Exploiting V2G to optimize residential energy consumption with electrical vehicle (dis)charging

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***Abstract*—The potential breakthrough of pluggable (hybrid) electrical vehicles (PHEVs) will impose various challenges to the power grid, and esp. implies a significant increase of its load. Adequately dealing with such PHEVs is one of the challenges and opportunities for smart grids. In particular, intelligent control strategies for the charging process can significantly alleviate peak load increases that are to be expected from e.g. residential vehicle charging at home. In addition, the car batteries connected to the grid can also be exploited to deliver grid services, and in particular give stored energy back to the grid to help coping with peak demands stemming from e.g. household appliances. In this paper, we will address such so-called vehicle-to-grid (V2G) scenarios while considering the optimization of PHEV charging in a residential scenario.**

In particular, we will assess the optimal car battery (dis)charging scheduling to achieve peak shaving and reduction of the variability (over time) of the load of households connected to a local distribution grid. We compare (i) a business-as-usual (BAU) scenario, without any intelligent charging, (ii) intelligent local charging optimization without V2G, and (iii) charging optimization with V2G. To evaluate these scenarios, we make use of our simulation tool, based on OMNeT++, which combines ICT and power network models and incorporates a Matlab model that allows e.g. assessing voltage violations. In a case study on a three-feeder distribution network spanning 63 households, we observe that non-V2G optimized charging can reduce the peak demand compared to BAU with 64%. If we apply V2G to the intelligent charging, we can further cut the non-V2G peak demand with 17% (i.e., achieve a peak load which is only 30% of BAU).

I. Introduction

Plug-in-(hybrid)-electric vehicles (PHEVs) will represent a significant new load on the existing distribution grids, especially as their penetration level increases (cf. the much debated goal in US of having one million plug-in EVs by 2015 [1]). Indeed, charging a single EV at home, for the average household means a doubling of the average load [2]. These changes in load patterns may require upgrades to (distribution) power grid components such as transformers. Uncoordinated charging also has an impact on the performance of the distribution grid in terms of power losses and power quality [3]. Hence, the charging of these vehicles must carefully be managed to avoid overloads or other power grid problems, by for example shifting the charging in time. This is possible, as personal vehicles are only used 4% of the time for transportation, and the remaining 96% can be used for other purposes [4].

However, PHEVs can also be of benefit towards the power grid, for example to store renewable energy which is intermittent by nature. If power generation becomes increasingly dependent on such renewable sources, supply and demand matching will obviously become more challenging [5]. Exploiting the flexibility in deciding when to charge a PHEV battery can partly alleviate this problem of intermittent (and unpredictable) energy supply. Moreover, the batteries may also be exploited as temporary storage of the fluctuating energy supply, and serve as energy storage resource that can give energy back to the grid while parked, also known as vehicle-to-grid (V2G) power [4]. Thus, not only can the renewable energy be used to power the transport functions of the PHEV, but V2G can also be exploited to deliver applications to the grid (peak power, spinning reserves, regulation, etc.).

Note that intelligent control strategies for (dis)charging EVs is part of a broader context called demand-side management (DSM), which is an active research topic. e.g., [6] proposes a distributed DSM approach based on game-theoretic energy scheduling (to reduce energy costs and the peak-to-average ratio, while maintaining privacy). Multi-agent systems based on virtual markets such as PowerMatcher [7] are another approach to DSM, where agents bid on an electronic market to determine an equilibrium price matching demand and supply.

In this paper, we will assess the optimal peak load reduction as well as the flatness of the load profile that can be achieved by intelligently scheduling EV battery charging. We investigate the maximal reduction achievable by an all-knowing scheduling algorithm that has full knowledge of the energy consumption (load profile) of a household, the arrival and departure times of an EV and its state-of-charge. We will compare scheduling with/without V2G and a baseline scenario without any intelligent charging. Thus, we set the performance boundaries of the peak load reduction and load flattening which would be achievable by any real-time, local control mechanism (such as aforementioned DSM approaches). To determine these boundaries in a case study, we use quadratic programming and our simulation tool [8].

The remainder of this paper is structured as follows: our problem statement is summarized in Section II. A brief overview of our simulation tool is listed in Section III. The mathematical formulation of the resulting optimization problem is detailed in Section IV. In Section V, we present the results of our case study comprising 63 households. Finally, conclusions and future work are synthesized in Section VI.

II. Approach and problem statement

Our earlier work [9] indicated that a distribution transformer's peak load caused by uncontrolled charging can be greatly reduced through local or iterative global energy control of the charging process of EVs at households. In particular, we proposed a *local* and a *global* control strategy to coordinate the PHEV charging process, comparing them to a business-as-usual (BAU) scenario where charging starts uncontrolled, as soon as the vehicles are plugged in upon arrival at home. The *local control* algorithm only considers the current household, to decide upon when to charge the car arriving there. Thus, we assess the possible advantage that could be offered by a so-called home energy controller, that takes decisions based on knowledge of the household energy consumption (e.g. exploiting historical data gathered by the local meter, and associated forecasts). The *global control* approach relied on sharing knowledge between the various homes (thus requiring communication and coordination between them), to try and make globally optimal decisions.

When compared to BAU, the *global* method results in the largest reduction of both the peak load (30% reduction in a scenario with 30% PHEVs) and load profile variability (75% reduction of the standard deviation between the values of the load profile in the same scenario). The *local* algorithm only performed slightly less good: 26% peak reduction and 58% reduction in load profile variability for 30% PHEV penetration. Even though the *local* algorithm is suboptimal (compared to the *global* method), it achieves a significant improvement compared to BAU. Note that such a local algorithm also would not necessarily require communication, or at least no exchange of data pertaining to other households. The latter is an important privacy concern.

Based on these considerations, we have opted in the current paper to further study the *local* control approach. We here present an extension of our local algorithm to cater for V2G: energy stored in the battery can later be fed back for local energy consumption within the household, thus further reducing the household peak load and load profile variability. We thus will compare local strategies with/without V2G.

The general problem we consider is the following:

Given

- *Grid topology* comprising the houses and the distribution grid interconnecting them;
- *Household loads*, specifying the electrical loads within the home, i.e. appliances, HVAC, etc.; and
- *PHEV status*, including the arrival and departure times, as well as state-of-charge;

Find

- when to charge the PHEV battery;
- if and when to decharge that battery for V2G operation;

Such that the peak net energy consumption, as well as its variability over time, is minimized.

We will model residential energy consumption as consisting of two parts: uncontrollable and controllable loads. Uncontrollable loads cannot be shifted in time and their energy consumption cannot be changed. Each household is characterized by a load profile for the uncontrollable loads that indicates the average uncontrollable load at each time of day. Controllable loads on the other hand can be shifted in time and their energy consumption can be changed. In this work, we only consider EVs as controllable loads. Note that, when considering V2G applications, the electric vehicles are not only considered as loads, but also as producers. Hence, we assume EVs to be controllable loads as well as controllable producers: at any given moment, a car's battery will either be charged, discharged, or left untouched.

We will determine a combined charging and discharging schedule. We consider the scheduling to operate for discrete time intervals, i.e. for time slots of equal size. The algorithm determines during which time slots an EV should charge or discharge and the rate at which this happens. Since we are focusing on a *local* approach, only knowledge of local power consumption is used. Also, the impact of other households and vehicles on the global load profile is not considered when determining the (dis)charging schedules. Therefore, the objective of the schedule will be to minimize local peak load and load profile variability. Clearly, the intention – which [9] proved to be achievable – is to affect the aggregate load profile comprising all households connected to a single distribution transformer. Even though the quadratic programming model described below is solved for each vehicle separately upon arrival at the charging point, we will assess its impact by showing the total load on the whole distribution feeders.

Note that we assumed a simplified, lossless model of the car's battery, which we assume to be characterized by (i) maximum storage capacity, and (ii) maximum charge/decharge power. For simplicity, in this work we disregard any battery inefficiencies such as self-discharge, loss of capacity (e.g. due to memory effects), etc.

III. Simulation tool

The smart grid simulator we have developed to facilitate smart grid research, combines models of the power grid itself as well as the information and communication technologies (ICT) that will be deployed in the smart grid. The main goals of our smart grid simulation environment are:

- Support the development of control algorithms for energy management and their corresponding software architectures.
- Enable analysis of communication requirements and impact of specific communication technologies on the performance of control algorithms.
- Enable evaluation of the impact of the control strategies on the power grid.
- Provide a flexible and modular environment.

To achieve these goals, we based our tool on OMNeT++, given its excellent performance [10]. For the assessment of power network characteristics, we integrated a Matlab module, based on the fast harmonic simulation method presented in [11]. For an overview of our simulator's architecture, we refer to [8].