MITIGATING RENEWABLE ENERGY GENERATION UNCERTAINTY BY DEADLINE DIFFERENTIATED PRICING

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Research in Progress

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Abstract

Electric vehicles are an important option to enable sustainable individual mobility. In order to leverage this potential, electricity for charging of electric vehicles needs to be provided by local renewable energy sources. Information systems can enable an efficient coordination of demand and supply in this setting. Forecast errors regarding energy generation from these sources are common but can be addressed by temporal flexibility of electric vehicle charging.

We use a pricing scheme called deadline differentiated pricing that incentivizes customers to accept job shifting of their charging processes. This approach is applied on a specific use case: A city car park offers charging spots for electric vehicles that is supplied by both a local photovoltaic system and conventionally from the grid. We evaluate the impact of energy generation forecast errors on operator profits based on the formulation of a stochastic mixed-integer optimization problem and empirical mobility and generation data. We show that deadline differentiated pricing is resilient to inaccurate forecasts for photovoltaic energy generation. Deadline differentiated pricing increases profits in all investigated scenarios by at least 8% as compared to a simple pricing approach. Additionally, it can increase the share of charging demand covered by renewable energy by up to 17%.

Keywords: Sustainable mobility, electric vehicle, charging coordination, renewable energy, demand side flexibility, energy informatics.

1. Introduction

Electric vehicles (EVs) are one of the most important options to enable sustainable individual mobility. In order to leverage this potential, the electricity for EV charging needs to be provided by renewable energy sources (RES). The utilization of RES, e.g. wind power for charging can reduce lifetime CO₂ emissions of EVs by more than 75% compared to conventional vehicles (Helms et al., 2010). In order to achieve this objective, EVs must coordinate their charging activity with the availability of electricity from (local) RES. This can support the grid integration of EVs in low voltage distribution grids, since balancing of intermittent generation can be performed locally (Richardson, 2013).

In order to reduce range anxiety and to increase the availability of EVs to respond to fluctuations in the power grid, additional charging infrastructure needs to be installed at public parking locations. Car parks then constitute new load clusters that aggregate the demand of a considerable number of vehicles. Local generators, like photovoltaic (PV) systems can be installed on, or in proximity to these new load clusters and thus address the objective described above. A crucial step to support the utilization of PV generated electricity is the ability to coordinate the charging of heterogeneous EV customers. Every vehicle has different constraints regarding the amount of energy the customer needs and the poten-
tial parking duration. A way to address this heterogeneity is to set monetary incentives that allow the exploitation of temporal EV flexibility potential. Following the deadline differentiated pricing (DDP) approach of Bitar and Low (2012) and the adaptation by Salah and Flath (2014) we investigate the following research questions for a car park for EVs with local PV generation:

- How sensitive is the operator profit regarding PV generation forecast errors?
- Which share of EV charging demand is satisfied by PV energy in profit optimal scenarios?

We formulate and evaluate a stochastic mixed-integer optimization problem that maximizes the profit of a car park operator by setting appropriate prices for charging (i.e. parking fees are not considered). DDP follows the assumption of rational EV customers and offers lower charging prices for customers that are willing to offer a higher level of temporal flexibility by taking advantage of interrupting or shifting their charging processes. We do not consider investment costs, e.g. for PV installations since our focus is on the operational level. We employ driving profiles from the German Mobility Panel (Zumkeller et al., 2008) and empirical data from southern Germany for parking durations in a car park and PV generation to obtain realistic conditions for our assessment. Thus, we create the foundations for the implementation of an energy informatics decision support artifact that integrates existing demand side flexibility of EVs and evaluate its robustness with respect to uncertainty in available PV generation.

In Section 2 we present related work in the domain of demand response and EV charging coordination. In Section 3 we develop the DDP model and describe details on input data while Section 4 provides the model evaluation. The conclusion in Section 5 recaps and discusses the implications of our findings.

2. Related Work

Demand Response (DR) and Demand Side Management (DSM) are crucial concepts of the smart grid. Information technology alleviates one of the major flaws of electricity markets: It enables the demand side to react in a dynamic fashion to changes in the supply situation (Strubac, 2008), (Strüker and van Dinther, 2012). Following Albadi and El-Saadany (2008), DR can be categorized into incentive based programs and price based programs. Incentive based approaches are common with large industrial customers and often involve direct load control of large loads at the customer site. This traditional approach has been extended by market oriented DR programs that allow customers to participate in demand bidding on the respective markets (Chua-Liang and Kirschen, 2009). Small customers, e.g. the commercial and residential sector, in turn would rather participate in a price based program that includes different levels of dynamic prices, starting with simple two-staged time-of-use tariffs, extending up to real-time prices based on the wholesale development situation (Albadi and El-Saadany, 2008). Our approach builds on the notion of dynamic pricing with a special focus on local generation. Since EVs are a load type with considerable DSM potential, there has been ample work on the possibilities of grid integration, e.g. Acha et al. (2010), Green et al. (2011), and on the assessment of economic implications in different market environments, cf. Flath et al. (2012). Wagner et al. (2013) investigate the economic profitability of EV fleets for the provision of frequency regulation in the case of Germany, and find that negative regulation can be profitable (Wagner, 2013).

Steuer et al. (2014) investigate a car park scenario, but remain limited to the economic assessment under the current German regulation regime instead of evaluating the options to activate EV demand side flexibility. Further work from Chen. (2013) also proposes online deadline oriented scheduling for parking garages but does not consider renewable energy in the coordination objective. In addition, the service level assumed for customers is different (the operator has to compensate unserved load) than in our work, where customers with an insufficient valuation are not served.

Sanchez et al. (2011) consider a parking garage scenario for 50 PHEVs and EVs and develop a charging heuristic that minimizes the share of unserved vehicle load given grid connection capacity con-
constraints. They do not consider renewable energy generation and only purchase electricity from the grid in a simple two-part tariff.

Different architectures for coordination and control of EV demand have been proposed (Schuller, 2015). Most approaches rely on centralized (hierarchical) coordination mechanisms in order to integrate EVs in DSM programs. Hierarchical mechanisms are prominent particularly in the context of commercial EV fleets. Eiselt et al. (2015) investigate the economic effects of an ICT mediated DR program for EV car sharing fleets and come to the conclusion that demand side flexibility could further improve the operative costs of EVs in fleet applications. In addition to the mediation of DR programs, information systems have also been employed to support planning decisions for the optimal deployment of charging infrastructure (Wagner et al., 2014).

Our work extends existing centralized approaches to assess the demand side flexibility of EVs in a car park or fleet environment. The gap we address is the consideration of local PV generation and the combination with a variable pricing scheme in this setting. In particular, we implement easy to use, robust economic incentives considering the uncertainty of PV energy generation.

3. Model and Simulation

With the deadline differentiated pricing (DDP) approach we want to exploit demand side flexibility by setting appropriate prices that incentivize customers to offer their temporal flexibility. We present the optimization model in Section 3.1 and provide the simulation input data needed to apply the approach on a car park EV charging case in Section 3.2.

3.1. Pricing Concept and Optimization Model

Essentially, DDP is a pricing concept that offers lower prices to customers who accept guaranteed job completion by a chosen deadline instead of demanding immediate job initiation. We build on Bitar and Low (2012) who derive theoretical properties and apply DDP to EV charging in car parks. Following the work of Salah and Flath (2014) we formulate a two-stage stochastic problem from the point of view of a car park operator as a linear program. The operator maximizes profits \( \Pi \) that are the sum of revenues generated through selling charging energy quantities \( a \) at prices \( p \) to each customer \( c \) minus the costs that arise from purchasing energy \( \eta^p \) from the grid at price \( \kappa \) if jobs cannot be supplied from local PV generation \( \eta^g \).

\[
\max_{p,\eta} \Pi = \sum_{c \in C} \sum_{d \in D} (p^d \cdot a^d_c) - \sum_{t \in T} (\eta^g_t \cdot \kappa_t) \tag{1}
\]

\[
s.t. \quad \sum_{t = t_c}^{d_c} \lambda^d_c \geq a^d_c \quad \forall d \in D, \forall c \in C \tag{2}
\]

\[
\sum_{c \in C} \sum_{t \in T} \lambda^p_{c,t} \leq \eta^p_t + \eta^g_t \quad \forall t \in T \tag{3}
\]

A key component of DDP is the price menu that consists of a number of tuples containing price \( p \) and duration \( d \) for possible job shifting. Prices are monotonously decreasing in the duration to ensure incentive compatibility (Bitar and Xu, 2013). To retain linearity, we assume that every vehicle has a charging point available upon arrival \( t_c \) and discretize a simulation day into 96 quarter-hour time slots. Constraint (2) ensures, that the charging process \( \lambda \), taking a specific number of time slots \( f \), is executed in the permitted time frame for each customer \( c \). Constraint (3) manages the energy provision by either intermittent PV energy generation \( \eta^p \) or from the grid \( \eta^g \).

Confronted with a price menu and assuming that customers know their time of stay at the car park upfront they can solve the following individual optimization problem. The customer’s objective is to maximize her net utility \( U_c \). We model it by subtracting price \( p \) from costs of her outside option \( o \),
e.g. charging at home, times a non-negative energy amount $a$ for each job shifting duration $d$ that suits her time of stay. For the illustrative purpose suppose the customer is offered a simple price menu: She has to pay 35 ct/kWh for an immediate job start and 30 ct/kWh if the job can be shifted up to 2h. The customer will park 3h, her job will last 1h and her outside option is to charge at home for 32 ct/kWh. Obviously she will decide to accept a job shifting of 2h to qualify for the lower price. And since $a_c - p^d = 32 - 30 > 0$, she will set $a^d_c = \bar{a}_c$ (full battery) to maximize her net utility.

$$\max_a U_c = \sum_{d \in D} (o_c - p^d) \cdot a^d_c \quad \forall c \in C \quad (4)$$

s.t. $0 \leq a^d_c \leq \bar{a}_c \quad \forall d \in D, \forall c \in C \quad (5)$

The customer’s optimization problem can conveniently be integrated into the car park operator’s optimization problem through reduction and transformation following these two observations:

- Monotonicity of the price menu induces rational customers to always choose the longest duration for job shifting with respect to their time of stay.
- The optimal decision strategy is greedy due to linearity of the customer’s net utility function: If price $p$ is lower than costs for outside option $o$, she will charge as much energy as possible bounded by the discharged battery capacity $\bar{a}_c$. Otherwise, charging would result in a negative net utility, forcing her not to charge at all.

Due to spatial constraints we refrain from going further into details and refer to the work of Salah and Flath (2014) who show that individual optimization problems of this kind can be transformed into linear constraints while retaining the important characteristics of incentive compatibility and individual rationality.

Since the focus of this work is on the effects of forecast errors of PV generation, energy $\eta^p$ generated by local PV installations is the only stochastic variable. Figure 1 depicts the links between the two stages of this stochastic problem. The price menu, decision variable of the first stage, is independent of specific realizations of the PV generation. The car park operator sets a price menu $p$ based on a single forecast that is assumed to represent all possible realizations of PV generation. Decision variables of the second stage – scheduling of jobs $\lambda$ and purchasing missing energy $\eta^g$ from the grid – are recourse variables, meaning that they are decided after the realization of the stochastic variable $\eta^p$ is revealed. To limit the notational burden and enhance readability, equations (1) – (5) have been formulated for the deterministic case. These formulations can easily be transformed to the stochastic case.

**Figure 1: Deadline differentiated pricing as a two-stage stochastic problem.**

### 3.2. Scenario and Simulation Setup

**Mobility:** Regarding mobility and parking data, we employ the German Mobility Panel (Zumkeller et al., 2008), a representative survey of mobility behaviour in Germany that is continuously recorded since 1997, and the empirical car park utilization distribution of a car park in the centre of a major city located in southern Germany illustrated on the right hand side of Figure 2. Combining this data with EV characteristics we obtain realistic inputs for the simulation, i.e. the length of stay and the resulting EV charging demand. On average, customers occupy parking lots for 3.5 h which exceeds the duration needed to meet their EV charging demand (0.75 h) by far. We assume car specifications similar to the Nissan Leaf (24 kWh capacity, consumption 0.18 kWh/km), which is currently the most widespread
electric vehicle, and a maximum charging speed of 11 kW at the car park. Since DC charging with higher charging powers requires additional and potentially more costly infrastructure, we focus on standard three phase AC charging.

**Customer utility:** As noted in Section 3.1 each customer’s cost for her outside option has a direct effect whether or not to charge at the car park given a specific price menu. EV owners will most probably own a charger at home and will consider charging at home as their outside option. Two thirds of the population’s cost for the outside option is modelled to be normally distributed with \( \mu = 35 \, \text{ct/kWh} \) and \( \sigma = 5 \, \text{ct/kWh} \). We assume that the other third is equipped with PV panels at home supplying a major part of their charging energy at lower costs. We model costs as normally distributed with \( \mu = 10 \, \text{ct/kWh} \) and \( \sigma = 2 \, \text{ct/kWh} \). In total we obtain a bimodal distribution.

**Arrival rate:** The earlier mentioned exemplary car park has approx. 1000 customers a day that mainly use the car park during daytime (cf. Figure 2). The German National Platform for Electric Mobility predicts that EVs will represent approx. 2.5% of all passenger cars in Germany in 2020. Commuting from rural into urban areas with EVs will be one of the most common use cases (Nationale Plattform Elektromobilität, 2012). Since this type of commuters represent a large target group at the analysed car park, we assume an EV customer share of 10% which results in 100 EV customers per day. We assign each of the 100 customers a mobility profile and cost for outside option. This process is repeated for each day of the year.

**Customer-facing complexity:** Considering that customers have limited time to decide which price and shift duration to choose, we limit the number of allowed price levels in a price menu. Obviously, this lowers profits for the car park operator, as customers will only offer the duration required to qualify for a cheaper price level. While this imposes a constraint on operator profits, its effects are minor. Previous simulation results have shown that allowing the car park operator to set four different price levels yields almost optimal profits – hereafter we evaluate this instantiation of DDP. As a benchmark scenario we choose a simple pricing approach that induces “as fast as possible” charging by omitting price incentives for job shifting. This is based on the current practice where fixed and mostly linear tariffs are employed for EV charging.

![Figure 2: PV generation (left) and car park utilization (right) of an exemplary day in summer](image)

**Renewable energy generation:** For our analysis we employ real world meteorological data obtained from southern Germany in 2013. Additionally, we employ the corresponding forecast of the TSO responsible for this region, Transnet BW (Schierenbeck et al., 2010). This forecast provides a general trend for the expected PV generation in the region but does not reflect local fluctuations in the availability of solar irradiation (cf. Figure 2).

**Supply:** The car park’s rooftop could accommodate PV panels of up to 200 kW peak (kWp) which could exceed the energy demand of 100 EV customers per day. Thus we also investigate scenarios starting at 20 kWp. Besides the free, but intermittent PV energy generation, the car park operator can procure an unlimited amount of energy from the grid at 30 ct/kWh undercutting the assumed household rate.
4. Evaluation

In this section we investigate to what extent the operator profit is affected by forecast errors of PV generation in DDP and simple pricing regimes. In addition, we evaluate the impact of different generation capacities on profit and the ability to utilize local PV to satisfy EV charging demand. For sake of statistical reliability we simulate every day of the year 2013 and compare the resulting profits. Since PV generation and customer data do differ from day to day, we normalize profits with a best case benchmark, which is DDP assuming perfect knowledge of the PV generation.

4.1. Operator Profit

We evaluate the effect of forecast errors and PV generation capacities on the operator profit. Forecast errors are assessed by the dynamic time warping (DTW) distance, cf. Berndt and Cliffords (1994). This error measure allows the comparison of time series while accounting for simple differences as time lags. In contrast to other common measures such as the mean absolute percentage error, DTW allows to better assess the relative similarity of compared time series. We also applied other metrics (e.g. Euclidian distance) still finding the reported relation to be consistent.

<table>
<thead>
<tr>
<th>Capacity (kWp)</th>
<th>20 kWp</th>
<th>50 kWp</th>
<th>100 kWp</th>
<th>150 kWp</th>
<th>200 kWp</th>
</tr>
</thead>
<tbody>
<tr>
<td>DDP</td>
<td>99.96 %</td>
<td>98.91 %</td>
<td>96.27 %</td>
<td>95.85 %</td>
<td>96.12 %</td>
</tr>
<tr>
<td>Simple Pricing</td>
<td>92.15 %</td>
<td>88.41 %</td>
<td>84.92 %</td>
<td>84.39 %</td>
<td>84.23 %</td>
</tr>
</tbody>
</table>

Table 1: Comparison of profits in different scenarios, normalized to the perfect knowledge benchmark.

The results show that DDP enables on average a 13% higher profit in relation to the simple pricing approach that does not elicit the customer’s demand side flexibility (cf. Table 1). Figure 3 shows the comparison between DDP and simple pricing and the resulting overall profit per day for all investigated scenarios. One dot represents the total profit generated in the respective pricing regime for one day. The plot thus allows an assessment of how well the applied pricing regime exploits the available demand flexibility of served EV customers. On the x-axis the forecast error of that simulated day, expressed by the DTW distance, is depicted.

![Figure 3: Effect of forecast errors on optimal profits per day in different scenarios. Shaded area represents the standard error of the linear trend in the respective pricing regime.](image)

Both pricing regimes degrade in their performance in the forecast error. The highest sensitivity regarding the forecast error is observed at a capacity of 100 kWp. At this capacity a substantial part of the available EV demand can be covered in an efficient manner. At further capacity increases forecast errors do not affect the profit as much since PV energy is generated in excess on many days. Similarly, for smaller capacities energy demand exceeds PV generation which leads to low forecast error effects. In the 20 and 50 kWp scenarios simple pricing is more sensitive (illustrated by the decreasing slope of the linear trend over forecast error) to forecast errors than DDP, which is surprising since setting prices with DDP generally requires more information. Simple pricing is mainly interested in the overall...
produced amount of energy to know how many customers to serve and therefore what price to set. In contrast, DDP additionally needs to know what length of flexibility is needed to bridge generation gaps. The ability of DDP to react to forecast errors by rescheduling loads apparently outweighs this. With increasing PV capacity this advantage diminishes. Job shifting becomes less important since the PV generation exceeds energy demand on many days. At 200 kWp simple pricing appears to be less dependent on forecast errors than DDP, but this effect is not likely to be statistically supported.

4.2. Load Shape Characteristics

The effect of different pricing regimes on the load shape of the car park is depicted in Figure 4. One can observe that simple pricing leads to similar, non-responsive load shapes that are mainly driven by the arrival time at the car park (cf. Figure 2). Differences in the load shape in the same pricing regime are due to the differing number of customers served in every scenario and to slight deviations in the resulting schedule that is determined by the optimization procedure.

At 20 kWp (79 kWh generated on this day) both DDP and simple pricing lead to a quite similar load pattern and met demand (307 vs. 296 kWh). The only difference is the slight shifting of EV demand from the generation minimum on midday to the two generation shoulders. For higher capacities this phenomenon is more accentuated.

For 50 kWp (198 kWh generated PV energy), the peak in the low generation times is reduced by DDP resulting in a lower met demand (320 vs. 474 kWh). In the 150 kWp case (594 kWh generated PV energy), DDP clearly shifts demand from the initial arrival time to the afternoon hours where PV generation is more abundant while similarly meeting demand (557 vs. 550 kWh). The resemblance in the morning hours with the load shape induced by simple pricing can be explained by constrained customers that do not offer enough flexibility to make use of the second generation maximum and are thus served directly in the beginning of their stay.

\[
\text{Figure 4: Load curves on the example day in summer in different generation scenarios.}
\]

4.3. Renewable Energy Utilization

The different scenarios that have been investigated differ in their ability to effectively utilize the available renewable energy. Figure 5 shows the results with respect to share of EV demand covered by PV generation, the relative utilization of the provided energy and the energy demand share that is being served overall. The results are faceted with respect to different seasons of a year that range from summer days with the highest generation over transition days that can have high energy production but also an increased variation in their generation pattern up to winter days that exhibit an overall low availability of PV energy.

It can be observed, that DDP can increase the share of EV demand that is covered by PV in every scenario. DDP has the highest improvement potential on summer days in the 50 kWp scenario where it increases the EV demand share served by RES by 17%. The overall utilized share of PV energy decreases in generation capacity. DDP always has a higher RES utilization rate than simple pricing due
to the possibility to shift jobs to times of high RES generation. In most scenarios simple pricing serves a higher share of customers at the expense of procuring energy from the grid which reduces the potential profit. DDP in turn can accommodate more customers only when considerable amounts of PV energy are available.

![Graph showing the comparison between Simple Pricing and DDP](image)

**Figure 5: Season type differentiated overview of generation scenarios depicted vs. the share of EV demand covered by PV, share of utilized energy and share of served energy demand**

5. **Conclusion and Outlook**

In this paper we assess the robustness of the profit generated by deadline differentiated pricing in the application case of a city car park that has local PV generation available. We show that DDP is resilient to inaccurate PV generation forecasts. In particular, DDP increases operator profits in all investigated scenarios by at least 8% as compared to simple pricing. For growing forecast errors it performs even better improving the profit by 13% on average. In capacity constrained settings (low PV supply and high EV demand) in the investigated scenario with 100 EV customers per day, we observe that the effect of forecast errors does not impact operator profits. For higher generation capacities, starting with the 50 kWp scenario, simple pricing becomes more sensitive to forecast inaccuracies than DDP. For 100 kWp the forecast error has the strongest effect in general, but both simple pricing and DDP are similarly responsive. For more than 100 kWp the effect of forecast error decreases since PV energy is available in excess and therefore planning errors barely influence performance.

DDP can further increase the share of EV demand covered by PV generation in nearly every scenario, achieving the highest increase of 17% over simple pricing in the balanced 50 kWp scenario on summer days. Our work shows that an implementation of a DDP artifact can improve the operator profits while additional complexity is kept to a minimum for the customers that are served at the car park. In addition, the utilization of PV energy can be substantially increased as compared to the standard simple pricing approach.

In future work we want to incorporate uncertainty regarding the customer’s private information, e.g. utility function, arrival date etc. and assess increased EV penetration scenarios with up to 100 % EV shares. Besides, we plan to extend the DDP concept towards quantity differentiation to better address the possibility of load shedding while at the same time taking care of range anxiety by setting a specific energy quantity guarantee. Further future work can also investigate this scenario on a strategic level by integrating the PV capacity size as a first stage variable into the – then multi-stage – stochastic problem.
References


