Impact of Charging Infrastructure and Policies on Electric Car Sharing Systems

Impact of Charging Infrastructure and Policies on Electric Car Sharing Systems

Alessandro Ciociola[a], Dena Markudova[a], Luca Vassio[a],
Danilo Giordano[b], Marco Mellia[a], and Michela Meo[a]
[a]Department of Electronics and Telecommunications, Politecnico di Torino, *first.last@polito.it*
[b]Department of Control and Computer Engineering, Politecnico di Torino, *first.last@polito.it*

***Abstract*— Electric Free Floating Car Sharing systems offer a convenient and environmentally-friendly way to move in cities. However, their design and deployment is not a trivial task. In this work, we focus on fleet charging management, aiming at maximizing the number of trips of users, while minimizing the cost of relocating cars for charging. In particular, we compare two different car charging infrastructures: a centralised charging hub in a highly dynamic zone of the city, and a distributed set of charging poles around the most-used zones, where users can eventually contribute to plug cars. For this scope, we build a data-driven mobility demand model and a simulator that we use to study the performance and costs of fleet charging management. As a case study, we first consider the city of Turin. Then, we extend the results to three other cities (Milan, New York City and Vancouver). Results show that, given enough charging capacity, a distributed infrastructure is superior in terms of both satisfied trips and charging relocation cost. Additionally, with the contribution of users, the relocation cost might decrease even further.**

I. Introduction

In the era of smart cities, transportation is becoming an important challenge to improve the urban life quality. As a consequence, in the last decade new mobility solutions have emerged. Some of these solutions aim at reducing private mobility in favour of multi-modal transportation (combining different transportation means) and shared mobility, such as car pooling, bike sharing, or car sharing. Car sharing, in particular, refers to a transportation mean in which a person autonomously rents a car, usually for a short period of time. This solution allows for higher car utilization and helps in reducing the number of cars on the streets, thus reducing pollution [1]. Two main branches car sharing emerged: the station based car sharing system, in which the user picks and parks the car in specific parking spots, and the Free Floating Car Sharing system (FFCS), in which the user picks and later parks the car anywhere within an operational area. This characteristic makes the latter more appealing for users, as it is more flexible. However, it also poses several challenges for the operator, especially if Electric Vehicles (EV) are employed. Indeed, with electric vehicles, the system has to ensure that the car has enough battery to allow the user to perform the desired trip without running out of energy. At the same time, the provider cannot continuously charge cars due to the Free Floating paradigm.

The research leading to these results is partially supported by the SmartData@PoliTO center for Big Data technologies and by PUNCH Torino.

In order to cope with this complexity, we investigate and compare two infrastructure placement policies to design an electric FFCS system. The main two scenarios we deploy are: (i) Charging hub - in which all the charging operations are performed into a single centralized charging infrastructure, controlled by the operator and (ii) Distributed charging poles - in which a number of charging poles are scattered around the city, where both the users and the operator can plug cars [2], [3].

First, we use real trip data from an existing non-electric FFCS [4] to create a more generic mobility demand model. This model is obtained by combining Poisson processes for time distribution of user requests, and Kernel Density Estimate for spatial demand. Then, we leverage this model to feed our event-based simulator, to study the impact of different parameters related to the charging strategy of EVs. We investigate the impact of charging infrastructure policies by means of three main performance metrics: the percentage of trips that could not be satisfied due to the absence of cars near the user - unsatisfied demand; the percentage of charging trips to take cars to charge that could not be satisfied - impossible charging trips; the cost in terms of time for the system to bring cars to a charging pole - relocation cost. As a first case study, we present a detailed analysis for the city of Turin (Italy). Then, we extend the main results to three other cities: Milan (Italy), Vancouver (Canada), and New York City (USA). Results show that the usage of a distributed charging infrastructure offers better performance than a single hub, for all metrics. The distributed infrastructure reduces the percentage of unsatisfied trips from 30% to less than 10% and the charging relocation cost. Moreover, if the users are allowed to contribute for charging the cars, the relocation cost can be lowered by a factor up to 8. Finally, the choice of the capacity threshold to bring the car to charge should be carefully analyzed, and the chosen value differs for each city.

The paper is organized as follows: in Section II we illustrate the demand model, along with a quantitative assessment of its performance. In Section III we describe the simulation software and its assumptions. In Section IV we analyze the results for the Turin case study. Then, in Section V we extend the analysis to the other cities. In Section VI we review existing scientific literature covering similar topics and, finally, we conclude and discuss future research directions in Section VII.

II. Demand model

In this Section, we introduce the data-driven mobility demand model used in our simulation study. The goal of the demand model is to find and generalize the probability distributions that represent the observed real data, in both time and space. We can later use it to generate samples and feed our event-based simulator. Input data are collected from the car sharing operator car2go[1], with the methodology shown in our previous work [4]. In a nutshell, these data describe real trips performed by users during 2017 in 23 cities. We model the demand in time using modulated Poisson processes, and in space using Kernel Density Estimation (KDE). To the best of our knowledge, the combined usage of these tools for mobility demand modelling is still unexplored.

A. Time estimation

We assume that user booking inter-arrival times are exponential random variables, and that the rate of arrivals varies with the type and the hour of the day. For simplicity, in this work we consider two types of day: workday (from Monday to Friday) and weekend (Saturday and Sunday). Within each day type, we consider 24 time bins of one hour each, each with a different arrival rate. The Poisson rate of bookings in a certain temporal slot is fitted to the average number of bookings occurring at the corresponding temporal slot in the data trace. Thus, the overall process takes the form of an inhomogeneous Poisson [5] one.

We use data of trips that occurred during three months in 2017 to fit the model and validate our assumptions. Figure 1(a) shows the quantile-quantile (Q-Q) plot of inter-arrival times in the original data trace (y-axis) and in the trace derived from the model (x-axis) for Turin. The inter-arrival time distribution is computed over the whole inhomogeneous Poisson process obtained with the 48 temporal slots. We can see that points are close to the bisector line, meaning that the Poisson process accurately represents the occurrences of bookings in time. The steps that are visible in the original time series depend on the 1 minute sampling interval that is used to record the trace [4].

We now quantify the residual error introduced by the assumption that the 48 temporal slots accurately model the trace. Indeed, there will likely be some variability in the same hours at different days. We define a relative residual error for each temporal slot t as the deviation of the number of trips generated by the model with respect to the number of trips in the trace:

$$\epsilon_t = \frac{\sum_{i \in \mathcal{I}_t} \left| \frac{\hat{N}_i - N_i}{N_i} \right|}{|\mathcal{I}_t|} \tag{1}$$

where $\mathcal{I}_t$ is the set of hours in the trace that maps to the temporal slot t, $|\mathcal{I}_t|$ its cardinality, and N_i and $\hat{N}_i$ are the real and the simulated trips at temporal slot t, respectively. For the case study of Turin, we report the 48 values of ϵ_t in Figure 1(b). As we can see, residuals are often less than 5%, with few peaks, like during the night and early morning of weekend days (4 am - 7 am). In this slots there are fewer trips, hence a higher variability and larger deviation.

B. Spatial estimation

Kernel Density Estimation (KDE) is largely used in the literature as a tool to analyse spatial patterns, as for example in [6], [7]. In this work, we use KDE to estimate probability distributions of the positions of origin and destination from input data. First, we divide the city in 500 m x 500 m blocks and assign an identifier to each of these zones. We allow users to pick cars within the same zone or from 1-hop neighboring zones. This zone width is compatible with the distance that a user is willing to walk to reach a car i.e., less than 500 m on average [8]. Then, in order to couple time and space estimation, we fit a bi-dimensional KDE on origin-destination couples for each temporal slot. In this way, we obtain 48 models summarising spatial mobility habits of users in time. We use a Gaussian kernel [9] and set the bandwidth matrix of KDE to the 2 x 2 identity matrix. We observed (not shown for brevity) that smaller bandwidth does not bring significant advantages for estimation, while a bigger bandwidth loses the granularity of city binning, and lead to a reduced precision in detecting spatial patterns.

In a nutshell, we use KDE as a spatial data smoothing tool, able to capture mobility patterns from rentals in the trace, while reducing the impact of noise or secondary finer-scale phenomena. In this subsection, we show the relative error produced by the smoothing effect of the KDE. We define the relative spatial error metric for the origin of trips in a zone z as:

$$\epsilon_z^o = \left| \frac{\hat{N_z^o} - N_z^o}{N_i^o} \right| \tag{2}$$

where N_z^o and $\hat{N_z^o}$ are the total number of trips in the trace and in the simulated trips, respectively. z is the considered origin zone.[2] Figure 1(c) shows ϵ_z^o for each zone on a choropleth map over the city of Turin. Most of the zones have residuals very close to 0, with few of them that reach 30% of residual error. Those correspond to zones with parks or limited access.

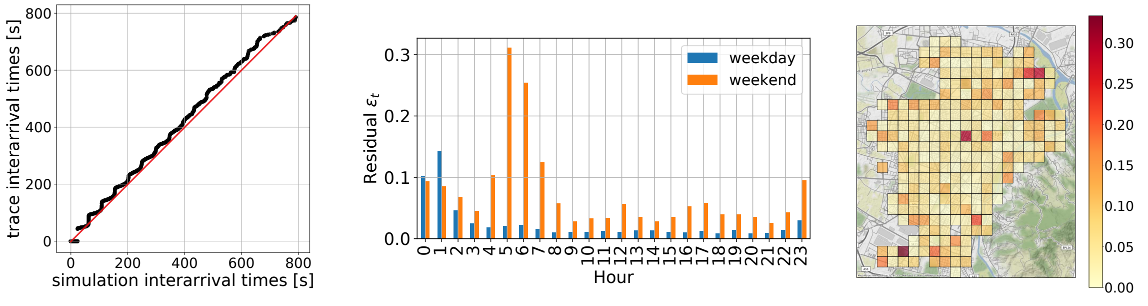
III. Simulation Model

Here we describe the principles and the assumptions of the simulator we design to model an electric FFCS system.

First, we use the demand model to determine the occurring trips. We assume the model to be stationary over time. When a new rental request is generated, the simulator looks for an available car with enough battery in the origin zone, or in any neighbouring zone. If available, the simulator takes the car and schedules a return event at a certain time to the destination zone. When a return event is processed, the simulator computes the consumed amount of energy and

[1] In 2019, car2go merged with Drive Now into the new service Share Now `https://www.share-now.com/`.

[2] The same computation holds for destination zones. Residuals are similar and not reported due to space limits.



(a) Q-Q plot of inter-arrival times

(b) Relative residuals per temporal slot ϵ_t

(c) Relative residuals per spatial zone ϵ_z^o

Fig. 1. Model validation in time and space - case study of Turin

then checks if the car should be charged. If so, it triggers a charging event for the car according to the designated policy (centralized hub or distributed charging poles). After a given simulation time (3 months in our case), we extract statistics about the number of satisfied and unsatisfied trips, the zones where there is unsatisfied demand, the number of charges, etc.

The software is written in Python and it uses the library SimPy[3]. Below we summarize the simulation assumptions and its main parameters.

Zoning. A city operating area is divided into square zones of dimension 500 m x 500 m. Each trip distance is computed as the Euclidean distance between the centroids of the origin and destination zones, multiplied by a correction factor of 1.4, to account for the roads and orography (as in [2]).

Cars and charging poles. All poles have the same characteristics, namely 3.7 kW nominal power and 92% charging efficiency. State of Charge (SoC) increases and decreases linearly with charging duration and driving distance, respectively, as in [10]. Cars are supposed to have the same characteristics as the MY2018 electric Smart ForTwo, namely 17.6 kWh battery capacity and 15.9 kWh / 100 km energy efficiency.

Before rental. A user requests a car in a certain zone. If there are cars in this zone, he/she takes the most charged one. If not, he/she looks in a 1-hop neighbouring zone. If there are no cars even in these 8 neighbouring zones with enough battery to reach the desired destination, the trip does not occur and it is marked as unsatisfied.

After rental - Charging process. At the end of a rental, we check if the car needs charging, i.e., if the car SoC is below a threshold α. If no charging is needed, the car is parked in the destination zone. If, instead, the SoC is below the threshold, the car is brought to charge according to the charging policy. It is charged until it reaches a SoC of 100% (full capacity). Relocation times are computed using 15 km/h as average speed (this accounts for parking times and traffic). Note that sometimes the car does not have enough energy to be relocated for charging. In this case, we relocate it anyway, but mark this trip as an impossible charging trip.

Charging infrastructure. The first charging infrastructure is a centralized hub. Cars in need of charge are relocated to the hub, which is assumed to be optimistically located in the zone of the city with the highest demand (usually in the center). The car sharing operator handles the cost of relocation, that we measure as the time to bring the car to the hub. The second charging infrastructure assumes a distributed solution. Charging poles are spread around the city, according to the strategy presented in [2], which places poles in the zones with the highest probability of being destination zones. Namely, poles are distributed in up to 10% of the zones, proportionally to the zone attraction as a destination. When a car needs charge, it is relocated to the closest free charging point. If there is no free charging pole anywhere in the city, the car queues at the nearest charging pole.

User willingness. When using the distributed policy, we assume that users could also help with the charging process. If users end their trip in a zone where there is a free charging pole, they plug the car with probability w, which represents their average willingness to contribute.

Performance metrics. To compare performance in different scenarios, we consider the following metrics:

Unsatisfied Demand: the unsatisfied demand measures the fraction of trip requests that are unsatisfied, due to no car with enough energy being in the origin zone or its neighbouring zones. It gives an indication of the quality of the service in terms of car availability for user requests.

Impossible charging trips: impossible charging trips measure the fraction of charging events for which a car that must be charged cannot reach any available charging station, due to insufficient battery level. This represents an additional cost for the system operator.

Relocation Cost: the charging relocation cost measures the cost of the charging process the FFCS operator has to face. We measure it as the average total time spent by the system operator to drive a car to charge, per month. When a car needs to be charged, the operator has to physically move it to an appropriate charging point.

[3] `https://simpy.readthedocs.io/en/latest/`

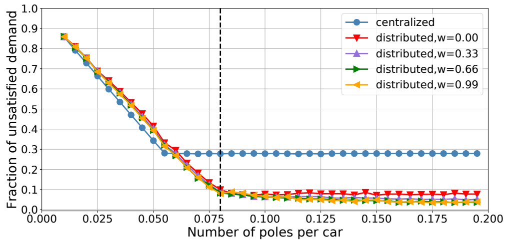


Fig. 2. Fraction of unsatisfied demand versus number of poles per car - Turin

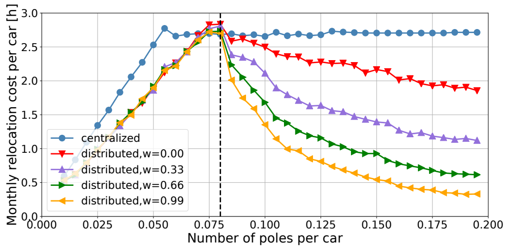


Fig. 3. Average monthly charging relocation cost per car versus number of poles per car - Turin

IV. Charging Infrastructure and Policy Comparisons - Turin Case Study

As a case study, we focus on the city of Turin (see Table I for its characteristics). In particular, we compare centralised and distributed charging scenarios, quantifying unsatisfied demand and charging relocation cost. We focus our attention on the impact of the following characteristics of the two charging infrastructures:

- the total charging infrastructure capacity in terms of total number of poles over fleet size;
- the charging threshold α;
- the users' willingness w to contribute (only in case of distributed infrastructure).

We start by setting α to 26%, which corresponds to the amount of battery that guarantees to cover the maximum possible distance within the operational area of Turin (i.e., 28 km). The number of cars is 400, as in the real data.

Figure 2 shows the percentage of unsatisfied requests as a function of the fraction of charging poles per car. First, observe the two macroscopic regimes: if the charging capacity of the system is too little, cars run out of battery and wait for a long time in charging queues. As such, users cannot find available cars (left part of the plot). When charging capacity is large, increasing it brings no benefits: the unsatisfied trips stabilizes on a value due to the mismatch between origin demand and cars availability (right part of the plot). The figure clearly shows the minimum number of charging poles that need to be installed; in the case of Turin it is 0.085 poles per car (32 poles, highlighted in the Figure with a vertical dashed line). Second, observe how an optimally placed centralised infrastructure performs visibly worse than the distributed one. This is again due to the mismatch between available cars and users' demand. The distributed infrastructure better spreads cars in the city after charging. Third, the user willingness plays a marginal role on reducing the fraction of unsatisfied requests. Their willingness contributes to keep the average SoC higher (not shown for the sake of brevity).

Figure 3 shows the relocation cost per car, i.e, the average time needed to relocate a car to a charging pole, measured in hours per month. There is a clear advantage in employing a distributed infrastructure, as the average distance to reach a suitable charging station is lower. Furthermore, in the distributed infrastructure, increasing the charging capacity is beneficial in terms of charging operations cost, since the infrastructure gets naturally more distributed. This does not happen with the centralised infrastructure as all poles are located at the same place, thus at the same distance. Even more beneficial is the scenario when the users help. In fact, even just a willingness equal to 0.33 almost halves the relocation costs.

We next analyze the fraction of impossible charge trips while varying the charging poles per car. Results, not reported here for the sake of brevity, show that the number of charging poles does not affect impossible charging trips which only depend on residual capacity at trip end, i.e., on α. With $\alpha = 26\%$, we observe less than 3% of impossible charge trips in the centralized scenario and less than 0.5% in the distributed scenario. This means that, among all charges that the system performs (when car residual capacity is less than α), only a handful remains with a SoC insufficient to be taken to charge.

To better understand the impact of the charging threshold, we perform experiments varying the parameter α. We set the charging capacity to 0.1 (i.e., 41 poles), as one of the possible trade-offs between unsatisfied trips, charging relocation cost and number of poles (Figures 2 and 3). Figure 4 shows the fraction of unsatisfied demand as a function of α. The higher the value of α, the higher is unsatisfied mobility demand. Recall that we must plug the car whenever the car SoC is below α: therefore, with high α, the system must charge cars more frequently, thus making them unavailable and reducing the effective fleet size. The centralized hub is largely affected by this parameter since after a charge cars get concentrated in the hub zone. By increasing α, more cars tend to be concentrated around the hub, making only trips originated near the hub possible. In a distributed infrastructure, this is less evident due to the spreading of cars after charging. A value of α too low implies that many times the cars are left with a low amount of energy, and thus they cannot satisfy the user demand. The user willingness has little impact, as in Figure 2. The unsatisfied demand reaches its minimum with $\alpha = 15\%$, only improving by 0.01 the fraction of unsatisfied demand with respect to the previously chosen value ($\alpha = 26\%$). Figure 5 shows the fraction of impossible charging trips as a function of α. Again, too low values of α imply more cars to reach a critical SoC at the end of a trip, resulting in impossible charging trips. This effect is stronger in the centralised infrastructure than

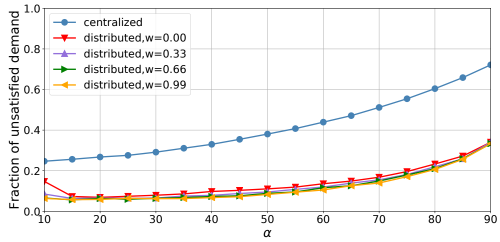


Fig. 4. Fraction of unsatisfied demand versus charging threshold α - Turin

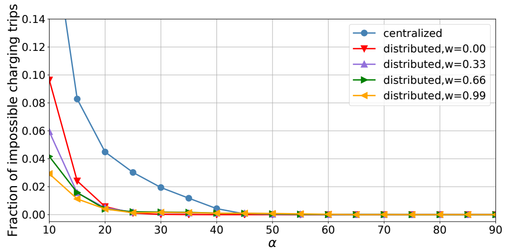


Fig. 5. Fraction of impossible charging trips versus charging threshold α - Turin

in the distributed one, due to the longer distance to reach the charging hub. Lastly, Figure 6 shows how charging relocation cost generally increases with α, as the system must charge cars more frequently.

To summarize, the number of poles per car should be defined so as to minimize the fraction of unsatisfied demand. The parameter α should be also studied. It shall be big enough to have enough energy to guarantee user trips, but if too large, cars require more frequent charging and are less employed by users, thus increasing relocation costs and unsatisfied demand.

V. Comparisons in different cities

Here we integrate and present results for multiple cities, namely Milan, Vancouver and New York City.[4] In Table I, we report the characteristics of the cities. Cities have different size, maximum distance within the city and fleet size. Moreover, also the car utilization differs in each city, from an average of only 2.5 daily rentals per car in New York City to 7.0 rentals per car in Milan. Based on the results of the previous Section, we consider the distributed charging infrastructure only, with a user willingness equal to 0.66. The value of α is chosen, for each city, according to the maximum distance that can be travelled in the city. In order to compare different cities with different fleet size, we show performance metrics as functions of the number of poles per car.

Figure 7 reports the fraction of unsatisfied trips while increasing the total infrastructure capacity. The minimum number of poles per car required to stabilise the fraction of unsatisfied trip varies from city to city. The difference among the cities is mainly due to the different car utilization

[4]The service in New York City is limited to the Brooklyn borough.

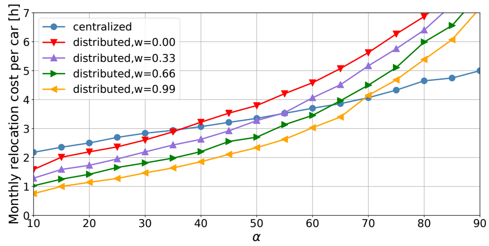


Fig. 6. Average monthly relocation cost per car versus charging threshold α - Turin

TABLE I
Statistics summary for each city.

City	Area $[km^2]$	Max distance $[km]$	Cars	Avg daily rentals per car	Charging thresh. α [%]
Turin	68	28	410	5.8	26
New York City	107	33	490	2.5	30
Milan	112	29	800	7.0	27
Vancouver	137	49	1 000	6.0	44

in terms of frequency of usage and trip distance (see Table I). Interestingly, in New York City, despite the large operative area, we reach system stability before any other city due to the smaller demand. However, this is scattered through the city, hence the fraction of unsatisfied trips does not go below 0.1.

In Figure 8 we report the relocation cost per car per month for each city. Here Vancouver exhibits the highest relocation cost, with a peak at 6.5 hours per month per car, due to its high usage and large operational area, which translates into a high α parameter (see Table I). By performing the α analysis as in the previous Section, we observe that we can cut the fraction of unsatisfied trips and the relocation cost by reducing the α parameter. In particular, changing the value of α in Vancouver from 44% to 20% allows us to lower the peak observed in Figure 8 from 6.5 to 4.0 of monthly hours per car.

VI. Related work

The related work about electric car sharing simulation and charging strategies is wide and covers different aspects. An extensive review of car sharing scientific literature is provided by [11]. This work analyses 137 published papers, classifying them under a certain number of taxonomy axes. Authors of [12] propose centralised, agent-based mechanisms to optimise charge of private EVs. In [13], authors explore the estimation of public charging demand of all EVs, for the city of Berlin. While the study is very detailed, it provides results for one city, using a commercial simulator with a demand model coming from a survey. Authors of [14] propose a framework for modelling and simulating the evolution of an electric car sharing system. Despite being fairly general and not computationally expensive, this model is fully parametric, makes strong assumptions about the probability distributions of the involved processes, and does not include geographical aspects. A more complete model is provided by [15], where it is presented a simulator

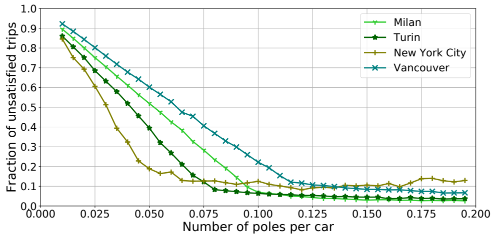


Fig. 7. Fraction of unsatisfied requests versus number of poles per car - Multiple cities with distribute infrastructures and $w = 0.66$

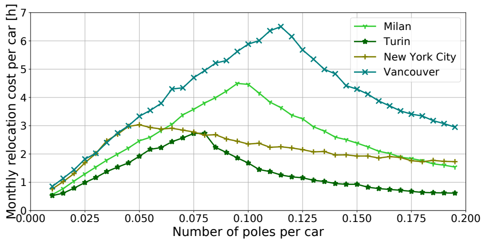


Fig. 8. Charging relocation cost versus number of poles per car - Multiple cities with distribute infrastructures and $w = 0.66$

with user requests and different relocation strategies. Authors in [16] simulate the operation of electric vehicles in urban car sharing networks with a focus on economical aspects. The work in [17] addresses the problem of insufficient vehicle utilization in electric car sharing systems by developing a framework which increases utilization, improves charging schedules, increases battery life and consequently mitigates range anxiety of users. In our previous works [2], [18], we developed a trace-driven simulator to face the problem of charging stations placement and user experience optimisation. We build on these work by implementing an event-driven simulator and focus on different scenarios with more complete performance metrics.

To the best of our knowledge, the combination of modelling, simulations and analyses of charging policies here presented has not been previously explored.

VII. Conclusion and Future Work

In this work, we developed a data-driven demand model and a simulator for the study of electric FFCS systems. We used our simulator to explore charging station infrastructures and policies in different cities. We showed that planning and designing a charging infrastructure is a complex problem that needs to be analyzed from many aspects to trade off among different metrics. Our results show that a distributed infrastructure with a little users' help offers better performance with respect to a optimally placed centralized infrastructure. We believe that our simulator can represent a powerful decision support tool for design and planning electric FFCS systems.

As a future work, we plan to scale the results with a larger number of user requests, and run simulations with more realistic assumptions. For example, as in [19], we will introduce the constraints given from the presence of human operators. Another important topic is relocation of cars, not only for charging, but to satisfy more user demand. Finally, we plan to approach the financial aspects of the system in terms of infrastructural and operational costs.

References

[1] R. Mounce and J. D. Nelson, "On the potential for one-way electric vehicle car-sharing in future mobility systems," *Transportation Research Part A: Policy and Practice*, vol. 120, pp. 17 – 30, 2019.

[2] 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.

[3] M. Cocca, D. Giordano, M. Mellia, and L. Vassio, "Data driven optimization of charging station placement for EV free floating car sharing," in *2018 21st International Conference on Intelligent Transportation Systems (ITSC)*, 2018, pp. 2490–2495.

[4] 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 *2017 IEEE Smart City Innovation (SCI)*, 2017, pp. 1–8.

[5] 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.

[6] J. A. Downs, "Time-geographic density estimation for moving point objects," in *Geographic Information Science*, 2010, pp. 16–26.

[7] X. Cai, Z. Wu, and J. Cheng, "Using kernel density estimation to assess the spatial pattern of road density and its impact on landscape fragmentation," *International Journal of Geographical Information Science*, vol. 27, no. 2, pp. 222–230, 2013.

[8] S. Herrmann, F. Schulte, and S. Voß, "Increasing acceptance of free-floating car sharing systems using smart relocation strategies: A survey based study of car2go hamburg," in *Computational Logistics*, 2014, pp. 151–162.

[9] 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.

[10] J. Brady and M. O'Mahony, "Modelling charging profiles of electric vehicles based on real-world electric vehicle charging data," *Sustainable Cities and Society*, vol. 26, pp. 203 – 216, 2016.

[11] F. Ferrero, G. Perboli, M. Rosano, and A. Vesco, "Car-sharing services: An annotated review," *Sustainable Cities and Society*, vol. 37, pp. 501 – 518, 2018.

[12] M. Usman, L. Knapen, A.-U.-H. Yasar, Y. Vanrompay, T. Bellemans, D. Janssens, and G. Wets, "A coordinated framework for optimized charging of ev fleet in smart grid," *Procedia Computer Science*, vol. 94, pp. 332 – 339, 2016.

[13] J. E. A. Michael Hardinghaus, Christian Seidel, "Estimating public charging demand of electric vehicles," *Sustainability*, vol. 11, no. 21, p. 5925, 2019.

[14] M. Clemente, M. P. Fanti, G. Iacobellis, and W. Ukovich, "Modeling and simulation of an electric car sharing system," *25th European Modeling and Simulation Symposium, EMSS 2013*, pp. 587–592, 2013.

[15] M. Repoux, B. Boyacı, and N. Geroliminis, "Simulation and optimization of one-way car-sharing systems with variant relocation policies," in *94th Annual Meeting of the Transportation Research Board, Washington D.C.*, 2015.

[16] S. Illgen and M. Höck, "Electric vehicles in car sharing networks – challenges and simulation model analysis," *Transportation Research Part D: Transport and Environment*, vol. 63, pp. 377 – 387, 2018.

[17] A. B. Brendel, S. Lichtenberg, B. Brauer, I. Nastjuk, and L. M. Kolbe, "Improving electric vehicle utilization in carsharing: A framework and simulation of an e-carsharing vehicle utilization management system," *Transportation Research Part D: Transport and Environment*, vol. 64, pp. 230 – 245, 2018.

[18] M. Cocca, D. Giordano, M. Mellia, and L. Vassio, "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.

[19] M. Nourinejad, S. Zhu, S. Bahrami, and M. J. Roorda, "Vehicle relocation and staff rebalancing in one-way carsharing systems," *Transportation Research Part E: Logistics and Transportation Review*, vol. 81, pp. 98 – 113, 2015.