Modeling Joint Charging and Parking Choices of Electric Vehicle Drivers: A Decentralized Control Approach for the Charging Service Provider

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ABSTRACT

Electric vehicles (EVs) offer significant opportunities to improve the sustainability of the road transport sector. But at the same time, the widespread adoption of EVs would create new challenges. For example, the spatio-temporal concentration of charging events in a high density residential or commercial area would place extreme demands on the power network, causing bottlenecks and grid instability.

This paper presents a novel approach to the typical decentralized control methods for EV aggregators or charging service providers. First, static price signals based on the anticipated demand define a set of “charging offers” that will be targeted to different segments of EV users. Prices are differentiated either only by time or both by time and place, thus allowing the comparison and the evaluation of both scenarios. Then a choice-based revenue management method is employed, in order to optimize the allocation of the generated “charging offers”, with respect to the revenue outcome for the charging service provider.

The charging coordination techniques are demonstrated through simulation. The data comes from the London Travel Demand Survey (LTDS) and particularly the trips around the Westfield shopping centre, one of the largest urban shopping malls in Europe, in order to represent out-of-home charging behavior for short intervals in a high-demand area. The findings suggest that in a first-come, first-served system, locational pricing might create opportunities both for increased revenue and relocation of charging events to less congested facilities. In the revenue management system, locational pricing favors significantly the total revenue outcome but without discharging vulnerable areas. However, since there are several agents with conflicting interests participating in the process (infrastructure owners, power system operator, EV drivers), there is the opportunity for the charging service provider to adapt the constraints according to the priority of his objectives.

Keywords: Electric vehicles, Revenue Management, Decentralized control, Charging service provider
1. INTRODUCTION

Road transport is one of the main contributors in greenhouse gas emissions (26% of the total emissions in the EU) and especially in CO$_2$ and CH$_4$ (1). The electrification of mobility can contribute to the decarbonisation of the transport sector, but to achieve massive commercialization there is a need for adequate recharging infrastructure. EV adoption is also associated with the ability to develop strategies to tackle “range anxiety” and reduce the drivers’ uncertainty regarding the new technology. Investment in public charging infrastructure and application of new business models to facilitate out-of-home recharging could play a major role in extending electric driving range.

On the other hand, the net benefit of EV use depends on the electricity generation mix at the time of recharging. Clusters of vehicles with similar spatio-temporal demand for electricity may introduce an additional burden to the power grid, especially at the distribution level (2). The demand for “clean electricity” can be achieved through the bundling of electric mobility and renewable energy in a smart grid environment with distributed generation and integrated communication technologies. In this context there is a need for a smart management system to coordinate charging demand and consumption from residential power resources.

The digitalization of the grid creates new opportunities for customer-centric management of EV charging demand. The provision of tailored electricity services to specific customer segments based on their energy consumption patterns (3) would help the energy suppliers and distribution network operators to manage demand in a sustainable way and at the same time to encourage behavioural shifts when they are needed.

In this paper, an integrated framework is introduced where transport and power agents co-exist and a decentralized control is applied that is reinforced by the explicit modeling of joint parking and charging preferences of EV drivers. Understanding and predicting charging behaviour for EVs would help the operator to apply customer-oriented services, successfully implemented in other service industries like airlines, hotels and car rental companies. The services offered to the users are a combination of certain charging characteristics and consume resources in two dimensions: a) the charging post (or in other words the parking space) where the vehicle plugs-in and b) the electricity drawn from the power network to the EV battery.

The paper is structured as follows. Section 2 presents the background and the conceptual framework for the implementation of decentralized control. The data along with the developed models and the simulation steps are described in Section 3, followed by a discussion of the findings in Section 4. Finally, Section 5 concludes the paper with a discussion on the implications of these findings and the areas of interest for further research.
2. BACKGROUND

EV recharging infrastructure can be characterized by its availability, its location (home, workplace, on-street etc.) and the delivered charging speed (4). In order to understand charging behavior, another important attribute is the “recharge potential”, i.e. the spatio-temporal correspondence between a parked vehicle and a charging outlet, which in (5) was found to peak between 12am and 6am and to reach a minimum from 10am to 4pm. Therefore, overnight home dwelling periods are expected to be the most prevalent and cost effective occasions to recharge electric vehicles.

Nevertheless out-of-home charging can play a very important role in alleviating range anxiety and in accommodating drivers that do not have a home recharge potential (e.g. in London, two thirds of the households do not have access to off-street parking (6)). The demand for out-of-home electricity for EVs can vary with the place and the nature of the activity. For example, regular parking stays in workplace locations are likely to be interrelated with extended, low-speed charging events whereas, occasional shopping trips are more suitable for brief and high-speed charging events. As a result charging speed would be inversely related to parking durations. However, drivers with typical daily patterns and home recharge potential could demonstrate a different behavior if they regularly top-off their vehicle’s battery at out-of-home locations, maintaining a high State of Charge (SOC) and avoiding high-speed and power intensive charging events.

Coordination of plugged-in EVs is a challenging task for public or private parking operators and for all types of facilities that provide parking places (e.g. park and ride stations, shopping malls etc.). Lack of familiarity with the new technology can complicate the management of charging infrastructure by parking operators, resulting in the emergence of an intermediate agent who would be contracted to carry out this task. In (7) the authors indicate this potential agent as an EV supplier-aggregator (EVSA) who sells electricity in various locations and is responsible for the aggregation. On the other hand, the parking operator can act as a Charging Point Manager (CPM), who, although an end user of electricity can make an agreement to resell it to third parties.

Taking into account some of the existing agents in the electricity market like the Distribution System Operator (DSO) who is responsible for the operation of the grid at a local level and the suppliers who sell the electricity to end users, the new EV-related agents will increase the complexity concerning the stakeholders’ responsibility (and authorization) to provide charging services. In privately owned parking facilities, the CPM or the aggregator should be responsible for the operation, while for on-street public places it would probably be an extra task for the DSO.

The aggregator or Charging Service Provider (CSP), functions as a bridge between electricity market players and individual EVs (8). Nevertheless, out-of-home recharging would require this agent to play an additional role, that of a revenue optimizer for the collaborating parking facilities.

Typically an aggregator has two options when implementing demand-side management: a) Centralized control: Plugged-in vehicles transmit information about their parking duration and their energy demand and there is a central entity that decides how to optimally allocate the available energy resources and b) Decentralized control: the provider announces the spatio-temporal distribution of electricity price so that the individual vehicle responses will lead to an optimal allocation. As a result, centralized control reaches an optimal solution but at a high
When the purpose of decentralized control for EVs is to optimize the operation of the local distribution network and to avoid congestion and overloads of local substations, then there is an important interrelationship with the spatial distribution of demand. Locational differentiation of electricity tariffs would reduce the distributional network investments at the first place and then it would allow behavioural changes and steering system participants to low energy demand areas (10). In practice locational pricing is applied in a nodal level (transmission grid level) and this is known as Locational Marginal Pricing (LMP) but there is not a lot of differentiation in the distributional level mainly because of the “deep” connection charges required to send the locational signal (11).

In the present study, charging coordination from the CSP is modelled with a novel technique based on the theory of revenue management (RM). RM methods have first made their appearance after the deregulation of the airline industry in the 1970s and their main concept was to sell the right product (e.g. economy or business tickets) to the right customer at the right price and time. The two possible ways of treating RM problems are a) quantity-based and b) price-based (12). The objective of a quantitative-based solution is to optimally allocate the available inventory by accepting or rejecting incoming reservations.

The advantage of using revenue management for EV fleet aggregation is that it allows the explicit modeling of recharging demand by incorporating discrete choice models in what is widely known

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**FIGURE 1:** CSP responsibilities and interactions with third parties.

The advantage of using revenue management for EV fleet aggregation is that it allows the explicit modeling of recharging demand by incorporating discrete choice models in what is widely known
as choice-based RM (13). EV driver’s response to different incentives is quite significant for the timing and locational decisions and the resulting choice-based network capacity allocation model (14) can demonstrate that there is a demand side to the problem apart from the supply side and the service appeal to the user should be taken into account. The CSP has a range of responsibilities (Figure 1) and in a previous study (14) we have performed a sensitivity analysis to understand the effect of initial capacity allocation in the revenue outcome as well as a sensitivity analysis in the choice parameters to identify the propagation of user preferences in the final result.

In this paper, the focus is on the dynamic operation area defined by three stakeholders: the EV drivers, the parking facilities and the DSO. Two initial vectors of prices are defined for the various services (“charging offers”) that the provider can deliver: one that is differentiated only in time and one that is differentiated in both time and location. The CSP must predict the future charging behavior of EVs and use this predicted demand to negotiate the power capacity with the DSO in advance, having in mind that any imbalance (higher or lower demand than anticipated) will have a certain cost. Then he optimally allocates the negotiated power to the contracted facilities, in order to optimize the revenue for the system as a whole.

Both levels of control can be classified as decentralized approaches because instead of enforcing a charging regime they give incentives to the drivers (price in the first case and service restrictions in the second) to move towards the optimal direction. Therefore they can be integrated with the behavioral aspect of the problem and help in the design of a customer-centric system. In the following section, the properties of the suggested framework will be explored via a simulation study for a commercial area of central London.

3. METHODS AND APPLICATION

3.1 Data and Simulation area

The data that we use for our simulation comes from the London Travel Demand Survey (LTDS) which is a household survey carried out by Transport for London since 2005 (15). LTDS provides information on the travel behavior and daily activities of people living in London, collected via a one day travel day diary with linked personal and household questionnaires. To analyse out-of-home charging choices and identify operational implications we have selected the wider area around the Westfield Shopping Centre in the White City district of London which attracts a significant amount of shopping and leisure activities (approximately 63,000 visitors per day in its first year of operation (16).

We select only non-walking trips that have their end in this area after 17:00, with a minimum of 30 mins and a maximum of 4-hours duration for the upcoming activity. We exclude activities that extend after 21:00 and are not shopping or leisure oriented. After the data processing stage, the remaining number of activities comes down to 78, and since the sample is small percentage of the population they can all be assumed as plug-in events for EVs and hence charging opportunities. It is considered that there are two parking locations with charging post availability where drivers could top-off their battery (Figure 2). Therefore trip ends located in the western zone could be directed to the west parking facility (700m from Westfield) whereas trip ends located in the eastern zone could be directed to the eastern parking facility (130m from Westfield).
The driving distance before the shopping/entertainment activity is calculated along with the remaining distance until the last trip back home. The amount of energy in kWh that is required to achieve this distance is estimated based on the electric fuel economy of one of the most competitive fully electric vehicles in the market, the Nissan Leaf. According to the U.S. Environmental Protection Agency (17), the 2013 model consumes electricity at 29kWh/100 miles (combined city and highway driving) which for a 24kWh battery capacity gives a range of 83 miles. The charging quantity is divided by the efficiency of the equipment (approximately 80%) and proportionally enlarged to reflect a higher need for out-of-home services and a lower home recharge potential.

The charging rate for the EVs is calculated based on their parking duration and the estimated energy quantity. Then, the distribution of power demand and parking place demand is used as a guideline for the strategic allocation of power network capacity. According to the data, the eastern facility has a significantly higher demand than the western one and the 19:00-21:00 is the peak hour period in both areas.

However, apart from the strategic allocation, the CSP needs to dynamically operate the charging infrastructure for these two parking facilities, predicting the incoming demand and maximizing the aggregated revenue. Moreover, there is a need for cooperation with the DSO, in order to minimize the imbalance level between the contracted power and the actual power distributed to the EV charging events. As a result the higher the level of remaining ‘unsold’ power the higher the cost for the CSP especially in peak periods.
First we describe the service bundles or “charging offers” that can be delivered by the CSP and the choice model under which the drivers make their selections. This choice model is applied in two contexts: a) a first-come, first-served scheduling scenario, where the arriving parking events are allocated sequentially and b) a revenue management model, where the heterogeneity in the rate of arrivals at the reservation system is simulated based on the initial distribution. For both cases there is a comparison between a non-locational pricing (NLP) system where similar charging offers have the same price at both parking locations and a locational pricing (LP) system where there is an incentive for the customers to charge their vehicle in the non-congested area.

3.2 First-Come, First-Served Scheduling (FCFS)

The charging events are first restricted to multiples of one-hour slots (e.g. 1, 2, 3 or 4 hours). The provider can then make available a certain range of “charging offers” for the different segments of customers. The discrete charging rates are: A=3kW, B=6kW, C=8kW and D=12kW, therefore rapid DC infrastructure is not included in the analysis. Combining the four charging rates with the hourly time slots and the two different parking facilities the provider has a complete offer set of 72 “charging offers” (e.g. [6kW,18:00-20:00, West parking facility] could be a possible option for an arriving driver).

Then, in order to tailor the services to the users, the CSP needs to follow a segmentation strategy. The first level of segmentation is quantity-based and it is the following: 1) Less than 6kWh, 2) Less than 12 kWh, 3) less than 18kWh and 4) up to 24 kWh. As it is anticipated, the segments that need a low quantity of electricity for charging their EVs are considerably larger than the large-quantity segments. The second level of segmentation is based on the time-availability at the parking facility and it is defined by the arrival and departure times of the EVs.

Finally, the third and most important level of segmentation is the heterogeneity in preferences of the arriving customers. In the applied choice model of EV charging, when the EV driver is presented with alternative charging offers the parameters that affects his final choice are: 1) the price of the charging offer, which is a function of the charging speed, the duration of the charging event and the time-of-day that it takes place (and the location in the scenario with locational pricing), 2) the walking distance from the parking facility to the final destination and 3) the willingness to modify the daily schedule to fit with the starting and ending time of the charging offer. The last parameter is following the logic of schedule delay (i.e. the difference between a desired time of arrival or departure and the actual time and the disutility associated with that difference. This can be either Schedule Delay Early (SDE) or Schedule Delay Late (SDL). However in the context these terms can be transformed in the Charging Delay Early (CDE) and Charging Delay Late (CDL), or in other words, the difference between the preferred arrival or departure time and the time that the driver has to reach the parking location in order to be able to buy his preferred charging option.

Combining the above parameters the utility that a segment $\ell$ of the EV drivers derives from consuming one of the charging offers $j$ is:

$$U^\ell_j = ASC_j + b^\ell_p p_j + b^\ell_{WD} WD_j + b^\ell_{CDE} CDE_j + b^\ell_{CDL} CDL_j$$

(1)

where
\[ p_j: \text{the price of charging offer } j \text{ (in £)} \]

\[ WD_j: \text{the walking distance from the parking facility that charging offered } j \text{ is provided to the final destination (in m)} \]

\[ CDE_j: \text{max } (0, \text{segment } l \text{ arrival time – charging offer } j \text{ charging start time}) \text{ (in hours)} \]

\[ CDL_j: \text{max } (0, \text{charging offer } j \text{ stop time – segment } l \text{ departure time}) \text{ (in hours)} \]

\[ b_\ell', b_{WD'}, b_{CDE'}, b_{CDL'}: \text{are the segment specific parameters for the respective variables} \]

\[ ASC_j: \text{is the alternative specific constant of charging offer } j. \]

The segment specific parameters are currently being estimated by the research team using a stated preference survey specifically designed for EV drivers, however in this study these parameters are approximated by existing estimates from previous studies in the broader parking choice modeling literature. As a result, the price parameter is fluctuating in the range of [-1.1, 0.1] and the walking distance parameter is derived from the egress time estimates and it is fluctuating in the range of [-0.3, -0.08] \((19)\). The \(b_{CDE}\) and \(b_{CDL}\) parameters are assumed to be in the same range with SDE and SDL estimates and for simplification they are distributed in the same range [-0.55, -0.05] even though usually there are dissimilarities between the two \((20)\). Another assumption made at this point is that the decision is unaffected by the urgency of the desired refill. In our survey we present the respondents with different “battery level” scenarios when they arrive at the charging facility in order to control for this aspect of the choice situation.

Considering two levels of sensitivity for each of the parameters that define the final choice of the EV driver, 8 segments have been constructed with mixed preferences for the charging offer attributes (e.g. segment 1: price [-1.1], walking distance [-0.3], Charging delay [-0.55] - segment 2: price [0.1], walking distance [-0.3], charging delay [-0.55] etc.). Combining these 8 groups with the other levels of segmentation (4 energy quantities and 7 dwelling periods) and excluding the unfeasible cases (e.g. charging up to 24kWh in an hour) we come up with a total of 160 customer segments. Each segment has a consideration set \(C_l\) which is a subset of the total set of charging offers \(J\) provided by the operator. These consideration sets are allowed to overlap between two different segments \((C_l \cap C_{l'}, \neq 0 \text{ for } l \neq l')\). Nevertheless, when an EV driver makes a choice, this choice is not affected by offers out of his consideration set. The probability of choosing the offer \(j\) is denoted as \(P^\ell_j\) and it is calculated with the Multinomial Logit model (MNL) as follows:

\[ P^\ell_j = \frac{e^{U^\ell_j}}{\sum_{k \in C_\ell} e^{U^\ell_k} + e^{U^\ell_0}} \quad (2) \]

where \(U^\ell_0\) is the utility that a segment- \(\ell\) driver obtains from not buying any of the charging offers.

In the simulation EV drivers arrive sequentially and then they have to make a choice between the charging offers in the two different facilities. If their preferred charging rate, time and location are available this offer is allocated to them. The preferred charging offer is the one with the higher probability among all the offers in the segment’s consideration set. If it is not available, they are evaluating two extra charging opportunities, randomly drawn based on the probability distribution of the offers in their consideration set. If all of these options are not available then the driver is considered as a non-allocated event and we have the arrival of the next driver. If at any of these three choice situations the utility from buying nothing is higher than for the other offers, then the driver leaves the system and is considered as a non-buying event. Finally when a charging event is
allocated, the CSP has to remove from his resources one charging post and a power level corresponding to the speed of the charging offer that has been sold. The simulation process is depicted in the flow diagram below (Figure 3).

![Flow Diagram of FCFS system.](image)

**FIGURE 3: Flow Diagram of FCFS system.**

The prices for the NLP and LP scenarios are respectively:

\[
P_{j,NLP} = bp \times RF_j \times TF_j \times CD_j
\]

\[
P_{j,LP} = bp \times RF_j \times TF_j \times AF_j \times CD_j
\]

- **P\(_{j,NLP}\)**: the price of the charging offer j in the non-locational pricing scenario
- **P\(_{j,LP}\)**: the price of the charging offer j in the locational pricing scenario
- **bp**: the base price of electricity (we assume that it is 10p/kWh)
- **RF\(_j\)**: the rate factor of charging offer j (high speed charging offers are penalized with a higher factor)
- **TF\(_j\)**: the time factor of charging offer j (charging offers that take place in peak-hours are penalized with higher factors)
- **AF\(_j\)**: the area factor of charging offer j (charging offers that take place in the east parking facility are penalized with higher factor only in the LP scenario)
- **CD\(_j\)**: the duration of the charging offer j (in hours)

The maximum price is presumed to be 55p/kWh, when there is a combination of peak-hour, high-speed and in the LP case high spatial demand, therefore the product of the factors is constrained to be below 5.5. Their values are derived from the normalized difference between the respective expected demands.
The revenue generated from each allocated EV driver is a function of the respective price of the charging offer that he buys. However, the provider must take into consideration the balancing between demand and the supply that is a result of negotiation in advance with the DSO. Therefore, each power unit that is not sold must be paid back to the DSO, multiplied by the imbalance factor, which depends on the level of demand at this period and, hence, in the simulation process it is assumed to be equal to the time factor. The net revenue generated from the CSP is the difference between the revenue from selling the charging offers and the imbalance costs.

### 3.3 Capacity allocation with Revenue Management

In a different simulation setting, the charging demand is optimized through a reservation system and a quantity-based revenue management method. The simulated demand now starts to arrive 24 hours before the start of the operation time but not in a sequential basis. Therefore a request for a 19:00-20:00 charging slot might arrive earlier than a request for a 15:00-17:00 charging slot. The arrival rates are synthesized so that the final distribution of customer segments is the same as the FCFS simulation.

The booking horizon is considered discrete and consists of \(T\) steps, indexed by \(t\). The reservation system opens at \(t=T\) and closes at \(t=0\) when the CSP starts operating and the reservations for next day are made available. It is a usual convention to assume that the time steps are discretized in such a way that the probability of more than one EV driver arriving at each step is negligible. The total set of network resources is \(m = m_1 + m_2\) (indexed by \(i\)) where \(m_1\) and \(m_2\) are the charging posts available in the west parking facility and in the east parking facility respectively. The CSP delivers \(n\) final charging offers (indexed by \(j\)) each of which consumes a set of the network resources and generates revenue equal to \(r_j\).

We use \(a_{ij}\) to indicate when a product \(j\) uses resource \(i\) (\(a_{ij} = 1\)) and when not (\(a_{ij} = 0\)). The set of all possible \(a_{ij}\) is represented by the charging post incidence matrix \(A\). Likewise we have the power incidence matrix \(B\). Each element \(b_{ij}\) of this matrix indicates the power in KW utilized, when charging offer \(j\) consumes resource \(i\) (\(b_{ij} = a_{ij}PW_j\)) where \(PW_j\) is the charging rate of this offer. The problem has two capacity dimensions that vary for each resource \(i\) and each time step \(t\): the number of available plug-in places \(x_{i,t}\) and the available power \(y_{i,t}\). In a vector form the two capacities are \(\vec{x}_t\) and \(\vec{y}_t\) with the initial capacity at the beginning of the booking horizon being \{\(\vec{x}_T, \vec{y}_T\}\).

The probability of a reservation arrival from each customer segment \(\ell\) at each step is \(\lambda_{\ell}\). We assume that \(\lambda_{\ell}\) and the segment mix are homogenous throughout the booking horizon. For each step \(t\), the CSP provides a subset \(S\) of his charging offers called the offer set. The decision variable of the optimization problem is which subset \(S\) should be made available at each time step so that revenue is maximised. A segment-\(\ell\) choice probability for a charging offer \(j\) is not affected by offers outside of the customer’s consideration set, even if they belong to \(S\). Therefore we have the probability vector \(\vec{P}_\ell(S) = \vec{P}_\ell(S_\ell)\) where \(S_\ell\) is the intersection of the offer and the consideration set. If we denote \(\vec{R}_\ell(S_\ell)\) the expected revenue generated from a segment-\(\ell\) reservation arrival we have:

\[
\vec{R}_\ell(S_\ell) = \sum_{j \in S_\ell} r_j P_j^\ell(S_\ell) \tag{5}
\]
In addition if $\bar{Q}^{x,l}(S)$ and $\bar{Q}^{y,l}(S)$ are the conditional probabilities of using a charging post on resource $i$ and a unit of power capacity on resource $i$ respectively, we have:

$$\begin{align*}
\bar{Q}^{x,l}(S) &= A \bar{p}^l(S) \\
\bar{Q}^{y,l}(S) &= B \bar{p}^l(S)
\end{align*}$$

The heuristic employed is called segment-based deterministic concave program (SDCP) (20, 21) and it is a widely adopted relaxation of the choice-based deterministic linear program (CDLP). Instead of sequentially solving for the expected revenue to go until the end of the reservation period for a dynamically changing network state, the decision variable in CDLP is $\tau(S)$: the number of steps throughout the reservation period that subset $S$ must be offered by the CSP. Since this is a deterministic approach to the original stochastic problem, this model provides an upper value approximation of the optimal revenue. CDLP is usually solved with column generation and it becomes NP-hard for overlapping consideration sets even for the MNL because it has an exponential number of columns (22). On the other hand, with SDCP, by implementing the column generation algorithm within each separate customer segment and optimizing for the respective decision variables $\tau(S)$, we can reduce computational time significantly and it is suitable for applications with generalized discrete choice models. The formulation of SDCP is:

$$\begin{align}
\nu^{SDCP} &= \max \sum_{\ell} \lambda_{\ell} \sum_{S_{\ell} \in C_{\ell}} R^\ell(S_{\ell}) \tau_{\ell}(S_{\ell}) \\
s.t. \quad & \sum_{\ell} \lambda_{\ell} \sum_{S_{\ell} \in C_{\ell}} \bar{Q}^{x,l}(S_{\ell}) \tau_{\ell}(S_{\ell}) \leq \bar{x}_T \\
& \sum_{\ell} \lambda_{\ell} \sum_{S_{\ell} \in C_{\ell}} \bar{Q}^{y,l}(S_{\ell}) \tau_{\ell}(S_{\ell}) \leq \bar{y}_T \\
& \sum_{S_{\ell} \in C_{\ell}} \tau_{\ell}(S_{\ell}) \leq \lambda_{\ell} T, \quad \text{for all } \ell \\
& \tau_{\ell}(S_{\ell}) \geq 0, \quad \forall S_{\ell} \subseteq C_{\ell}
\end{align}$$

The optimal revenue in this formulation is the expected revenue generated when offering subset $S_{\ell}$ times the number of times this subset is offered, summed across all the possible subsets that now can be enumerated and the various customer segments. The first two constraints are the capacity constraints. The meaning of the third constraint is that the number of times a subset is provided to a specific segment should be at most equal to the number of arrivals from this segment. Finally the decision variable should be always greater or equal to zero.

The tailored services offered by the CSP, the behavioural model, the price factors and the calculation of imbalance cost are the same with the FCFS simulation. In the following section the findings from the two approaches are presented.

4. FINDINGS

The results from the simulations are evaluated based on the following metrics:

- The revenue generated from the allocated charging events
- The lost revenue opportunity from the non-allocated charging events
- The load factors of the system
- The imbalance cost from the remaining ‘unsold’ power

For both simulations, we perform a comparison of NLP and LP scenarios and identify the potential benefits of the second approach. In Figure 4 it can be seen that moving from NLP (a) to LP (b), the remaining ‘unsold’ power is higher for the east parking facility and lower for the west parking facility. This is due to the fact that there is an incentive for people to charge in the non-congested area and there are some displacements of charging events there. This is also observable in the power load graphs, where the consumption in kWs remains relatively stable for the system in total, but the level of consumption is almost equalized between 0.85 and 0.88 for the two facilities.

The revenue outcomes of the two strategies can be better explained through table 1. In the NLP scenario the CSP generates a total of 92.3 with the higher proportion originating from the facility close to Westfield with the higher demand. The same applies for the lost revenue opportunity, because the drivers that could not be allocated to a charging post, probably because their preference was for a higher charging duration, including the depleted resources in earlier periods, would be more for the high-demand facility. On the other hand the imbalance costs that must be paid back to the DSO are dependent on the aggregated electricity demand at this period. Therefore unexploited capacity in peak hours would induce a higher unit cost for the CSP. After subtracting the estimated imbalance costs the CSP generates £83.7 revenue for the two parking facilities.

FIGURE 4: System load factor and remaining power for the time of operation (FCFS) for non-locational pricing and locational pricing.
Implementing LP and promoting charging events in the less-congested area, both revenue and imbalance costs are increasing for the east parking facility, because allocated EVs pay more for the same service, whereas the ones that change their decision reduce the load factor in this location. However combining costs and benefits, the total revenue generated is higher for the specific facility. On the other hand, both revenues and imbalance costs are decreasing for the west facility, with the net effect being negative in this case. In total, the LP strategy presents a 22% increase in total revenue but in a more disaggregate level, it is decomposed in a 17% loss for the west parking facility compared to a 27% gain for the east parking facility. Therefore, when the objective of the CSP is revenue maximization for the wider area, this might have contradictory effects for the various agents. However the application of marginal prices based on the prediction for the spatial distribution of EVs is shown to relieve the congested area, and the provider can use the re-distributed demand in his negotiation with the DSO, avoiding the imbalance costs from the unutilized capacity.

**TABLE 1 Disaggregated revenues and costs (FCFS) for non-locational pricing and locational pricing**

<table>
<thead>
<tr>
<th>Parking Location</th>
<th>East Parking Facility</th>
<th>West Parking Facility</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hour starting at:</td>
<td>17:00</td>
<td>18:00</td>
<td>19:00</td>
</tr>
<tr>
<td>NLP Revenue (in £)</td>
<td>4.6</td>
<td>13.8</td>
<td>31.3</td>
</tr>
<tr>
<td>NLP Lost Revenue (in £)</td>
<td>9.2</td>
<td>12.5</td>
<td>8.8</td>
</tr>
<tr>
<td>NLP Imbalance costs (in £)</td>
<td>0.02</td>
<td>0.27</td>
<td>1.94</td>
</tr>
<tr>
<td>NLP Total (Revenue – Imbalance Cost)</td>
<td>4.6</td>
<td>13.5</td>
<td>29.4</td>
</tr>
<tr>
<td>LP Revenue (in £)</td>
<td>6.2</td>
<td>18.0</td>
<td>42.5</td>
</tr>
<tr>
<td>LP Lost Revenue (in £)</td>
<td>10.6</td>
<td>15.6</td>
<td>7.7</td>
</tr>
<tr>
<td>LP Imbalance costs (in £)</td>
<td>0.033</td>
<td>0.29</td>
<td>3.41</td>
</tr>
<tr>
<td>LP Total (Revenue – Imbalance Cost)</td>
<td>6.2</td>
<td>17.7</td>
<td>39.1</td>
</tr>
</tbody>
</table>

Adding a second level of control with the integration of the revenue management system, we observe a different system response (Table 2). First, the initial level of power capacity has been increased for this simulation because the optimization algorithm was allocating all available kWs to the arriving EVs and did not allow a performance-comparison between the NLP and the LP scenarios. If we consider that NLP is the base-case, then LP leads to an increase of 21% in the total revenue generated by decreasing the power load factor in the west parking facility and increasing it in the east one. This model behavior is opposite to what we want to achieve with LP but it is normal
because the RM’s objective is to maximize revenue by limiting the availability of cheaper “charging offers” i.e. the ones in the low-demand parking facility.

Reversing the area factor in the price, and making the distant “charging offers” more expensive results to a significant increase in the power factor and in the individual revenue for the west parking facility, however there is a decrease of 11% from the initial revenue and additionally an increase of the power load factor for the sensitive facility. Therefore, it is important to understand what the CSP wants to achieve as a side-objective to the system revenue maximization. The reverse LP, as it stands, is beneficial for the west facility but damaging for the east facility. On the other hand if there is a need to reduce the power load factor in the sensitive area, this could be achieved by tightening the relevant constraints and finding the new optimal allocation.

### TABLE 2 Revenue management performance under NLP, LP and reverse LP strategies

<table>
<thead>
<tr>
<th>Parking Location</th>
<th>East Parking Facility</th>
<th>West Parking Facility</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hour starting at:</td>
<td>17:00</td>
<td>18:00</td>
<td>19:00</td>
</tr>
<tr>
<td><strong>NLP</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Power Load (in kW)</td>
<td>9.9</td>
<td>47.8</td>
<td>165.5</td>
</tr>
<tr>
<td>Impalance cost (in £)</td>
<td>4.5</td>
<td>4.3</td>
<td>0</td>
</tr>
<tr>
<td>Power Load Factor</td>
<td>0.83</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Net Revenue (in £)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>LP</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Power Load (in kW)</td>
<td>10.7</td>
<td>87.0</td>
<td>165.5</td>
</tr>
<tr>
<td>Impalance cost (in £)</td>
<td>4.43</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Power Load Factor</td>
<td>0.91</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Net Revenue (in £)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>REVERSE LP</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Power Load (in kW)</td>
<td>12.74</td>
<td>15.37</td>
<td>165.45</td>
</tr>
<tr>
<td>Impalance cost (in £)</td>
<td>4.23</td>
<td>7.88</td>
<td>0</td>
</tr>
<tr>
<td>Power Load Factor</td>
<td>0.95</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Net Revenue (in £)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
5. DISCUSSION AND CONCLUSIONS

This paper is focused on the effects that clusters of EVs recharging at the same time might have on the electricity distributional grid. A novel decentralized approach to control the charging events in out-of-home private parking facilities has been suggested. The control framework is developed for a charging service provider (or aggregator) and the objectives are 1) to incentivize drivers to plug-in their EVs during off-peak periods and in low energy demand areas and 2) to maximize the aggregate revenue from all the contracted parking facilities in the area of interest.

The analysis is based on two simulations. The first takes place at actual “travel time” where the CSP delivers a set of “charging offers” (i.e. bundles of charging rate, price, duration and location) and the drivers arrive sequentially and choose one of the available options or leave without charging. The second simulation takes place at “pre-travel time” and EV driver arrive at a reservation system up to 24 hours in advance of the actual parking event and are presented with subsets of the available “charging offers”. Apart from the varying price signals that reflect the willingness to pay and the needs of different segments of the EV drivers, in the second simulation the choice set is adjusted at each time step of the reservation period in order to maximize revenue for the CSP from the incoming requests.

One limitation of the presented framework is the difficulty to accurately predict future behaviour based on the current system. The public acceptance of pricing out-of-home charging events has yet to be evaluated and a robust validation of the model would require revealed EV drivers’ preferences. Moreover, the discretisation of the charging offer characteristics (i.e. charging duration and charging rate etc.) which is necessary to create a tractable optimization problem limits the capability of the model to cover a wider range of the attribute space. Finally the quantity of the recharge in our simulation is drawn from a probability distribution while someone might argue that it is endogenous to the charging offer characteristics and hence the choice component would require a discrete-continuous approach to be more realistic.

Three noteworthy conclusions emerged from this study. First, when we don’t apply revenue management but the price signals are tailored to the various segments of EV customers, the location pricing approach improves the system revenue significantly and it smoothes the spatial distribution of charging demand. Second, when revenue management is introduced, the revenue performance is still improved using LP, but the relocation of charging events is difficult without tightening the constraints of the optimization problem. Finally, LP increases imbalance costs in both cases, yet the results from similar simulations could improve the pre-planning of required power in the negotiations between the CSP and the DSO.

Another issue to arise is the complexity in the developing interactions between the multiple agents. While the control problem is formulated to maximize revenue for the aggregated system, this will rarely be equally beneficial for all the infrastructure owners and service providers involved. On the other hand the revenue maximization does not always result in minimization of imbalance cost. There could be scenarios where imbalance costs increase significantly (e.g., when carbon-intensive generation units are utilized) negating the benefits from revenue maximization.

Further research will be needed to understand the various relationships and the extent to which they are affected when there is increasing uncertainty for the charging demand. To turn this concept into a practice-ready application it would be crucial to use the appropriate communication
systems and smart meter information, in order to mitigate this uncertainty that some operators might be unwilling to take. Regarding the reservation system, the operators would need to develop a strategic plan of how to deal with late arrivals or cancellations so that there is no compromise to the benefits of the suggested framework.

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REFERENCES


