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Decentralized charging control strategy of the electric vehicle aggregator based on augmented Lagrangian method

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ABSTRACT

Uncoordinated charging of large-scale electric vehicles can affect the safe and economic operation of distribution power system. As an intermediary between power grid and individual electric vehicle, electric vehicle aggregator can play an important role in the coordination and management of electric vehicle charging. In this paper, we develop a decentralized EV charging control strategy of the electric vehicle aggregator for scheduling the flexible charging demand of plug-in electric vehicles in residential distribution networks. First, the centralized charging control model of the electric vehicle aggregator aiming at the maximization of its revenue under the background of time of use price mechanism is established, meanwhile meeting individual charging requirements and satisfying distribution network constraints. Then a decentralized charging control strategy of the electric vehicle aggregator based on the augmented Lagrangian method and the alternating direction multiplier method is proposed. The electric vehicles can decide their charging plan locally with the decentralized strategy, which can eliminate the problem of high communication cost, low computing efficiency and privacy protection caused by the centralized charging control model in practical application. The effectiveness of the proposed strategy is evaluated with a representative distribution network model.

1. Introduction

Electric vehicles (EVs) have been proved to be effective in reducing greenhouse gas emissions and mitigate oil dependency. With the popularity of EVs, the uncoordinated charging of large-scale EVs can cause great damage to the security, stability and economy of power system [1,2]. EV load is more flexible and controllable compared to the traditional power load. Therefore, the coordination of the charging process of EVs is of great significance to reduce the adverse effects to power grid and improve the power supply reliability and resource utilization efficiency [3,4]. In general, EV charging control schemes can be divided into centralized control strategy and decentralized control strategy [5,6].

In the centralized control strategy, the control center accepts the charging requirements of all EVs under its jurisdiction, and then centrally solving all charging schemes for EVs and issue to EV's intelligent charging unit according to the objective functions and constraints. For example, a centralized charging control strategy to minimize the distribution network loss has been devised in [7] and a centralized charging control strategy is presented to maximize the operating income of the charging station under the TOU tariff mechanism in [8]. Although the centralized charging control strategy can get the optimum solution, it can cause high communication cost, low computing efficiency and privacy protection in practical application.

Different from the centralized control strategy, the decentralized control strategy does not need the upper control center to centrally solve the charging program, but through the control signal transmission to solve the charging program dispersedly [9]. In [10], a decentralized EV charging control scheme for the provision of valley-filling in the context of residential distribution network is developed. And a novel shrunken primal-dual subgradient (SPDS) algorithm was proposed to solve the formulated problem in a decentralized way. In [11], a decentralized charging optimization strategy is designed based on the demand response model, combined with variance costs and node price, but its validity depends on the accuracy of the demand response model. In [12], a hierarchical optimal charging strategy for EV aggregator is presented. Dantzig-Wolfe decomposition is used to decompose the formulated linear programming problem into subproblems that are solved by each EV. EV aggregator is responsible for solving the formulated master problem in the DWD algorithm and shares the price signals with EVs to ensure the optimal charging scheduling of EVs at the charging station.

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Nomenclature

Variables, Parameters and Sets

B_c	Battery capacity of electric vehicle
η_c	Charging efficiency of electric vehicle
p_{max}	Maximum charge power of electric vehicle
$T_{i,a}$	Plug-in grid time of electric vehicle i
$T_{i,d}$	Departure time of electric vehicle i
$SOC_{i,e}$	Desired state of charge (SOC) when electric vehicle i finish charging
$SOC_{i,s}$	Initial state of charge (SOC) when electric vehicle i start charging
$M_{i,d}$	Daily travel miles of electric vehicle i
E_{p100}	Electricity required for traveling 100 km
N_d	Number of nodes connected to electric vehicles under distribution network
T	Total length of the simulation time (set as one day in this paper)
N_j	Collection of electric vehicles access to node j
$p_{ei,t}$	Charging power of vehicles i during time t
ϕ_t	Time-of-use electricity price in the period of time t
$V_{j,t}$	Voltage at node j during time t
$P_{j,t} + jQ_{j,t}$	Complex power comes from node j to $j + 1$ during time t
$r_j + jx_j$	Complex impedance between node j and node $j + 1$
$p_{j,t} + jq_{j,t}$	Complex power absorbed by node j during time t

The alternating direction method of multipliers (ADMM) has emerged as a powerful technique for large-scale structured optimization. It can decompose the objective function of the original problem into several subproblems to solve in parallel. In [13], a decentralized decision-making algorithm for optimal power flow implementation is presented and using ADMM to solve OPF in a distributed fashion. In [14], a network-constrained EV charging is formulated as a convex quadratic program to minimize the power supply cost while respecting critical voltage regulation and substation capacity limitations and tackled using a decentralized scheme based on ADMM. In [15], the spatial coupling of EV charging decisions due to transformer capacity limits is tackled via a combination of the ADMM and PGD. In [16], aiming at the goal of peak load shifting, an optimal decentralized charging (ODC) is presented, and the correctness and feasibility of the method are proved theoretically.

As an intermediary between power grid and individual EVs, EV aggregator participate in the management of EVs [17,18]. It is foreseeable that the number of EVs under the jurisdiction of EV aggregator will grow rapidly in the future, and there is a lack of decentralized charge control research for EV aggregator [19].

Unlike other literatures, the ultimate goal of this paper is to develop a decentralized EV charging control framework for EV aggregator to achieve the maximum revenue under local EV and distribution network constraints. The contribution of this paper is twofold. First, a decentralized charging control model for EV aggregator based on Augmented Lagrangian method is proposed, which can alleviate the oscillation phenomenon in the traditional Lagrangian relaxation method by introducing the quadratic term. Secondly, the combination of ADMM algorithm and ODC method is used to solve the decomposition term in the objective function and the coupling between EV charging scheme under the same node. In addition, Each EV calculate the charging plan locally only according to the control signal issued by the node and customers' privacy can be guaranteed as their charging information will not be transmitted through the communication network.

The rest of this paper is structured as follows. In Section 2, the centralized charging control model for aggregator is constructed to introduce the local constraints of EVs and distribution network constraints. Section 3 first presents the decentralized charging model of EVs for aggregator, followed by the decentralized control scheme and the combination of ADMM algorithm and ODC method. Simulations and result analyses are given in Section 4. Section 5 concludes this paper and envisions the future work.

2. Centralized charging control model for aggregator

In this paper, the scene is set as follows: based on a power distribution network, an EV and the aggregator reach an agreement. Aggregator provide the EV with charging pile, other infrastructure and some services like battery repair and replacement on the condition of meeting user's basic charging needs. And the EV should accept the dispatching of aggregator during the charging period. The aggregator pays the electricity company for buying electricity while the EV pays the charging service fee to the aggregator. Aggregator aims at maximizing the charging revenue, taking the EV charging demand constraints and distribution network security constraints into account, making the charging plan and applying to the EV intelligent unit. The following part will describe the centralized charge control model for aggregator.

2.1. Objective function of centralized charge control model

The objective function of centralized charge control model, can be set as the difference between the cost of purchasing electricity from the wholesale market and the charging revenue of EV owners for charging service [20]. The specific expression is as shown in (1):

$$\max \quad \sum_{j=1}^{N_d} \sum_{t=1}^{T} \sum_{i \in N_j} p_{ei,t} \Delta t (c - \phi_t) \tag{1}$$

The subscript j is the number of the node, t is the number of the control period, i is the number of the EVs, Δt is the duration of control period of time (set as 15 min in this paper), then there is a total of 96 control periods in a day, c is the revenue of EV owners for charging service. The objective function (1) is equivalent to:

$$\min \quad \sum_{j=1}^{N_d} \sum_{t=1}^{T} \sum_{i \in N_j} p_{ei,t} \Delta t (\phi_t - c) \tag{2}$$

2.2. Constraint conditions of centralized charging control model

The EV charging constraints and distribution network security constraints are considered when aggregator making charging plans.

2.2.1. EV charging constraints

(1) State of charge (SOC, the battery charge as a percentage of battery capacity) constraints

$$SOC_{i,e} \leqslant 0.95 \tag{3}$$

$$SOC_{i,e} \geqslant SOC_{i,s} \geqslant 0.2 \tag{4}$$

The EV can achieve the desired charge power in the specified charging time. Eq. (3) indicates that the maximum value of expected battery charge state at the end of the charge is 0.95. Eq. (4) indicates that the general requirements of the battery power state should be greater than 0.2 to extend the battery cycle life and prevent excessive discharge.

In this paper we use the Monte Carlo method to sample the travel data of EVs. The end time and the start time of the trip can be expressed as the normal distribution approximately and the daily travel miles can be expressed as the lognormal distribution approximately. Based on this, the initial SOC of EV i can be calculated by formula (5).