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A hierarchical algorithm for optimal plug-in electric vehicle charging with usage constraints☆

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ABSTRACT

We present a hierarchical offline coordination algorithm for charging of Plug-in Electric Vehicles (PEVs), in which PEVs aim to optimally charge their batteries, subject to usage constraints along the day. With this algorithm, each PEV adjusts its charging strategy according to the price information, which is provided by an aggregator, while usage schedule constraints are respected at every iteration. A non-anonymous version of the algorithm is able to operate under communication failures. Both versions of the algorithm are proven to converge to the set of optimal solutions of the charging problem. This solution is optimal in the sense that it minimizes the cost of the consumed energy by both PEV and non-PEV loads. The solution has a valley-filling profile, since it leads to a configuration where PEVs aim to charge at low demand hours, minimizing, if possible, load peaks that are known to degrade the performance of power systems. In order to show convergence, we present an invariance result for difference inclusions, which works under a set of assumptions where LaSalle invariance principle does not apply. The algorithm performance is demonstrated throughout simulations.

1. Introduction

Plug-in Electric Vehicles are being proposed as an important element in flexible load control that can both help alleviate environmental transportation costs and our dependency on petroleum energy sources. However, a large penetration of PEVs may also negatively affect the operation of the power system, by creating new demand peaks and system overload (Farmer, Hines, Dowds, & Blumsack, 2010). These phenomena incur into additional stress on generation, transmission and distribution systems, which translates into increased costs for users and electric generation companies. In order to lower the burden PEVs create on power systems, and at the same time decrease end-user costs, new algorithmic approaches on PEV charging are being designed with the goal of achieving peak-shaving solutions. This manuscript contributes in this regard by proposing a novel algorithm that allocates PEV load at low-demand hours, while accounting for planned PEV scheduling constraints.

Diverse control architectures have been proposed to minimize power demand and to avoid the rise of new load peaks: centralized, distributed, and hierarchical. In a fully distributed setting, the network is solely comprised of PEVs, which exchange information with a subset of neighboring PEVs and make decisions based on that information. In a hierarchical architecture (also referred to as "decentralized" in the literature), agents engage in a similar process, but employing a special tree communication structure and minimal communication interaction. According to this distinction, we find the following related works in the literature.

The paper (Mets, Verschueren, Haerick, Develder, & De Turck, 2010) formulates an optimization problem which is solved in a centralized manner to come up with a valley-filling solution. In Masoum, Deilami, Moses, Masoum, and Abu-Siada (2011), a centralized PEV charging coordination strategy is proposed in order to shave demand peaks as well as minimize distribution losses. A supervisor controls the battery charging policies for all the PEVs in Caramanis and Foster (2009), with the aim of minimizing costs and regulating voltage. In Ardakanian, Rosenberg, and Keshav (2013), a distributed online approach is followed, in order to decide charging rates for each time. To this end, each electric vehicle uses measures of the instantaneous congestion of those nodes of the grid, by which power flows towards it. The authors of Gharesifard, Basar, and Dominguez-Garcia (2013) introduce a pricing-based

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two-layer control algorithm for charging/discharging of PEVs. The algorithm is distributed, exploiting consensus-algorithm ideas. The characterization of the solutions and performance analysis are made via game theory and nonlinear analysis. Neither of the above works considers constraints based on usage schedule.

In Ahn, Li, and Peng (2011), optimal charging trajectories are computed using linear programming. The authors propose two hierarchical algorithms to solve the problem. The first requires information about a centralized solution, particularly about the cost function gradient, while the second one assumes that each PEV computes a valley-filling solution based on the average charge requirements from all PEVs. No guarantee of optimality is provided. The work Zhongjing, Callaway, and Hiskens (2011) introduces an algorithm that computes optimal charging strategies for a large population of PEVs. A bargain is performed between an energy coordinator and the PEVs, which leads to a valley-filling solution that minimizes the overall energy price. In this work, all PEVs are considered to have the same charging schedule. The paper Gan, Topcu, and Low (2013), generalizes the setting of the previous work. The bargaining idea is similar to the one in Zhongjing et al. (2011), but it is assumed that PEVs have constraints on the maximal amount of energy that can be charged into their batteries at each time, as well as deadlines for complete charge. The result in Gan et al. (2013) is also extended to an asynchronous iteration, under mild connectivity assumptions and for non-anonymous interactions between the utility and PEVs. The works Gan et al. (2013), Zhongjing et al. (2011) present algorithms that are based on the solution of local convex optimization problems in a repeated way. Although convex optimization problems can be efficiently solved, each iteration involves several computationally expensive steps (e.g., solution of linear equations systems) which must be carried out sequentially. These algorithms have been proven to exhibit asymptotic convergence to the optimal solution of the problem.

The contributions of this work are twofold. We present a novel hierarchical approach, the Price Leveling algorithm, based on local interaction rules that meet usage schedule constraints. In this way, our algorithm is represented by a nonlinear difference equation, which only involves sums, and products. This improves on the required computational effort as compared to Gan et al. (2013) and Zhongjing et al. (2011), in which at each iteration a convex optimization problem must be solved by each PEV. This presents two main advantages. First, algorithms with lower computational requirements reduce errors in online implementations. Secondly, they allow for the use of cheaper computational devices in offline implementations, which is of concern to both grid operators and users.

The usage constraints we consider are described by energy requirements that must be achieved by each PEV before certain times of the day, in order to meet user needs. In addition, this algorithm also respects the bounds on the charging rate for each PEV battery. We further present a Non-Anonymous Price Leveling algorithm, a version of our algorithm in a non-anonymous interaction setting under communication failures. In order to analyze our algorithms, we present an invariance result for discrete-time set-valued systems, which is more general than the LaSalle invariance principle for difference inclusions. This result is instrumental for our proof of convergence to an optimal generalized valley-filling solution. Simulations demonstrate the validity of the theoretical results, and illustrate how the algorithm would perform under anonymous time-varying interactions. A preliminary version of this work was presented in Cortés and Martínez (2013), where the Price Leveling algorithm did not account for usage constraints or time-varying interactions. A weaker version of the theoretical results was also presented in Cortés and Martínez (2013) without proof.

This paper is organized as follows: in Section 2, we formulate the PEV charging problem under scheduling constraints, as an optimization problem, and we also present some results to characterize the optimal solution of this problem. In Section 3, we introduce the Price Leveling algorithm, and present some characterization of its behavior, as well as the convergence analysis towards the set of optimal solutions of the PEV charging problem. In Section 4, we present the Non-Anonymous Price Leveling algorithm to work in a scenario with communication failures. In Section 5, we show simulation results for a specific scenario with communication failures. Conclusions and future directions are presented in Section 6.

Notation: Let A, B be subsets of X. Define $A \setminus B = \{a \in X \mid a \in A, a \notin B\}$. If the set A is finite, define $|A|$ as the number of elements of A. Let z be a vector in $\mathbb{R}^q$, $q \in \mathbb{N}$. Then $\|z\|$ denotes the euclidean norm of z. For $r > 0$, define $B_r(z) = \{y \in \mathbb{R}^q \mid \|z - y\| \leq r\}$. Let S be a set in $\mathbb{R}^q$. Then, $S + B_r(0) = \{y \in \mathbb{R}^q \mid \exists z \in S \text{ s.t. } \|z - y\| \leq r\}$. For a function $V : \mathbb{R}^q \to \mathbb{R}^s$, and the set-valued map $F : \mathbb{R}^m \rightrightarrows \mathbb{R}^q$, define $V \circ F : \mathbb{R}^m \rightrightarrows \mathbb{R}^s$, such that $V \circ F(z) = \{y \in \mathbb{R}^s \mid \exists \xi \in F(z) \text{ s.t. } W(\xi) = y\}$. For a function $f : \mathbb{R} \to \mathbb{R}$, let us denote the derivative of f by f'.

Next, we introduce some symbols that will be used throughout the document:

T: Length of the optimization horizon
$\tau = \{1, \dots, T\}$: Optimization horizon (set of slots)
$I = \{1, \dots, N\}$: Set of PEVs
$W_i \subset \tau \cup \{T + 1\}$: Set of 'in-use' time slots for agent $i \in I$
$Z_i \subset \tau$: Set of 'charging-available' time slots
$\{Z_i^\ell\}_{\ell=1}^{m_i}$: Partition of Z_i
$\{W_i^\ell\}_{\ell=0}^{m_i}$: Partition of W_i
$\mathcal{Z}_i^n = \bigcup_{\ell=1}^n Z_i^\ell$: Cumulative elements of the partition $\{Z_i^\ell\}_{\ell=1}^{m_i}$
$\mathcal{W}_i^n = \bigcup_{\ell=0}^n W_i^\ell$: Cumulative elements of the partition $\{W_i^\ell\}_{\ell=0}^{m_i}$
$\mathbf{n}(i, t)$: Element in the charging available partition for agent (or PEV) i, $\{Z_i^\ell\}_{\ell=1}^{m_i}$, containing $t \in Z_i$
m_i: Number of elements in the partition of Z_i
$d = NT \sum_{i \in I} m_i$: Dimension of the algorithm state
$\mathcal{F}_i$: Feasible charging set for PEV i
$\mathcal{F}$: Feasible charging set for all PEV
$\overline{\mathcal{F}}$: Set of admissible states for the Price Leveling algorithm
D_t: Non-PEV demand at time slot t
$u_{i,t}$: Charging rate at time slot t for PEV i
u_i: Charging profile for PEV i
u: Charging profile for all PEVs
$w_{i,t}$: Energy-usage requirement for time slot t for PEV i
x_t: PEV aggregate demand at time slot t
$L_t = D_t + x_t$: Overall demand at time slot t
$\vartheta_{i,t}$: Battery state of the ith PEV at time slot t
ϑ_{i,t_n}: Battery state at time slot $t_n = \max \mathcal{Z}_i^n$ for $n \in \{1, \dots, m_i\}$, and PEV i
α_i: Efficiency of the ith battery charger
β_i: Capacity of the ith battery
p_t^k: Energy price at time slot t, iteration k computed by the aggregator
$\{\Upsilon_l\}_{l=1}^{m+1}$: Partition of τ associated to the optimal load profile
y: State of the Price Leveling algorithm.