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A probability transition matrix based decentralized electric vehicle charging method for load valley filling

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ABSTRACT

This paper presents a decentralized control method to schedule EV (electric vehicle) charging loads to fill the overnight load valley while meeting customers' charging requirements. A PTM (probability transition matrix) is calculated at the aggregator side as the control signal to guide EV charging processes based on submitted EV charging schedules. Elements of the PTM represent the transition probabilities of moving a charging load from one time period to another. At the EV side, each EV individually updates its charging schedule according to its charging requirements and the PTM. Then the updated schedules are sent back to the aggregator. This process is repeated iteratively until convergence. In this method, no optimal control problems need to be solved locally so that its implementation on the EV side requires low computation capability. Simulation results show that the proposed method can create desired EV charging schedules for load valley filling within only several iterations, making it suitable for real-time implementation.

1. Introduction

Due to the growing concerns related to high dependence on fossil fuels and environmental pollution, EVs are becoming increasingly popular around the world. It is expected that EVs will grow massively in the next decade [1], which will also bring great energy demand to the power grid. A number of researches show that uncoordinated charging of large number of EVs will have a significant impact on power grid operation, especially on power distribution systems. Problems include overloading distribution feeders and transformers, resulting in shortened device lifetimes [2–4]. However, under proper control, EVs can also become an important part of the smart grid as interruptible loads and distributed energy storage devices. Various EV control methods have been proposed to decrease the network losses [5,6], shift loads from peak to valley hours [7], minimize the operational cost [8], offer ancillary service [9], balance renewable energy fluctuations [10], and serve as spinning reserves [11]. Most of these methods are designed to work in a centralized manner. Recently, particular attention is paid to decentralized EV control methods because of their advantages on dealing with large-scale optimization problems. By distributing computational tasks to each EV, individual customer charging constraints can be considered locally instead of at the aggregator level. In a typical decentralized control method, firstly initial charging schedules of EVs are sent to the aggregator. Then, the aggregator calculates a control signal to guide individual EV's charging, which will be broadcast to each EV. The EVs will make adjustment on their charging schedules according to the control signal and send the revised schedules back to the aggregator. This process is repeated iteratively until the aggregator receives satisfying charging schedules.

Different decentralized control methods have been proposed to coordinate EV charging [12–24]. Dynamic price is the most commonly used control signal to guide EV charging in decentralized control methods, because of its system-wide broadcast nature [12–16]. Refs. [12,13] develop strategies to coordinate the charging of autonomous EVs to fill the overnight load valley using concepts from non-cooperative games. In [14], how to choose a pricing strategy to incentivize EVs so as they collectively provide the amount of energy that the aggregator has been asked for is studied. Refs. [15,16] demonstrate a novel day-ahead pool market mechanism enabling flexible demand participation in electricity markets. This mechanism involves a two-level iterative process, consisting of the independent local price response sub-problems of customers

Abbreviations: EV, electric vehicle; PTM, probability transition matrix; BIP, binary integer programming problem; SOC, state of charge; MRE, maximum relative error.

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and the global price update algorithm for reaching an optimal clearing solution. In [17] distributed EV charging algorithms for relative average fairness and maximum utilization are proposed with greatly enhanced scalability and reduced communication requirements. Ref. [18] demonstrates a decentralized EV charging selection algorithm which maximizes user convenience levels while meeting predefined circuit-level demand limits. In [19] a coordinated home energy management architecture which can be used to control EVs is proposed. The customers locally compute their scheduling solutions using domestic user information and with message exchange only among their neighbors. To avoid line and transformer congestion in the distribution network, a real-time distributed charging algorithm is proposed using the dual-decomposition approach in [20], which is inspired by rate control algorithms in computer networks such as TCP.

Considering load valley filling is one of the most important applications of EV coordinated charging, how to schedule EV charging loads to fill the load valley by decentralized control is studied in [12,13,21–24]. Ref. [21] introduces a formulation of decentralized control for EVs to fill the overnight demand valley when the communication delay exists and the prediction of non-EV demand is not accurate. In [22] a decentralized EV control method for load valley filling is proposed and it is proven that the algorithm converges to optimal charging profiles, irrespective of the specifications of EVs, even with asynchronous computation. Ref. [23] demonstrates a decentralized EV charging algorithm to minimize the distribution system load variance based entirely on the current power system states. In [24] a nested optimization approach that decomposes the EV valley filling problem into separable sub-problems is proposed, and then the decomposed problem is solved using a non-smooth separable programming technique.

In this paper, we propose a completely new decentralized control method for load valley filling. The concept of PTM from the Markov chain model is adopted and used as the control signal to guide EV charging, which is different from other models in published related works. Similar to the definition in Markov chain model, the element of the PTM at the ith row and jth column represents the transition probability of moving a charging load from time j to time i. On the EV side, each EV updates its charging schedule according to the PTM and its individual constraints. Compared to methods proposed in some related works [12,13,22], no optimization problems need to be solved on the EV side in the PTM method. Therefore, its implementation requires low computation capability. The PTM method is designed to control heterogeneous EVs. Parameters of controlled EVs such as capacities, SOCs, rated charging powers and so forth can be different. The control variables of the PTM method are the on/off charging states of each EV. To implement decentralized control for load valley filling, charging power of EVs is usually considered as continuous decision variable [12–17,21,22,24]. Compared to modulating charging power of each EV, an on-off control strategy may be simpler and more practical [25] and can be extended the case that charging power of EVs cannot be continuously modulated.

The rest of this paper is organized as follows. In Section 2, the decentralized control method of EVs for load valley filling, the PTM-based method, is proposed. The simulation results are presented in Section 3. Some discussions on the proposed method are provided in Section 4. Section 5 concludes the paper.

2. Control methodology

For comparisons and clear explanation of the proposed method, firstly we illustrate the centralized charging control problem. A centralized optimization problem for scheduling charging loads of a heterogeneous EV population to fill the load valley in the on-off charging mode can be formulated as:

$$\begin{aligned} \min \quad & \sum_{t\in\tau}(P_t + D_t)^2 \\ \text{s.t.} \quad & P_t = \sum_{n\in\nu} s_{n,t},\ t\in\tau; \\ & \eta\sum_{t\in\tau} s_{n,t}\Delta t = E_n,\ n\in\nu; \\ & s_{n,t} = 0 \text{ or } R_n,\ t\in\tau_n,\ t\in\tau,\ n\in\nu; \\ & s_{n,t} = 0,\ t\notin\tau_n,\ n\in\nu. \end{aligned} \tag{1}$$

where τ denotes the set of time period $\{1, 2, 3, \ldots, T\}$, P_t denotes the total EV charging load at time t, D_t denotes the predicted base load at time t, ν denotes the set $\{1, 2, 3, \ldots, N\}$, N denotes the number of controlled EVs, $s_{n,t}$ denotes charging status of the nth EV at time t, R_n denotes the rated charging power of the nth EV, η denotes the charging efficiency, Δt denotes the time interval, E_n denotes the required energy of the nth EV, and τ_n denotes the feasible charging period of the nth EV.

In the centralized control method, EVs need to send their individual information, such as the required energy, the rated charging power and the feasible charging periods to an aggregator. Then the aggregator solves (1) and sends the solution $\boldsymbol{P}_{\text{opt}}$ back to EVs. Since (1) is a BIP problem, the computational complexity increases exponentially with N, resulting in high computational complexity. To deal with the large-scale BIP optimization problem, a decentralized approach, the PTM method, is proposed.

2.1. Flow chart of the PTM method

Fig. 1 shows the flow chart of the proposed PTM method. In the first step, the aggregator calculates the submitted total charging load $\boldsymbol{P}$ ($\boldsymbol{P} \in \boldsymbol{R}^n$) and the desired total charging load $\boldsymbol{P}^*$ ($\boldsymbol{P}^* \in \boldsymbol{R}^n$) according to charging schedules sent by EVs.

$$\boldsymbol{P} = \sum_{n\in\nu} \boldsymbol{S}_n \tag{2}$$

where $\boldsymbol{S}_n$ denotes the charging schedule of the nth EV. $\boldsymbol{P}^*$ is the optimal solution of (3), which is the relaxed optimization problem of (1):

$$\begin{aligned} \min \quad & \sum_{t\in\tau}(P_t + D_t)^2 \\ \text{s.t.} \quad & 0 \le P_t \le \sum_{n\in\nu} R_n,\ t\in\tau; \\ & \eta\sum_{t\in\tau} P_t\Delta t = \sum_{n\in\nu} E_n. \end{aligned} \tag{3}$$

Compared with (1), the decision variables in (3) are the total charging loads instead of charging schedules of each EV and constraints of each EV are ignored. The first constraint represents that the total EV charging load should not exceed the sum of the rated charging power of all the EVs. The second constraint represents that the total energy requirement should be satisfied. Thus the optimization problem becomes a convex quadratic programming problem with linear constraints and the runtime of the solving is much less than the BIP approach. $\boldsymbol{P}^*$ is an approximation of $\boldsymbol{P}_{\text{opt}}$, which fills the overnight valley perfectly. In the proposed method, $\boldsymbol{P}$ approaches to $\boldsymbol{P}^*$ iteratively instead of solving problem (1) to get $\boldsymbol{P}_{\text{opt}}$ directly. The aggregator calculates the PTM as the control signal and broadcasts it to guide each EV to update its charging schedule. Then updated schedules are sent back to the aggregator.