Abstract

Ambitious goals of electric vehicle (EV) penetration may conflict with the capabilities of today's power system. Especially simultaneous charging at home may lead to significant load spikes or grid stability issues. Prior research has identified the need for appropriate coordination approaches. This research focuses mostly on coordinating system loads ignoring local grid constraints. The suggested mechanisms either are centralized control approaches ignoring user preferences or based on the electrical energy cost. We propose to complement these approaches by using mechanisms from revenue management for perishable assets.

First, we formalize charging coordination as a minimal revenue management problem and then derive an appropriate advance sale mechanism. By accounting for heterogeneous customer segments, this approach can achieve a socially efficient allocation of available charging capacity. Using a local neighborhood scenario, we evaluate the impact of such an approach.

1. Introduction

Governments in several countries have announced ambitious goals for EV sales [1-3]. In addition, leading research institutions have released a variety of publications on the expected growth of EV sales [4], [5]. In summary, the various experts expect a strong growth in EV numbers, albeit the estimated figures vary widely.

Several research communities are trying to predict and analyze the impact of EVs on the electricity grid. Research in the areas of electrical engineering, economics and information systems has shown that EV charging increases load significantly, and therefore leads to bottlenecks especially in distribution grids [6]. Additionally, EV charging may have substantial impact on power quality in the grid including transformer overloads, voltage deviations, branch congestions, power losses and phase imbalances. Knowing the grid limitations, simulation studies try to predict the effects on the power system or the maximum EV penetration levels. Results of these simulations show that penetration levels between 10-40% can lead to bottlenecks in the grid. These can be addressed by either reinforcing the grid or by applying coordinated charging [7-9].

Coordination approaches that just maximize penetration of EVs are too shortsighted since they ignore the presence of different customer valuations for charging capacity. We extend the literature on coordination of EV charging by adapting capacity control mechanisms from perishable asset revenue management (PARM) in order to allocate the available charging capacity to achieve a higher overall welfare. The article is structured as follows: Section 2 reviews the related literature on EV grid integration and revenue management. In section 3 we describe and formalize EV charging as a PARM problem with a focus on capacity and customer modeling. Section 4 provides a solution approach including a simple numerical example. Section 5 concludes and provides an outlook to future research opportunities.

2. Related Work

We can identify two technical reasons for charging coordination: aggregate load management (balancing electricity demand and supply) and local distribution grid constraints (a limited number of EVs that can be charged simultaneously). Therefore, EV charging has two technical value components: electrical energy charged (electricity price) and charging power utilized (capacity cost). Unlike the majority of prior economic research on charging coordination, we want to focus on managing charging power capacity with respect to differences in customer valuation of the charging service itself ignoring the price of electrical energy. Given this focus on capacity management, the
relationship to the revenue management becomes evident.

2.1. EV charging coordination

Optimization of EV charging patterns with the goal of shifting load into off-peak periods have already been discussed in 1983 [10]. In recent years, the number of publications on EV charging coordination and grid integration has grown significantly. The different disciplines focus on various aspects of the charging coordination problem. Whereas electrical engineers tend to minimize power losses [11], maximize EV integration [12], or optimize system parameters [13], [14], economists are more likely minimizing cost for power suppliers or minimizing cost for EV drivers [15], [16].

Several mechanisms are used to coordinate EV charging. They range from a central optimal planning authority [11], [17] to decentralized approaches like time-of-use pricing [12], [18] or coordination based on local grid parameters [19]. More recently, computer scientists suggested online mechanism design as a promising approach to coordinate the system under the assumption of drivers acting in their self-interest [20].

Literature focuses on balancing EV charging and electricity generation and only few authors consider physical grid constraints [11], [12], [20], [21]. We concentrate on managing potential distribution grid congestions and ignore balancing of electricity demand and supply.

2.2. Revenue Management

Revenue management (RM) provides firms with decision tools and processes for better leveraging demand potentials. It requires an integrated approach with both respect to organizational units (e.g., marketing, operations) and decision scope (strategic and tactical). On the strategic level, firms set capacity levels and long-term demand management while on the tactical level they make pricing and quantity decisions [22]. RM has its origin in the airline industry [23]. Today, it is widely applied in other capacity-constrained industries, e.g., hospitality services and car rental [24]. Utilities, as well, are introducing revenue management in the form of dynamic electricity pricing for industrial and residential customers. However, Tsaloli and Van Ryzin [22] note that capacity control approaches have not yet been applied in the electricity business.

In general, revenue management is most effective for situations where the good cannot be stored (e.g., services), capacity is fixed and customers can be segmented. According to Weatherford and Bodily [25] in these situations, the challenge is to find ‘the optimal tradeoff between average price paid and capacity utilization’. They propose the term PARM to describe approaches addressing this challenge. In the simplest PARM case, a firm has to control the capacity of a single resource, e.g., tickets for one flight. They also provide an exhaustive taxonomy for PARM problems. As with all services, EV charging capacity cannot be saved. Moreover, it is fixed in the short term since power system and grid upgrades require substantial investments. Therefore, the charging coordination problem can be interpreted as a PARM problem.

The extensive revenue management literature on these problems provides guidance and well-established capacity control strategies (e.g., protection levels or bid-prices) which may lend themselves to application to EV charging coordination. These observations motivate our approach to apply PARM-like modeling to EV charging coordination. Our goal is to properly formalize the relevant resource and demand terms to be able to apply well-established mechanisms from the revenue management literature.

3. Modeling EV charging as a revenue management problem

Given the observations in the last chapter, we want to model residential EV charging as a RM problem. We focus on managing the EV charging capacity on the distribution grid level. More specifically, we focus on the capacity of a suburban neighborhood transformer substation. This is a key challenge for future scenarios where a significant number of commuters own EVs and want to charge their cars at home. This section describes how we model and formalize the charging capacity and the demand characteristics of the customer population. We aim to formalize this problem using the concepts from the revenue management literature.

3.1. Charging capacity

We assume that the transformer’s power capacity is the fixed bottleneck in the distribution grid. Furthermore, we look at a single charging period and require the customers to charge at a constant power over the charging period’s length $T$. Let $P$ denote the aggregate available transformer power rating. The local utility will want to reserve an amount $\delta$ of the transformer capacity for non-charging activities in the neighborhood. The transformer capacity available for charging is then $P_c = (1 - \delta)P$. During any given charging period a charge energy amount of $C = P_c \cdot T$. 

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T is available for EVs as diagramed in Figure 1. For such a control strategy to work electricity providers handle EV charging through separate tariffs independent of other loads. This is in line with observations in the real world where several energy providers offer EV-specific tariffs.¹

![Figure 1 Available charging capacity](image)

When customer j demands a charge $d_j$, she will occupy a constant power level of $d_j/T$ over the course of the charging period. This is depicted in Figure 2. Although customers are requesting a charge energy amount, they effectively need to choose a charging power level. For sake of brevity and without loss of generality we restrict our analysis to the charging demand terms $d$ and the aggregate capacity $C$. As customers’ charging requests may be of arbitrary size capacity $C$ is continuous. This is a slight variation of typically discrete capacity units (e.g., seats or rooms) in the classic RM problems.

![Figure 2 Charging at continuous level over complete charging period](image)

Using the above-mentioned restrictions on charge requests allows us to reduce the problem to a single-dimensional allocation problem of the total charging capacity $C$. This makes the problem computationally more tractable than with varying charge power or total charge durations shorter than $T$. These more general charging programs can be approximated by equivalent rectangular ones with identical area or by using the convex hull of the charging period and the charge power requests (see Figure 3).² Given our scenario of overnight charging at home, the restriction to rectangular charging programs provides a meaningful research setting.

Allowing customers to vary both charge power and timing gives rise to a bin-packing problem where the optimal scheduling of charge jobs needs to be evaluated – i.e. the optimal fitting of charge jobs into the available charging capacity. Such richer settings may be necessary for the analysis of other scenarios and provide interesting opportunities for future research. The literature on parallel machine scheduling problems [26] and revenue management for flights with multiple flight legs [27] may provide interesting analogies for tackling more general model specifications.

![Figure 3 Approximation of general charge programs](image)

### 3.2. Customer demand

Customer heterogeneity is a central element for characterizing the demand for services. It is also the cornerstone of revenue management approaches. In our basic scenario we exemplarily assume two types of EV charging service demand: regular charging demand $d_r$ (e.g., commuters charging their car after work) and short-term charging demand $d_s$ (e.g., preparing for a spontaneous trip). In a real world setting such differentiation is often obtained by means of appropriate tariff design. Again, more granular demand segmentations may be required to describe richer real

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² Clearly, future research will need to characterize the performance of these heuristics or derive more appropriate, more effective ones.
world scenarios. We, furthermore, assume that the demand from the two segments arises strictly sequentially (\(d_r\) before \(d_s\) — the subscripts standing for regular and spot demand) but charge at the same time, as specified by the capacity scenario. Both regular and short-term demand arise very close to the charging time (e.g., on the same day) and we, therefore, do not consider last minute changes or cancellations.\(^3\)

We model the two demand types as independent populations of customers with randomly distributed charging requests. Each population \(i\) consists of \(n_i\) customers who will each request a stochastic charge amount \(d_j\sim\mathcal{F}_i\), where \(\mathcal{F}_i\) is a population-specific probability distribution. The \(d_j\) are treated as independent\(^4\) random variables arriving in random order. A customer of any segment that is faced with a capacity shortage is assumed to accept a partial charge \(d_i = \min\{d_j, C - \sum_{k=1}^{j-1} d_k\}\). When dealing with capacity limitations, this assumption allows us to aggregate the customer populations into a single demand term each. These segment demands are denoted by \(D_r = \sum_{j=1}^{n_r} d_j\) and \(D_s = \sum_{j=1}^{n_s} d_j\).\(^5\)

Given its more spontaneous occurrence the willingness to pay per capacity unit of short-term charging \(\theta_s\) is assumed to be higher than for commodity-like regular charging capacity, that is \(\theta_r < \theta_s\). Such higher price-sensitivity of early demand is a standard assumption in the revenue management and services marketing literature [25], [28]. We will abstract from prices and revenue and rather optimize with respect to total welfare. This simplification again offers many opportunities for extending the basic model. Denoting capacity allocated to the two customer segments by \(C_r\) and \(C_s\), this realized total welfare is then given by \(\Pi = \min\{C_r, D_r\}\theta_r + \min\{C_s, D_s\}\theta_s\).

Clearly, the bottleneck of the available charging capacity \(C\) only applies if the probability of aggregate demand exceeding capacity is strictly positive. In this case, the value of at least one of the minimum terms in the definition of \(\Pi\) is determined by the allocated capacity value.

### 4. Allocating EV charging capacity

As noted before grid limitations are met either by capacity investments or by coordinated charging schemes. The simplest way to allocate EV charging is accepting registrations in a first-come, first-served manner. Since the \(d_r\) arise before the \(d_s\), the regular demand will have the full capacity available for purchase under this minimal allocation and coordination rule. See Figure 4 for an illustration. Given the higher willingness to pay of spot customers, this is not socially efficient as there may be a significant number of spot charging requests turned down due to already placed and allocated regular charging requests blocking capacity. Therefore, leveraging the two segments' different willingness to pay would allow a more efficient allocation of charging capacity.

![Figure 4 First-come, first-served scheme](image)

### 4.1. Improving coordination using revenue management

Revenue management approaches can be categorized into price- and quantity-based control mechanisms [22]. The former include decisions on how to set prices and how to adjust them dynamically over time. Retail promotions and B2B procurement auctions are typical examples for these mechanisms. Quantity-based demand-management decisions comprise versioning and the control of availability of a product or service. Typical approaches are protection limits or bid prices. For capital-intensive resources Wu et al. [29] propose an options-based approach.

Charging of electric vehicles occurs frequently; depending on the miles traveled even daily charging is possible. At the same time, a single charge has very low cost. This stands in contrast to traditional applications of revenue management where transactions are few and costly. An appropriate control mechanism for residential EV charging should thus be as simple as possible. Hence, complex schemes like dynamic pricing or options on capacity are less appropriate in this setting.\(^6\)

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\(^3\) Economically, cancellations typically do not add any special insights besides the optimality of overbooking.

\(^4\) In light of the revenue management literature, this specifically means that we rule out the possibility of group arrivals.

\(^5\) Pooling the segments’ requests and applying a proportional rationing scheme would yield the same distributional properties of \(D_r\) and \(D_s\) but may induce the customers to bid strategically.

\(^6\) For fleet operators managing multiple EVs this may very well be different.
4.2. A two-class reservation scheme

As noted by Weatherford and Bodily [25], the simplest control mechanism for single-resource capacity is the introduction of different discount classes. Limited and discounted advanced sales are a characteristic form of this type of capacity management. Typically, capacity must be limited and marginal costs must be sufficiently small for discounted advance sales to be profitable [28]. This coincides with the minimal specification of the single resource reservation problem with two discount classes as identified by Littlewood [30].

As spot demand arises after regular demand, this quantity-based policy requires protecting some capacity for spot customers. Discounted regular sales are accepted as long as the protection level for spot capacity is not violated. Figure 5 illustrates this capacity control mechanism. The policy is solely characterized by the protection level $Q_s$.

![Figure 5 Capacity control mechanism](image)

4.3. Optimal protection level

The sequence of events for the two-class reservation approach is depicted in Figure 6. There are always at least $Q_s$ units of capacity available for spot demand. Compared to the non-protection scheme more valuable spot demand can be served, resulting in an allocation of charging capacity that is more efficient. Since protecting capacity curtails sales to regular customers, the benefit from an additional protected unit of capacity needs to outweigh this lost revenue. Hence, we can derive the optimal protection level for spot demand $Q_s^*$ with a simple analysis of the marginal revenue of both classes. For a continuously distributed demand, this optimum is characterized by equal values for the expected marginal revenue from protecting an additional unit of capacity and the revenue of selling the capacity in advance:

$$\theta_r = \theta_s \cdot \mathbb{P}(D_s > Q_s^*)$$

Let $\mathbb{F}_s$ denote the cumulative probability density function of total spot demand for EV charging, that is $\mathbb{F}_s(X) = \mathbb{P}(\sum_{j=1}^{n_s} d_j \leq X)$. Using Littlewood’s rule the optimal protection limit $Q_s^*$ is given by

$$Q_s^* = \mathbb{F}_s \left( 1 - \frac{\theta_r}{\theta_s} \right)$$

Protecting $Q_s^*$ units of charging capacity for spot demand is an optimal policy balancing the gains from being able to meet extra spot demand against the certain loss from turning down regular customers.

![Figure 6 Two-class reservation scheme](image)

Without protection, regular demand $D_r$ arises strictly before spot demand. Spot customers have only the remaining capacity available which is not used by regular demand. More valuable requests for spot demand cannot be served. Social welfare is calculated via:

$$\text{Min}(C, D_r) \cdot \theta_r + \text{Min}(\text{Max}(0, C - D_r), D_s) \cdot \theta_s$$

With the introduction of a protection limit $Q_s^*$ regular demand can be turned down and more valuable spot demand can be served to increase social welfare:

$$\text{Min}(C - Q_s^*, D_r) \cdot \theta_r + \text{Min}(C - \text{Min}(C - Q_s^*, D_r), D_s) \cdot \theta_s$$

4.4. Numerical example

We use a simple numerical example to illustrate how protecting EV charging capacity may increase total welfare. To derive meaningful parameters we develop a scenario based on a suburban neighborhood and the overnight charging for one typical working day. We assume the neighborhood with approximately 200 households served by a single substation with 220 kW available power for EV charging overnight, i.e. between 10 pm and 6 am. Furthermore, we assume a total number of 200 EVs in the neighborhood with 90 percent being regular customers and 10 percent spot customers. Beside the different valuation of charge

Footnote 7: Typical substations serve 30 - 500 households [33].
capacity, the two customer groups also differ with respect to their driving patterns reflected by different mean charge amounts. Regular customers on average have a lower demand per day than spot customers. This seems reasonable since we assume most of the regular customers as commuters with foreseeable driving patterns and short to medium driving distances. Whereas the demand of spot customers arises at short notice and we assume the reason to be unplanned trips for which the spot customers need to fully charge their EV. In this setting the expected total demand of spot and regular customers equals the available charging capacity.

Greene [31] proposes to model the daily travel length of limited-range vehicles as being Gamma-distributed. The Gamma distribution allows a reasonable representation of empirical driving profiles. An application to German commuter data [32] indicates the validity of this approach (see Figure 7). Given an approximate one-to-one correspondence between driving distance and energy consumption an application of this model to EVs then yields daily battery discharge amounts to be Gamma-distributed as well. We follow this reasoning and for ease of exposition restrict our attention to the Erlang distribution instead of the Gamma distribution. Then, charging demand $d_j$ is assumed to be Erlang distributed with $\text{Erl}(\lambda_j, k_j)$. The rate parameter $\lambda_j$ and shape parameter $k_j$ for regular and spot customers are chosen to appropriately reflect the differences in driving patterns.

Specifically, we assume mean travel distances of 40 km for regular and 80 km for spot customers. With an average consumption of 0.2 kWh/km we obtain mean charging requests of 8 kWh and 16 kWh. Using the same rate parameters $\lambda = \lambda_r = 0.5$ the shape parameters obtain as $k_r = 4$ and $k_s = 8$. Table 1 summarizes the most important input parameters for this example of EV charging in a suburban neighborhood.

### Table 1 Summary of input parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Available transformer capacity $P_c$</td>
<td>220 kW</td>
</tr>
<tr>
<td>Charging duration $T$</td>
<td>8 hours</td>
</tr>
<tr>
<td>Available charging capacity $C$</td>
<td>1760 kWh</td>
</tr>
<tr>
<td>Population of regular customers $n_r$</td>
<td>180</td>
</tr>
<tr>
<td>Demand mean value regular customer $\theta_{r}$</td>
<td>8 kWh</td>
</tr>
<tr>
<td>Demand variance regular customer $\sigma_{r}$</td>
<td>16</td>
</tr>
<tr>
<td>Avg. total demand of regular customers $\mu_r$</td>
<td>1440 kWh</td>
</tr>
<tr>
<td>Willingness to pay regular customer $\theta_{r}$</td>
<td>1</td>
</tr>
<tr>
<td>Population of spot customers $n_s$</td>
<td>20</td>
</tr>
<tr>
<td>Demand mean value spot customer $\theta_{s}$</td>
<td>16 kWh</td>
</tr>
<tr>
<td>Demand variance spot customer $\sigma_{s}$</td>
<td>32</td>
</tr>
<tr>
<td>Avg. total demand of spot customers $\mu_s$</td>
<td>320 kWh</td>
</tr>
<tr>
<td>Willingness to pay spot customer $\theta_{s}$</td>
<td>1-4</td>
</tr>
</tbody>
</table>

Using capacity protection as described in section 4.2 we can calculate the optimal protection level $Q_1^*$. Since the sum of Erlang random variables is again Erlang we can express the distribution of $n$ customers in closed form that is $\text{Erl}(\lambda_r n \cdot k_j)$. Given a difference in willingness to pay between regular customers and spot customers the optimal protection limit $Q_2^*$ obtains as

$$Q_2^* = \text{Erl}(\lambda_s, n_s k_s)^{-1} \left(1 - \frac{\theta_{r}}{\theta_{s}}\right).$$

We use a simulation run with 10,000 trials to evaluate the effects on social welfare. This simulation shows a welfare increase for protecting EV charging capacity in comparison to a first-come, first-served charging policy. A major influencing parameter is the spread between valuation of regular and spot customers. An increase of the spread leads to higher welfare increases with revenue management – e.g., 0.7% for $\theta_{s} = 2$ or 2.0% for $\theta_{s} = 4$. Figure 8 shows the development of total welfare when increasing the

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8 Given the fact that in our example the available capacity is sufficient for average demand, these increases in welfare seem to be in line with other use cases of revenue management. According to [34] revenue gains of 2-5% are typical for airlines that implemented yield management.
valuation of spot customers to four times the valuation of regular customers.

In comparison to maximization of EV penetration the protection level based approach inherently results in burnt capacity, i.e. capacity protected for spot customers but unused in the end. Therefore, by increasing the spread in valuation the amount of burnt capacity increases as well.

Figure 8 Impact of expected utilization

We have shown that even in this situation where on average the available charging capacity should be sufficient, revenue management allocates capacity to customers with more valuation and increases social welfare. In settings where the expected total demand differs from the available capacity, the efficiency of the proposed revenue management approach changes. Figure 8 shows the impact of different levels of expected utilization. If the expected demand exceeds the available charging energy, revenue management can increase the overall welfare even more.

However, in this case an investment in network may be another option. Future research might reveal the optimal threshold for investments into the grid instead of using coordination approaches like revenue management. On the other hand, a 2% decrease of expected utilization results in a significantly lower increase in welfare. This means that in distribution grids where capacity exceeds demand the value of our proposed coordination approach diminishes.

### 5. Conclusion and outlook

Increasing EV penetration levels require coordination of charging activity with respect to both aggregate load management and distribution grid capacities. We argue that, so far, coordination mechanisms for the latter bottleneck are not socially efficient if ignoring customer heterogeneity. By providing a basic model specification, we show that coordination of distribution grid capacity for EV charging can be modeled as a PARM problem. A two-class reservation scheme provides an efficient solution to this problem and using simulation, we characterize the potential welfare impacts.

The proposed control mechanism is appropriate in situations where transformer capacity is a bottleneck. Social welfare increases with the expected utilization of charging capacity. If the expected charging demand greatly exceeds available capacity, an investment in the local distribution grid and transformer capacity is preferable. Table 2 provides a classification of the complete model along the taxonomy presented by Weatherford and Bodily [25].

<table>
<thead>
<tr>
<th>Table 2: A basic EV charging PARM model</th>
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<tbody>
<tr>
<td><strong>Resource model</strong></td>
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<tr>
<td><strong>Prices</strong></td>
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<tr>
<td>Willingness to pay</td>
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<td>Discount price classes</td>
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<td>Group reservations</td>
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<tr>
<td>Diversion</td>
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<tr>
<td>Displacement</td>
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<tr>
<td>Show-up of reservations</td>
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<tr>
<td>Bumping procedure</td>
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<td>Decision rule</td>
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With this paper, we specifically aim at demonstrating the relevance of RM techniques for addressing the challenges posed by the coordination of EV charging. By providing ample opportunities to expand and improve on, our minimal PARM model for EV charging coordination thus serves as a platform for future work in this direction. We use categories from the Weatherford and Bodily taxonomy to structure possible extensions:

**Prices**: Our static welfare approach ignored price and cost effects on demand and supply. Clearly, a provider-centric model would rather have to focus on profit maximization. Furthermore, realizing that power and energy are separate value components of EV charging one can easily envision models where capacity pricing is driven by the price for electrical energy – charging demand may be high when energy prices are low.
Discount price classes: The RM literature provides a large body of research for handling models with more than two customer segments.

Group reservations: Allowing individual customer demand to be dependent on each other creates the possibility of modeling customer groups or EV fleets.

Resource: Dropping the single time slot assumption is necessary for modeling applications that are more realistic. As noted before the research on revenue management for multi-leg flights and multi-machine scheduling may guide this relaxation. Such an extension also affects the following aspects of the RM problem.

Diversion: In a model with multiple sequential charging time slots, the different time slots may constitute substitute products for the customers. This customer diversion both complicates the revenue management problem but also provides the operator with additional degrees of freedom to optimize capacity utilization. Diversion can also occur in a repeated setting with a single time slot. In this case, multiple reservations may be open simultaneously possibly leading to inter-temporal diversion effects.

Displacement: Sequential time slots may also give rise to conflicting customer requests: A customer charging for only one slot can block a customer charging for two slots – such displacement effects are also a problem in RM for multi-leg flights.

Show-up of reservations, bumping: Stochastic show-ups or the possibility to deny service to advance customers for a compensation payment (bumping) may equip providers with additional strategic levers.

Decision rule: In our model, clearly the static booking limit constitutes an optimal policy. This may not be the case in a more complex setting. However, the limitations on the available control strategies imposed by EV charging characteristics may continue to hold.

We are convinced that insights from revenue management can have a profound impact on the EV business models of both electrical power companies as well as EV mobility providers like BetterPlace. This article provides some ideas and guidance to address these upcoming challenges in a systematic way.

6. References


