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Consensus-based coordination of electric vehicle charging considering transformer hierarchy☆

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ABSTRACT

The paper considers the coordination of electric vehicle (EV) charging where the loading on the transformers that serve the distribution feeders is taken into account. A decentralized control method is designed such that self-interested EVs are motivated to achieve global benefits. The formulation has a hierarchical structure. At the lower level, each transformer broadcasts a price signal to the EVs that it supplies, and the EVs individually determine their optimal charging strategies. At the upper level, the communication network between transformers is described as a graph and a consensus algorithm among the transformers is used to obtain a group consensus price that reflects the system generation cost. Each transformer then establishes a price which is composed of the consensus price together with a contribution that accounts for its loading characteristic. An update algorithm is developed which converges in a few (typically around ten) iterations to the unique and efficient (socially optimal) solution.

1. Introduction

The charging demand associated with a high penetration of electric vehicles (EVs) could have a significant impact on the grid if not carefully integrated (Denholm & Short, 2006; Hadley & Tsvetkova, 2008). A wide 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). With the restructuring of power systems and the advent of responsive grid technologies, distribution system operation will be characterized by active demand side participation and the emergence of a variety of scheduling (transactive) techniques (Parvania, Fotuhi-Firuzabad, & Shahidehpour, 2013; Rahimi & Ipakchi, 2012; Samadi, Mohsenian-Rad, Schober, & Wong, 2012; Torriti, 2012). Hence, sophisticated control strategies will be required to manage demand-side participation, dispatch optimization and other services.

These control issues are addressed by considering a system where EVs obtain energy through transformers that have limited capacity (Zou, Hiskens, & Ma, 2017a). Numerous centralized methods for scheduling the charging behaviour of EVs have been developed, with an overview provided by Clement-Nyns et al. (2010), Galus and Andersson (2008), Sundstrom and Binding (2010) and associated references. However, decentralized methods are potentially more practical as they maintain EV privacy and autonomy, and eliminate requirements for centralized communications and computing resources. This paper extends a consensus-based charging coordination scheme developed in Zou, Hiskens, Ma, and Liu (2017b) which established a distributed protocol to avoid the need for a central entity (e.g. market operator) to compute or broadcast information. As adopted in the literature, coordination in such a distributed protocol is often formulated as consensus or group agreement problems (Andreasson, Dimarogonas, Sandberg, & Johansson, 2014; Hug, Kar, & Wu, 2015; Olfati-Saber, Fax, & Murray, 2007; Olfati-Saber & Murray, 2004; Ren & Beard, 2008), where the aim is to achieve agreement between connected agents in a network. Hence, this paper establishes models of EVs and transformers, as well as the interaction topology of distribution networks with multiple transformers, and designs a decentralized coordination strategy that ensures the system will converge to the efficient (globally optimal) strategy.

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Nomenclature

$\mathcal{T}$	time horizon
T	number of time periods in the time horizon, $T = \lvert\mathcal{T}\rvert$
$t \in \mathcal{T}$	time index
ΔT	length of a time period
$\mathcal{M}$	set of transformers
M	number of transformers, $M = \lvert\mathcal{M}\rvert$
$m \in \mathcal{M}$	transformer index
$\mathcal{N}$	set of EVs
N	number of EVs, $N = \lvert\mathcal{N}\rvert$
$\mathcal{N}_m$	set of EVs supplied by transformer m
N_m	number of EVs supplied by transformer m, $N_m = \lvert\mathcal{N}_m\rvert$
$n \in \mathcal{N}_m$	EV index
$\mathcal{G}$	graph of transformer communication topology
$\mathcal{E}$	set of edges of graph $\mathcal{G}$
A	adjacency matrix of $\mathcal{G}$
a_{mn}	(m, n) entry of A
D_m	number of neighbours of transformer m
L	Laplacian of $\mathcal{G}$
l_{mn}	(m, n) entry of L
φ_m	rating (capacity) of transformer m
β_{mt}	weighting factor on the penalty for exceeding transformer m rating at time t
d^c_{mt}	background demand carried by transformer m at time t
$\mathcal{T}_{mn}$	times $t \in \mathcal{T}$ at which EV $n \in \mathcal{N}_m$ is available to charge
$u_{mn,t}$	power consumption of EV $n \in \mathcal{N}_m$ at time t
$\boldsymbol{u}_{mn}$	charging strategy of EV $n \in \mathcal{N}_m$
$\boldsymbol{u}$	charging strategy of all the EVs
$\bar{u}_{mn,t}$	maximum charging power of EV $n \in \mathcal{N}_m$ at time t
Ξ_{mn}	maximum energy storage capacity of EV $n \in \mathcal{N}_m$
Γ_{mn}	maximum average power $\Xi_{mn}/\Delta T$ of EV $n \in \mathcal{N}_m$
δ_{mn}	weighting factor on EV $n \in \mathcal{N}_m$ obtaining maximum energy
d_{mt}	total demand on transformer m at time t
d_t	total demand at time t
$\boldsymbol{p}$	price profile
$f_{mt}(\cdot)$	losses of transformer m at time t
$r_{mt}(\cdot)$	cost of operating transformer m at time t
$h_{mn}(\cdot)$	benefit function of EV $n \in \mathcal{N}_m$
$g_{mn,t}(\cdot)$	local cost function of EV $n \in \mathcal{N}_m$ at time t
$\upsilon_{mn}(\cdot)$	valuation function of EV $n \in \mathcal{N}_m$
$\nu_{mn,t}(\cdot)$	marginal valuation function of EV $n \in \mathcal{N}_m$
$J(\cdot)$	system cost function
$c_t(\cdot)$	generation cost function
$J_{mn}(\cdot)$	individual cost function of EV $n \in \mathcal{N}_m$

The decentralized approach explored in this paper is motivated by a real-time price model proposed in Ma, Zou, and Liu (2015) and Ma, Zou, Ran, Shi, and Hiskens (2016). Under the proposed scheme, participating EVs simultaneously determine their optimal charging strategies with respect to a given price. This approach is consistent with real-time price models that have been widely considered for demand response management (Mohsenian-Rad & Leon-Garcia, 2010; Samadi, Mohsenian-Rad, Schober, Wong, & Jatskevich, 2010) and EV charging/discharging coordination (Gan, Topcu, & Low, 2013; Ma, Callaway, & Hiskens, 2013; Ma et al., 2015, 2016; Wu, Mohsenian-Rad, & Huang, 2012). First, each individual EV calculates its optimal charging strategy with respect to a price profile broadcast by its supply transformer, and then each transformer estimates a price that reflects the system generation cost. This second phase adopts a typical consensus algorithm where transformers exchange their individual price profiles with their neighbours and in so doing reach an agreed price profile. By adding a price contribution that reflects their own loading, each transformer determines a revised price profile which is rebroadcast to their EVs for recomputing optimal strategies, and the process repeats.

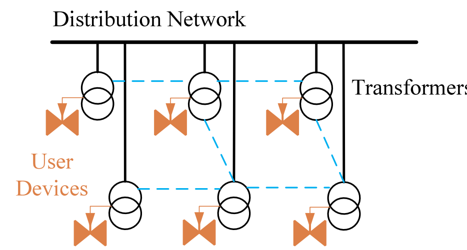

Fig. 1. Electricity transaction architecture via transformers.

The connectivity of the communications graph topology is key to achieving consensus. If the graph is connected, transformers will reach an average consensus asymptotically and the group decision will be the average of the individual price profiles. Under mild conditions, the proposed iterative process is guaranteed to converge. Furthermore, the converged price is coincident with the optimal system price, so the resulting collection of charging strategies is efficient. The convergence rate of the algorithm follows directly from the proof of convergence, though simulation results will illustrate that actual convergence is much faster than the theoretical upper bound.

The paper is structured as follows. An economic model for transformers and EVs is formalized in Section 2, followed by a centralized EV charging coordination process in Section 3. A decentralized coordination algorithm is developed in Section 4 and its convergence is analysed. Simulation results are presented in Section 5 to demonstrate algorithm performance. Section 6 provides conclusions and discusses ongoing research.

2. Model formulation

The paper considers EV charging coordination under a framework where EVs are connected to the distribution network through transformers, and transformers interact with each other via a local communications network, as illustrated in Fig. 1. The objective is to coordinate the EVs to minimize the overall system cost over a time horizon $\mathcal{T} = \{1, \dots, T\}$. Let ΔT denote the length of a time period.

2.1. Transformer interaction topology

Suppose there are M transformers, $\mathcal{M} = \{1, \dots, M\}$. The communication topology of the transformers can be described as a graph, denoted $\mathcal{G} \triangleq \langle \mathcal{M}, \mathcal{E} \rangle$, where $\mathcal{E}$ is the set of edges. If transformer n can exchange information with transformer m directly ($m, n \in \mathcal{M}$), then there is an edge $e = (m, n) \in \mathcal{E}$ between them and n is called a neighbour of m. That is, edges are communication links among transformers. Generally, the information flow between two transformers is bidirectional, so it is assumed that all the graphs considered in this paper are undirected, i.e. if $(m, n) \in \mathcal{E}$ then the edge $e = (n, m)$ also belongs to $\mathcal{E}$.

Let $A \in \mathbb{R}^{N \times N}$ denote the adjacency matrix of $\mathcal{G}$, with,

$$a_{mn} = \begin{cases} 1, & \text{if } (m, n) \in \mathcal{E} \\ 0, & \text{otherwise,} \end{cases}$$

where a_{mn} is the (m, n) entry of matrix A associated with $\mathcal{G}$. Since it is invalid that transformers exchange information with themselves, set $a_{nn} = 0$, and $a_{nm} = a_{mn}$ since $\mathcal{G}$ is an undirected graph.

For each transformer $m \in \mathcal{M}$, let D_m denote the number of neighbours of m. Then $D_m = \sum_{n \in \mathcal{M}} a_{mn}$. By definition (Olfati-Saber et al., 2007;