The Impact of Regulated Electric Fleets on the Power Grid: the Car Sharing Case

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Abstract—On-demand mobility services, such as bike and car sharing, are experiencing an exponential growth and are expected to play an essential role in future transportation systems. In addition, car sharing is recognised as a key driving force for the diffusion of electric vehicles (EVs) in urban areas. The impact of a regulated fleet of shared electric cars on the power distribution grid is expected to be significant and very different from that of privately-owned EVs due to: the different mobility patterns (e.g., higher vehicle utilisation, shorter parking times), and the dependence of charging opportunities on the specific layout of the car-sharing station infrastructure. However, these issues are not sufficiently investigated in the research literature. To fill this gap, in this work we make the following two main contributions. First, we formulate a stochastic facility location problem for the optimal deployment of the car sharing stations to provide probabilistic guarantees on parking availability. Second, we analyse the energy demands of the car sharing system under different deployment scenarios and charging technologies, including power sharing. Finally, to test how well our model can be applied to the real world we leverage on a data-driven evaluation methodology based upon the travel demands of an existing car sharing operator.

Index Terms—car sharing, infrastructure planning, charging policy, power sharing, mobility dataset.

I. INTRODUCTION

There is a general consensus among experts, major industry players and policy makers that the diffusion of autonomous, connected and electric vehicles (EVs) will be an essential part of the future of transportation systems [1]. In particular, the need for cutting greenhouse emissions, as well as the increasing social concerns about a more environmentally sustainable lifestyle and economy, are fostering the adoption of EVs [2]. So far, the predominant market of electric cars has consisted of private owners, who primarily charge their vehicle at home and during night hours. However, the EV landscape is rapidly evolving and radically new markets and usage models are emerging [3]. On-demand mobility is undoubtedly one of the most important of such emerging trends in transportation.

The idea behind on-demand mobility services is that a vehicle is a commodity that can be shared among a group of people using peer-to-peer or business-to-consumer models. The recent and ongoing exponential growth of on-demand mobility services like ride sharing, car and bike sharing, and last-mile delivery services are clear examples of the shift towards this new mobility model. A commonality among most on-demand mobility services is that they are established using a commercial fleet of vehicles (e.g. bikes, cars, light-duty or mission-specific vehicles), which is typically operated by a company or a public organisation. Interestingly, market analysts estimate that purely commercial fleets, shared and non-shared, already accounts for 30% of the market for new electric vehicles and this trend is expected to increase [3].

In this study we focus on car sharing systems, a representative case of on-demand mobility services in which customers can rent for short periods of time a shared vehicle either from designated stations that are owned and operated by the provider of the car sharing service, or from on-street parking places. Mobility experts believe that car sharing services could be a key driving force to promote EV deployment by facilitating access to EV technologies and making EVs a normal part of the urban environment [4]. However, electric car sharing will not only be very impactful on the urban transportation system but also on the planning and management of the power grid. Specifically, the travel patterns of an electric shared vehicle are significantly different from that of a privately-owned EV. In particular, private cars are highly under-utilised and stay parked most of the time, which facilitates the control of the charging process. On the contrary, rental periods of shared vehicles are typically short, thus charging requests are frequent and batteries should be rapidly recharged. To the best of our knowledge, the characterisation of the impact of electric car sharing services on the power distribution grid remains largely unexplored in the research literature. Recent works have analysed spatiotemporal energy demands for EVs in urban areas, but only for scenarios with privately-owned cars [5]. It is also important to point out that in a station-based car sharing system charging occurs at designated locations. Thus, the deployment of the car sharing infrastructure has also an impact on the congestion problems of the power distribution grid (e.g., stations with many parking places may generate high peaks of energy demand) [6].

Although it is clearly important to develop a more precise understanding of the general properties of electric car sharing systems, it is also essential to investigate how emerging trends and recent technology advancements will change these properties. As far as the impact of an electric car sharing system on the power grid is concerned, one of the most important of such advancements is power sharing. Power sharing denotes the capability of using one charging station to recharge simultaneously multiple EVs. There are various types of power sharing technologies and in Section II we present the most relevant ones. Intuitively, power sharing has the potential to reduce the cost of the necessary recharging infrastructure. However, it could also change the charging process in an unexpected way because average charging rates decrease (the power provided by the charging station is distributed among
multiple vehicles), which results into longer charging periods. A preliminary study of the charging process for a station-based car sharing system employing power sharing technologies is presented in [7].

To address the aforementioned issues, in this work we make two main contributions. First, we formulate a stochastic optimisation problem to determine the location and capacity of car sharing stations in order to probabilistically satisfy requirements on parking availability. Our problem is a variant of classical facility location problems with stochastic demands and congestion [8]. Second, we quantify the energy demands of a car sharing system under various deployment scenarios, accounting for realistic travel demands, statistics of energy consumption from crowdsourced data, and power sharing technologies. To assess the effectiveness of our deployment model we adopt a data-driven evaluation methodology that uses the travel patterns of a large-scale free-floating car sharing system operator as data sources. Our results show that most stations require a small capacity (less than four parking slots) but a few large stations (up to 15 parking slots) are necessary to provide guarantees on parking availabilities in areas with large car turnovers. Furthermore, our results indicate that power sharing may have a negligible impact on charging power peaks when fast charging technologies are employed because charging periods are quite short.

The rest of this paper is organised as follows. In Section II we describe existing power sharing technologies. Section III presents the car sharing data used for evaluation. In Section IV we describe the planning framework for the car sharing infrastructure. In Section V we show results based upon our car sharing data. Then, Section VI draws final conclusions and discusses future work.

II. POWER SHARING

Power sharing can be supported through a new type of charging stations, namely multiple outputs multiple cables (MOMC) charging stations [9]. A MOMC station has multiple cables which can charge several EVs simultaneously\(^1\), and the current for each cable can be varied and adjusted following different objectives, such as low peak loads or fair charging of connected vehicles. A MOMC station has the potential benefit of reducing infrastructure investments because it is equivalent to multiple co-located, conventional charging stations with a single cable.

\(^1\)EV Supply Equipment (EVSE) manufactures (e.g., ChargePoint) are already commercialising multi-cable charging stations.

A different kind of power sharing exists, which does not require the replacement of the charging points but it is directly supported by EVs. More precisely, various foldable and stackable vehicles have been recently developed that can connect to each other through a docking interface. This allows to stack, drive but also recharge vehicles in a train. In other words, when connected, the vehicles can share the power of a single charging station. Examples of this new class of electric vehicles are the EO Smart Connecting Car\(^2\) or the ESPRIT vehicle, which is currently under development within the H2020 European Project ESPRIT [10], and is illustrated in Figure 1. It is also interesting to observe that the docking capability of ESPRIT vehicles not only allows power sharing when the vehicles are connected to a charging station, but also when unplugged. In particular, a vehicle with high battery energy can transfer part of its energy to a vehicle in the road train with insufficient residual energy.

III. CHARACTERISING TRAVEL AND CHARGING DEMANDS IN FREE-FLOATING CAR SHARING

The dataset that we use in this study is composed of all the pickup and drop-off events of electric shared vehicles for a free-floating car sharing service provider operating in The Netherlands. Data is collected every minute for a period of one month and a half between May and June 2015. The dataset comprises more than 51000 trips for a fleet of about 400 electric vehicles. Each observation reports the type of event (pickup or drop-off), the time, the geographical coordinates and the status of the vehicle (mainly, battery level). No information is available on the trip trajectory or the customer. Note that a similar characterisation, but for a station-based car sharing service is presented in [11]. In this work, we have considered a free-floating system because it provides a better understanding of the spatial distribution of the service demands than a station-based system. Indeed, in a station-based car sharing system the vehicle pickups and drop-offs are already constrained by the limited number of locations of the deployed stations.

We start from estimating the car sharing demands by dividing the urban area into non-overlapping cells of side 200 meters and counting the average total number of pickup events per cell and per day, which is shown in Figure 2. The results indicate that the travel demand is highly inhomogeneous with many “inactive” cells, namely cells without a single customer’s request. Furthermore, in most active cells the number of pickups ranges from 4 to 8. It is important to point out that these travel demands provide the empirical data to validate the planning problem described in the following section.

In Figure 3 we plot the histogram of the energy consumed, in terms of SOC decrease, per trip. The results indicate that the discharge for most of the trips is below 20%. Interestingly, there is a very small percentage of trips that have a negative discharge. This can be explained by noting that customers may have intermediate stops during their rental period, during which they can recharge the rented vehicle at private or public charging points. Clearly, the lower the SOC decrease, the smaller the total energy that should be used to recharge the

EVs. As better explained in the following sections, small battery consumptions result in short charging periods, whose duration depends on the charging power supported by the EVs.

IV. INFRASTRUCTURE PLANNING IN STATION-BASED CAR SHARING SYSTEMS

In the previous section we have derived the spatial distribution of travel demands in a free floating car-sharing system, i.e., when the vehicles can be picked up or dropped off at any location within the service area. It is reasonable to assume that the same demand patterns would occur in an equivalent station-based system deployed in same area. In this case, pick-ups and drop-off would be interpreted as the desired origins and destinations of the requested trip. Then, each customer would be characterised by a maximum walking distance he/she is willing to walk to reach the closest station with an available vehicle. This sets a coverage constraint on the deployment problem, which is of the set-covering type [12]. The complexity of the deployment problem is mainly due to the stochasticity of the system demand, which induces random congestion on the shared resources (vehicles and stations).

A. Planning objectives

Important questions to address in a station-based car sharing system are: how many stations to deploy? at which location to deploy them? how to size each station? [13] One of the most important objectives of a station-based car sharing operator is to ensure that there is at least one available parking space, with some pre-specified probability, when a customer wants to drop-off a vehicle at a given station. In principle, the car sharing operator would also like to guarantee that there is at least one available vehicle when there is an incoming customer’s rental request. However, guarantees on car availability are difficult, or impossible in some cases, to achieve by simply increasing the station capacity. Specifically, when cars are requested very frequently picked up quickly adding more parking spaces might be useless and the only solution for the car sharing operator would be to would be to perform some kind of vehicle redistribution [14]. Thus, in this study we focus only on the first type of constraint, i.e., parking availability. Clearly, the location of car sharing stations is also influenced by the need for ensuring the largest possible coverage of the customers’ expected demands – which means that only a station located within a certain coverage radius from the location where the rental request is generated may provide service. On the other hand, the size of the car sharing infrastructure is limited by the deployment costs and the total capital investments that the car sharing operator can afford. In the following we formulate a variant of a set-covering problem, where the objective is to minimise the total cost of deployment while satisfying parking availability and coverage constraints [15].

B. Problem formulation

For the sake of simplicity, we assume that the urban area $A$ in which the car sharing infrastructure should be deployed is partitioned into a set $N$ of non-overlapping square cells. For all $i, j \in N$, $\text{dist}(i, j)$ denotes the shortest distance in number of hops (i.e., cells) between cells $i$ and $j$. As mentioned above, car pickups and drop-offs in a cell can be served only by stations that are within a pre-specified hop-distance $R$ (called coverage radius) from that cell. Without loss of generality, we assume that stations are placed at the center of cells. Thus, the coverage around a station located at cell $i$ can be defined as the set $C(i) = \{ j \in N | \text{dist}(i, j) \leq R \}$. Vice versa, we say that a cell $j$ is covered if there exists at least one car sharing station at most $R$ hops away from $j$.

Now, let us assume that a potential station is deployed at cell $i$. The travel demands associated to this potential station can be modelled as two stochastic processes. More precisely, the drop-off events in the coverage area $C(i)$ of the station can be modelled as a Poisson process with rate $\lambda_i$. As for the pickup events, we assume that the time between two consecutive pickups of parked cars follows an Exponential distribution with rate $\mu_i$. Please note that these approximations are commonly adopted in the modelling of on-demand mobility systems [16], [17].

The decision variables of the planning problem are $x_i \in \{0, 1\}$, with $x_i$ equal to 1 if a car sharing station is deployed
at the centre of cell $i$ and 0 otherwise, and $k_i \in \mathbb{N}$, where $k_i$ indicates the number of parking spaces that are allocated to the car sharing station at cell $i$. Clearly, $k_i \geq 1$ if and only if $x_i > 0$. This is equivalent to writing $(1-x_i)k_i + x_i(1-k_i) \leq 0$. Note that the coverage condition for cell $i$ is also equivalent to state that $\sum_{j \in C(i)} x_j \geq 1$.

The parking availability $A_p(i)$ of a cell $i$ that hosts a station can be defined as the steady-state probability that a vehicle arriving at that station finds an available parking space. We assume that there is a minimum required parking availability $\beta \in (0, 1]$, i.e., $A_p(i) \geq \beta$. To stochastically model the availability function $A_p(i)$, we adopt a queueing theoretical approach similarly to [16] and we model a station located at cell $i$ as an $M/M/1/k_i$ queue. We remind that $\lambda(i)$ and $\mu(i)$ denote the total drop-off and pickup rates of vehicles, respectively, for the cells in the subset $C(i) \subset N$. For the sake of notation convenience, let $\rho_i = \frac{\lambda(i)}{\mu(i)}$. Finally, let $\pi_n$ denote the steady state probability that there are $n$ jobs in an $M/M/1/k_i$ queue with utilisation $\rho_i$. Then, we can write that:

$$\beta \leq A_p(i) = 1 - \pi_{k_i} = 1 - \frac{(1-\rho_i)^{k_i}}{1-\rho_i^{k_i+1}}. \quad (1)$$

Now we are able to formulate the stochastic optimisation problem to minimise the deployment cost of the infrastructure while satisfying the aforementioned constraint. Specifically, let us assume that $C_s$ is the annual depreciation cost of a car sharing station (inclusive of the charging point) and $C_p$ is the annual cost of a single parking space. Then, the optimisation problem is simply given by:

$$\min \sum_{i \in N} C_s x_i + C_p k_i \quad \text{s.t.} \quad (1-x_i)k_i + x_i(1-k_i) \leq 0 \quad \text{(3)}$$

$$k_i \geq \log_{\rho_i} \frac{(1-\beta)}{(1-\beta\rho_i)} \quad \text{(4)}$$

$$\sum_{j \in C(i)} x_j \geq 1 \quad \text{(5)}$$

$$x_i \in \{0, 1\}, k_i \geq 0 \quad \forall i \in N \quad \text{(6)}$$

Note that constraint (4) is an algebraic manipulation of relationship (1). Set cover problems are known to be NP-hard but a greedy search can provide near-optimal solutions [18]. Specifically, our greedy algorithm works by selecting, at each step, the candidate station that covers the greatest number of pickup/drop-off events that are still uncovered, and by assigning to the station the smallest value of $k_i$ that satisfies the constraint (4).

V. PERFORMANCE EVALUATION

In this section we assess the validity of our model and solution method using the dataset of pickup and drop-off events of the real car sharing system introduced in Section III. Then, we characterise the recharging process under various deployment scenarios with and without power sharing.

A. Results on infrastructure planning

From the car sharing data we can obtain the correspondent $\lambda(i)$ and $\mu(i)$ values that are needed for solving the set-covering problem in Equation (2). Note that, to obtain more precise and fine-grained planning, in the following experiments we use cells of side 100 meters while in Section III the results referred to cells of side 200 meters. Furthermore, due to space constraint, in this section we show only results for $C_p = 0$ and $\beta = 0.95$, which is a stringent requirement for parking availability. Note that $C_p = 0$ is equivalent to set as planning objective the minimisation of the number of deployed stations. In the following we analyse in depth the impact of this assumption.

Figure 4 shows the number of deployed stations as a function of the coverage radius. We remind that a coverage radius $R$ means that a customer is willing to walk a maximum distance of $R \times 100\sqrt{2}$ meters to a car sharing station from his/her origin (the same constraint also holds for the destination). Intuitively, results show that a looser coverage constraint leads to a sparser car sharing infrastructure. For instance, by doubling the coverage radius from 2 to 4, the number of deployed stations is more than halved. It is also interesting to observe that car sharing stations are deployed only on a small percentage of the potential cells, i.e., cells for which there are pickup/drop-off events within the coverage $R$. For instance, for $R = 2$ car sharing stations are deployed in less than 9% of the potential cells.

![Fig. 4. Number of deployed car sharing stations versus the coverage radius.](image)

![Fig. 5. Distribution of assigned station capacity.](image)
Figure 5 shows the histogram of the capacity assigned to each station as a function of the coverage radius. Intuitively, a long coverage radius leads to a sparse car sharing infrastructure in which there are stations comprising many parking spaces. On the other hand, when the coverage radius is short there are many more stations in the network and this reduces the need of stations with many parking spaces. It is also interesting to observe that in all considered scenarios the number of small stations (with up to three parking spaces) is large and it ranges from 30% to 45%.

In the following experiments we consider both 3-phase fast charging stations and single-phase slow charging station as specified in [19]. Specifically, among the many charging rates that are allowed we test three 3-phase levels, namely $P_{\text{fast}} \in \{10, 22, 43.5\}$ kW, and two single phase levels, namely $P_{\text{slow}} \in \{3.3, 7.4\}$ kW. Furthermore, we assume that shared cars are ESPRIT vehicles [10], i.e., light-weight quadricycles that are expected to be equipped with a 4KWh battery. Since the energy consumption model of an ESPRIT vehicle is not yet known, as in [7] we take as reference that of a Renault Twizy, a popular quadricycle with a similar battery (6.1kWh). Specifically, when an EV is dropped off at a station after a trip, we compute the energy consumed for the trip as $8.32 \frac{d}{100}$ kWh, where $d$ is the trip distance in kilometres, which corresponds to the average consumption of a Twizy4.

In Figures 7a and 7b we show the average duration of charging periods for a deployment with $R = 2$ and $R = 4$, respectively. As expected, the higher the charging power, the shorter the charging periods. Surprisingly, there is a negligible difference between the average duration of charging periods with and without power sharing for the same maximum charging power. This counterintuitive result can be explained by observing that, according to our battery consumption model, the energy typically requested by a car dropped off at a station is small. Furthermore, as shown in Figure 2, car pickups and drop-offs in a cell are sporadic and the inter-departure time intervals are generally longer than the average charging periods. This means that there are a few opportunities for charging multiplexing at a car sharing station, i.e., multiple vehicles are rarely charged simultaneously at a station. This explains why there is no point in having multiple charging points at the same car sharing station. Clearly, the outcome would change with a more frequent utilisation of the shared chargers, or larger battery consumptions.

B. Results on charging demands

In current station-based electric car sharing systems each parking space is equipped with a charging point. Power sharing could provide a significant reduction in deployment costs by requiring only one charging point per car sharing station, independently of the station capacity. However, in any case the layout of the station infrastructure constrains the recharging process. Generally speaking, the lower the number of car sharing stations, the fewer the charging opportunities. In this section we aim at obtaining a better understanding about the interplay between the infrastructure planning and the spatial and temporal distribution of recharging demands, as well as at quantifying the impact of power sharing.

4We have taken this average consumption from http://www.spritmonitor.de/en/, which is a website where users track the consumption of their cars. For our estimation, we have selected the users with the highest number of reported consumption data.
result because it indicates that charging points are significantly under-utilised and power sharing can be introduced without affecting the quality of the charging process, i.e., without negatively affecting the battery SOC at departure times.

Finally, Figure 9 illustrates the charging demand patterns for a representative day. It is evident the existence of peak and off-peak periods. In particular, main power peaks exist at morning and afternoon times, while night hours are characterised by limited activity. However, the power demands are generally low and easily manageable by the power grid.

In this work, we have investigated the problem of optimal siting and sizing of parking stations in a car sharing system. The key features of our planning methodology are: i) to take into account the stochastic demand of a car sharing system, and ii) to provide probabilistic guarantees on the availability of parking spaces for dropped-off cars. Using a dataset of real pickup and drop-off events from a large free-floating car sharing operator we have validated the effectiveness of our model and solution method. Then, we have investigated the energy demands of an electric car sharing fleet under various deployment scenarios. The most important results of our study is that power sharing technologies can be used without negatively affecting the state-of-charge of departing vehicles and ensuring a significant reduction in infrastructure investments.

As future work, we want to extend our modelling framework to jointly perform the optimal planning of the parking and charging infrastructure. The objective would be to determine where to deploy charging points and which power to allocate them. Furthermore, we intend to complicate the problem formulation to include guarantees on vehicle availability besides guarantees on parking availability. It is worthwhile to mention that it might be impossible to provide stringent vehicle availabilities by simply controlling the deployment of the car sharing infrastructure, thus fleet sizing and relocation strategies should also be considered. Finally, we want to replicate our investigation using car sharing data from other cities.

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