Optimal Bidding Strategy of a Plug-in Electric Vehicle Aggregator in Day-ahead Electricity Markets

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Abstract—With a potential future large-scale introduction of plug-in electric vehicles (PEVs), the introduction of a new entity, the PEV fleet aggregator, is envisaged. Among other tasks, the aggregator would be responsible for managing charging and purchasing electricity on behalf of the vehicles. PEV load can be considered flexible since vehicles are typically used only intermittently and, therefore, their demand can be shifted in time. In this paper we consider the problem of an aggregator bidding into the day-ahead electricity market with the objective to minimize charging costs while satisfying PEVs’ flexible demand. The available charging flexibility depends on vehicle driving patterns, which determine the arrival and departure times and trip energy consumption. To take driver end-use constraints into account the fleet is modeled as a virtual storage resource with power and energy characteristics that depend on vehicle behavior. The bidding strategy of the aggregator is modeled as a bilevel problem. The upper-level problem represents the charging cost minimization of the aggregator subject to the power and energy constraints of the fleet. The lower-level problem represents the market clearing where the bids of other market participants are not known ex ante. Mathematically this problem can be described as a mathematical problem with equilibrium constraints (MPEC), which is implemented in the form of a mixed-integer linear program. Results show that with flexible charging, costs can be significantly reduced compared to inflexible charging. Moreover, even with a simple mechanism to guess the bids of other market participants, results close to a perfect information benchmark can be achieved.

I. INTRODUCTION

In the context of climate change mitigation and energy security, an increasing electrification of the vehicle fleet is seen as one important contribution to the reduction of greenhouse gas emissions and fossil fuel demand. When plug-in electric vehicle (PEV) shares reach a significant level, managing their charging becomes important, both to avoid voltage and congestion problems in the grid [1], [2], as well as from an economic perspective to reduce the costs of charging [2], [3]. PEV demand can be considered flexible since most vehicles are parked for a long time and most trips do not require the full energy that can be stored in a PEV battery. However, any charging management or “smart-charging” scheme should take driver needs into account in order not to disrupt vehicle end-use. A so-called aggregator could be in charge of managing charging and purchasing electricity on behalf of the PEV owners. By agreeing to a charging management scheme, vehicle owners would benefit from lower electricity rates for charging. This is because the aggregator can exploit charging flexibility to reduce the costs of charging and can share part of the so derived benefit with the PEV owners.

The role of the aggregator in integrating PEVs in power system structures is discussed in several publications [4]–[9]. The aggregator clusters a large number of small flexible loads/storage devices, which individually only have a small impact on the system, but as a group can be used as a powerful resource. The aggregator is envisaged to directly or indirectly manage vehicle charging [4], e.g. to minimize charging costs, but also to provide ancillary services to the grid [9], such as regulating power. The aggregator would serve as an interface between vehicle owners and other entities, such as energy service providers, as well as transmission and distribution system operators.

A number of papers address the aggregator’s cost optimization problem, where the costs of purchasing electricity are minimized subject to constraints related to PEV demand. In many of these approaches prices are considered an exogenous parameter, unaffected by PEV demand [10]–[12]. This assumption is probably not realistic, even for penetration rates as low as 2%, as will be shown later in the results section. Other authors take the impact of PEV demand on prices into account [13], [14]. In [13] a quadratic dependency between electricity prices and total load is assumed, while in [14] both a linear and a non-linear dependency are explored based on a regression model. However, the relationship between load, i.e. the sum of accepted demand bids, and the market price is not a simple one. Whether a demand bid is accepted or not depends on the willingness to pay for electricity (demand bid price) and on the bids of the other market participants. Without modeling the bidding process as such it is difficult to determine a bidding strategy for the aggregator. Existing models focus on optimal demand volumes given endogenous/exogenous prices, but not on the corresponding bid prices to achieve these. Another issue to be considered is that the market clearing price is not known ex ante. Only some of the mentioned approaches deal with this fact [10], [12], [14].

Another important aspect of charging optimization is the modeling of the fleet, which ultimately determines the charging demand and its associated flexibility. Since charging is not
an exogenous input, but a variable managed by the aggregator. PEV demand forecasting is different to that of conventional loads. Therefore, instead of an expected demand profile, the aggregator needs to determine a set of constraints that the optimal charging profile should satisfy. To assess the available flexibility, it is necessary to model the driving patterns of the fleet. In [12] vehicle movements are simulated using a discrete-state, discrete-time Markov chain from which the available demand flexibility is derived. In [14] information on individual driving patterns is clustered into representative aggregated PEVs with the help of a k-means algorithm.

In this paper we propose a strategy for a PEV aggregator bidding in the day-ahead market, where we explicitly model the bidding process. The bidding strategy is based on the approach proposed in [15] for the bidding of a strategic producer. Both driver end-use constraints, as well as the uncertainty in the bids of other market participants are taken into account in the model. The problem is formulated as a bilevel problem where the upper level represents the cost minimization, which is constrained by the available flexibility of charging demand, while the lower level represents the market clearing process. The market bids are guessed based on past data. To determine the available charging flexibility, the fleet is aggregated into a virtual storage with energy and power constraints which vary over time. These are parametrized aggregating information on individual driving patterns obtained from a transport simulation.

We compare the results of the bidding strategy with uncertainty in the other participants’ bids with a) the bidding strategy with perfect information b) a surplus maximizing certainty in the other participants’ bids with a) the bidding over time. These are parametrized aggregating information on the available charging flexibility, the fleet is aggregated into a virtual storage with energy and power constraints which vary over time. These are parametrized aggregating information on individual driving patterns obtained from a transport simulation.

The main findings are the following.

- Charging costs can be significantly reduced if PEV demand is managed compared to an uncontrolled demand.
- The costs of the bidding strategy with uncertainty are only slightly higher than those under perfect information, even if a simple strategy is used to guess the other bids.
- The aggregator can usually not exercise market power.

II. METHODOLOGY

A. Notation

Constants:

\[ \Delta t \quad \text{Time step duration} \]
\[ \eta \quad \text{Charging efficiency of PEV aggregation} \]
\[ E_{\text{dep}}^{(t)} \quad \text{Energy drop from vehicles departing at time } t \]
\[ E_{\text{arr}}^{(t)} \quad \text{Energy contribution of vehicles arriving at time } t \]
\[ s_{\text{bid}}^{(t)} \quad \text{Price of supply bid } s_j \text{ at time } t \]
\[ s_{\text{ask}}^{(t)} \quad \text{Price of demand bid } d_k \text{ at time } t \]
\[ P_{\text{max}}^{(t)} \quad \text{Max aggregated charging power at time } t \]
\[ P_{\text{min}}^{(t)} \quad \text{Min aggregated charging power at time } t \]
\[ M \quad \text{Very large number} \]

Variables:

\[ p^{(t)} \quad \text{Market clearing price} \]
\[ s_{\text{bid}}^{(t)} \quad \text{Price of aggregator's demand bid at time } t \]
\[ E^{(t)} \quad \text{Energy content of PEV aggregation at time } t \]
\[ P_{\text{max}}^{(t)} \quad \text{Accepted volume of supply bid } s_j \text{ at time } t \]
\[ P_{\text{max}}^{(t)} \quad \text{Accepted volume of demand bid } d_k \text{ at time } t \]
\[ P_{\text{max}}^{(t)} \quad \text{Accepted volume of aggregator's demand bid at time } t \]

The upper/lower bounds of these variables are represented with overlines/underlines.

Dual variables:

\[ \lambda^{(t)} \quad \text{Supply demand equilibrium} \]
\[ \mu_{\text{min},s_j}^{(t)} \quad \text{Supply bid } s_j \text{ volume lower bound} \]
\[ \mu_{\text{max},s_j}^{(t)} \quad \text{Supply bid } s_j \text{ volume upper bound} \]
\[ \mu_{\text{min},d_k}^{(t)} \quad \text{Demand bid } d_k \text{ volume lower bound} \]
\[ \mu_{\text{max},d_k}^{(t)} \quad \text{Demand bid } d_k \text{ volume upper bound} \]
\[ \mu_{\text{min},a}^{(t)} \quad \text{Aggregator's demand bid volume lower bound} \]
\[ \mu_{\text{max},a}^{(t)} \quad \text{Aggregator's demand bid volume upper bound} \]

Integer variables:

\[ \omega_{\text{min},s_j}^{(t)} \quad \text{Supply bid } s_j \text{ volume lower bound} \]
\[ \omega_{\text{max},s_j}^{(t)} \quad \text{Supply bid } s_j \text{ volume upper bound} \]
\[ \omega_{\text{min},d_k}^{(t)} \quad \text{Demand bid } d_k \text{ volume lower bound} \]
\[ \omega_{\text{max},d_k}^{(t)} \quad \text{Demand bid } d_k \text{ volume upper bound} \]
\[ \omega_{\text{min},a}^{(t)} \quad \text{Aggregator's demand bid volume lower bound} \]
\[ \omega_{\text{max},a}^{(t)} \quad \text{Aggregator's demand bid volume upper bound} \]

B. Fleet model

To formulate a bidding strategy, it is first necessary to estimate the energy needs of the fleet over time, as well as the available charging flexibility. Individual driver end-use constraints depend on driving patterns, i.e. on departure and arrival times and trip energy consumption. For the simulations discussed in this paper, driving patterns are obtained from a transport simulation called MATSim [16]. MATSim is an agent-based transport simulation where each agent has a set of activities to be performed (e.g. work, shopping, etc.) and the optimization selects the driving patterns that maximize agents’ utility, taking into account factors such as the induced traffic and the available means of transportation.

An aggregation model is needed to condense driving pattern information into a form that can be used in the aggregator’s cost optimization. Here the PEV fleet is modeled as a virtual storage which clusters the batteries of PEVs connected to the grid at each point in time. Therefore the energy capacity and available charging power of the virtual storage change over time. It is assumed that PEVs are plugged in if they are parked for at least one hour, no matter the location.

Given individual driving patterns, we determine the potential minimum and maximum battery energy content and
charging power of each vehicle over time. This information is aggregated to find constraints on the virtual storage’s energy content and charging power.

The aggregator’s optimization is therefore subject to the following constraints:

\[
E^{(t)} = E^{(t-1)} + P_a^{(t)} \cdot \eta \cdot \Delta t + E_{arr}^{(t)} - E_{dep}^{(t)} \quad \forall t
\]

\[
E^{(0)} = E^{(T)}
\]

\[
E_a^{(t)} \leq E^{(t)} \leq E_c^{(t)} \quad \forall t
\]

\[
P_a^{(t)} \leq P_a^{(t)} \quad \forall t
\]

The first equation represents the evolution of the energy content of the virtual storage over time, which depends on the aggregated charging power and on the arrivals and departures of PEVs. The second constraint ensures that enough energy is purchased, i.e., the energy content at the end of the period is equal to the energy content at the beginning of the period. Finally, (3) and (4) enforce the upper and lower bounds of the energy content and charging power of the virtual storage.

The bounds of the virtual storage’s energy content, as well as an exemplary energy content profile, are shown in Fig. 1. It can be seen that two dips occur around 8 a.m. and 6 p.m., mainly due to commuting to/from work. Moreover, most of the vehicles are parked between 2 a.m. and 6 a.m.

C. Bilevel model

The goal of the aggregator is to find a bidding strategy for the day-ahead market that minimizes the cost of purchasing the charging energy while satisfying PEV driver end-use constraints, modeled as constraints on a virtual storage. The electricity price is the outcome of a market clearing process, given the aggregator’s demand bids and the other participants’ supply and demand bids. It is assumed that the other participants do not adjust their bids in response to the aggregator’s bidding behavior. The aggregator’s bidding strategy can be modeled as a bilevel problem where the upper level problem corresponds to the aggregators’ cost minimization, while the lower level problem corresponds to the market clearing process, i.e. the maximization of supplier and consumer surplus. This can be formulated as follows:

\[
\min_{E^{(t)}, b_a^{(t)}} \sum_t p_s^{(t)} \cdot P_a^{(t)}
\]

subject to (1)-(4) and

\[
p_s^{(t)} = \lambda^{(t)}
\]

Where the accepted bid volume \(P_a^{(t)}\) and market clearing price \(p_s^{(t)}\) stem from the solution of the lower level problem.

\[
\min_{P_s^{(t)}, P_{dk}^{(t)}, P_{a}^{(t)}} \sum_{s,j,t} b_{s,j}^{(t)} \cdot P_{s,j}^{(t)} - \sum_{d,k,t} b_{d,k}^{(t)} \cdot P_{d,k}^{(t)} - \sum_t b_a^{(t)} \cdot P_a^{(t)}
\]

subject to

\[
P_{s,j}^{(t)} = P_{dk}^{(t)} + P_a^{(t)} \cdot \lambda^{(t)} \quad \forall t
\]

\[
0 \leq P_{s,j}^{(t)} \leq P_{min,s,j}^{(t)} + P_{max,s,j}^{(t)} \quad \forall t, \forall s_j
\]

\[
0 \leq P_{dk}^{(t)} \leq P_{min,d,k}^{(t)} + P_{max,d,k}^{(t)} \quad \forall t, \forall d_k
\]

In the lower level problem, the total surplus of the market participants is maximized (7), given the supply and demand equilibrium (8) and bid volumes (9)-(11). The Lagrange multiplier of the supply demand equilibrium constraint represents the market clearing price, as seen by the aggregator in the upper level problem (6).

The lower level problem is linear, and therefore can be replaced by its Karush-Kuhn-Tucker conditions. This leads to the following additional constraints:

\[
b_{s,j}^{(t)} - \lambda^{(t)} - P_{min,s,j}^{(t)} + P_{max,s,j}^{(t)} = 0 \quad \forall t, \forall s_j
\]

\[
-b_{d,k}^{(t)} + \lambda^{(t)} - P_{min,d,k}^{(t)} + P_{max,d,k}^{(t)} = 0 \quad \forall t, \forall d_k
\]

\[
-b_a^{(t)} + \lambda^{(t)} - P_{min,a}^{(t)} + P_{max,a}^{(t)} = 0 \quad \forall t
\]

\[
0 \leq P_{s,j}^{(t)} \leq P_{min,s,j}^{(t)} + P_{max,s,j}^{(t)} \quad \forall t, \forall s_j
\]

\[
0 \leq P_{dk}^{(t)} \leq P_{min,d,k}^{(t)} + P_{max,d,k}^{(t)} \quad \forall t, \forall d_k
\]

\[
0 \leq P_{a}^{(t)} \leq P_{max,a}^{(t)} \quad \forall t
\]

The non-linearities associated with the complementarity slackness conditions (15) - (20) can be linearized with the introduction of integer variables, denoted \(\omega\), as described in [15].

\[
P_{s,j}^{(t)} \leq (1 - \omega_{min,s,j}^{(t)}) \cdot M \quad \forall t, \forall s_j
\]

\[
\mu_{min,s,j}^{(t)} \leq \omega_{min,s,j}^{(t)} \cdot M \quad \forall t, \forall s_j
\]
\[ P_{d_j}^{(t)} \leq (1 - \omega_{\text{min},d_j}^{(t)}) \cdot M \quad \forall t, \forall d_k \]  
\[ \mu_{\text{min},d_j}^{(t)} \leq \omega_{\text{min},d_j}^{(t)} \cdot M \quad \forall t, \forall d_k \]  
\[ P_{a}^{(t)} \leq (1 - \omega_{\text{min},a}^{(t)}) \cdot M \quad \forall t \]  
\[ \mu_{\text{min},a}^{(t)} \leq \omega_{\text{min},a}^{(t)} \cdot M \quad \forall t \]  
\[ T_{s_j}^{(t)} - P_{s_j}^{(t)} \leq (1 - \omega_{\text{max},s_j}^{(t)}) \cdot M \quad \forall t, \forall s_j \]  
\[ \mu_{\text{max},s_j}^{(t)} \leq \omega_{\text{max},s_j}^{(t)} \cdot M \quad \forall t, \forall s_j \]  
\[ T_{d_k}^{(t)} - P_{d_k}^{(t)} \leq (1 - \omega_{\text{max},d_k}^{(t)}) \cdot M \quad \forall t, \forall d_k \]  
\[ \mu_{\text{max},d_k}^{(t)} \leq \omega_{\text{max},d_k}^{(t)} \cdot M \quad \forall t, \forall d_k \]  
\[ T_{a}^{(t)} - P_{a}^{(t)} \leq (1 - \omega_{\text{max},a}^{(t)}) \cdot M \quad \forall t \]  
\[ \mu_{\text{max},a}^{(t)} \leq \omega_{\text{max},a}^{(t)} \cdot M \quad \forall t \]  

Finally, the objective of the upper level problem (5) can be linearized using the strong duality theorem. For further details on this procedure we refer to [15].

\[
\sum_{t} p_{a}^{(t)} \cdot P_{a}^{(t)} = \sum_{s_j,t} b_{s_j}^{(t)} \cdot P_{s_j}^{(t)} + \sum_{d_k,t} b_{d_k}^{(t)} \cdot P_{d_k}^{(t)} + \sum_{s_j,t} \mu_{\text{max},s_j}^{(t)} \cdot T_{s_j}^{(t)} + \sum_{d_k,t} \mu_{\text{max},d_k}^{(t)} \cdot T_{d_k}^{(t)}
\]

In summary, the problem can be formulated as the following mixed integer linear problem.

\[
\min_{\Phi} \left\{ \sum_{s_j,t} b_{s_j}^{(t)} \cdot P_{s_j}^{(t)} - \sum_{d_k,t} b_{d_k}^{(t)} \cdot P_{d_k}^{(t)} + \sum_{s_j,t} \mu_{\text{max},s_j}^{(t)} \cdot T_{s_j}^{(t)} + \sum_{d_k,t} \mu_{\text{max},d_k}^{(t)} \cdot T_{d_k}^{(t)} \right\}
\]

With the optimization variables:

\[
\Phi = [E_{(t)}, b_{a}^{(t)}, P_{d_k}^{(t)}, P_{a}^{(t)}, \mu_{\text{min},a}^{(t)}, \mu_{\text{max},a}^{(t)}, \omega_{\text{min},a}^{(t)}, \omega_{\text{max},a}^{(t)}, P_{s_j}^{(t)}, P_{d_k}^{(t)}]
\]

Subject to the constraints (1)-(4), (8)-(14), (21)-(32) and:

\[
\mu_{\text{min},s_j}^{(t)}, \mu_{\text{max},s_j}^{(t)}, \mu_{\text{min},d_k}^{(t)}, \mu_{\text{max},d_k}^{(t)}, \mu_{\text{min},a}^{(t)}, \mu_{\text{max},a}^{(t)} \in \mathbb{R}^+
\]

\[
\omega_{\text{min},s_j}^{(t)}, \omega_{\text{max},s_j}^{(t)}, \omega_{\text{min},d_k}^{(t)}, \omega_{\text{max},d_k}^{(t)}, \omega_{\text{min},a}^{(t)}, \omega_{\text{max},a}^{(t)} \in \{0, 1\}
\]

**D. Bidding strategy**

To be able to apply the described bilevel optimization, the aggregator needs to guess the bids of the other market participants, since these are not known to him before he places his own bids. The strategy we analyze in this paper is a simple strategy where the aggregator uses the bids from the days of the previous week as the best guess for the bids of the days of the current week. For example for a given Monday at noon, the bids of the previous Monday at noon are used. This information is commercially available at power exchanges such as the European Energy Exchange (EEX) in the form of aggregated price curves.

The optimization described in the previous subsection generates two important results:

- The accepted aggregator bid volumes, which represent the optimal aggregated charging profile.
- The optimal aggregator bid price, which is in all cases equal to the clearing price.

Due to uncertainties regarding the market bids and the corresponding clearing prices, using this strategy without modification would usually mean that either excess or insufficient energy is purchased, even if prices are close to the expected price. However, the aggregated charging profile contains information about the times at which it is cheaper to purchase energy. Moreover, it has the advantage that it satisfies the power and energy constraints of the virtual storage (1)-(4). Therefore the obtained optimal charging profile is used as a reference to determine the final bids. For this purpose, the bid volume is set equal to the accepted bid volume and a markup is added to the bid price obtained from the bilevel optimization.

**E. Benchmarks**

The results obtained with the described bidding strategy are compared with four other theoretical benchmark cases.

1) **Reference without PEV**: Reference market clearing without the participation of the PEV aggregator.

2) **Perfect information**: In this case we consider the bilevel problem described in subsection II-C; however, here we assume that the bids of the other participants are known to the aggregator ex-ante. The resulting charging costs set the lower bound for approaches with imperfect information.

3) **Central dispatch**: Here the charging profile is obtained which maximizes supplier and consumer surplus of the existing market participants while satisfying the constraints of the PEV aggregation. That is:

\[
\min_{P_{s_j}^{(t)}, P_{d_k}^{(t)}, P_{a}^{(t)}} \sum_{s_j,t} b_{s_j}^{(t)} \cdot P_{s_j}^{(t)} - \sum_{d_k,t} b_{d_k}^{(t)} \cdot P_{d_k}^{(t)}
\]

subject to (1)-(4) and (8)-(10). This theoretical case represents the optimum from a system perspective.

4) **Inflexible PEV demand**: In this case we assume that charging is left uncontrolled, i.e. that each PEV starts charging as soon as it is parked, and calculate the associated aggregated charging profile. The aggregator has to purchase this energy in the market, independent of the price. This
is equivalent to a bid with the maximum allowed bid price and the aggregated charging energy at each time step as the bid volume. By comparing the result of the flexible charging approach with these results, the value of charging flexibility and charging management can be assessed.

III. RESULTS

To validate the proposed approach we simulate the bidding strategy and benchmark cases with aggregated price curves of the spot market for electricity for the bidding area Germany/Austria, which were obtained from the European Energy Exchange (EEX). The simulation period spans the year 2012. We assumed a 2% penetration of PEVs in Germany and Austria, which corresponds to almost one million PEVs. The transport simulation model used in this paper [16] is based on Swiss transport data and represents driving patterns on a typical weekday. With this transport data it is therefore not possible to make a quantitative analysis of the potential impact of PEV penetration on the German/Austrian electricity spot market. However, no equivalent tools exist for Germany and Austria. Nevertheless, it is still possible to qualitatively test the performance of the described bidding strategy and assess the importance of charging flexibility, which is the goal of this paper.

First, we compare the costs of the bidding strategy with those of the benchmark cases. Average costs per MWh are shown in Table I for the simulated year 2012. It can be seen that the difference between the central dispatch case and the perfect information case is very small. This implies that usually the aggregator cannot exercise market power against the other market participants. Moreover, the bidding strategy performs well compared to the perfect information benchmark. This result was achieved with the simple guessing strategy for the market bids described in subsection II-D. If a more sophisticated method is used, the results could become even closer to the perfect forecast benchmark. Finally, the uncontrolled charging strategy (inflexible demand) leads to much higher costs than any of the other strategies, e.g. to 46% higher costs compared with the perfect information case.

Further, we analyze some typical patterns in the results. Figure 2 shows hourly spot prices and trading volumes, as well as energy purchased by the aggregator for the different cases during one week. As stated previously, it can be seen that the perfect information case and the central dispatch case lead to very similar results. At the simulated penetration rate of 2%, PEV demand only represents a small percentage of the traded volume (about 1%), however the impact on prices is clearly visible. Therefore the assumption of exogenous prices which is often used in the literature is not justified, even at relatively low penetration rates. With perfect information, PEV demand is shifted to the night, when prices are low, and also some charging takes place between the two daily price peaks. The latter cannot be avoided since there is not enough flexibility to shift all demand to the less expensive night hours due to end-use constraints. It can be seen that the price profile under perfect information has a valley-filling type of structure: At the time periods with PEV demand prices become flat. The price profiles under the bidding strategy are similar to those under perfect information, but as expected, are not identical to the latter. By comparing the aggregator demand (Fig. 2c) for the case with perfect information and for the bidding strategy, it is clear that the profiles have a similar structure, with a large peak during night and a smaller one during the day. However, they do not match perfectly because the bidding strategy is based on an imperfect forecast of the market bids. Finally, it can be seen that with inflexible charging, demand is more evenly distributed throughout the day. Inflexible demand is higher between the morning and evening and shows peaks that often coincide with the price peaks in the market. This explains the much higher costs associated with the inflexible demand.

IV. CONCLUSION

In this paper a bidding strategy for a PEV aggregator bidding in the day-ahead market is introduced. The described scheme takes into account both the uncertainty in market bids and the constraints on the available demand flexibility, which are derived from a transport simulation. Results show that the proposed bidding strategy performs well, even with a simple guessing mechanism for the market bids. Moreover, charging costs can be significantly reduced compared to a case where PEV demand is not managed. Furthermore, it seems that most of the time the aggregator cannot exercise market power against other market participants.

Further research will focus on improving the guessing strategy for the market bids and on taking into account uncertainty in driving behaviour, as has been done previously by the authors in [17].

ACKNOWLEDGMENT

The authors would like to thank the Institute for Transport Planning and Systems of the ETH Zurich for the transport simulation data. This research was carried out within the project Technology-centered Electric Mobility Assessment, sponsored by the Competence Center for Energy & Mobility, SwissElectric Research and the Erdöl-Vereinigung.

REFERENCES


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<th>TABLE I</th>
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<tr>
<td>COST COMPARISON [€/MWh]</td>
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Fig. 2. Results for the week June 4th - June 10th, 2012.


