Incorporating Valley Filling and Peak Shaving in a Utility Function based Management of an Electric Vehicle Aggregator

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Abstract—Shifting load away from the system peak into evening hours when the load is low and the network’s capacity is high is referred to as peak shaving and valley filling. This paper develops an approach to enforce such a charging behavior to a large fleet of individual electric vehicles. The vehicles move in a transportation network which is mapped to a realistic urban electricity distribution system. Each vehicle features a utility function based on which the charging is controlled. The algorithm tunes the utility function parameters in order to initiate the desired charging behavior. Individual behavioral constraints, such as a desired state of charge when leaving, are fully considered.

Index Terms—Plug In Electric Vehicles, Load Management, Valley Filling, Peak Shaving, Distribution Networks

I. INTRODUCTION

It is anticipated that Plug-in Hybrid Electric Vehicles (PHEVs) and Electric Vehicles (EVs), commonly referred to as Plug-in Electric Vehicles (PEVs) in this paper, will revolutionize the transportation sector, drastically improving its sustainability. At the same time, they offer many advantages for power systems. PEVs are envisioned to introduce the possibility of a distributed storage for electricity. When clustered and controlled properly, the aggregated PEV storage can be used for different purposes, such as the provision of ancillary services [1] or balancing the power infeed prediction error of renewable energy sources [2], [3]. One solution for the aggregation and control of the vehicles under liberalized market conditions is a new entity referred to as PEV aggregator [4]. Such aggregators may function also as virtual power plants for the sake of the power system [5], [6]. A discussion on integration issues into current frameworks is found in [7] while [8] delineates possible solutions for an efficient integration.

However, the wide scale adoption of PEVs will likely create challenges for the electricity infrastructure. Studies show that uncontrolled charging of large numbers of PEVs will stress the electricity network by causing asset overloading or endangering power quality through excessively low voltages [9].

Intelligent algorithms managing the charging behavior of PEVs can avoid such negative effects. Charging control minimizes distribution network losses [10], or shifts excessive load to later times which offer more capacity [11]. Another approach is to shift PEV load from high load to low load hours, i.e., typically night hours. This is referred to as valley filling [12]. Often, valley filling approaches consider complete information on the vehicle side. Without paying much attention to the behavioral constraints of individual vehicles, their demand is aggregated and shifted from day into the night time [13]. In such cases, behavioral constraints and their energy demand could be disregarded as vehicles could not be able to reach the next planned location.

This paper develops a utility function based algorithm for valley filling. The PEV aggregator is assumed to control the charging behavior. The aggregator considers behavioral constraints, i.e., the desired energy and the parking duration, of each individual PEV. Each PEV incorporates a utility function. By tuning the utility function parameters, a desired charging behavior is imposed by the aggregator, i.e., charging at peak load times is avoided and shifted to low load hours. Even peak shaving, i.e., energy infeed from PEVs at peak load times, can be achieved with this approach. Here, for brevity, no attention is paid to economic considerations.

The paper is organized as follows. The following section describes the system model, comprising representations of the transportation and the electricity distribution system of an urban area. Then, the hierarchical, distributed charging control, which is able to temporarily shift excessive load, is described. Section IV introduces the concept of reachable levels for valley filling and peak shaving. Section V explains the utility function parameter tuning procedure and Section VI shows case studies. The paper concludes with a summary and an outlook in Section VII.

II. THE POWER AND THE TRANSPORTATION SYSTEM OF THE CITY OF ZURICH

Traffic flows are simulated through the behavior of individual vehicles, which are modeled as agents. MATSim, an agent based transport simulation framework with focus on large scenarios, is used to simulate the agent behavior [15]. Figure 1
The charging control concept of the PEV Managers is based on mechanism design, a subclass of game theory which is agent related [16], [19]. It is assumed that a PEV agent gains benefit by having a certain energy in its battery. Intuitively, the benefit should be low when the battery is empty and it should be high when the battery is full. The marginal benefit, i.e., the infinitesimal change in benefit due to the infinitesimal change of SOC, should decrease the higher the SOC is. The more energy is stored in the battery, the lower the sensitivity for acquiring additional energy, and hence the lower the increase in benefit. The latter characteristics of the benefit function are achieved by defining it according to

\[ b_{v,n} \left( \Omega_{v,n}(T) \right) = \alpha_{v,n} c^B_{v,n} \Omega_{v,n}(T) - \beta_{v,n} C^B_{v,n} \Omega_{v,n}(T)^2 \]

with \[ \Omega_{v,n}(T) = soC_{v,n}(T) - soC_{v,n}^{\min} + q_{v,n} \]
\[ \forall v \in V_n(T), \forall n \in N \]

where the PEVs connected at node \( n \) are denoted through \( v \in V_n(T) = \{1, 2, ..., N_v(n) \} \forall n \in N \) .

(3)

The parameter \( soC_{v,n}(T) \) is the SOC of the vehicle, \( C^B_{v,n} \) denotes the battery capacity of PEV \( v \), \( \alpha_{v,n} \) and \( \beta_{v,n} \) define the maximal marginal benefit and the slope of the marginal benefit. The parameter \( \alpha_{v,n} \) is set to the value of the current gasoline price. The parameter \( q_{v,n} \) is a variable for the change of SOC. The variables \( V_n(T), N \) denote the set of connected vehicles and the set of nodes, respectively.

A utility function can be derived in order to make use of the mathematical concepts of mechanism design and to allow PEV agents to bid for the potentially scarce good of electric power at a congested distribution grid node. The utility function is derived from the benefit function by multiplying the benefit function with the agent specific parameter \( \theta_{v,n}(T) \) and subtracting a cost, which is derived from an exogenously transmitted or endogenously determined control price signal \( \pi_n(T) \). If a specific node is congested, the control price signal is endogenously determined by the utilized algorithm [11], [16]. Hence, the utility function is formulated as

\[ u_{v,n}^{G2V} \left( \Omega_{v,n}(T), \pi(T), \theta_{v,n}(T) \right) = \]
\[ \theta_{v,n}(T) \alpha_{v,n} C^B_{v,n} \left( \Omega_{v,n}(T) \right) - \theta_{v,n}(T) \beta_{v,n} C^B_{v,n} \left( \Omega_{v,n}(T) \right)^2 \]
\[ -\pi_{n} \left( T, \Theta_n(T) \right) C^B_{v,n} q_{v,n} \left( T, \theta_{v,n}(T) | \Theta_n(T) \right) \] (4)

with

\[ q_{v,n} \left( T, \theta_{v,n}(T) | \Theta_n(T) \right) = \frac{p_{v,n} \left( T, \theta_{v,n}(T) | \Theta_n(T) \right)}{\zeta(T) C^B_{v,n}} \] (5)

where \( p_{v,n} \) is the power assigned to the PEV and \( q_{v,n} \) is the energy in per unit of the battery capacity. The variable \( \Theta_n(T) \) is the set of all personal parameters of the connected vehicles at node \( n \) in a time step [16].

Given certain game theoretic theorems, the agents bidding process, which is based on the utility functions, can be avoided and an optimization can be formulated. The optimization determines the outcome of an auction among the agents. It is performed by each PEV Manager. It maximizes the total utility and distributes available power optimally to the connected...
PEVs. The optimization maximizes

\[

g^\text{Gv} = \sum_{v \in \mathcal{V}, n} u_{v,n} \left( \Omega_{v,n}(T), \pi_{v,n}(T), \theta_{v,n}(T) \right)
\]

subject to

\[

\begin{align*}
    p_{v,n}^\text{min}(T) & \leq p_{v,n}(T, \theta_{v,n}(T) | \Theta_{n}(T)) \leq p_{v,n}^\text{max}(T) \\
    s_{v,n}^\text{min} & \leq s_{v,n} \leq s_{v,n}^\text{max} \\
    p_{v,n}(T) & \leq \sum_{v \in \mathcal{V}_n(T)} p_{v,n}(T, \theta_{v,n}(T) | \Theta_{n}(T)) \leq P_{\text{max}}(T) \\
    \forall v & \in \mathcal{V}_n(T), \forall n \in \mathcal{N}.
\end{align*}
\]

Constraint (7a) ensures that the power with which a PEV is charged is within the limits of the physical connection. Constraint (7b) gives that each PEV is not overloaded or more than fully depleted. The last constraint ensures that the maximum capacity of the transformer to which the PEVs are connected is not violated by the power drawn by the vehicles.

The management scheme shifts excessive PEV load to later times where the base load, i.e., the inflexible household load, is lower. If the particular load node should be heavily loaded for long times, it is possible that PEVs will not be able to achieve their desired SOC before departure in this scheme. This can be bypassed by making their load inflexible. However, this comes at the cost of other, flexible PEVs [16].

Obviously, network challenges such as overloaded transformers on a higher voltage level, low voltages or overloaded lines are not mitigated by this configuration of PEV demand management. Therefore, a hierarchical scheme is used to mitigate these issues.

A Supervisory PEV Manager (S-PEV Manager) is installed at the transformer between the 150 kV and the lower voltage level (or at the busbar to which the transformer is connected). It controls the underlying PEV Managers on the 11 kV and 22 kV network.

The S-PEV Manager is able to mitigate transformer and line overloading in the part of the network for which it is responsible. The mitigation of excessively low voltages is achieved by using a Thevenin equivalent for the zone fed by a particular transformer. The S-PEV Manager utilizes a similar optimization algorithm as the PEV Manager whose formulation is found in [16], [18]. The S-PEV Manager considers the charging setpoints of its underlying PEV Managers and changes them in order to avoid network issues.

The PEV aggregator is assumed to be in charge of this control architecture and to manage the charging behavior of the vehicles. It constantly exchanges information with the Distribution System Company (DisCO) in order to keep the network in a secure state. For such services, the PEV aggregator can be reimbursed [16]. Valley filling offers the possibility to take advantage of low electricity prices and an increased network capacity during night time as well as of avoiding additional load peaks.

**IV. INTRODUCING THE CONCEPT OF REACHABLE LEVELS FOR VALLEY FILLING AND PEAK SHAVING**

In order to perform valley filling and peak shaving, the PEV aggregator needs to assess the amount of energy which can actually be shifted into low load periods. This amount depends on the charging flexibility of each vehicle, i.e., on the ratio between minimum charging time and parking duration.

The case of 4 different vehicles is illustrated in the lower part of the figure. Vehicle 1 is parked only during the HLP. Its parking duration is indicated through the black horizontal line. The time needed in order to charge the desired amount of energy is shown by the colored bar below the black line. The level of charging flexibility is indicated by the color of the bar, i.e., a red color indicates a low charging flexibility and a green color means a high charging flexibility. Vehicle 1, its complete desired energy needs to be charged during the HLP. Furthermore, as the time to charge this energy is almost as long as the parking duration, the bar is colored red. This vehicle incorporates little flexibility when being charged. For the other vehicles the situation is different. Vehicle 4 offers the highest charging flexibility. The following derivation is performed for the HLP but is equivalent for the LLP. The fraction of energy which is charged during the HLP is calculated by

\[
    \Delta E_{v,n} = \Delta E_{v,n} \frac{PD_{HLP}}{PD_{v,n}}.
\]
where $PD_{v,n}^{HLP}$ denotes the vehicle’s parking duration during the HLP and $PD_{v,n}$ indicates its total parking duration. This approach assigns more load to the HLP than assuming that vehicles would be charged with maximum power during the LLP. The latter approach would remove all charging flexibility during the LLP as every agent would be fully scheduled. Therefore, no control could be exercised.

Finally, the energy which is needed to determine the reachable level during the particular period is given by

$$\Delta E^\text{reach,1} = \sum_{n=1}^{N} \sum_{v=1}^{N_{PEV}} \Delta P_{v,n}^{\text{HLP}}.$$ (10)

Based on this energy a reachable load level can be calculated according to

$$E^\text{reach,1} = \frac{T \left( L^\text{reach,1} - L(T) \right)}{3600},$$

where the variable $T$ gives the length of time step $T$ in seconds and $H$ denotes the heaviside function.

The resulting reachable levels are conceptually illustrated in Fig.4. The blue area illustrates $E^\text{reach}$, which is the energy to be charged during one specific load period. The second reachable level, colored in orange, illustrates energy which can be fed back during very high load periods.

V. TUNING OF UTILITY FUNCTION PARAMETERS TO ACHIEVE VALLEY FILLING AND PEAK SHAVING

Having determined the reachable levels, the aggregator can tune the utility function parameters of its fleet in order to impose the desired charging behavior. Before tuning the parameters, the benefit and the utility function are analyzed to investigate the parameters influence on the charging behavior. The utility function is extended in order to incorporate V2G behavior allowing for peak shaving.

A. Analysis of the benefit and the utility function for charging purposes

The benefit function attributes a value to the energy stored in the battery of the particular vehicle. This value needs to be positive in order to achieve a charging behavior of the connected fleet. Investigating the boundary case of the benefit function gives

$$b_{v,n} \left( \Omega_{v,n}(T) \right) = 0$$

$$\Rightarrow \alpha_{v,n} \Omega_{v,n}(T) - \beta_{v,n} \Omega_{v,n}(T)^2 = 0,$$ (12)

where it follows that

$$\Omega_{v,n}(T) = 0 \quad \vee \quad \Omega_{v,n}(T) = \frac{\alpha_{v,n}}{\beta_{v,n}},$$ (13)

and hence the zeros of $b_{v,n}$ are found for

$$soc_{v,n}(T) + q_{v,n} = \frac{soc_{v,n}^{min}}{\beta_{v,n}} + soc_{v,n}^{min}.$$ (14)

For $\alpha_{v,n} \geq \beta_{v,n}$ it follows that $soc_{v,n}(T) + q_{v,n}(T) \geq 1$. The benefit function has the shape of an inverse parabola. Setting the maximum of the benefit function outside of the feasible battery operation bounds ensures that the desire to charge increases only until the feasible energy bound is reached. From the first derivative of the benefit function

$$\frac{db_{v,n}}{dq_{v,n}} = 0$$ (15)

one can calculate

$$\theta_{v,n}(T)C_{v,n}^{B} \alpha_{v,n} - 2\theta_{v,n}(T)C_{v,n}^{B} \beta_{v,n} \Omega_{v,n}(T) = 0$$ (16)

which gives

$$\Leftrightarrow \left( soc_{v,n}(T) - soc_{v,n}^{min} + q_{v,n} \right) = \frac{\alpha_{v,n}}{2\beta_{v,n}}.$$ (17)

Setting $\beta_{v,n} \geq 0$ and for $\alpha_{v,n} \geq 2\beta_{v,n}(1 - soc_{v,n}^{min})$, it follows that the maximum of the benefit function lies beyond the bound $soc_{v,n}(T) = 1 - soc_{v,n}^{min}$, which causes the marginal benefit to be positive for the complete range of feasible SOC states.

In order to find a proper value for $\beta_{v,n}$, the case of $\pi(T) = \pi^{\text{day}}_{\text{max}}$ can be investigated as this situation offers, together with the highest value of $\theta_{v,n}(T) = \theta_{v,n}^{\text{max}}$, the highest incentive to the vehicles to charge. For the computation of the lower bound for $\beta_{v,n}$, the first derivative of the utility function

$$\frac{du^{\text{GV}}_{v,n}}{dq_{v,n}} = 0$$ (18)

is investigated. It gives

$$C_{v,n}^{B} \alpha_{v,n} - 2\beta_{v,n} \Omega_{v,n}(T) - C_{v,n}^{B} \pi^{\text{min}}_{\text{day}} = 0$$ (19)

and therefore

$$\Rightarrow \beta_{v,n} = \frac{\alpha_{v,n} - \pi^{\text{min}}_{\text{day}}/\pi^{\text{max}}_{\text{day}}}{2 \cdot \left( soc_{v,n}(T) + q_{v,n} - soc_{v,n}^{min} \right)}.$$ (20)

Assuming that the vehicle is fully charged gives

$$\beta_{v,n} = \frac{\alpha_{v,n} - \pi^{\text{min}}_{\text{day}}/\pi^{\text{max}}_{\text{day}}}{2(1 - soc_{v,n}^{min})}.$$ (21)

The vehicle with the highest energy valuation and a fully charged battery will incorporate a marginal utility of zero. Note that this definition of $\beta_{v,n}$ fulfills the conditions derived from the calculation given in (15)–(17).

Setting the derivative of the utility function to zero and solving for $q_{v,n}$ allows one to determine the amount of energy which is charged by a vehicle of the fleet given the tuned parameters $\alpha_{v,n}, \beta_{v,n}$. Performing the derivation for the general case of $\theta_{v,n}(T)$ gives

$$q_{v,n}^{\text{GV}} = \frac{\alpha_{v,n} - 2 \cdot \beta_{v,n} \cdot \left( soc_{v,n}(T) - soc_{v,n}^{min} \right) - \pi(T)}{2 \cdot \beta_{v,n}}$$ (22)
The third case shows a situation where the value of expected by this particular vehicle.

The utility function needs to be adapted for the V2G case. Note that $q_{v,n} = q_{V2G}^{G2V}$ which indicates that the energy amount is derived from the utility function of a charging situation, hence $q_{V2G}^{G2V} \geq 0$. Computing the derivative of it according to

$$
\frac{du_{V2G}^{G2V}}{d\alpha_{v,n}} = \frac{\pi(T) - \pi_{min}/\theta_{max}}{\alpha_{v,n} - \pi_{min}/\theta_{max}}^2.
$$

Note the superscript $V2G$ indicates that the calculated energy amount is strictly valid for a discharging situation, hence $q_{v,n}^{V2G} \leq 0$. In order to integrate the peak shaving option into the PEV Manager utility function, which so far only modeled a charging behavior charging, one can utilize a mixed integer nonlinear formulation. This proves computationally expensive, especially since large numbers of vehicles are considered. The problem is bypassed by closely investigating both parts of the integrated utility function.

Figure 6 illustrates both parts of the integrated utility function for four different cases when tuning $\alpha_{v,n}$. In Fig. 6(a) the two different utility function parts reach their maximum for positive values of $q_{v,n}^{G2V}$ and $q_{v,n}^{V2G}$. However, $u_{V2G}^{G2V}$ is not defined for positive values and hence, only $u_{G2V}^{V2G}$ can be used. This is a valley filling situation. In Fig. 6(b) both utility function parts reach a maximum in the left half plane. However, only $u_{G2V}^{V2G}$ is defined here. This is a typical peak shaving situation. Figure 6(c) shows maxima for both utility function parts lying in areas where the respective functions are both defined. In this case both utility functions would need to be calculated. However, since the controlling entity would like to impose a consistent behavior of the fleet, only one utility part can actively be chosen. For example, if the aggregator would like to impose a charging behavior of its fleet, it will choose the right utility function, as it wants $q_{v,n}$ to be positive. Figure 6(d) shows a situation where the maximum of $u_{G2V}^{V2G}$ lies in the negative half plan and the maximum of $u_{V2G}^{G2V}$ in the positive. Since both utility functions are not defined for these values of $q_{v,n}$, the best solution can be achieved for $q_{v,n} = 0$.

**B. Achieving peak shaving behavior by adapting the utility function**

The utility function needs to be adapted for the V2G case. Battery costs and the cost of the energy which is discharged during peak load times need to be considered. The utility function is adapted to

$$
u^{G2V}_{v,n}(\Omega_{v,n}(T),\pi(T),\theta_{v,n}(T)) = \theta_{v,n}^{GB}(T)\beta_{v,n}^{GB}(\Omega_{v,n}(T) - \theta_{v,n}(T))C^{GB}_{v,n}(\Omega_{v,n}(T))^2 - \left(\pi(T) - \frac{\pi_{min}}{\theta_{max}} - \frac{\beta_{min}}{\theta_{max}}\right)C^{GB}_{v,n}\theta_{v,n}(T)\theta_{v,n}(T)\Omega_{v,n}(T).
$$

**C. Tuning of the utility function parameters**

The parameters are tuned in such a way that the aggregated charging or discharging behavior complies with the reachable level determined before. Using the difference between the reachable level and the underlying system load, an average
amount of energy, which needs be charged by the connected PEVs can be calculated. This average energy amount allows for reaching the predefined reachable load level in the time step $T$. The desired average amount of energy, $q^{G2V,\text{avg}}_{\text{des}}(T)$, to be charged is determined by

\[
q^{G2V,\text{avg}}_{\text{des}}(T) = \frac{H(L^\text{reach,1} - L(T))(L^\text{reach,1} - L(T))}{4CB_v N^V(T)},
\]

with $\sum_{n=1}^N N^V_n(T) = N^V(T)$. In the V2G case the average discharged energy during intervals where peak shaving is desired is calculated as

\[
q^{V2G,\text{avg}}(T) = \frac{H(L^\text{reach,2} - L(T)) - 1)(L^\text{reach,2} - L(T))}{4CB_v N^V(T)}.
\]

Now, one can determine $\alpha_{v,n}^{\text{tuned}}$ in order to obtain the desired value of $q^{G2V/V2G,\text{avg}}(T)$ of the connected fleet. The computation of $\alpha_{v,n}^{\text{tuned}}$ is performed before each time step, therefore the parameters become dependent on $T$, hence

\[
\alpha_{v,n} \rightarrow \alpha_{v,n}^{\text{tuned}}(T),
\]

\[
\beta_{v,n} \rightarrow \beta_{v,n}^{\text{tuned}}(T).
\]

Reasonable bounds for $\alpha_{v,n}^{\text{tuned}}(T)$ are chosen as

\[
\alpha_{v,n}^{\text{min}} = \pi^{\text{min}}_{\text{day}} + \epsilon, \quad \epsilon << 1,
\]

and $\alpha_{v,n}^{\text{max}} = 5\pi^{\text{max}}_{\text{day}}$, as a maximum bound in order to allow a large tuning flexibility during high price signal phases. The following procedure allows a fast determination of a suitable value for $\alpha_{v,n}^{\text{tuned}}(T)$:

1) The lower bound $\alpha_{v,n}^{\text{min}}$ and the higher bound $\alpha_{v,n}^{\text{max}}$ are set.

2) Then the average of $\alpha_{v,n}^{\text{min}}$ and $\alpha_{v,n}^{\text{max}}$ is computed and chosen to be the actual $\alpha_{v,n}^{\text{tuned,}i}$, where $i$ refers to the iteration: $\alpha_{v,n}^{\text{tuned,}i}(T) = \frac{\alpha_{v,n}^{\text{min}} + \alpha_{v,n}^{\text{max}}}{2}$. The iteration stops if the difference between the new $\alpha_{v,n}^{\text{tuned,}i}(T)$ and the one from the iteration before, $\alpha_{v,n}^{\text{tuned,}i-1}(T)$, is smaller than a certain value $\delta_\alpha$ chosen to 0.005. It defines the convergence criterion for this algorithm. The last value for $\alpha_{v,n}^{\text{tuned,}i}\text{and}(T)$ is retained.

3) The variable $q^{G2V/V2G,\text{avg}}_{\text{avg}}(T,\alpha)$ is then calculated for $\alpha_{v,n}^{\text{tuned,}i}(T)$, $\alpha_{v,n}^{\text{min}}$, and $\alpha_{v,n}^{\text{max}}$. Note the additional dependency on $\alpha$ as it is now becomes a variable. Since the SOC of the different PEVs is known, $q^{G2V/V2G,\text{avg}}_{\text{avg}}(T,\alpha_{v,n}^{\text{tuned,}i}(T))$ can easily be calculated using (23) taking into account the current price signal. Then, $q^{G2V/V2G,\text{avg}}_{\text{avg}}(T,\alpha_{v,n}^{\text{tuned,}i}(T))$ is computed by summing the values $q^{G2V/V2G,\text{avg}}_{\text{avg}}(T,\alpha_{v,n}^{\text{tuned,}i}(T))$ and dividing by the number of the vehicles. This calculation is computationally inexpensive.

4) Two cases are differentiated:

- $|q^{G2V/V2G,\text{avg}}_{\text{avg}}(T,\alpha_{v,n}^{\text{min}})| \leq |q^{G2V/V2G,\text{avg}}_{\text{avg}}(T,\alpha_{v,n}^{\text{max}})|$
- $|q^{G2V/V2G,\text{avg}}_{\text{avg}}(T,\alpha_{v,n}^{\text{tuned,}i}(T))| \geq |q^{G2V/V2G,\text{avg}}_{\text{avg}}(T,\alpha_{v,n}^{\text{max}})|$

In this case, $\alpha_{v,n}^{\min}$ is chosen to be the new lower bound and $\alpha_{v,n}^{\text{tuned,}i}(T)$ is chosen as the new upper bound.

$|q^{G2V/V2G,\text{avg}}_{\text{avg}}(T,\alpha_{v,n}^{\text{tuned,}i}(T))| \leq |q^{G2V/V2G,\text{avg}}_{\text{avg}}(T,\alpha_{v,n}^{\text{min}})|$

$|q^{G2V/V2G,\text{avg}}_{\text{avg}}(T,\alpha_{v,n}^{\text{max}})| \geq |q^{G2V/V2G,\text{avg}}_{\text{avg}}(T,\alpha_{v,n}^{\text{min}})|$

In this case, $\alpha_{v,n}^{\text{tuned,}i}(T)$ is chosen to be the new lower bound and $\alpha_{v,n}^{\text{max}}$ is chosen as the new upper bound.

5) The iteration is restarted from the first step again.

At the end of the iteration, the a value for $\alpha_{v,n}^{\text{tuned}}(T)$, meaning the one that gives rise to $q^{G2V/V2G,\text{avg}}_{\text{avg}}(T,\alpha_{v,n}^{\text{tuned}}(T))$ close to the desired average energy to be consumed, is retained. Then $\beta_{v,n}^{\text{tuned}}(T)$ is determined using equation (21).

VI. PERFORMING VALLEY FILLING AND PEAK SHAVING WITH LARGE NUMBERS OF PEVS

In the following, three simulation examples are presented which use the tuning method. The knowledge on the PEV behavior is provided by the agent based transportation simulation. It includes activities such as staying at home, going to work, education, shopping and leisure activities, all located in Zurich. The transportation simulation provides information on the temporal parking behavior and on the desired energy per vehicle during its parking time. Pervasive charging possibilities are assumed which feature a 3.5 kW connection. In this example, between 170'000 and 230'000 vehicles are connected for charging at the same time.

A management framework defines the modes: uncontrolled, controlled charging and V2G mode as well as mode transfers [7]. Vehicles which have to attain their desired SOC, leave the controlled charging mode, where their parameters are tuned, and charge in the uncontrolled mode at full connection power. These cars influence the tuning of the utility function parameters of the other cars. For simplicity, a constant price signal is assumed in the first two examples. In the third example a high price is used during peak load hours to foster V2G behavior. The network is assumed to act as a copperplate.

The result of the first example is illustrated in Fig. 7. The tuning of the parameters avoids load peaks from PEV charging in the city. The black, dotted line shows the city’s base load. The base load includes a high and a low load period. The red, dashed line shows the city’s load if all vehicles are charged in uncontrolled mode, i.e, they connect and charge at full power. The additional load is substantial. Uncontrolled charging leads to a load peak at 09:30. During night hours, the load drops to a level close to the city’s base load, e.g., at 04:00.

The load curve of the PEV fleet is substantially modified by the tuning algorithm. It is illustrated through the green curve and follows a rectangular shape according to the reachable levels calculated with (9). Load peaks during the day are avoided. Instead, a load plateau is created. The maximum load is reduced from 915 MW to 772 MW. During the night hours the load valley is filled. The load level stays rather constant at 485 MW. Note that the large number of PEVs and their relatively high energy consumption causes the city’s consumption to almost double. The approach takes full advantage of the vehicles’ charging flexibility. The load level in the controlled charging case exceeds the reachable level between 20:00 and 23:00 due to vehicles which charge in uncontrolled mode. During this period, their load cannot be compensated by switching other vehicles off.
Figure 8 illustrates the impacts of the vehicle fleet’s charging behavior on the country load curve of Switzerland. Again, the black, dotted graph shows the country’s load curve without electric vehicles. The red, dashed and the green line show the load for the uncontrolled and the controlled, i.e., tuned, case, respectively. It can be seen that the country’s peak load is increased. In the controlled case, the country’s peak load is increased less than in the uncontrolled charging case.

The second example performs valley filling for the country load curve, i.e., the country load curve serves as input. The utility function parameters are tuned in order to fill the valley of the country’s load curve. The result is shown in Fig. 9. The valley between 24:00 and 05:00 now exhibits a load plateau higher than in the previous example. Later, the load curve is quite similar to the one before. However, the load until 11:00 is lower in the controlled case than in the previous example. Here, only PEVs in the uncontrolled mode charge. They have to charge in order to attain their desired SOC before departure. Load is shifted to the late afternoon or, if possible, into the night.

Figure 10 shows the impact of the valley filling behavior on the underlying load curve of the city. The shape, which is dominated by two plateaus in the last example, is altered. The load peak in the city occurs later than in the uncontrolled case as much charging is shifted away from the country’s load peak time at 11:30. The load valley hours at night are filled. The load during the night shape exhibits a rather spiky behavior, determined by the country’s load curve.

The third example shows how the PEV fleet can be utilized to perform peak shaving and valley filling taking the country’s load curve as the reference. As seen in Fig. 11, the country’s load valley during the night hours is filled. A little load plateau starting at 07:15 can be seen due to the second reachable level. The load imposed by vehicles between 07:30 and 09:00 is solely due to vehicles in the uncontrolled charging mode.
In order to reduce load during phases when it is particularly high, a third reachable level is introduced. Without it, vehicles would start to discharge at 08:00 and peak shaving would end before the load system peak is reached because a comparatively small number of vehicles is available to supply energy. Also, vehicles arriving after 08:00 feature an almost empty battery. The load peaks between 09:00 and 12:00 are reduced. Only a small part of the base load is supplied by the PEVs as PEVs in uncontrolled mode impose a substantial, additional load. The energy which is discharged between 09:00 and 12:00 is reacquired later. After 18:00 a small difference between the load curves is seen. Vehicles often do not offer sufficient flexibility to postpone their charging until valley hours. The impact of the peak shaving and valley filling charging behavior on the city’s load curve is illustrated in Fig. 12. The load curve in the controlled charging case incorporates many load peaks. During the V2G mode, power is fed back to the transmission system only at 11:15. Otherwise, vehicles, which load peaks. During the V2G mode, power is fed back to the load curve in the controlled charging case incorporates many flexibility to postpone their charging until valley hours.

VII. SUMMARY AND OUTLOOK

The paper builds upon several other contributions using a utility function approach. A large fleet of individual PEVs is simulated in the transportation network of Zurich. The network is mapped to the electricity network, comprising several voltage levels. A tuning algorithm which alters the utility function parameters in dependence of an external price signal is used to achieve valley filling and peak shaving.

The charging behavior takes into account individual energy constraints of the PEVs to ensure that each vehicle is able to reach the next location. The case studies show that achieving valley filling in an urban area does not necessarily lead to valley filling on a country wide scale. Imposing it on a country wide scale, however, can cause severe load peaks in the distribution network of a city.

The paper assumes that the capacity of the transformers on the lowest voltage level is never exceeded by the charging behavior of the fleet. This does not necessarily need to be the case. It needs to be investigated whether such a flat charging behavior can be achieved if transformer and line capacity constraints are considered in the intelligent charging algorithm.

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REFERENCES


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