Decision Support for Electric Vehicle Charging

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ABSTRACT

Many hopes lie on the introduction of electric vehicles (EV): reduction of transportation-related emissions, reduced dependence on oil imports, and improved integration of renewable energy sources. Meeting these goals will require a significant number of EVs on the streets and it will also require intelligent charging coordination. Through dynamic rates or local energy trading smart grids incentivize load flexibility required for taking advantage of renewable generation availability. For EVs to respond to these incentives intelligent charging protocols are required. These protocols should aim to minimize electricity costs and emissions while simultaneously securing customers' driving requirements.

We describe and characterize the relevant problems and solution concepts on how to achieve smart charging behavior. Optimal smart charging concepts are not directly applicable for practical DSS. To address this shortcoming we develop relaxed and heuristic optimization approaches. We evaluate these solutions approaches using simulations based on empirical mobility and electricity price data.

Keywords

Electric vehicles, smart grid integration, decision support

INTRODUCTION

Road transportation accounts for over 20% of CO2 emissions in the USA and the European Union.[1] Therefore, this sector plays a crucial role in meeting global CO2 reduction goals. Besides introduction of stricter efficiency regulations many countries push forward the electrification of individual mobility (Federal Government of Germany 2009; The White House 2011). While electric vehicles always operate locally (tank-to-wheel) emission-free, the more relevant total emission balance (well-to-wheel) critically hinges on the electricity mix used for charging the vehicle. Figure 1 signifies that EVs can achieve emission reduction only if the charging power comes from renewable energy sources (e.g., wind or solar).

However, these energy sources are highly intermittent and their increasing share challenges the operational stability of today's power system. Large-scale EV charging will interlink the transportation sector with the electric power sector and introduce significant new loads which will put additional stress on the electricity system. At the same time these charging loads are temporally flexible and are thus promising candidates for applying demand side management (DSM) approaches. Smart integration of electric vehicles will reduce the threats to power system stability. To the contrary, they may even offer balancing capacity for intermittent generators and thus help to stabilize the grid (Lund and Kempton 2008; Kempton and Tomić 2005).

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[1] http://ec.europa.eu/clima/policies/transport/vehicles/index_en.htm,
http://www.eia.gov/environment/emissions/ghg_report/pdf/0573%282009%29.pdf

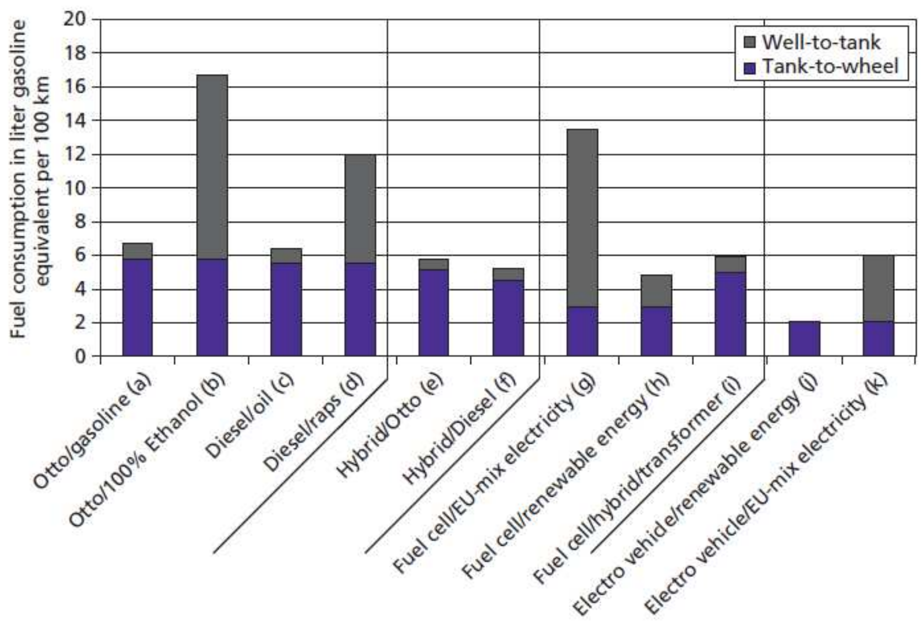

Figure 1. Emission statistics of different vehicle technologies (Ballentin, Hartmann, Kopp, Loewel, Sund and Templ 2011)

To realize these potentials vehicle operators clearly have to adapt their charging behavior to external price signals or cede control of their vehicle (Lopes, Soares, and Almeida 2009). The latter is problematic as customers most probably will expect EV usage to be similar to conventional vehicle usage – non-availability of EVs due to low charging levels will unlikely be accepted by customers. On the other hand reacting to price signals may very well be a challenging task for most users as it potentially involves assessing personal driving habits, analysis of price path dynamics as well as understanding of vehicle range and charging properties. Gonzalez (2005) notes that such complex and dynamic decision making situations are difficult and will often exceed individuals' cognitive resources. In line with this reasoning we argue that EV users will need decision support systems or charging automation to achieve truly smart charging behavior on the individual level.[2]

We develop an integrated view on the challenges which such a smart charging controller will need to address and describe potential implementation approaches. The remainder of this paper is structured as follows: First we provide an overview on recent trends and developments in the smart grid and electric vehicle sector. We then describe different smart charging strategies with respect to their information requirements and evaluate these strategies using simulations based on empirical driving and price data.

SMART GRIDS AND ELECTRIC VEHICLES

The development of the smart grid is a crucial prerequisite to realize potential advantages through integration of electric vehicles in the existing and future power system. The smart grid provides possibilities to monitor and control the system status on a granular local level in real time. Hence, power system control changes from 'blind' manual operations on higher voltage levels into a more sophisticated dynamic task in a complex granular system (Ipakchi and Albuyeh 2009). However, since the main goal of power system control is to optimally balance supply and demand over space and time, more granular decisions provide ample opportunities to improve overall efficiency. In addition higher granularity in control and monitoring tasks, the possibility to exchange data and share information enables the development of new control and influence models – for example new decentralized algorithms or variable rates. In particular the historic rule that supply follows demand gradually changes into a more system with both sides being flexible.

A flexible demand is controlled or influenced by DSM system which potentially leads to benefits in power system. Along with balancing generation and consumption, DSM can reduce investments in the grid and the cost of generation (Strbac 2008) while customers can expect savings in their electricity bill (Albadi and Elsaadany 2008). Two polar DSM approaches

[2] Such smart charging devices in EVs can be seen as a form of mobile decision support as described by Shim et al. (2002).

are typically assumed: centralized direct load control and decentralized incentives to influence consumption. A mix of both approaches is decentralized load control based on local parameters and predefined contracts for specific loads.

Our focus in this paper is decision support for EV charging on an end consumer level where users have to act based on decentral incentives in the form of locally variable prices (Alvarado 2005). Price-based coordination approaches are key concepts of DSM (Strbac 2008) and presented in the following section. In addition EVs are specific types of loads and imply special technical requirements which we discuss subsequently.

Variable pricing

In their seminal work Schweppe, Caraminis, Tabors and Bohn (1988) provide an overview on the theory and implementation of time- and space-varying electricity prices. In addition the prices on an individual user level can be dynamically dependent on other attributes like usage, current load or aggregate consumption. However, in most countries residential electricity customers are still offered simple linear tariffs. Time-of-use (TOU) tariffs exist mostly in form of long-term contracts with two different prices - high prices in hours with high consumption and low prices typically during the night. Since these prices are not flexible in the short-term TOU tariffs are not flexible enough to influence consumer demand dynamically to achieve all benefits of DSM (Borenstein, 2005). So far only few field tests in the context of research projects used more complex pricing schemes for end consumers. With high-demand business customers, utilities typically make bilateral agreements on sheddable load and peak prices based on individual load and requirements. On an end consumer level these contracts seem to create unacceptable transaction costs.

Special tariffs for EVs slowly appear on the market. Similar to pricing schemes for end users these are simple TOU tariffs with peak and off-peak prices or at most with seasonal differences and increasing prices in consumption.[3] Pricing schemes which dynamically exploit residential DSM potentials are currently not available for households and EVs.

Electric vehicles

In comparison to typical household loads like refrigerators, washing machines and other electric appliances, EVs have some special characteristics due to technical restrictions and usage patterns. Overall EV charging can increase household demand for electric energy significantly. Overall one EV consumes approximately one third of an average US household. With approximately two vehicles per household the electrification of individual mobility creates significant additional load to existing household consumption.[4]

In addition to the mobility needs of drivers the current technical restrictions of EV batteries and charging infrastructure pose boundaries to charging flexibility. Firstly, battery capacity in electric vehicles is limited due to cost as well as size and weight since the volumic energy of batteries is low in comparison to fuel. Therefore the range of EVs is limited and lower than with normal internal combustion engine vehicles. Secondly, the charging speed of EV batteries is limited due to physical constraints of the batteries and the charging infrastructure. Hence, refueling is much slower for EVs and can hardly be done en route. Typical charging speed at home is around 3 kW which means approximately 8 hours charging time for a full charge of a 24 kWh battery. Faster charging speeds at 11 kW are possible with special plugs and quick charging stations with over 50 kW are in development and testing. Faster charging offers both, quick mobility range for driving needs and more flexibility for intelligent charging to support power grids. In the long-term EVs should not only support the power system by scheduling their charging load appropriately. Several research contributes envision EVs to moreover provide vehicle-to-grid services by feeding electricity back into the grid (Kempton and Tomić, 2005). Since vehicles are parked more than 90% of the time, the wide scale adoption of EVs could provide a flexible storage opportunity for the power system.

Electric mobility faces two major challenges: ensure the driving needs of the consumer and avoid negative influences or even support the efficiency of the power grid. Despite the limitations about one third of the drivers could successfully apply an EV now available on the market if they make on few days adaptations in their driving pattern (Pearre, Kempton, Guensler and Elango, 2011; Greene, 1985).

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[3] http://www.npower.com/campaigns/ev/juice-e/index.htm and http://www.pge.com/tariffs/tm2/pdf/ELEC_SCHEDS_E-9.pdf

[4] The US Department of Energy rated the fuel economy of two EVs in 2012 – the Nissan Leaf with 34 kWh/100 miles and the Mitsubishi i-Miev with 30 kWh/100 miles. An average driver with approximately 13,500 miles/year therefore increases the consumption of electric energy by approximately 4,000 kWh. For details we refer to the US Energy Information Administration http://205.254.135.24/tools/faqs/faq.cfm?id=97&t=3 and the US Department of Energy: http://www1.eere.energy.gov/vehiclesandfuels/facts/2010_fotw618.html.

EV CHARGING STRATEGIES

In the literature on economic EV grid integration charging strategies are the key concept for describing an EV charging schedules is. A charging strategy determines when and how much to charge based on currently available information. The fundamental trade-off in this decision is between flexibility of mobility and availability of the vehicle on the one hand and cost savings or system compliance on the other hand. Following the DSM notion of price signals we focus on price-oriented EV charging strategies that enforce vehicle availability for planned trips as a constraint.

A central question for the design of appropriate decision support is the availability of information that can be considered, e.g. planned trips, future prices, forecasts. More information typically leads to better decisions. However, a full foresight of all necessary parameters is in reality at least creating huge effort or even impossible. Another open question is the mobility risk level that customers are willing to accept. As mentioned above EVs have limited range which is often seen as one major obstacle of electric mobility. So far no information is available on whether and to which level drivers will accept intelligent charging as it may impact vehicle availability.

Simple Charging Protocol

The simplest strategy for electric vehicles is to charge the battery whenever possible, i.e., independent of any other decision factors like battery state of charge (SOC) or charging costs. This “as fast as possible” (AFAP) approach is often referred to as “dumb charging” and is equivalent to operators beginning the charge process at maximum power directly after returning to home.[5]

Remark 1: AFAP charging maximizes an EV’s range at any given time

Moreover, AFAP charging requires no information on future trips of the EV customer. Therefore, it can be used to analyze the feasibility of any given driving profile under EV battery restrictions and provides a maximum range benchmark. At the same time simple charging is completely static and cannot be influenced by external signals (e.g. price, congestion or renewable generation signal). Intelligent charging strategies need to improve on this minimal strategy with respect to these aspects while compromising vehicle availability to the user as little as possible.

Optimal Smart Charging

Previous work on economic EV charging optimization typically formulates the optimal charging problem as a linear program (Sioshansi 2012; Sioshansi, Fagiani, and Marano 2010). The objective is typically to minimize the vehicle operator’s total cost subject to meeting the driving profile’s trip requirements as well as charging and capacity constraints.[6] These models yield the cost-minimal charging pattern for realizing the mobility needs of any feasible driving profile. Describing the time horizon as a set of time slots [0..T] we denote the current cost of charging by c_t, the current battery state of charge by SOC_t, the maximum charging amount by $\overline{\phi}$, the total battery capacity by $\overline{SOC}$, the discharge amount from driving by γ_t the program to determine the optimal charging vector $\phi^* = \langle \phi_0, \ldots, \phi_T \rangle$ obtains as follows:

$$\min_{\phi} \sum_{t \in [0..T]} (c_t \cdot \phi_t) \tag{1}$$

subject to

$$0 \leq SOC_t \leq \overline{SOC} \;\; \forall\, t \in [0..T] \tag{2}$$

$$0 \leq \phi_t \leq \kappa_t \;\; \forall\, t \in [0..T] \tag{3}$$

$$\kappa_t = \begin{cases} \overline{\phi} \text{ if vehicle is parked at charger} \\ 0 \text{ if vehicle cannot be charged} \end{cases} \tag{4}$$

$$SOC_t = SOC_{t-1} + \phi_t - \gamma_t \;\; \forall\, t \in [0..T] \tag{5}$$

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[5] Charging “as fast as possible” is equivalent to completing the charging process as early as possible. It thus means starting as early as possible *and* charging at the maximum possible power level.

[6] These models are variants of the classic storage optimization approach by Daryanian, Bohn and Tabors (1989).

Equation (1) is the objective function which is minimizing total charging costs, (2) ensures the battery level remains within the proper range, (3) and (4) limit the charging amount to account for location and charger capacity and (5) is the storage carry-over condition reflecting the temporal interdependence between time slots. The optimization program clearly requires perfect knowledge of both future power prices as well as the vehicle's future trips.

The greedy optimization behavior will exploit the minimum allowed battery level of 0 in Equation (2) to react to later low price realizations. While this behavior does not violate the optimization constraints it will effectively minimize the vehicle's service level for spontaneous trips. Both the perfect information requirement and the minimization of spontaneous EV range limit the practical relevance of optimal smart charging. Relying on these optimal results we may, therefore, overestimate the impact from economic charging coordination. Still, the results from optimal smart charging provide a robust upper bound to benchmark non-optimal strategies against. In the following subsections we suggest two relaxations addressing price knowledge and availability level to increase the practical applicability of optimal smart charging. Such relaxations will be crucial elements for developing robust EV decision support systems.

Price Backcasting

Given the highly stochastic behavior of electricity prices the perfect information assumption underlying optimal smart charging is difficult to justify. Sioshansi, Denholm, Jenkin and Weiss (2009) address a similar forecasting problem for the operation of centralized electricity storage systems. They use "stale" prices from the prior week to derive the optimal policy and evaluate its effectiveness using the prices of the current week. Due to the regular weekly price patterns and the stable operation of large storage systems they achieve approximately 80% of the optimal profits.

However, optimal EV charging occurs in a more "spikey" fashion – i.e., the charger is mostly idle except for a few very low cost time slots when charging occurs. This limits the potential of backcasting for EV charging optimization. Therefore, we modify the Sioshansi et al. (2009) approach by using fictive price vectors obtained as weighted linear combinations of the past and the future price vector, $\widetilde{c_t} = \lambda c_{t-T} + (1-\lambda)c_t$. In a practical implementation such updates could be near-time weather or demand forecasts indicating when lower electricity prices occur. The linear mix of backcast and forward-looking prices aims to illustrate this relation.

Minimum Battery Level

Range anxiety is commonly considered a major adoption obstacle for range-limited vehicles (Eberle and von Helmolt, 2010). The linear optimization program as specified above does not reflect this issue. More drastically, the optimal charging policy typically exhibits regular discharging down to SOC levels of 0 in order to capture later cheap price occurrences. From a user's perspective such SOC trajectories would be highly discomforting. Ideally, we want to counter such undesired behavior by requiring the vehicle to be charged below a certain battery level $\underline{SOC}$. Clearly, we cannot simply enforce SOC > $\underline{SOC}$ as this would be equivalent to never using the battery capacity between 0 and $\underline{SOC}$. However, we can achieve the desired result of triggering charging activity below $\underline{SOC}$ when possible by adding an additional constraint to the linear program:

$$\phi_t \geq \kappa_t \frac{\underline{SOC} - SOC_t}{\underline{SOC}} \; \forall \, t \in \; [0..T] \tag{6}$$

Remark 2: The charging amount enforced from securing the minimum charge levels varies with the difference between SOC_t and $\underline{SOC}$ – the farther below the threshold the current battery is, the higher is the enforced charging amount. This formulation retains the linear program properties which facilitates efficient calculation. Moreover, this reflects behavioral aspects as the urgency of recharging is clearly greater at low SOC levels.

Figure 2 illustrates the effect on exemplary SOC trajectories from 30kWh battery packs. In the $\underline{SOC}$=25% case the resulting trajectory charts almost identical to the case of optimal charging with a 22.5kWh battery. This suggests that many drivers could achieve their typical driving behavior with much lower total vehicle range than typically expected. More importantly this also means a minimum SOC adapted charging protocol can greatly increase their vehicle's standby range without sacrificing the potentials of cost-oriented smart charging.

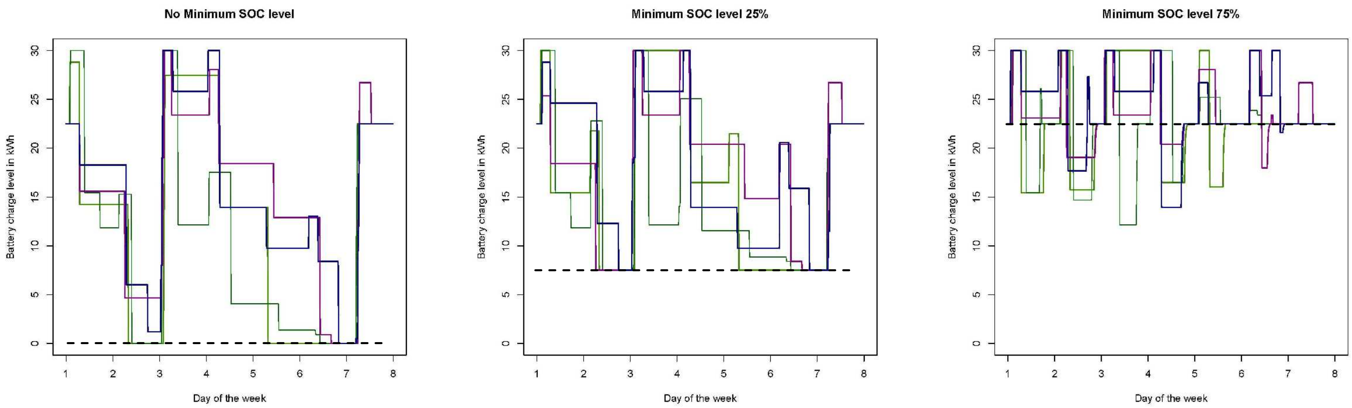

Figure 2. SOC trajectories with different minimum thresholds

Heuristic Smart Charging

While optimal smart charging fully endogenizes external signals it is difficult to implement as it relies on full availability of future trip information. We want to complement prior work on EV charging strategies with a notion of smart charging based on a heuristic strategy. Unlike optimal smart charging the heuristic smart charging decisions should not depend on knowledge of future prices or trip plans but should rather condition decisions on currently available information (e.g., charging price, battery state-of-charge). However, by waiving charging opportunities and thus departing from the naive as fast as possible strategy we need to provide information on the upcoming trip to guarantee driving profile feasibility.

Remark 3: *Without advance information on an upcoming trip a charging strategy that is not AFAP cannot guarantee the same driving profile feasibility as simple charging.*[7]

Therefore, to still guarantee the same profile feasibility as achieved by simple AFAP charging we need to introduce some form of advance information. One way of doing so is by specifying a critical SOC level SOC_t^* for each time. Only when the battery level is below this threshold the EV will request a charging amount $\phi_t = SOC_t^* - SOC_t$ to be able to complete its next trip. We refer to this charging approach as an ALAP strategy as it ensures driving availability "as late as possible". Regular morning commutes lead to SOC_t^* typically inducing charging activity in the early morning/ late night. Given prevailing low night-time electricity prices average charging costs are typically decreasing when moving from the AFAP to the ALAP charging regime. However, we want to emphasize that as the ALAP charging strategy does not internalize any economic incentives it is not per se any smarter than AFAP charging.

While the ALAP strategy does not respond to economic incentives it can easily be adapted to do so. Charging as late as possible offers the opportunity to observe current prices and use these observations to improve its charging costs. However, to do so in a meaningful some basic statistical information (e.g., distributional properties such as mean or median of the electricity prices) is required. Using this information we can formulate a threshold strategy ALAP+ where the vehicle is charged either if $SOC_t < SOC_t^*$ or if $c_t < c^*$. The threshold c^* can be adapted to a driver's driving behavior in order to maximize the strategy's effectiveness.

Categorization of Charging Strategies

We have addressed the information requirement challenge of formulating smart charging strategies for EV decision support. Table 1 summarizes our findings by categorizing the above mentioned charging strategies according to their informational requirements. In addition to optimal smart and simple AFAP charging we identify and characterize non-polar strategies which are able to internalize external information without requiring perfect foresight. We argue that in situations without information on either future prices or upcoming trips the only applicable charging strategy is the AFAP strategy: This follows from Remark 1 and the realization that without price information we cannot formulate a meaningful strategy other than AFAP as we do not have an objective function.

[7] Any trivial example with a long surprise trip can serve to intuitively prove this claim.

		Upcoming trip information		
		full	*some*	*none*
Future price information	*full*	**Optimal smart charging**	Optimal with minimum SOC	n/a
	some	Optimal with stale prices	ALAP charging (Optimal with stale prices, minimum SOC)	
	none	n/a	ALAP charging	**Simple charging (AFAP)**

Table 1. Taxonomy of charging strategies

EVALUATION

Having understood the information challenge influencing the design of charging decision support we want to evaluate the charging strategies. We extract the driving profiles of 1,000 employees from the German Mobility Panel (Zumkeller, 2010).[8] While the original driving profiles where recorded using conventional vehicles, we use them to create fictive EV driving to profiles. To do so we replicate the driving profiles from the mobility panel assuming they were completed by homogeneous EVs. Presuming a certain initialization battery level we can track the EV state-of-charge (SOC) over the course of time and identify charging requirements which can be mapped against the charging availability as provided by the location model. This approach is warranted as the most trip distances in our data set are well achievable with typical EVs and after excluding driving profiles that are impossible to fulfill with a current EV 912 valid profiles remain for the simulation. We compare the charging costs of the simple, (backcast) optimal smart and heuristic smart charging strategies. Furthermore, we look at the effect of price updates for backcast optimal charging.

Charging cost comparisons

Average charging costs per customer using the different charging strategies are depicted in Figure 3 (a). As expected, simple AFAP charging clearly results in overall highest charging costs as charging is scheduled completely independent from any prices. Given low night-time electricity prices ALAP charging despite also ignoring the price signals does clearly better. ALAP+ charging with a price threshold results in another improvement. Especially, drivers with higher average charging profit from this strategy. The optimal charging approaches based on full trip information do even better. These results suggest that trip information is actually more important than price information.[9] This observation is supported by the very low charging costs achieved by optimal charging with stale prices. Furthermore, figure 3 (b) shows that we are able to greatly improve these results by introducing fictive price vectors derived from linear combinations of past and future prices.

The results remain very good with ratios as high as 3:1. Therefore, baseline weekly price patterns seem to be sufficiently stable with limited information being able to capture the concrete differences between the current and the prior week. Therefore, we argue that effective charging decision-making can already be achieved with limited price information. On the other hand, our results suggest that drivers will profit from early planning of future trips with their vehicle.

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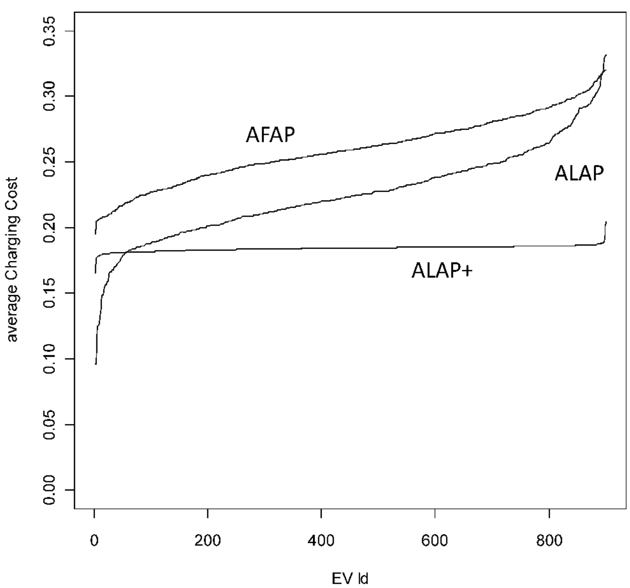
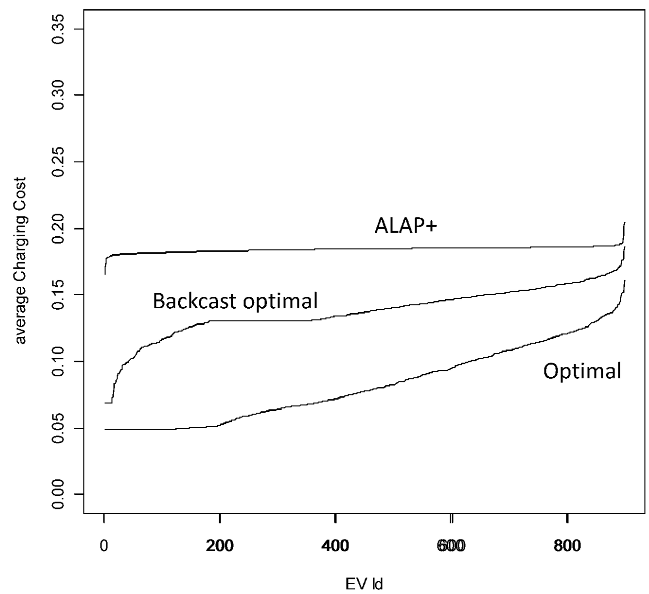
[8] Empirical driving statistics from other industrial nations seem to be more or less aligned with the German data (cf. e.g., Sioshansi 2012, Flath, Gottwalt and Ilg 2012, http://cabled.org.uk/press-download/first-years-findings).

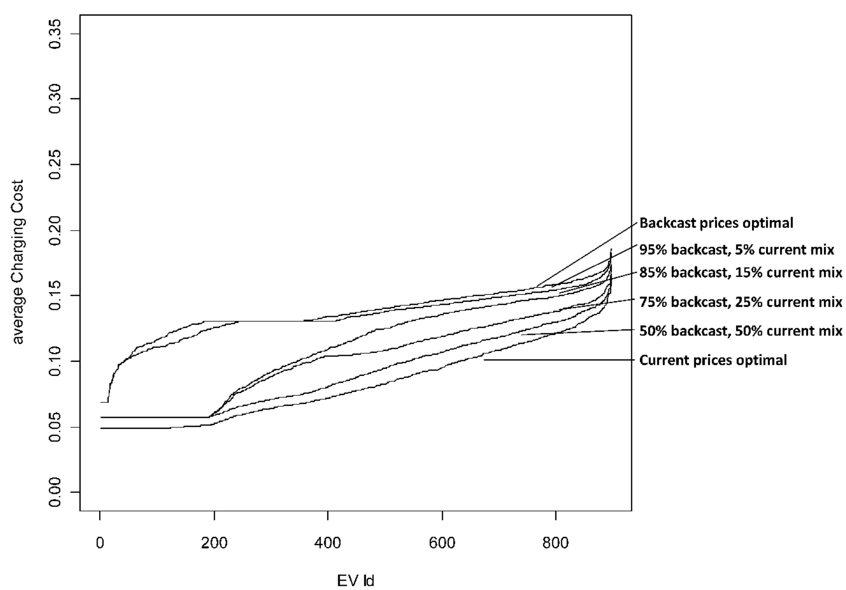
[9] For illustration purposes the graphs report the average electricity cost per kWh in Euros. Annual savings potentials critically hinge on individual driving distances. For a discussion of individual saving potentials we refer to Dietz, Ahlert, Schuller and Weinhardt (2011) and Schuller, Ilg and van Dinther (2012).



(a) Heuristic charging



(b) ALAP+ and optimal charging



(c) Backcast optimal charging with price forecasts

Figure 3 Average charging cost per kWh for different charging strategies

Towards EV decision support

Clearly, deriving optimization approaches and models is only the first step in providing driver decision support. Lending to Power (2002) the charging strategies described above should be embedded in a *model-driven DSS*. Such a system needs to access the relevant and necessary data points (e.g. battery state, power prices, charging speed) and enable the user to specify driving requirements, minimum range parameters as well as optimization objectives (cost, carbon content, battery health). Depending on rate complexity (dynamic prices vs. static prices) the system may or may not require real-time communication capabilities. Furthermore, we could imagine that the system actively learns about the operator's driving behavior and may suggest parameter improvements in order to improve user decisions. As of now it is unclear if such a system would be integrated into the electric vehicle or into the charging infrastructure.

CONCLUSION AND OUTLOOK

With the electrification of electric mobility and the smart grid roll-out, opportunities arise to intelligently use electric vehicles to support the power system and at the same time reduce cost for individual mobility. Since the decisions need to be adjusted dynamically based on current system state and individual preferences, an automation of this decision making is necessary.

We propose a taxonomy to categorize charging strategies based on the availability of information on future trips and prices. So far most scientific publications focused on polar strategies like optimization with full information or simple charging without any information. In addition to using these strategies as benchmark we further develop additional charging strategies that require less information input which is closer to reality. At the same time we model these strategies to tackle main obstacles of electric mobility like range anxiety and total cost. Our evaluation shows that heuristic charging strategies with very low information requirement can greatly reduce the individual electric energy cost in comparison to simple charging strategies. Moreover, we find that accurate trip information is of greater importance for effective charging coordination than price foresight.

In addition to tailoring the charging strategies an important point is the education and information of EV owners and drivers. Firstly, to overcome range anxiety the drivers need to be educated on how much range they really need every day. Secondly, based on a specific driving profile the cost drivers for individual mobility can be benchmarked. A bigger battery can for example lead to cost reductions per kWh and therefore to lower cost over the vehicle's lifetime. On the other hand if only short ranges are necessary a large battery may be too large and therefore too expensive. Finally, we may see a rise of inter-modal / hybrid transportation systems based on car ownership, car sharing and public transport. Within such mixed systems drivers will have even more options to choose from and individual strategies will have to be aligned.

The complexity users will be faced with further signifies the importance of decision support systems within the future mobility system.

ACKNOWLEDGEMENTS

The authors thank the anonymous reviewers for valuable suggestions.

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