor Car Wash Prices. https://www.doctorcarwash.it/prezzi.html. Accessed: 2020-07-09.

[33] (2020) Car2Go Prices in Turin. https://www.car2go.com/IT/en/turin/costs/. Accessed: 2020-07-09.