The Impact of Charging Strategies for Electric Vehicles on Power Distribution Networks

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***Abstract*—This work investigates four different generic charging strategies for battery electric vehicles (BEVs) with respect to their economic performance and their impact on the local power distribution network of a residential area in southern Germany. The charging strategies are Simple Charging (uncontrolled), Smart Charging (cost minimal), Vehicle to Grid Charging (V2G) and Heuristic V2G Charging. The simulation setting includes a high share of local renewable generation as well as typical residential load patterns to which different penetration levels of BEVs are added for the evaluation. Prices are determined on a regional energy market with agents representing the participating households (including PV generation and BEVs) as well as the traditional supply for the local power distribution network via the point of common coupling (PCC). Results show that Smart and V2G Charging lead to cost reductions for electric mobility of 40 % or 75% respectively per week and household. At the same time additional stress is put on the distribution network which shows a need for further coordination of BEV charging.**

I. Introduction

A growing world population and an increasing standard of living are major global trends that pose a number of problems in the upcoming years. One of the resulting challenges is the question on how to satisfy growing demand for energy, which by the year 2030 is expected to increase by 44% compared to the level of the year 2010 [1]. The increasing market share of intermittent, fluctuating energy sources makes the traditional paradigm, where power generation follows consumption, challenging and thus amplifies the problem of continuously balancing supply and demand at all levels in electric power networks [2], [3]. In order to retain a robust, sustainable and economically efficient power system, demand side management approaches where consumers actively contribute to a balanced grid (e.g. by responding to price signals) have to be implemented [4]. As individual mobility is expected to undergo a significant transformation towards electric vehicles in upcoming years, the transportation sector becomes a major provider of flexible electricity consumption and storage (e.g. V2G). While battery electric vehicles (BEVs) add an additional burden to the power grid if charging is scheduled during times of peak load, they also exhibit huge potential for demand response scenarios. However, whether this potential can be exploited in practice depends significantly on the BEVs' charging strategies as well as on the design of the power system itself.

In order to gain insight on how BEVs will influence future power grids, in this paper the impact of an increasing market share of BEVs on a residential power distribution network is investigated. As the impact of BEVs on the power network is mainly determined by the charging strategies used, four generic charging strategies are compared regarding their performance: The first strategy allocates charging slots to periods with low market prices; the second strategy additionally supports discharging during times of high prices (V2G); the third strategy takes the urgency to recharge the vehicle's battery with respect to the next trip into account; and the fourth strategy implements a baseline behavior that charges the battery at the maximum possible charging speed as soon as the vehicle is connected to the grid. In order to evaluate the performance of the different strategies, the load characteristics of a real residential power distribution network severely penetrated by PV generation is simulated within an energy market framework. The simulation relies on historic EEX prices and assumes BEVs with a battery characteristic similar to BMW's MINI-E. The work shows how an intelligent design of charging strategies can improve integration of RES into the power market, while rendering electric mobility more economically.

The paper is structured as follows. After related work is outlined in Section II, Section III introduces the setup of the simulation model used for evaluating the BEVs' charging strategies. The strategies themselves are then presented in Section IV and the results of the simulations are discussed in Section V. Finally, Section VI concludes with a summary of the work.

II. Related Work

BEVs have a huge potential in stabilizing the increasingly fluctuating energy supply. The capacity factor of regular vehicles is about 4 % [5], thus assuming the same usage pattern, it is obvious that the batteries of BEVs could be used for grid services or short term storage of excess energy for nearly all of the remaining time. This concept, well known as Vehicle-to-Grid (V2G) and introduced by [5] and further analyzed in [6] and [7] renders vehicles as integral part of the power system. The predominantly economically motivated approaches of [6] and [8] show that providing ancillary services for the power

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grid can be beneficial for a limited number of BEV-owners. But as BEV numbers are expected to increase in Germany and Europe [9] the question to what extent BEVs impact national and regional power networks arises. Work conducted by [10] and [11] shows that at the beginning power networks can cope with the additional load, but a higher diffusion rate of BEVs starts to put additional stress on the local distribution networks in which BEVs are predominantly expected to be charged. They also show that a coordinated way of satisfying the BEV demand can significantly improve the stable operation of distribution network equipment. These approaches with a more technical focus are supplemented by work looking into the additional network losses [12] that are caused by BEV charging or the increased costs for peak load capacity extensions caused by BEV electricity demand [13], [14]. Most of the mentioned approaches focus either on the technical optimization of grid operations and cover economic aspects only in a basic fashion (e.g. simple two rate tariffs [11]), while this work is considering more detailed demand patterns based on real world data and at least hourly changes in variable prices while still looking into the impacts on local distribution networks.

III. Model Setup

In this section, the simulation model as well as the underlying assumptions are described. The simulation models the distribution network as well as a regional electricity market with two types of participating agents: The Household Energy Agent managing the consumption/generation of a single connection point and the Point-of-Common-Coupling Agent (PCC) representing the connection between the regional and the superordinate grid. In the following, the four components of the simulation model are described in detail.

A. Distribution Network

The model of the distribution network is based on the current power network of an existing German village characterized by a high share of renewable electrical energy sources, notably PV installations. The power distribution network examined in the work at hand comprises 320 households and 21 PV installations . Furthermore, a medium-to-low-voltage power transformer connects the power distribution network to the superordinate power network.

In order to evaluate utilization of the power network, power flows between connection points within the power distribution network are at the first place assumed to be not limited by the electrical lines installed in the model region. The load factors are calculated by assuming the transmission capacity of the power distribution network to be equal to the corresponding peak load $P^{max} = P^{peak}$. By comparing the peak loads observed in the simulation with the real constraints of the power distribution network critical situations can be identified.

B. Household Energy Agent

Household Energy Agents manage energy consumption and, if available, renewables as well as the charging process of the BEV. Generally, each household agent is responsible for one or more devices. In the simulation three different devices for one household are considered: (*i*) charging of BEVs, (*ii*) photovoltaic power generation, and (*iii*) the general household load representing all other devices.

TABLE I: Distribution of mobility profiles with respect to population groups and the corresponding weekly driving distances [15, p. 64] for both, original and generated, driving profiles

	Employees	Part-Time Employees	Retired People	Unemployed People
Share	40.3%	14.7 %	34.7 %	10.3 %
$\overline{d}^{gen}$ [km]	222	134	127	83
μ_d^{MOP} [km]	302	172	153	122

1) Battery Electric Vehicle: Charging of the BEV is subject to its mobility profile and is assumed to be possible at the user's home only. Driving profiles for individual vehicles are generated by a driving profile generator [15] that is based on empirical data from a long-term German mobility panel [16]. The generated mobility profiles capture the temporal distribution of driving behavior, but the generated profiles are characterized by smaller than real world driving distances. Weekly average driving distances of generated mobility profiles are between 15% and 30% (dependent on the population group) smaller than the distances driven in the original, unrestricted mobility profiles (Table I). This fact limits the comparison of synthetically created profiles with real world driving behavior, but at the same time delivers results that are closer to the introductory phase of electric mobility, when a BEV's driving range is expected to be limited by its battery capacity.

The electric vehicle used in the work at hand is BMW's MINI E. This vehicle was chosen for its large battery and potent charge/discharge characteristics (Table II). Due to the potent batteries of the MINI-E, only a neglectable number of the generated driving events has to be canceled. The batteries of the BEV are modeled as storage devices with imperfect charge and discharge efficiencies. A round-trip efficiency of $\eta_{charge} \cdot \eta_{discharge} = (0,93)^2 \approx 86,5\%$ is assumed for storing and later feeding energy back to the power grid.

TABLE II: BMW MINI E specifications [17]

Power Consumption	[kWh/km]	0.14
Max Range	[km]	250
Top Speed	[km/h]	152
Maximum C-Rate	[1/h]	$\frac{1}{3}$
Full Charging time	[h]	3
Capacity (Usable)	[kWh]	35 (30)
(Dis-)Charging Efficiency	[%]	93
Round-trip Efficiency	[%]	86,5

The vehicles' batteries are assumed to be fully charged at the beginning and the end of the week, while they can have any valid state during the week.

2) PV modules: The only source of renewable energy generation included in the simulations are PV modules. For the simulations, real-world solar surface areas of the model region and radiation data of southern Germany [18] are used as an input to achieve realistic PV generation patterns. The generated power of the PV modules equals the product of solar intensity and the PV systems' conversion efficiency η^{PV}, which is assumed to equal 12%. This value is lower than real-world efficiencies to compensate for the assumption that installations track the sun throughout the day (which is usually not the case).

3) General Load: Each individual household's consumption pattern is derived from the standard load profile H_0 commonly used in the German energy market. To this end, the standard load profile is divided into independent sub-profiles. These sub-profiles, if added up, represent the standard load profile. Then, each sub-profile is assigned a weight factor (e.g. number of household occupants). Totaling the weighted sub-profiles returns a modified and scaled standard load profile that is used in this work (Fig. 1). The profile constructed for one day is repeated over the whole simulation period, i.e. one week.

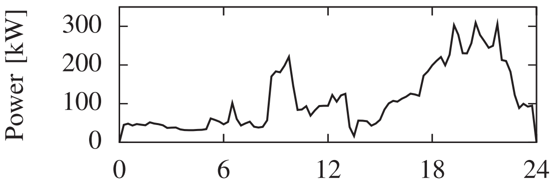


Fig. 1: Aggregate power consumption of 320 households for one day

The simulation runs' scope covers up to 88 BEVs, installed PV generation capacity of 384 kW, and electric energy consumption of 320 two-person households with an average consumption of 3800 kWh/a [19].

C. Point-of-Common-Coupling Agent

Whenever the quantities supplied and demanded regionally do not coincide, i.e. the regional renewable generation does not suffice to cover current regional consumption (which is the case most of the time), additional energy needs to be supplied to the power distribution network. This is realized by introducing a Point-of-Common-Coupling (PCC) that links the regional to the superordinate power network. The PCC is governed by an agent that trades electricity on the wholesale market as well as on the regional electricity market. This agents is thus able to compensate for electricity shortages or surpluses in the regional grid. The European Energy Exchange (EEX) is used as the wholesale market in the simulation. Its spot prices of the first six months of 2010 were normalized to a weighted average price of €0.20/kWh, close to the average price private end consumers paid in 2010 in Germany. In all simulation runs, the PCC agent is using normalized prices of one week in April of 2010 for its bid and ask offers on the energy market (Fig. 2). This specific week was selected as it lacked public holidays and was neither a summer nor winter week with corresponding intermediate solar radiation.

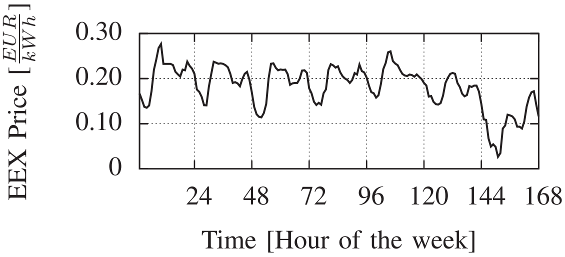


Fig. 2: Normalized EEX-Spot prices for April 19-25, 2010

D. Regional Electricity Market

To ensure that the quantities fed into and drawn from the power distribution network are balanced at all times, they have to be sold or purchased on a regional electricity market. For this purpose, agents submit bids (or asks) to the market platform that are in turn used to determine market prices and allocations. The simulation is based on the market framework presented in [20] and implements an allocation rule that maximizes social welfare. The payment rule ensures that each successful agent pays / receives the same price. This uniform price is determined by the proposal with the lowest successful bid price.

Trading on the energy market is divided into three phases: Bids and asks are submitted by the agents to the market platform first, subsequently an allocation and market price is computed by the market mechanism, while the physical exchange takes place at last. To ensure liquidity also in case of only few market participants, the market is designed as a call-market in which bids are collected and matched periodically at predetermined points in time. The simulations presented in this paper cover one week and the the length of one time slot is set to $\tau = 15$ minutes as this is the metering interval currently used by utilities. Furthermore, to keep the strategy space as simple as possible we assume in the simulations that only one time interval is open for proposal submission at a time.

IV. Strategies

The strategy used by an individual agent in the market place defines price-quantity pairs that the respective agent bids for a specific time slot t on the energy market.

A. Simple Charging

Simple Charging charges the BEV's battery immediately after the vehicle has returned to its user's home at the maximum possible charging rate that is either limited by the battery's C-rate c_{max} or the state-of-charge SOC_t at the beginning of time slot t. Charging stops once the battery is fully recharged or the vehicle is used for driving purposes. Charging power P_t is determined by the following function:

$$P_t^{simple} = \begin{cases} \min\left(\frac{1-SOC_t}{\tau}, c_{max}\right) \cdot C \cdot \frac{1}{\eta_{charge}}, & \text{if } SOC_t \leq 1 \\ 0, & \text{else,} \end{cases} \quad (1)$$

where C represents the usable battery capacity.

B. Smart Charging

Smart Charging shifts the charging process to periods of expected low prices, thus minimizing the expected cost K of electric mobility to the vehicle's user. Dynamic Programming [21], [22] is used as an optimization method to optimize the BEV's charge schedule P_t with respect to costs, while taking into account individual driving profiles and the battery's technical limitations. Given an expectation about future prices p_t (Fig. 2), each agent optimizes its charge-schedule individually, resulting in an individually optimal charge schedule, i.e. information on when to charge how much energy.

$$\begin{aligned} \min_{P_t^{strategy}} \quad & K = \sum_t p_t \cdot P_t^{strategy} \cdot \tau \\ & = \sum_t p_t (P_t^{HH} - P_t^{battery} - P_t^{PV}) \cdot \tau \\ \text{s.t.} \quad & 0 \leq P_t^{battery} \leq c_{max} \cdot C \qquad \forall t \end{aligned} \tag{2}$$

C. Vehicle-to-Grid (V2G)

The strategy Vehicle-to-Grid (V2G) extends the strategy Smart Charging by additionally feeding back energy stored in the BEV's battery during times of elevated electricity prices, i.e. when price spreads between high and low prices are large enough to cover the assumed cost of battery use and losses due to imperfect battery charge/discharge efficiencies.Thus, the objective function for V2G remains the same as in the case for Smart Charging, but in contrast to Smart Charging, V2G allows discharging energy for off-vehicle use:

$$\text{s.t.} \qquad -c_{max} \cdot C \leq P_t^{battery} \leq c_{max} \cdot C \qquad \forall t \tag{3}$$

D. Heuristic Vehicle-to-Grid

The strategy Heuristic Vehicle-to-Grid (H-V2G) derives its price-quantity pairs from the vehicle's individual driving schedule. The ask prices equal the bid prices plus the assumed cost of battery use (ask prices are higher than bid prices).

Prices (for both bids and asks) are a function of three factors: The time remaining until the next driving event, the current SOC and the SOC required to successfully complete the next driving event, i.e. the amount of energy required to return home without running out of energy. These three factors are incorporated into one term representing the 'flexibility' regarding the charging process by the BEV's battery (Fig. 3). Different from the previous strategies, H-V2G does not rely on assumptions about future prices, instead, only the vehicle's mobility profile is used to compute bid and ask prices. The associated bids and asks submitted to the energy market depend on the presence of the BEV at the user's home, its SOC, as well as the corresponding mobility profile. Excess energy (energy from renewable sources that cannot be used by the agent's consumers, i.e. household and BEV) is offered at a low price on the energy market. Energy from the agent's RES that could be either stored or directly sold on the market is offered at $p^{potential\_charge}$. Energy that could potentially be discharged from the BEV's battery is offered at $p^{potential\_discharge}$ (Fig. 3). Energy consumption that cannot be covered by a combination of the agent's RES generation and battery discharge is supplied to the agent via the energy market. The associated bid price is chosen such, that supply is ensured, i.e. the bid price for quantities of essential energy, $p^{essential}$, is set sufficiently high by the respective agent.

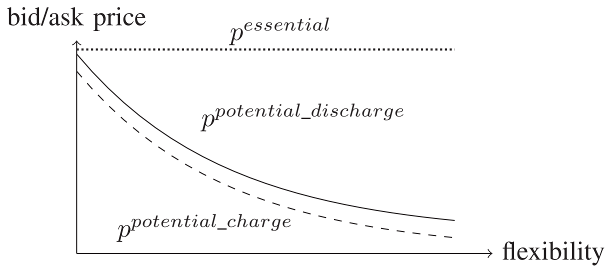


Fig. 3: Heuristic V2G: Bid / ask prices over flexibility

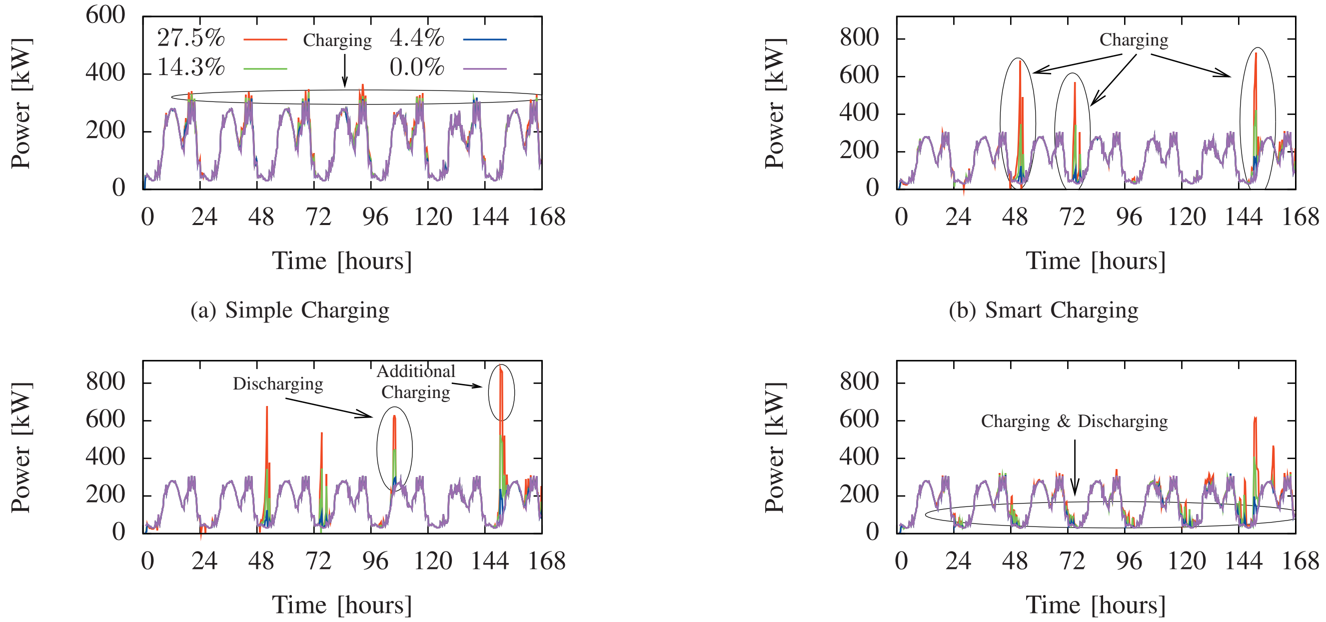
V. Results and Discussion

The adoption of electric mobility increases the amount of electric energy drawn from the power distribution network at least by the amount used for mobility purposes. Figures 4a - 4d show for each charging strategy the additional load required for charging of BEVs and compare the results for different BEV market shares (4,4%, 14,3% and 27,5%) to the baseline scenario without BEVs (0%).

Applying the zero-intelligence strategy Simple Charging, the charging process takes places after the return of the BEVs to their owners' homes, i.e. mostly in the evenings. The load resulting from the recharging process increases already existing peak loads (Fig. 4a). As the market share of BEVs grows, these peak loads can be expected to increase further.

If the strategy Smart Charging is used to control the charging process of the BEVs, charging takes places at nighttimes in order to minimize the cost of electric mobility to BEV owners (Fig. 4b). Due to identical expectations about future prices (Fig. 2), the timing of the charging process is highly aligned between the different agents, resulting in additional peak loads at nighttimes. Typically such an increased demand could be reduced through the dynamic pricing used in the Regional Electricity Market (and the corresponding demand response effect) as introduced in Section III-D. However, the simulations indicate that due to the coupling with the superordinate power network the prices in the Regional Electricity Market are largely dictated by the PCC and thus local increase in demand does not necessarily lead to an price increase. Consequently, no peak shaving can be observed as demand response effect.

The result of the strategy V2G, as illustrated in Fig. 4c, is that nightly peaks from recharging the BEVs continue to exist. Using this strategy and assuming a cost of battery usage of €0.20/kWh, feeding stored energy back to the power network is economical at some points in time, e.g. around Friday late morning (see Fig. 2). To replenish the energy discharge from the battery, additional charging takes place on Sunday morning, around hour 150, when prices arrive at the



(a) Simple Charging

(b) Smart Charging

(c) V2G at an assumed cost of battery use equal to €0.20/kWh

(d) Heuristic-V2G at charging cycle costs of €0.20/kWh

Fig. 4: The impact of charging strategies on network load during one week for different BEV market shares

week's minimum. Thus, this strategy results in an even more pronounced peak load at the end of the week.

In case the strategy Heuristic-V2G is applied, charging is successfully shifted to non-peak periods without causing the nightly peaks observed for Smart and V2G Charging (Fig. 4d). Still, one peak towards the end of the week is observed but can be neglected in the analysis (simulation artifact[1]).

If agents have similar expectations about future electricity prices, charging and discharging is shifted to identical future points in time even though each agent optimizes its charge-discharge schedule individually. This behaviour therefore results in considerable peak loads requiring distribution networks with high capacities. Table III gives an overview of the resulting load factors LF that characterize the utilization of a power network. The load factor is defined as the ratio of average load $\overline{P}$ over the entire simulation time relative to the maximum observed peak load P^{max}:

$$LF = \frac{\overline{P}}{P^{max}} \tag{4}$$

As P^{max} can be seen as the maximum capacity the distribution network has to support, one can say that a higher load factor implies a better utilization of the network. In the worst case (27,5% BEV market share and V2G Charging) the utilization of the network infrastructure decreased by 60%, while in the best case (4,4% BEV market share and V2G Charging) even an improvement of 4% can be observed with the introduction of BEVs. Note that the load factor for the strategy H-V2G is distorted due to the peak towards the end of the week (simulation artifact). Without this artifact, utilization would be considerable higher.

[1]The peak at the end of the week results from coordinated charging, as all vehicles are required (in the simulation) to complete the simulation at the end of the week with a fully recharged battery.

TABLE III: Overview of load factors

BEV share [%]	0	4,4	14,3	27,5
Baseline	0,51			
Simple		0,498	0,479	0,452
Smart		0,516	0,388	0,235
V2G		0,519	0,317	0,200
H-V2G		0,499	0,401	0,283

The different strategies influence the cost of electric mobility for users of BEVs. The cost of electric mobility equals the product of quantity purchased (or sold) $P_t \cdot \tau$ and the market price p_t summed over the time interval $[0, T]$.

$$K^{strategy} = \sum_{t=0}^{T} (P_t \cdot \tau) \cdot p_t \tag{5}$$

Figure 5 illustrates the payments with electric mobility for an average agent from the population described in Table I. 205km, if the profiles were representative.) The Simple Charging approach results on average costs of K^{simple} =€4.39 per week and vehicle. Using the strategy Smart Charging costs can be decreased to €2.58. The payment resulting from V2G turns positive for low enough costs of battery use. At the highest cost of battery usage assumed in the work at hand (€0.20/kWh), V2G does not yet result in a profit, but decreases costs per vehicle and week in comparison to Smart Charging further to 1.06 EUR, which is approximately one quarter of the payment resulting from Simple Charging. Heuristic V2G (at assumed cost of battery use of €0.2/kWh) results in weekly payments of €1.78. Assuming zero costs of battery usage, weekly profits

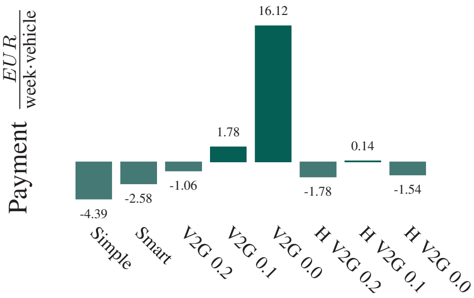


Fig. 5: Average payments resulting from different charge-discharge strategies (costs are negative, profits are positive)

can attain values of up to €16.12 per vehicle for the strategy V2G.

In summary, moving from simple to more sophisticated charging strategies improves energy costs for the BEV holders acting as price takers. However, the strategies Simple, Smart and V2G Charging increase peak loads and reduce network utilization. The simulations indicate that the Heuristic V2G provides the best trade-off between energy cost minimization and utilization of the power distribution network.

VI. Conclusion and Outlook

As the share of BEVs increases, they gain considerable influence on the power system. Depending on the implemented charging strategies the effect of BEVs can be beneficial, e.g. storage capacities of batteries are used as flexible loads for demand side management, or they may worsen the problem of grid congestion, e.g. increase the load peaks in the electricity grid. In order to investigate the influence of different charging strategies on a distribution network, the power system of a residential area in southern Germany is simulated with a changing share of BEVs and four different charging strategies. The simulations show that naive charging strategies – that either charge instantly once the car is connected to the grid or that collectively shift charging to low price periods – tend to increase existing peak loads (already for small BEV market shares). Providing power to off-vehicle applications (e.g. V2G) may reduce energy costs for the BEV owner but often adds additional peaks. Although relaxing the assumption of perfect price forecasts or moving to more sophisticated charging strategies (e.g. Heuristic V2G) may attenuate the negative effect, the tendency towards increased peak loads remains as the design of today's electricity markets economically incentivizes behaviour that is unfavorable for the power system. In order to achieve a higher utilization of the power system, the individual economic incentives of the BEV holders have to be aligned with actual network usage costs. This coupling requires an electricity market that prices-in the constraints of the underlying physical network (e.g. as suggested in [23]), which is an important future research area especially for close-meshed distribution networks.

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