Optimal Charging of Electric Vehicle Fleets for a Car Sharing System with Power Sharing

Elisabetta Biondi, Chiara Boldrini, Raffaele Bruno
Institute for Informatics and Telematics (IIT-CNR), Pisa, Italy
{elisabetta.biondi, chiara.boldrini, raffaele.bruno}@iit.cnr.it

Abstract—Electric car sharing services have been growing in popularity in the last years but operators are striving to reduce the costs of deploying and managing their charging infrastructure. Charging technologies that offer power sharing have the potential to achieve this goal but at the cost of increasing management complexity. In order to address this problem, in this work we propose an efficient optimized charging methodology that minimizes recharging costs when power sharing is used and also takes into account customer satisfaction. To this aim, we formulate the recharging problem as a two-step optimization problem, considering a realistic energy pricing scheme, and we evaluate this solution using real traces of parking times in a French station-based car sharing system. We show that significant cost savings can be achieved without impacting customer satisfaction and also reducing the strain on the grid with respect to a baseline approach.

Index Terms—Charging algorithm, car sharing, power sharing, convex optimization, mobility data sets.

I. INTRODUCTION

Car sharing systems have recently been introduced in many cities across the world, and an important number of them features shared electric vehicles (EVs) [1]. The most widespread form of car sharing service is one-way car sharing. In this case, a shared vehicle may be picked up from and returned to any of the designated stations that are owned and operated by the provider of the car sharing service. Stations have the necessary infrastructure for parking and recharging the vehicles. Note that the number of dedicated parking lots may vary between stations and this determines the station capacity.

The economic viability of car sharing is still an open issue and profit margins tends to be small [2]. Thus, car sharing operators are increasingly looking for more efficient ways to reduce infrastructure and operational costs. In the context of station-based car sharing systems the problem of determining the number and location of the service stations that would minimise infrastructure costs, as well as the minimal fleet size, has clearly received a lot of attention [3]. However, when the infrastructure is already deployed, the recharging policy becomes a key means to ensure cost-effective operations. More specifically, car sharing operators aim at minimising the total energy cost to recharge their electric fleet without affecting the level of service offered (e.g., guaranteeing that a customer arriving at a station will find a vehicle with enough battery to complete the planned trip). It is important to point out that there is an extensive literature on charging scheduling in the case of large populations of stationary EVs, typically to mitigate the negative impact of uncoordinated charging on power systems (e.g. [4], [5]). However, these solutions mainly target residential scenarios and they are not directly applicable to car sharing systems because the mobility patterns of shared vehicles induce frequent asynchronous arrivals and departures to charging facilities. Thus, we need a charging model that can take into account the dynamics in the duration of charging times, as well as the spatial and temporal imbalance of EV charging demands.

Recent advancements in charging and EV technologies, among which power sharing, are promising new and unpredicted opportunities to drastically reduce the cost of the necessary recharging infrastructure in electric car sharing systems. More precisely, power sharing denotes the capability of using one charging station to recharge simultaneously multiple EVs. In general, power sharing can take two different forms. In the simplest case, the same charging station can have many charging ports and be able to distribute the power from a single circuit to multiple EVs [6]. Note that dual-port stations have been recently commercialised that already offer power sharing features\(^1\). Besides this, new classes of stackable lightweight electric cars are being designed that allow to stack, recharge, and drive vehicles in trains. Figure 1 illustrates an example of such stackable cars, which are currently under development within the European Project ESPRIT [7]. Specifically, the mechanical and electrical connection between these two-passenger cars allows charging them in train when parked at the station. This can increase the car-sharing operators’ revenues by reducing the cost of installation (only one charging supply equipment to serve multiple parking spaces), while supporting, due to their small size, the growing demand for charging spots. Despite its many advantages, power sharing introduces the problem of how to optimally distribute energy among the vehicles that are connected to the same charging station. A dynamic load balancing strategy needs to be implemented to allow an efficient transfer of energy between the stacked vehicles.

The objective of this paper is twofold. First, we develop an optimisation framework to recharge the electric fleet of one-way car-sharing systems using power sharing, accounting for both

customers’ preferences and electricity tariffs. More specifically, we formulate a convex programming problem to maximise the profitability for the car sharing operator by trading off the charging costs and the customer disutility, i.e., the dissatisfaction of a customer that collects an EV with a battery level lower than the expected value. In order to reduce the combinatorial complexity, the proposed optimisation strategy decomposes the global optimisation problem in two steps, separating local and network-wide control decisions. To the best of our knowledge, there are no previous studies on recharging strategies that simultaneously consider the dynamic pickup and drop-off of vehicles and the use of power sharing technologies. Second, we validate the efficiency of the proposed charging model using data from a large French car sharing operator. The dataset is composed of all the plug-in and unplug times of approximately 2000 electric cars at 885 stations in Paris and the surrounding area for the whole month of April 2015.

II. RELATED WORK

For a dynamic system in which EVs enter and leave charging stations continually, the related literature is sparse. The works closest to our contribution are [8], [9] (which focus on a network of charging stations) and [10] (which focuses on recharging a fleet of EVs owned by a single entity). In [8], a stochastic model is used for allocating power and rerouting EV in a network of charging stations with the goal of reducing the strain on the power grid. The work in [9] builds upon [8] but solves the problem using a game-theoretic approach. Differently from these works, we take the perspective of a car sharing operator and we move the focus from reducing the strain on the power grid to reducing the energy costs for the car sharing system, assuming that it is the energy provider that implements a pricing scheme that discourages unbearable loads on the power grid. Finally, the work in [10] targets a very similar scenario to the one we consider here (EV fleet with single owner) but it is more oriented towards the modelling aspects and, for this reason, relies on assumptions that are very strong in practice. In particular, in [10] the authors assume a single charging station with an infinite number of plugs and that vehicles do not contend with each other for power. Differently, the contention between EVs is essential to a system with power sharing and the model we propose is able to take this into account.

III. SYSTEM MODEL

We consider a car sharing system that operates a fleet of \( V \) electric vehicles, whose set is denoted by \( V = \{1, 2, \ldots, V\} \), and manages a recharging infrastructure of \( S \) stations, whose set is denoted by \( S = \{1, 2, \ldots, S\} \). Without loss of generality, we use a discrete time model to represent a day. More precisely, each day is divided into \( N \) periods (time slots) of equal duration, indexed by \( n \in \{1, 2, \ldots, N\} \). Let us denote with \( i_n \) the end time of the \( n \)th time slot. Thus, it follows that the \( n \)th time slot, say \( T_n \), corresponds to the time interval \([i_{n-1}, i_n]\). For the purpose of our investigation \( i_0 \) is assumed as 00:00AM. A time slot is the time frame over which recharging optimisation is performed. Finally, we assume that the cost parameters discussed in Section IV-B do not vary within a given \( T_n \).

In this study we take into account the temporal variability of charging duration due to the mobility patterns of EVs. In fact, with power sharing, the power that the charging point can provide has to be divided among all the parked vehicles that need charging, and the set of parked vehicles dynamically changes over time. Let \( t^d_{v,s} \) and \( t^u_{v,s} \) be the time instants at which vehicle \( v \) arrives at and departs from charging station \( s \), respectively. For simplicity, as in [5], we assume that plug-in and unplug times of vehicles are known and modelled using historical information from past equivalent days. We call the interval between \( t^u_{v,s} \) and \( t^d_{v,s} \) the connection time of vehicle \( v \) to the charging infrastructure.

Since vehicles arrive and depart asynchronously, the number of vehicles that are connected to a station during a given time slot is variable (see Figure 2 for an example of the events during a generic time slot). Hence, we can divide each time slot \( T_n \) into \( \omega_s \) subintervals \( \sigma_{s,n}^k \) during which there are no arrivals/departures at station \( s \). For convenience of notation, we denote with \( \Omega_n = \{1, 2, \ldots, \omega_s\} \) the domain of the index \( k \). Now, we can introduce some auxiliary variables that will be useful in the formulation of the optimisation problem. Specifically, for each \( k \in \Omega_n \) it is well defined the set \( \mathcal{W}_{s,n}^k \) of vehicles that are connected to station \( s \) during the \( k \)th subinterval of time slot \( T_n \). Then, the set of vehicles that are connected to station \( s \) during time slot \( T_n \) is simply given by \( \mathcal{W}_{s,n} = \bigcup_{k=1}^{\omega_s} \mathcal{W}_{s,n}^k \).

Finally, we assume that each charging station is equipped with an energy control system (ECS). Each ECS can communicate with a central controller that supervises the recharging procedures in the entire charging infrastructure, as well as with the battery management systems of the connected EVs. Through the ECS, the car sharing operator can control the charging rate of each EV. More precisely, at the beginning of each time slot and for each station \( s \in \mathcal{S} \) the car sharing operator determines the charging vector \( P_{v,s,n,k} \) for each vehicle \( v \in \mathcal{W}_{s,n} \), which is expressed as follows:

\[
P_{v,s,n,k} = \{p_{v,n,s,n,k}\}_k \quad (1)
\]

where \( k \) is such that \( k \in \Omega_n \) and \( v \in \mathcal{W}_{s,n}^k \) and \( p_{v,n,s,n,k} \) is the charging power assigned to vehicle \( v \) for subinterval \( \sigma_{s,n}^k \). In other words, we require that the charging power is maintained constant at least during a subinterval, but it can be adjusted by the car sharing operator at the beginning of each new subinterval.

Now, let \( E_v(t) \) be the state of charge of the battery of vehicle \( v \) at time \( t \) (expressed in kWh). We assume that the car sharing operator wants to ensure that an EV has a default battery level equal to \( E^d \) when unplugged from the charging facility. This target state of charge at departure can be scaled down if, for instance, the cost of energy in a time slot is particularly high.
However, there is a trade-off between saving money and losing customer satisfaction due to vehicles poorly charged, and this is discussed in Section IV-B. Let us ignore for a moment the tolerance on the target state of charge and assume that vehicles should leave the station with charge $E_d$. Focusing on a specific connection time, it is straightforward to derive that the total energy that should be provided to vehicle $v$ when connected to station $s$ is equal to $E_{v,s} = E_d - E_v(t^s_{v,s})$. It is important to point out that vehicle $v$ would receive that amount of energy during the entire connection time with station $s$. Hence, a fraction of the $E_{v,s}$ energy is given by the station $s$ to vehicle $v$ in each time slot of the connection time. More formally, let $E_{v,s,n}$ denote the fraction of the total energy demand that is provided to vehicle $v$ in time slot $T_n$ when connected to station $s$. Then, it holds that:

$$E_{v,s} = \sum_{t=0}^{T_n} E_{v,s,n} \tag{2}$$

assuming that $t^s_{v,s}$ belongs to $T_l$ and $t^d_{v,s}$ belongs to $T_{l+r}$, with $r \geq 0$. How to allocate energy claim $E_{v,s}$ to the time slots in which vehicles $v$ is parked at station $s$ will be discussed in Section IV-A. For further information about the model and a summary of the notation used, please refer to [11].

IV. RECHARGING ALGORITHM

Scheduling the recharging of an EV in a car sharing fleet implies determining the energy claim of the vehicle (i.e., how much it should be charged per time slot, corresponding to $E_{v,s,n}$ in Equation 2) and the charging rate (i.e., what is the charging profile $P_{v,s,n}$ in terms of charging power and length of the charging session). In principle, these two elements could be optimised simultaneously but this would require setting a long temporal horizon for the optimisation problem (because parking times at stations can be longer than a single time slot), which would significantly increase the problem size. To address this issue, in this work we have chosen a two-step optimisation approach. In the first step, we statically allocate vehicles’ energy claims to each time slot in which EVs are parked at stations. Then, in the second step of the algorithm (Section IV-B) we solve the optimisation problem regarding the charging profile, to which individual vehicles’ energy claims are fed as input parameters. With this two-step approach we are able to decouple recharging sessions that take place in different time slots: being able to focus on shorter timeframes simplifies the optimisation as it reduces the dimensions of the problem. Furthermore, the allocation of the energy claims implements a local decision problem that is restricted to individual stations, while a global optimisation problem is solved only to determine the charging profiles that can sustain these energy claims.

A. Step 1: Allocation of energy claims

In this section we present two simple strategies for performing allocation of energy claims.

a) Time Linear Allocation (TLA): TLA is a simple strategy that recharges a vehicle linearly with the connection time. For the sake of example, if the parking time of vehicle $v$ at station $s$ spans 10 minutes, of which 2 minutes in time slot $n$ and 8 minutes in time slot $n+1$, vehicle $v$’s energy claim will be $\frac{2}{10} E_{v,s}$ for the first time slot and $\frac{8}{10} E_{v,s}$ for the second one.

b) Price Linear Allocation (PLA): PLA recharges vehicles in such a way that less energy is claimed in slots where the energy cost is higher. Again assuming that the connection time of vehicle $v$ to station $s$ spans the time slots from $T_l$ to $T_{l+r}$, with $r \geq 0$, this can be summarised as follows:

$$E_{v,s,n} = \frac{1}{\sum_{j=n}^{l+r} \frac{1}{C_j}} [E_d - E_v(i_{n-1})] \tag{3}$$

where $n \in \{l, l+1, \ldots, l+r\}$, $E_v(i_{n-1}) = E_v(t^s_{v,s})$ for $n = l$, and $C_n$ is the cost of energy in time slot $T_n$. For example, if the parking time of vehicle $v$ at station $s$ spans two time slots and the energy cost in the first one is $2\text{€/kWh}$ while the cost in the second one is $4\text{€/kWh}$, vehicle $v$’s energy claim would be $\frac{2}{3} E_{v,s}$ in the first time slot, and $\frac{1}{3} E_{v,s}$ in the second time slot.

Please note that for both TLA and PLA the energy claim for time slot $n+1$ takes into account the actual state of charge at the end of the previous time slot, i.e., $E_v(i_{n-1})$. In fact, it can happen that there is not enough power at the station to satisfy the energy claims of vehicles, hence $E_v(i_{n-1})$ can be smaller than $E_{v,s,n-1} + E_v(i_{n-2})$. With this approach, we can catch up later with recharging in less loaded time slots.

B. Step 2: Minimum-cost recharging

After the completion of Step 1 discussed in Section IV-A, the Energy Control System is able to estimate how much energy should be assigned to vehicle $v$ parked at station $s$ during time slot $n$. However, energy claims do not take into account the fact that other EVs at the same station may be competing for the same energy and that the total power at the station may not be enough for satisfying all requests. In addition, even when the power is sufficient to address all requests, it may not be cost-effective for the car sharing operator to satisfy all of them, due to the possibly high cost of energy in time slot $n$. Then, given all these constraints, what is the best strategy for recharging EVs, or, in other words, how should the car sharing operator set $P_{v,s,n}$ for $T_n$?

In order to address this question, we assume that the car sharing operator formulates the recharging optimisation problem as a multi-objective optimisation. The first objective function for the optimisation model is the total cost of the energy that is bought by the car sharing operator during the $n$th time slot. This cost can be generically denoted as $C_n(P)$, and it may be a function of both time ($n$ in this case) and the total power $P$ used by the system. In this work, we focus on a real-time pricing (RTP) scheme, which is typically used both in practice by electricity providers and as reference in the related literature [10]. In this case, $C_n(P)$ is simply given by $C_{RTP}^n(P) = a_n$, where $a_n \geq 0$ varies with time and is predetermined by the energy retailer the day ahead. Then, the total cost for the energy can be computed as $C_R^{RTP}(P) \cdot P$.

Note that $C_R^{RTP}(P) \cdot P$ is a convex function of $P$. Since we assumed that during a subinterval $\sigma_{n,k}$, the power supplied by station $v$ to its connected vehicles remains constant, we have that the total load at the station in the subinterval is $\sum_{v \in \mathcal{V}_{n,k}} P_{v,s,n,k}$. Summing up these quantities for all the stations we obtain the total load in the system.
The second objective function is the customer disutility, which models the dissatisfaction of the customers that collect an EV with a battery level lower than the expected value (i.e., $E^d$). Since the car sharing operator is interested in minimising its operational costs, it can be willing to tolerate a small penalty cost that is given by the loss of customer satisfaction to save recharging costs. This penalty cost balances the monetary gain of reducing costs, so as to provide a feasible, even if not optimal, solution. With this modification, the objective function needs to include an additional term $\rho \sum_{s, v, n} o_{v, s, n} : E_{v, s, n}$, while the right-hand side of Equation 5 becomes $(1 - \gamma_{v, s, n} - o_{v, s, n}) E_{v, s, n}$.

V. Evaluation

The proposed recharging strategies have been evaluated on historical data of a real-life one-way station-based car sharing system operating in Paris, France.

Dataset: The dataset is composed of all the plug-in and unplug times of ~2600 electric cars at 885 stations in Paris and the surrounding area for the whole month of April 2015. To validate our approach, we select one representative day from this dataset (Wednesday April 1st, 2015), for which we run our recharging algorithm. Note that this dataset was collected with the granularity of 2 minutes. In order to run the TLA and PLA strategies (Section IV-A) we would need to know the initial state of charge $E_v(t^a_{v, s})$ for each connection time. Unfortunately, we do not have the initial state of charge $E_v(t^a_{v, s})$ for each vehicle. To overcome this problem, we have generated plausible movements in the following way: i) at time $t = 0$, all vehicles, both parked at stations and moving, are assigned a unique identifier; ii) when a vehicle leaves a station $s$, it is added to the set $\mathcal{M}$ of vehicles on the move; iii) when a new vehicle enters a station $s$, the identity of this vehicle is chosen among those of the vehicles in set $\mathcal{M}$, considering that plausible matches involve vehicles which would have moved from station $s$ to station $d$ with a speed in the range $[10, 50]$ km/h. Ties are broken choosing uniformly at random among all plausible matches. The selected vehicle is then removed from set $\mathcal{M}$ and assigned to station $d$.

Cost parameters: For the real-time pricing function $C^{RTP}(P) = a_n$, we take the energy costs for April 1st, 2015 from the French day-ahead electricity market. Thus, for each time slot $n$, parameter $a_n$ is taken from the cost in the corresponding time slot. In the following, we assume $T_n = 6$ minutes. The penalty costs are set to one third of cost $a_n$ for each time slot $n$.

Charging points at stations and EVs: In this study we consider 3-phase fast and rapid charging AC stations as specified in [13]. Among the many charging rates that are allowed we test three levels, $P_{s} = 10kW$, $P_{s} = 22kW$ and $P_{s} = 43.5kW$. We assume that vehicles are ESPRIT vehicles [7], light-weight quadricycles that are expected to be equipped with a 4kWh battery level. More formally, we let $C^p_{s, n}$ be the penalty cost that is associated to a unit of missed energy (expressed in terms of €/kWh) at station $s$ during the $n$th time slot.

To simultaneously optimise these two conflicting objectives, we apply a simple scalarisation approach by considering the weighted sum of all objectives. Then, the car sharing operator solves the optimisation problem in Table I to determine the optimal recharging strategy. The decision variables are $p_{v, s, n, k}$, i.e. the power assigned to each vehicle $v$ parked at station $s$ during the $k$th subinterval of the $n$th time slot, and $\gamma_{v, s, n}$, i.e. the fraction of the required energy $E_{v, s, n}$ that it is not provided by station $s$ to vehicle $v$ during the $n$th time slot. Constraint (5) states that the energy supplied to each vehicle connected to a station $s$ in the $n$th time slot should be equal to a fraction $1 - \gamma_{v, s, n}$ of the required energy $E_{v, s, n}$. Constraint (6) restricts the charging rate of station $s$ to be below the maximum power $P^{max}$. Constraint (7) restricts the penalty loss to be less than $\gamma^{max}$. When $C^{\text{ref}}_n = C^{RTP}_n$, the above problem is a linear programming problem that can be solved with very efficient exact methods.

In general, the optimisation in Table I is unfeasible when no charging allocation can be found that satisfies the constraints. For example, this can happen when the total claimed energy at a station is much higher than the energy the station can provide, even after factoring in the tolerance $\gamma$. From the point of view of the car sharing operator, having a reasonable charging allocation even when the optimisation goals cannot be met is crucial to its operations. For this reason, in practice, we use a regularised version of this problem that has always feasible solutions. This is obtained by introducing “phantom” variables $o_{v, s, n}$ (also called elastic in the related literature [12]) that relax the constraints sufficiently to allow the solution of the new problem to be feasible and to be a good configuration for the original problem. More precisely, variables $o_{v, s, n}$ are used to represent unsatisfied claims, i.e., energy that could not be provided to an EV because the energy budget of the station was exhausted. The weight (cost), say $\rho$, associated to these variables is sufficiently large to ensure that they are only selected if the original problem is unfeasible.
battery. Vehicles are not recharged beyond a 90% state of charge (SOC). Since we avoid charging at high SOC (above 90%) and low SOC (below 10%) we can assume that the recharged energy is a linear function of the charging rate. The consumption of an ESPRIT vehicle is not yet known, thus 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, which corresponds to the average consumption of a Twizy$^4$.

Recharging strategies and benchmark: Since, to the best of our knowledge, no recharging strategy for car sharing systems with power sharing has been yet proposed in the literature, we compare our optimised recharging strategies against a greedy strategy in which the available power of a station is simply divided among the parked EVs that need recharging. This corresponds to what happens in real car sharing systems with no central energy controller. Against this benchmark we evaluate the proposed strategies, which we denote as PLA-RTP (price-linear allocation with real-time pricing) and TLA-RTP (time-linear allocation with real-time pricing) respectively. We test these strategies considering both the version with zero penalty for customer satisfaction (denoted with suffix P0) and with penalty $\gamma^{max} = 0.3$.

Metrics: We evaluate our recharging strategies from three perspectives, that of the car sharing operator that wants to minimise its costs, that of the customers of the car sharing service that want to complete their trips without running out of battery, and finally that of the energy provider. Thus, for each recharging strategy, we show the total daily costs, the SOC when vehicles arrive at stations (thus, before recharging) and the SOC after vehicles leave stations (after recharging). For both the benchmark and the proposed optimised strategies, the total cost is computed multiplying the energy consumed in each time slot by the cost of energy in that time slot, and then adding up these costs over the whole day. The energy provider perspective is studied taking into account the power consumption over the day, the peak load (maximum power supplied to the system), and the load factor (defined as the ratio between the average load and the peak load) [14].

For a summary of the above settings, please refer to [11].

A. Results

We start off with the car sharing operator perspective and in Figure 3 we plot the total cost paid by the car sharing operator during one typical day of fleet operation. We observe that, while the proposed optimised strategies are all pretty much equivalent from the cost standpoint, they offer a reduction when compared to the costs of the benchmark strategy. Specifically, the car sharing operator can save up to approximately 10%. It is important to point out that we have analysed a worst-case scenario from the perspective of cost savings because real-time pricing electricity tariffs are not dependent on the load (which is much smaller with the proposed strategies, see Figure 6, than with the benchmark) and they vary slowly when compared to EV mobility. Thus, it is expected that more significant cost savings are possible with load-dependent electricity prices, but this is left as future work. Two other interesting observations can be derived from Figure 3. The first one is that the maximum charging rate has a negligible impact on the total cost. As better explained in the following, this is mainly due to the fact that EVs dropped off at a station typically require a small energy to be recharged (less than 1.2kWh on average). Thus, using very high charging rates is not needed in most cases. The second observation is that the introduction of the penalty does not significantly alter the cost savings with respect to the case without penalty, with savings being in the order of 1% – 2% with a penalty of 0.3 (i.e., the car can be given up to approximately one third less than the required energy for reaching a 90% SOC). This can be due to the fact that a feasible solution to the optimisation problem is not always found (the problem exploits the elastic variables that we have discussed in Section IV-B), thus requests are capped anyway, regardless of the penalty.

We measure the Quality of Service perceived by the user in terms of SOC of vehicles. The rationale for this choice is that the user does not care for the specific recharging strategy implemented by the car sharing operator, as long as it does not affect his/her trips. Thus, we assume that the proposed optimised strategies are safe to be adopted if the energy provided to vehicles is enough for them not to be forced to interrupt a trip because they have run out of battery. Figure 4 confirms that this is the case: no vehicle arrives at a station with SOC smaller than 10%, and in general the vast majority of vehicles are dropped off with a SOC between 70% and 80%. To complete this analysis, we also plot the SOC of vehicles when they are picked up by users (Figure 5). We observe that with the greedy benchmark strategy, vehicles are fully recharged when they leave the station, while with the proposed optimised strategies the SOC at departure is above 60% for more than 90% of vehicles. The fact that vehicles are not always fully recharged does not affect user trips, and this shows that the proposed strategies are able to strike a trade-off between saving money and providing a satisfying experience to the users of the car sharing system. Please note that in Figures 4-5 we have omitted the TLA-RTP strategy for the sake of readability, since its SOC distribution was substantially matching that of the PLA-RTP strategy.

Finally, we take the perspective of the energy provider and we study which strategy is to be preferred based on how it impacts the energy grid. To this end we plot the instantaneous power supplied to the system (Figure 6) and the load factor (Figure 7). From Figure 6 (please note the different scales for the y-axis
under the H2020 ESPRIT (653395) project. This work was partially funded by the European Commission to handle loads and higher load factors than a simple greedy approach. The results shown demonstrate that not only our proposed strategies reduce the strain on the energy grid with respect to the benchmark. In addition, please note that this performance is a side-effect of our formulation, since, as we have discussed before, we had not included the power grid perspective directly into the optimisation problem.

VI. CONCLUSIONS
In this study we have considered the problem of minimising the recharging cost of the electric fleet of one-way car-sharing systems using power sharing. To cope with the problem complexity, we have formulated a two-step optimisation framework that separately assigns EVs’ energy claims to each time slot and the charging profiles for each station. We have tested the proposed solution using a real-life trace of pickup and drop-off events at the stations of a large car sharing operator in Paris. The results shown demonstrate that not only our proposed strategies reduce the costs for the car sharing operator without affecting the quality of service perceived by the users, but also provide smaller peak loads and higher load factors than a simple greedy approach.

ACKNOWLEDGMENT
This work was partially funded by the European Commission under the H2020 ESPRIT (653395) project.

REFERENCES