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Distributed coordination of electric vehicles for conforming to an energy schedule

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ABSTRACT

This paper proposes a distributed electric vehicle (EV) coordination mechanism enabling the management of the charging/discharging set-points of an EV fleet. A distributed iterative algorithm is introduced to manage EV charging/discharging in the intra-day operation aiming to meet the mobility energy requirements of the EV fleet respecting the day-ahead schedule of the EV aggregator. The proposed distributed EV charging coordination can be applied considering any day-ahead energy scheduling profile defined by the EV aggregator's business policy.

1. Introduction

The participation of electric vehicles as individual entities to the electricity markets (i.e. wholesale and ancillary services) is impractical due to the limited EV battery capacity. The aggregation of the battery capacities of geographically dispersed EVs and the coordination of their operation can form a virtual storage capacity capable to participate into electricity markets and to offer ancillary services to the grid (i.e. peak shaving, frequency and voltage regulation, balancing, etc.). Several papers [1–9] have been published in the literature about the benefits derived from the EV grid support services, considering unidirectional and especially, bidirectional power flow between EV and the grid. The major issues when considering bidirectional power flow are the battery degradation, the need for upgrade of the EV power electronic interfaces and the additional ICT requirements. Despite these problems, it is shown in economic and technical research studies [1–9], that the bidirectional operation can maximize market and network benefits.

EV mobility and space disparity are the major difficulties in managing dispersed storage resources forming virtual associations, in comparison to the conventional battery storage stations. EV mobility implies additional operational constraints, which make EV coordination a very complicated task. Several EV management schemes have been proposed in the literature, e.g. Ref. [10], aiming at different coordination objectives, such as cost minimization, voltage support, peak shaving/"valley-filling", frequency support, harmonic and reactive power compensation. Various methods can be implemented for EV coordination, such as Nash certainty equivalence and mean-filed games, "max-weight" policy, auction or Lagrangian Relaxation based optimization, non-dominated sort genetic algorithms, droop-based control, resistance emulation methods, etc. Moreover, the objectives of EV charging coordination can be met by applying decentralized [11–21] or centralized control algorithms [22–31]. The major advantage of decentralized control is its potential for real-time implementation due to the reduced computational requirements achieved by the decomposition of the centralized problem into local sub-problems coordinated by control signals.

This paper introduces a distributed EV coordination for optimally tracking an energy schedule. The core of the proposed EV coordination is based on the optimal decentralized protocol for EV charging presented in Ref. [13], which is developed for tracking a given profile considering only unidirectional power flow (i.e. charging mode). The unidirectional EV coordination comprises one set of decision variables $X_{ch} = \{X_{ch,1}, X_{ch,2}, \ldots, X_{ch,N}\}$, where $X_{ch,i,} = \{X_{ch,i}(1), \ldots, X_{ch,i}(T)\}$, defining the optimal EV fleet charging set-points for each hour of the examined period T. The control signals generated by the EV aggregator aim to define the charging set-points of a number of EVs in order to achieve the "valley-filling" concept. In this paper, the EV coordination method described in Ref. [13] is extended to support bidirectional power flow between the EV battery and the grid. The implementation of bidirectional power flow introduces one additional set of decision variables $X_{dch} = \{\mathrm{X}_{\mathrm{dch},1}, \mathrm{Xd}_{\mathrm{ch},2}, \ldots, \mathrm{X}_{\mathrm{dch,N}}\}$, where $\mathrm{X}_{\mathrm{dch,i,}} = \{\mathrm{X}_{\mathrm{dch,i}}(1), \ldots, \mathrm{X}_{\mathrm{dch,i}}(\mathrm{T})\}$, to represent the discharging operation. The two decision variables for each EV ($\mathrm{X}_{\mathrm{ch,i}}$, $\mathrm{X}_{\mathrm{dch,i}}$) are

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Nomenclature

$BatC_i$	Battery replacement cost (400$/kWh)
$Comp_i(t)$	Compensation factor of the i-th EV to account for unplanned departures
Dci	Battery degradation cost
$Deg_i(t)$	Battery degradation
E[]	Expected value function
Efi	Efficiency of EV charger
ExU, ExD	Expected percentage of regulation up/down capacity dispatched each hour
ExR	Expected percentage of responsive reserve capacity dispatched each hour
FPi(t)	Final power draw of *i*-th EV considering regulation/responsive reserves
L(t)	System net load at time t
Mc_i	Battery capacity of i-th EV
Mk	The price of energy EV users are charged ($0.01/kWh)
$MnAP^{for}_{aggr}/MaxAP^{for}_{aggr}$	Forecasted min/max additional power draw
$MnAP_i(t)$, $MxAP_i(t)$	Min/max additional power draw of i-th EV
$MnAPr_i(t)$ $MaxAPr_i(t)$	Real min/max additional power draw of i-th EV
MnL, MxL	Min, max day-ahead forecasted net load
$Mp_i(t)$	Maximum power draw of i-th EV at time t
N	Number of coordinated EVs
P(t)	Energy price at time t
Pbatlow	Lower safe operational limit of EV battery
$p_i(t)$	Energy discharged due to the discharge efficiency
$POP^{for}_{aggr}(t)$	Aggregator's energy schedule at time t
$POP_i(t)$	Estimated operating point of ith EV
$Plug_i(t)$	Dual variable defining the non-commuting hours (1 holds for plugged-in EVs and 0 holds for non grid-connected EVs)
PRr(t)	Forecasted price of spinning reserve at time t
PRu(t), PRd(t)	Forecasted price of regulation up/down at time t
$p^v(t)$	Aggregator's virtual price signal at time t
Ru(t), Rd(t)	Aggregator's regulation up/down capacity
Rr(t)	Aggregator's responsive reserve capacity
$RsRP_i(t)$	Reduction in power draw available for spinning reserve of i-th EV
$SOC_i(t)$	State of charge of i-th EV's battery at time t
SOC_{min}, SOC_{max}	Low and max state of charge of the i-th battery
$Trips_i(t)$	Battery consumption after i-th EV travel at time t
U()	The symbolic representation of a function
u_c, u_d	Integer variables for charging/discharging
$X^{\nu}_{ch,i}(t)$	Charging set-point of i-th EV at time t of the v-th iteration of the EV energy coordination algorithm
$X^{\nu}_{dch,i}(t)$	Discharging set-point of i-th EV at time t of the v-th iteration of the EV energy coordination algorithm
$X^{v}_{i}(t)$	Aggregated EV power profile at time t of the v-th iteration of the EV energy coordination algorithm

interdependent, since during any timeslot t the variables $X_{ch,i}(t)$ and $X_{dch,i}(t)$ cannot be simultaneously true (non-zero). For this reason, two auxiliary binary variables are introduced to restrict such an operation. In this way, the EV coordination algorithm in Ref. [13] is transformed from a quadratic, linear constrained problem to a mixed integer, quadratic one, which requires more complex optimization approaches.

The optimal scheduling method developed in Ref. [9] is utilized in order to generate a day-ahead charging/discharging profile. It is important to underline that the proposed EV coordination method can satisfy any optimal energy scheduling method without any limitation, respecting at the same time the EV operational constraints.

The contribution of this paper lies in the following aspects:

I. It extends the EV coordination algorithm for tracking a given profile presented in Ref. [13], from unidirectional power flow (i.e. charging mode), also to bidirectional power flow (i.e. charging and discharging mode) between EV battery and the grid.
II. It implements the Bender Decomposition method for defining the optimal response of each EV, to the aggregator's control signals. There are several methodologies for solving this mixed-integer quadratic problem, including mixed-integer, nonlinear programming (MINLP) problems (MINL), such as Bender Decomposition, Branch and Bound, Outer Approximation, Feasibility Approach, etc. The widely adopted Bender Decomposition methodology is applied in this paper.
III. It provides a convergence analysis of the proposed EV coordination algorithm.

The rest of the paper is organized as follows. Section 2 presents briefly the adopted optimal day-ahead EV scheduling for generating the tracking profile. Section 3 presents the enhanced distributed EV coordination algorithm for tracking the day-ahead scheduling profile in the intra-day operation. Section 4 presents the case study. The simulation results are presented and analyzed in Section 5. Finally, Section 6 concludes.

2. Optimal EV scheduling

The optimization approach developed in Ref. [9] aims to maximize the aggregator's revenues (Eq. (1)) considering ancillary services (regulation up/down and spinning reserve) by exploiting the bulk energy in the car batteries. The main advantage of this algorithm is that it allows asymmetric bidding of regulation up and down and bidding of capacities of energy and services lower than the available EV battery capacity.

The day-ahead optimal EV scheduling is formulated as:

$$\mathrm{Max} f = \sum_{t=1}^{T}(PRu(t)Ru(t) + PRd(t)Rd(t) + PRr(t)Rr(t)) + Mk\sum_{i=1}^{N}\sum_{t=1}^{T}$$

$$\left(E\left\{FP_i(t)\right\}\right) - \sum_{i=1}^{N}\sum_{t=1}^{T}\left(E\left\{FP_i(t)\right\}P(t)\right) - \sum_{i=1}^{N}\sum_{t=1}^{T}(Deg_i(t)) \quad (1)$$

s.t

$$h_{1,i,t} = POP_i(t)(1 - Plug_i(t)) = 0 \quad (2)$$

$$h_{2,i,t} = MxAP_i(t)(1 - Plug_i(t)) = 0 \quad (3)$$

$$h_{3,i,t} = MnAP_i(t)(1 - Plug_i(t)) = 0 \quad (4)$$

$$h_{4,i,t} = RsRP_i(t)(1 - Plug_i(t)) = 0 \quad (5)$$

$$h_{6,i} = SOC_i(1) - \sum_{t=1}^{T} Trips_i(t)$$

$$+Ef_i\sum_{t=1}^{T}(POP_i(t) + \rho_i(t)) - Mc_i = 0 \quad (6)$$

$$g_{1,i,t} = (MxAP_i(1) + POP_i(1))Ef_i + SOC_i(1) - Mc_i \le 0 \quad (7)$$