Centralized and decentralized Approaches to Smart Charging of plug-in Vehicles

Marina González Vayá, Student Member, IEEE, and Göran Andersson, Fellow, IEEE

Abstract—A large penetration of electric and plug-in hybrid electric vehicles would likely result in increased system peaks and overloading of power system assets if the charging of vehicles is left uncontrolled. In this paper we propose both a centralized and a decentralized smart-charging scheme which seek to minimize system-wide generation costs while respecting grid constraints. Under the centralized scheme, vehicles’ batteries are aggregated to virtual storage resources at each network node, which are optimally dispatched with a multiperiod Optimal Power Flow. On the other hand, under the decentralized scheme, price profiles broadcasted to vehicles day-ahead are determined so that the optimal response of individual vehicles to this tariff achieves the goal of cost minimization. Two alternative tariffs are explored, one where the same price profile applies system-wide, and another where different prices can be defined at different nodes. Results show that compared with uncontrolled charging, these smart-charging schemes successfully avoid asset overloading, displace most charging to valley hours and reduce generation costs. Moreover they are robust in the face of forecast errors in vehicle behavior.

Index Terms—plug-in hybrid vehicles, electric vehicles, smart charging, demand side management

I. INTRODUCTION

It is widely accepted that the electrification of transportation could play a significant role in the abatement of carbon emissions, provided that the electricity used for this purpose has a low carbon intensity. However, this new and mobile load also constitutes a challenge for power systems operation and planning. Consequently, in the last decade much attention has been directed to the potential utility system impacts [1], [2] and grid impacts [3]–[5] of electric mobility. A number of studies show that adverse impacts could be reduced by some sort of controlled charging or smart charging. However, simple schemes such as a dual tariffs are not necessarily beneficial at large vehicle penetrations [6]–[8]. Another important part of the literature has been devoted to the role that electric vehicles and plug-in hybrid electric vehicles (denoted as plug-in vehicles in the following analysis) could play in supporting the system with ancillary services and in integrating stochastic generation from renewable energy sources [9]–[12].

The focus of this paper is on smart charging schemes, both centralized and decentralized. Under both types of schemes a so-called “aggregator” could aggregate vehicle demand and buy electricity on behalf of plug-in vehicles. Its role would depend on the type of scheme, with centralized schemes obviously requiring a more active role from the aggregator, who would directly control the charging. A comprehensive literature survey on the economic and technical management of this agent can be found in [13].

First, centralized approaches proposed so far are briefly discussed. In [14] an optimal charging strategy from the perspective of an aggregator of electric vehicles is presented. Based on the driving patterns of the fleet, the aggregator determines the charging (and discharging) profile that minimizes operation costs while satisfying the demand of the fleet. Vehicles are aggregated to a reduced number of vehicle types, which are selected with a k-means algorithm according to the similarity of their driving patterns. The paper investigates both the case where the aggregator is a price-taker and the case where it influences prices. Electricity price variations were modeled through regression based on historical data. Another centralized approach is presented in [15], where individual charging profiles of vehicles in a distribution network are computed by minimizing total charging costs given an exogenous cost vector. Grid constraints are introduced through an iterative process, so that overloading of system assets is avoided.

Situated halfway between centralized and decentralized approaches, [16] introduces a predictive, distributed and hierarchical charging control of plug-in hybrid electric vehicles (PHEV) in a large urban area. A set of PHEV managers distributes potentially scarce power among vehicles at each 11/22kV transformer by maximizing total utility. A supervisory PHEV manager works at a the 150kV-11/22kV level and administers the charging of PHEV managers at the lower voltage levels, thus ensuring that transformers at the higher voltage level are not overloaded and that there are no voltage violations. The response of vehicles, which are modeled as agents, is controlled through prices. These are initially constant, but are endogenously increased in the case of congestion to avoid overloading.

On the other hand few decentralized approaches have been proposed so far. An approach linked to the Nash certainty equivalence principle and mean-field game models is described in [17]. Each vehicle minimizes not only its charging costs but is also penalized if it deviates from the average charging behavior of the PHEV population. There is a charging negotiation procedure where the utility collects individual charging strategies and updates the aggregate PHEV demand until convergence. It is shown that valley-filling can be achieved if the factor penalizing deviation from average behavior is not too low and if the fleet is homogeneous. This scheme needs bi-directional communication because of the nature of the negotiation procedure. On the other hand, the approach proposed in [18] makes use only of information on the forecasted total

M. González Vayá and G. Andersson are with the Power Systems Laboratory, Department of Information Technology and Electrical Engineering, ETH Zurich, Switzerland. Contact: {gonzalez,andersson}@eeh.ee.ethz.ch
power demand and local information such as estimated plug off time of a vehicle and its state of charge (SOC). First, the set of individual charging profiles minimizing system costs (including a carbon tax) are determined. Here vehicles are grouped into 100 sets to make the problem tractable. Then the decentralized algorithm seeks to emulate these results by only using the information mentioned above.

So far, current models either do not include grid constraints [14], [17], [18] or assume prices that do not reflect the actual impact of the charging on the supply side [15], [16].

In this paper we propose a centralized scheme where the dispatch of plug-in vehicles is performed by aggregating batteries to virtual storage resources at each network node and dispatching those resources within a multiperiod Optimal Power Flow (OPF) which minimizes system generation costs. The OPF concept has already been used in the context of electric mobility in [19] to analyze the effect of a dealer managing battery swapping stations on Locational Marginal Prices in the PJM (Pennsylvania-New Jersey-Maryland) interconnection. However, this framework does not include any particular fleet modeling because a battery swapping business case is analyzed. The advantage of an OPF approach is that it includes endogenous prices which reflect the costs of electricity supply as well as the scarcity of transmission capacity, since congestions are taken into account. Constraints associated with battery characteristics and driving behavior are also integrated in the centralized scheme through the modeling of the virtual storage resources.

Centralized approaches have the advantage that the reaction of vehicles can be directly controlled. However, they pose the problem of consumer acceptance. As an alternative to the centralized approach, we describe a price-based decentralized approach. The purpose is not to develop a complex decentralized approach but to analyze the impact of an approach where information, in this case Time of Use (TOU) tariffs, is simply broadcasted to vehicles in advance, e.g. day-ahead. It is assumed that each vehicle will optimize its charging based on this information. The best possible outcome of this kind of scheme is determined by choosing the TOU tariff whose anticipated response by vehicles minimizes generation costs and does not lead to asset overloading. Two variants of the decentralized approach will be examined: one with system-wide tariffs and another that allows different tariffs at different nodes.

It will be shown that, compared with uncontrolled charging, both the centralized and decentralized approaches described in this paper successfully reduce generation costs and prevent the overloading of network assets, as most additional demand takes place during low demand hours. Moreover, the centralized approach and the decentralized approach with nodal prices result in a load profile with close to perfect valley-filling. Conversely, the decentralized approach with system-wide prices leads to high simultaneity in charging and therefore does not lead to a smooth load profile. Results also show that these approaches are robust against imperfect forecasts in driving behavior.

First, methodological aspects will be dealt with in section II. These aspects include the modeling of driving patterns (II-A) as well as the formulation of the centralized charging (II-B) and decentralized charging schemes (II-C). Then, in section III, the results of the different charging schemes will be analyzed and compared. Finally, section IV concludes the paper.

II. METHODOLOGY

In this section, the methodology used to model driving patterns and to determine charging profiles according to a centralized and a decentralized scheme will be described.

The following notation will be used:

- \( P_{G_i} \): Power produced by generator \( G_i \)
- \( n_{G_i} \): Marginal cost of generator \( G_i \)
- \( P_{L_j} \): Power consumed by load \( L_j \)
- \( P_{L_j,ref} \): Reference load \( L_j \) (load w/o vehicles)
- \( P_{V_k,con} \): Rated power connection of vehicle \( V_k \)
- \( P_{V_k} \): Power consumed by vehicle \( V_k \)
- \( C_{V_k} \): Battery capacity of vehicle \( V_k \)
- \( E_{V_k} \): Energy content of the battery of vehicle \( V_k \)
- \( E_{V_k,cons} \): Driving energy consumption of vehicle \( V_k \)
- \( SOC_{V_k} \): Battery state of charge (SOC) of vehicle \( V_k \)

*min*: minimum SOC

*req*: required SOC

*trip*: SOC needed for the next trip

- \( \eta_{V_k} \): Charging efficiency of vehicle \( V_k \)
- \( \eta_{V_k} \): Driving efficiency of vehicle \( V_k \)
- \( \eta_{V_k} \): Efficiency of vehicle \( V_k \)
- \( \eta_{V_k} \): Efficiency of vehicle \( V_k \)
- \( \eta_{V_k} \): Efficiency of vehicle \( V_k \)

- \( \eta_{V_k} \): Energy content of virtual battery \( V_{B_j} \)
- \( \eta_{V_k} \): Energy drop from vehicles departing from \( V_{B_j} \)
- \( \eta_{V_k} \): Energy contribution of vehicles arriving at \( V_{B_j} \)
- \( \eta_{V_k} \): Average charging efficiency of \( V_{B_j} \)

- \( p_n \): Price seen by vehicles at node \( n \)
- \( P_{n,m,ref} \): Maximum rated power of line or transformer \( l_m \)
- \( \Omega_{L_j} \): Set of \( V_k \) associated with total load \( L_j \)
- \( \Omega_{L_j} \): Set of \( G_i \) and \( L_j \) associated with node \( n \)
- \( D_{n,m} \): Power transfer distribution factor associated with line \( l_m \) and node \( n \)
- \( t \): Time step number \( t = \{1...T\} \)
- \( \Delta t \): Time step duration

A. Driving patterns modeling

When attempting to define demand profiles it is necessary to forecast driving patterns. This will set constraints on the flexibility of vehicles’ demand. The inputs needed for this purpose are the trips performed with a vehicle, the timing and duration of these trips and the energy consumed during each of them. The parking location is also required to map each vehicle to a network node. Moreover, if the type of location is known (e.g. home or work), scenarios of the type ‘only home charging’ can be defined. Inputs concerning the set of trips, departure time, trip duration and parking location for different individuals were obtained from the 2005 Swiss mobility survey [20]. Expected consumption was approximated by multiplying trip distances detailed in this survey with an average consumption of 0.2 kWh/km. An important feature of the driving patterns is that at any point in time, more than half
of the fleet is parked. This fact justifies why vehicles should be considered as a flexible load. The proportion of vehicles being parked on a weekday is shown in Fig.1.

B. Centralized charging

The goal of the centralized charging scheme is to minimize overall system costs while taking into account both network constraints and plug-in vehicles’ driving needs. The effect of the additional demand on prices is implicitly taken into account. As it would be computationally too expensive to do so, this is considered to be inelastic while the plug-in vehicle load is considered to be flexible. The last two constraints are related to the virtual storage. It has to be ensured that cost minimization does not lead to storage depletion over time (7) and that the energy content of the storage remains always within specified bounds (8). The upper bound in (8) is simply the sum of capacities connected to a certain node, while its lower bound is given by the aggregation of individual SOC requirements:

$$E_{VB,j}^{(t)} = \sum_{\Omega_{\ell_{i,j}}} SOC_{V_{k},req} \cdot C_{V_{k}}$$ (9)

The required SOC of a particular vehicle is either its minimum SOC given by the battery manufacturer or the SOC necessary to be able to bridge the next trip if the vehicle is about to depart.

$$SOC_{V_{k},req} = \begin{cases} SOC_{V_{k},min}, & \text{if } V_{k} \in \Omega_{L_{j}} \cap V_{k} \in \Omega_{L_{j}+1} \\ SOC_{V_{k},trip}, & \text{if } V_{k} \in \Omega_{L_{j}} \cap V_{k} \notin \Omega_{L_{j}+1} \end{cases}$$ (10)

This problem can be formulated as a linear program and can therefore be solved efficiently with commercially available solvers.

To be able to compare the centralized approaches with the decentralized ones, a further step is needed. The centralized approach described is based on the aggregation of vehicle batteries, which might lead to slightly optimistic results. For this reason, a further step distributes the nodal load among vehicles according to criteria such as the time to departure and the SOC, which provide information about the urgency of charging. This is detailed in Appendix A.

C. Decentralized charging

Here, we investigate a decentralized charging approach based on the broadcast in advance of hourly prices. We assume that each driver seeks to minimize their charging costs while respecting the constraints given the battery size, its charging power level and its driving needs. Moreover, we assume that driving patterns themselves are not affected by the tariff. To analyze the best possible outcome of this kind of scheme, the TOU tariff that leads to anticipated nodal charging profiles which minimize generation costs is determined.

This optimization problem can be written as follows:
The constraints of the optimization problem related to individual charging behavior refer to the limits on the vehicle’s power connection (14), the bounds of its battery (15) and the dynamics of the energy content of its battery (16), which takes into account the energy needed for driving $E_{V_k,cons}$.

Clearly, a tariff has to have some additional properties. Particularly, it should allow the aggregator to make a reasonable profit. However, these kinds of constraints can be added a posteriori, because the outcome of the optimization problem defined in (13)-(17) is only affected by the shape of the price profile, not by its absolute value. Therefore the price profiles can be arbitrarily scaled to comply with other criteria without changing the optimal outcome.

The overall optimization problem is not convex, and each function evaluation is costly, as they imply solving the optimization problem of each individual vehicle. Two variants of the optimization problem were simulated, which were solved in different ways: one variant with system-wide tariffs $p_n^{(t)} = p^{(t)}$ and another with nodal tariffs. In the case of system-wide tariffs and hourly prices, only 24 optimization variables are necessary, so the problem can be efficiently tackled by commercially available non-convex optimization solvers. However, with nodal prices the number of necessary variables is multiplied by the number of nodes, so computational time becomes prohibitive. In this case a genetic algorithm was used to solve the optimization problem, with which satisfactory solutions were obtained even with a relatively low number of function evaluations. More details on the performance of the genetic algorithm are given in Annex B. The embedded individual vehicle optimization problems as well as the OPF were formulated as linear programs. Several individual optimization problems were solved simultaneously using parallel computing, which sped up the process.

### III. Results

To test the proposed approaches and compare them with the situation prior to the introduction of plug-in vehicles and with a situation with uncontrolled charging, the following scenarios were simulated:

- **Reference scenario**: scenario without plug-in vehicles.
- **Uncontrolled charging**: vehicles start charging as soon as they park until their batteries are full or until they are disconnected to be driven again.
- **Centralized charging**: smart charging according to the model in subsection II-B. Results will show for the ideal case and for the realistic case where aggregated load is distributed among vehicles, causing deviations from the ideal profiles to appear.
- **Decentralized charging with system-wide prices**: smart charging according to the model in subsection II-C where prices vary over time but not across nodes $p_n(t) = p^{(t)}$.
- **Decentralized charging with nodal prices**: smart charging according to the model in subsection II-C where prices vary over time and across nodes. This offers an additional degree of freedom, but implies the charging of different prices to different sets of customers, which might be problematic.

All scenarios were simulated with a model of the Swiss transmission network (380/220 kV). Data concerning the network was obtained from the Swiss transmission system operator, Swissgrid. The modeled network comprises 191 nodes, 246 lines and 21 transformers. Moreover data on 134 major generators was collected and the total load profile corresponding to the load on the Swiss system on a winter weekday (particularly Wednesday 16 December 2009) [21] was assigned to the individual load nodes according to the underlying population. In Switzerland electricity demand is higher in the winter, so the winter load was chosen because it represents a more critical situation. The timeframe chosen for the simulation was one day, which was in turn divided into hourly steps.

Concerning the vehicle fleet, a 25% plug-in vehicle penetration, which would correspond to a fleet of 1 million plug-in vehicles in Switzerland, was assumed. A large penetration was chosen deliberately in order to clearly discern the effects of the different charging scenarios. An inhomogeneous fleet was assumed, assigning a battery capacity of 24 kWh (like the battery of the Nissan Leaf) to the 50% of the fleet traveling larger daily distances and a capacity of 16 kWh (like the battery of the GM Volt and the Mitsubishi iMiEV) to the rest. We considered different available charging power ratings and assumed that vehicles would always choose the lowest rating necessary. Although this choice was not endogenously modeled, subjecting higher ratings to an additional fee would result in such behavior. In most cases (96%) slow charging at 3.5 kW would be sufficient, while in some cases semi-fast charging at 11 kW or fast charging at 50 kW would have to be used. This is shown in Table I along with other important vehicle parameters. Furthermore, we assume ubiquitous charging; that is, that each vehicle could potentially charge at any parking location.
In the following, the results of the different charging scenarios will be discussed. First, we refer to the uncontrolled charging scenario, which can be seen as the worst case scenario against which improvements from smart charging can be ascertained. Fig. 2 shows the different system load profiles resulting from the different charging strategies. It can be seen that under uncontrolled charging, plug-in vehicles’ additional load coincides with the existing demand peaks. This leads to an overloading of some network assets, visible as red peaks ranging above the 100% loading limit in Fig. 6. Uncontrolled charging also leads to the highest additional generation costs, as detailed in Table II.

A substantial improvement can be already achieved with the simplest of the smart charging schemes: decentralized charging with system-wide prices. With this approach, charging during peak hours is avoided and in effect, costs are reduced. Although asset loading increases at the time where most charging takes place, around 5 a.m., loading stays within the specified limits, as seen in Fig. 6. However, this strategy has obvious shortcomings: The best time for charging is overnight, when the reference load reaches the lowest point, but at this time most vehicles are parked, as seen in Fig. 1. This leads to a high level of charging simultaneity and induces a peak almost as high as the load present during shoulder hours. Due to this new shape of the load profile, more power plant start-ups and shutdowns will be necessary, which would lead to higher costs. As our analysis only considers marginal costs, this fact is not reflected in the results, but should be kept in mind. Allowing for different prices at different nodes, as in the decentralized charging with nodal prices scenario, means that charging takes place at different nodes alternatively, so that a flatter load profile is achieved, as seen in Fig. 2. This in turn reduces costs. Finally, the least-cost charging profile is achieved with centralized charging, even if aggregation errors are taken into account. However, there is not a marked difference in terms of costs among the different smart charging scenarios.

Furthermore, the robustness of the smart charging schemes in the face of an imperfect forecast of vehicle behavior was analyzed. For this purpose, we created a set of 100 alternative driving patterns for each vehicle based on the original pattern. This was done by subjecting departure times, trip durations and trip consumptions to a random deviation generated with a truncated normal distribution. A standard deviation of departure time and trip duration of 15 minutes and a standard deviation of consumption of 1 kWh were assumed. The impact of the forecast error on costs is shown in Fig. 3. It can be observed that the average price increase is less than 0.1 €/MWh for any of the scenarios and even negative in some cases. The average impact on the total load profile is also relatively low with a deviation of around 20 MW in the different scenarios, as seen in Fig. 4. However, the maximum deviation more than triples the average deviation in all scenarios and is most salient in the decentralized charging with system-wide prices scenario. Finally, the lack of information didn’t lead to any overloading of grid assets in all 100 variants of the fleet that were modeled. Altogether it can be said that effects of uncertainty in individual driving behavior had only a reduced impact in terms of costs and load deviations under the assumptions taken. This is probably due to the fact that many of the deviations in individual behavior canceled each other out, so that the overall impact was limited. However, in cases where deviations in behavior are highly correlated, e.g. due to some unexpected traffic or social phenomenon, the impacts could be more severe. In order to increase the robustness of the smart charging schemes against forecast errors, the optimization problems described in section II could be formulated as stochastic problems taking into account the randomness of vehicle behavior.

### IV. Conclusion

A large penetration of electric vehicles would most probably have detrimental impacts on the power system if charging is left uncontrolled. Smart charging, which can take place in a centralized or decentralized fashion, could help reduce generation costs and system strain. It is important to address both supply side aspects and grid constraints when shaping charging
profiles. However schemes proposed so far only consider one of the aspects. In this paper we have introduced a centralized scheme based on the aggregation of vehicles’ batteries into virtual storage resources at each network node, which were optimally dispatched within a multi-period OPF. This way, generation costs could be minimized while taking into account grid constraints and driving needs. Alternatively a decentralized scheme in the form of a TOU tariff to which vehicles react optimally was defined. This tariff, which could optionally take different values at different network locations, was also designed with the goal of minimizing system costs while not violating network constraints. It was shown that although centralized charging leads to the least-cost solution, the results of a decentralized pricing scheme with nodal prices were comparable, both in terms of costs, shape of the system load and robustness against day-ahead forecast errors in driving behavior. This would seem to speak for decentralized schemes, as they enjoy better customer acceptance and have lower communication requirements. However, the current analysis only included grid constraints at the transmission system level. Even if the additional load is successfully displaced to valley hours under both schemes, no mechanism was defined to guarantee that transformers at the distribution level will not be overloaded if vehicles are charging simultaneously at the same location. On the one hand, the centralized algorithm could be extended to a hierarchical scheme to include constraints in lower voltage levels. On the other hand, a price-based scheme could not so easily avoid simultaneity in charging at a low voltage transformer if prices at a particular transformer are the same for all vehicles. Further work will concentrate on the integration of lower voltage levels constraints in the optimization to gain a better understanding of this matter.

APPENDIX A
DETERMINING INDIVIDUAL CHARGING PROFILES UNDER CENTRALIZED CHARGING

Based on the nodal charging profiles obtained from the centralized charging scheme described in section II-B, individual charging profiles have to be determined. In some cases deviations from the optimal nodal charging profiles will appear, as the optimization is based on the aggregation of individual batteries and is therefore simplifying individual constraints. The distribution of the aggregated nodal load among vehicles is done time step by time step, with a heuristic method assigning a priority or urgency value $U_{V_k}$ to each vehicle based on its current SOC versus its required SOC, and also its time to departure versus its time to charge to the required SOC ($\Delta t_{V_k,dep}$ and $\Delta t_{V_k, char}$ respectively). First, the algorithm identifies plug-in vehicles whose demand has to be considered as inelastic, if any. Those vehicles need to charge in the time step under consideration if they are to depart with the required SOC. In this manner it is ensured that driving will not be negatively affected by controlled charging. Then, for the rest of vehicles an urgency value is assigned calculated as

$$U_{V_k}^{(t)} = \frac{k}{\Delta t_{V_k,dep}^{(t)} - \Delta t_{V_k, char}^{(t)}} + \left(\frac{SOC_{req}^{(t)}}{SOC^{(t)}}\right)^2$$

where $k$ is a tuning parameter. This is just a possible way to assign the priority value, other forms could also be conceivable. However, based on experience, the total charging profile does not seem to be very sensitive to the particular form used or to parameter $k$. Once the priority value has been determined, vehicles with higher priority are set to charge in the time step under consideration if they are to depart with the required SOC. In this manner it is ensured that driving will not be negatively affected by controlled charging. Then, for the rest of vehicles an urgency value is assigned calculated as

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MWh. After the first generation, costs are already inferior to the value of $78.20 \, €/MWh$, which is the value under the decentralized charging with system-wide prices as seen in Table II. In early generations costs decay rapidly, but this pace eventually slows down. This implies that the number of generations could be limited to a reduced number to avoid lengthy computations with little impact on the results.

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REFERENCES


Marina González Vayá was born in Valencia, Spain in 1985. She received the diploma in Electrical Engineering and Information Technology from the Technische Universität München, Germany and the Ecole Supérieure d’Electricité (Supélec), France in 2010. After that she joined the Power Systems Laboratory of ETH Zurich, where she is currently a PhD student. Her research focuses on electric mobility’s impact on power systems and vehicle to grid.

Göran Andersson (M’86, SM’91, F’97) obtained his M.S. (1975) and Ph.D. (1980) degrees from the University of Lund, Sweden. In 1980 he joined ASEAs, now ABB’s, HVDC division in Ludvika, Sweden, and in 1986 he was appointed full professor in electric power systems at KTH (Royal Institute of Technology), Stockholm, Sweden. Since 2000 he is full professor in electric power systems at ETH Zurich (Swiss Federal Institute of Technology), where he also heads the powers system laboratory. His research interests include power systems dynamics and control, power markets, and future energy systems. Gran Andersson is a fellow of the Royal Swedish Academy of Sciences, and of the Royal Swedish Academy of Engineering Sciences. He is Editor-in-Chief of IET Proceedings Generation, Transmission and Distribution, and the recipient of the IEE PES Outstanding Power Educator Award 2007 and of the George Montefiore International Award 2010.
Fig. 6. Asset loading profiles resulting from the different scenarios