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Efficient decentralized coordination of large-scale plug-in electric vehicle charging☆

Zhongjing Ma [a], Suli Zou [a], Long Ran [a], Xingyu Shi [a], Ian A. Hiskens [b]

[a] School of Automation, Beijing Institute of Technology (BIT), and the National Key Laboratory of Complex System Intelligent Control and Decision (BIT), Beijing 100081, China

[b] Department of Electrical Engineering and Computer Science, University of Michigan, Ann Arbor, MI, USA

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ABSTRACT

Minimizing the grid impacts of large-scale plug-in electric vehicle (PEV) charging tends to be associated with coordination strategies that seek to fill the overnight valley in electricity demand. However such strategies can result in high charging power, raising the possibility of local overloads within the distribution grid and of accelerated battery degradation. The paper establishes a framework for PEV charging coordination that facilitates the tradeoff between total generation cost and the local costs associated with overloading and battery degradation. A decentralized approach to solving the resulting large-scale optimization problem involves each PEV minimizing their charging cost with respect to a forecast price profile while taking into account local grid and battery effects. The charging strategies proposed by participating PEVs are used to update the price profile which is subsequently rebroadcast to the PEVs. The process then repeats. It is shown that under mild conditions this iterative process converges to the unique, efficient (socially optimal) coordination strategy.

1. Introduction

As the population of plug-in electric vehicles (PEVs) grows, the electrical power drawn by chargers will begin to impact the grid. Numerous studies have explored the potential consequences of a high penetration of PEVs on the power grid (Denholm & Short, 2006; Hadley & Tsvetkova, 2008; Koyanagi & Uriu, 1997; Rahman & Shrestha, 1993; Yu, 2008). At the system-wide level, control strategies tend to focus on filling the overnight valley in background demand. A wider range of control objectives have been considered at the distribution level where uncoordinated charging may induce localized overloading, excessive losses and voltage problems (Clement-Nyns, Haesen, & Driesen, 2010; Fernández, Román, Cossent, Domingo, & Frías, 2011; Galus & Andersson, 2008; Hermans, Almassalkhi, & Hiskens, 2012; Kelly, Rowe, & Wild, 2009). It is quite uncommon, however, to find studies that also take into account the effects of charging control on the health of the PEV batteries. This paper addresses the need for a charging coordination scheme which considers the tradeoffs between system-wide economic efficiency, distribution-level limitations and battery degradation concerns.

Charging behavior affects key battery characteristics, including the state of health, the resistance impedance growth and the cycle life, which are all strongly related to the energy capacity of a battery (Bashash, Moura, Forman, & Fathy, 2011; Wang et al., 2011). Intermittent charging may also shorten the battery lifespan (Gan, Topcu, & Low, 2012). Optimal charging strategies that take into account both the total energy cost and the battery state of health have been studied for single PEVs (Bashash et al., 2011; Cheng, Divakar, Wu, Ding, & Ho, 2011). These ideas form the basis for the extension, undertaken in this paper, to large-scale coordination.

Many studies have employed centralized methods for scheduling the charging power of PEVs, see Clement-Nyns et al. (2010), Galus and Andersson (2008) and Sundstrom and Binding (2010) and references therein. However individual PEVs are likely to desire autonomy, and optimizing over a large population of PEVs

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E-mail addresses: mazhongjing@bit.edu.cn (Z. Ma), 20070192zsl@bit.edu.cn (S. Zou), 110992@bit.edu.cn (L. Ran), sxywd0602@aliyun.com (X. Shi), hiskens@umich.edu (I.A. Hiskens).

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Table 1
List of key symbols.

$\mathcal{T}$	Charging horizon
$\boldsymbol{u}_n$	$(u_{nt}; t \in \mathcal{T})$, charging strategy of the nth PEV over the horizon $\mathcal{T}$
$\|\boldsymbol{u}_n\|_1$	$\sum_{t\in\mathcal{T}} u_{nt}$, total energy delivered to the nth PEV over the horizon $\mathcal{T}$
$\boldsymbol{u}_n^{**}$	Efficient charging strategy for PEV n
$\boldsymbol{p}^{**}$	Generation marginal cost with respect to $\boldsymbol{u}^{**}$
$\boldsymbol{u}_n^{*}(\boldsymbol{p})$	Optimal charging strategy of the nth PEV with respect to price profile $\boldsymbol{p}$

will have high computational complexity. Therefore centralized scheduling may be impractical. As an alternative, decentralized methods preserve individual authority and distribute the computational burden (Gan, Topcu, & Low, 2013; Ma, Callaway, & Hiskens, 2013).

Time-based strategies for scheduling PEV charging have difficulty effectively filling the night-time demand valley (Callaway & Hiskens, 2011). Likewise, strategies that rely on a fixed price schedule tend to result in suboptimal demand patterns. In contrast, this paper is motivated by a real-time price model which has been widely applied for demand response management (Mohsenian-Rad & Leon-Garcia, 2010; Samadi, Mohsenian-Rad, Schober, Wong, & Jatskevich, 2010) and electric vehicle charging/discharging coordination (Fan, 2012; Gan, Chen, Wierman, Topcu, & Low, 2013; Waraich et al., 2009; Wu, Mohsenian-Rad, & Huang, 2012). In this formulation, the electricity price is given by the generation marginal cost as a function of the total demand.

In the decentralized approach to charging coordination proposed in this paper, participating PEVs simultaneously determine their optimal charging strategy with respect to an energy price forecast. These proposed charging strategies are used to estimate the total demand over the charging horizon. An updated price forecast is obtained as a weighted average of the previous price forecast and the generation marginal cost evaluated at this latest demand forecast. The revised price is (re)broadcast to the PEVs, and the process repeats. This scheme is formalized in Section 4 where it is shown that convergence is guaranteed under mild conditions. Upon convergence, the price profile is coincident with the generation marginal cost over the charging horizon. As a consequence, the resulting collection of PEV charging strategies is efficient (socially optimal). Moreover, convergence is obtained without the need for artificial deviation costs to damp oscillations, as in Ma et al. (2013) and Gan et al. (2013). Cost terms introduced to mitigate the effects of local demand peaks and battery degradation play the same role as congestion pricing used for traffic control in communication networks (Kelly, Maulloo, & Tan, 1998), which has been adopted in Fan (2012) to schedule PEV charging.

The paper is organized as follows. Section 2 formalizes the concept of charging strategies, and motivates the costs associated with peak demand reduction and battery degradation. Centralized (socially optimal) coordination of PEV charging is considered in Section 3. A novel decentralized charging coordination algorithm is presented in Section 4 and convergence is analyzed. Simulations in Section 5 illustrate various characteristics of the algorithm. Section 6 concludes the paper and discusses ongoing research. A summary of the key notation used throughout the paper is provided in Table 1.

2. Formulation of PEV charging coordination

2.1. Admissible charging strategies

Consider the charging control of a large population of PEVs, $\mathcal{N} \equiv \{1, \dots, N\}$, over the horizon $\mathcal{T} \equiv \{0, \dots, T-1\}$. For each PEV, $n \in \mathcal{N}$, the charging power over the time period $t \in \mathcal{T}$ is denoted by u_{nt} (with units of kW).[1] A charging strategy $\boldsymbol{u}_n \equiv (u_{nt}; t \in \mathcal{T})$ is *admissible* if,

$$u_{nt} \begin{cases} \geq 0, & t \in \mathcal{T}_n \\ = 0, & t \in \mathcal{T} \setminus \mathcal{T}_n, \end{cases} \tag{1a}$$

and

$$\|\boldsymbol{u}_n\|_1 \equiv \sum_{t\in\mathcal{T}} u_{nt} \leq \Gamma_n, \tag{1b}$$

where $\mathcal{T}_n \subset \mathcal{T}$ is the charging horizon and Γ_n is the energy capacity of the nth PEV. The parameters $\mathcal{T}_n$ and Γ_n are determined by external factors such as driving style and vehicle type (Lee, Bareket, & Gordon, 2012). The set of admissible charging controls for the nth PEV is denoted by $\mathcal{U}_n$.

Coordination of PEV charging across a large population has generally sought to minimize total generation cost over the charging horizon, see for example Denholm and Short (2006), Gan et al. (2013) and Ma et al. (2013). In contrast, the coordination strategies developed in this paper seek to manage the tradeoff between total generation cost and local costs arising from high distribution-level demand and PEV battery degradation. These latter costs will now be discussed.

2.2. Demand charge

Distribution-level impacts of PEV charging include line and transformer overloading, low voltages and increased losses. All these effects are a consequence of coincident high charger power demand u_{nt}. Therefore undesirable distribution-grid effects can be minimized by encouraging PEVs to charge at lower power levels. This can be achieved by introducing a demand charge,

$$Cost_{demand,nt} = g_{demand,nt}(u_{nt}) \tag{2}$$

whereby PEVs incur a higher cost as their charging power increases, i.e. $g_{demand,nt}(\cdot)$ is a strictly increasing function. This charge is in addition to the cost of the energy delivered to the battery, and is consistent with existing tariff structures for larger consumers (Deliso, 2013).

2.3. Battery degradation cost

The $LiFePO_4$ lithium-ion battery has been widely used in a variety of electrical vehicles. A degradation cost model for $LiFePO_4$ battery cells is formulated in Forman, Stein, and Fathy (2013), based on the evolution of battery cell characteristics developed in Forman, Moura, Stein, and Fathy (2012) and Moura, Forman, Bashash, Stein, and Fathy (2011). This degradation model expresses the energy capacity loss per second (in Amp $\times$ Hour $\times$ Sec^{-1}) of a cell with respect to the charging current I and voltage V:

$$\mathfrak{d}_{cell}(I, V) = \beta_1 + \beta_2 I + \beta_3 V + \beta_4 I^2 + \beta_5 V^2 + \beta_6 IV + \beta_7 V^3, \tag{3}$$

with the parameters $\beta_i, i = 1, \dots, 7$, specified in Forman et al. (2013, Table I). The degradation cost for a battery cell charging at constant I and V for a period ΔT Sec is therefore,

$$\mathfrak{g}_{cell}(I, V) = P_{cell} \Delta T V_{cell} \mathfrak{d}_{cell}(I, V) \tag{4}$$

where P_{cell} is the price ($/Wh) of battery cell capacity.

The cell voltage V_{cell} of a lithium-ion battery changes with its state of charge (SoC) (Kim, Seo, Chun, Cho, & Lee, 2012; Prosini, 2005). More specifically, as the SoC of a cell varies from zero to a very low value $soc_\ell > 0$, V_{cell} rises rapidly from zero to its nominal

[1] If the tth time period has length ΔT, then the energy delivered over that period is $u_{nt} \Delta T$.