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Parking-based EV Collective Charging Control Strategy Design: A Mean-field Game Approach

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ABSTRACT

This paper investigates a collective control problem for a parking-based large-scaled EVs. A parking under electric energy management by a virtual power plant is targeted under assumption of decentralized charging/discharging rate control of the individual EVs. A decentralized charging control strategy is proposed by solving a mean-field game problem with the cost function that balancing between the collective charging behavior and the charging level of each EV. Simulation results is finally demonstrated to validate the proposed control strategy.

Keywords: Electric vehicles; Collective control; Charging strategy; Mean-field game.

NONMENCLATURE

Abbreviations	
EV	Electric vehicle
SoC	State-of-charge
MFG	Mean-field game
VPP	Virtual power plant
Symbols	
N	Number of EVs
t	Time

1. INTRODUCTION

Motivated by the global trend of the electrification of vehicle powertrain, electric vehicles (EV) became a big load for electric power grid that is difficult to manage the global behavior, since as a mobility tool, the EVs is managed individually with uncertainty and stochasticity for satisfying mobility demand of human life. How to manage the uncertain load caused by a large-scaled, but scattered EVs is a challenging issue for the power grid operation. A feasible way is the idea of virtual power plant (VPP) which is recently focused attention due to friability in economic operation for a massive, distributed energy resources [1]. However, VPP is planning the trading schedule based on a horizon ahead prediction, for example a few hours or half-day, for buying and selling the electric energy. This means that the charging/discharging behavior of the EV cloud have to match the planning for guarantee of stable operation of the whole energy systems. Therefore, a new challenging issue debated to EV users is how to achieve a collective charging behavior by distributed control of individual EV.

In the last decade, distributed control of EVs has been spotlighted by both of research fields of power system and vehicle power engineering. Most attention has been focused on corporative control between the power grid operation and EV charging [2,3]. From the view of developing charging control strategy, model predictive approaches have been investigated which taken the stochasticity and the uncertainty in mobility demand into account [4]. Indeed, impact of thousand-level EV cloud is considered in the network-constrained economic dispatch problem [5]. Several approaches have been proposed to provide a solution of distributed charging control problem for a large-scaled EVs. A comprehensive survey on the distributed charging control algorithm is very recently published in [6] where the formulation of optimization problem is classified from the view of operational and cost aspects of grid operation, EV users, and aggregators, respectively. Under the configuration of electric energy system mentioned above, essential feature of distributed charging strategy is that a collective charging/discharging

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behavior of a large-scaled EVs must be implemented to match the power supply panning by VPP without requirement of sharing the state-of-charge (SoC) of each vehicle and communicated the control strategy each other in the EV cloud. The charging decision should be made based on the local information.

Meanwhile, the mean-field game (MFG) theory is initially proposed by [7] and [8] which provides a new theoretical tool to describe the mean-field behavior of a large population of agents with dynamics. This innovative theoretical tool enables us to develop a model-based distributed control algorithm to achieve a desired collective behavior with feedback of local information only. Indeed, there have been a few trials to apply the MFG theory in charging control of large-scaled EVs. For example, [9] develops the collective target tracking mean-field control for fleets of plug-in EVs. [10] proposes a decentralized competitive charging coordination algorithm for a large population of plug-in EVs. A day-ahead mobility-based power trade planning and real-time MFG-based charging control scheme has been studied in [11].

This paper addresses a parking-based collective charging/discharging control problem by using MFG theory. Under assumption that a horizon-based loo-ahead planning is given by VPP, we focus our attention to develop a decentralized MFG-type charging control strategy by considering the impact of EV charging in the sense of mean-field behavior. The cost function for optimization is motivated from [12], however, the proposed solution is obtained from the model of the SoC distribution. This new idea enables us to obtain the decentralized control law by policy iteration algorithm. The developed control strategy is validated based on a numerical simulation.

2. MODEL AND PROBLEM FORMULATION

2.1. Background

Consider the residential areas, where a large-scaled EVs denoted by the finite set $\mathcal{A} = \{1, \cdots, N\}$ are parking in the charging station and being charged as shown in Fig. 1. The charging station is electrically connected to the main grid with ability of supply electric power to the charged EVs. It is assumed that all the EVs share the same dynamical model of charging behavior of SOC and the numbers of the EVs N is very large.

Next, the modeling of these vehicles is introduced firstly and then the problem formulation is given.

2.2. Modeling

In the following, we introduce the model for EVs

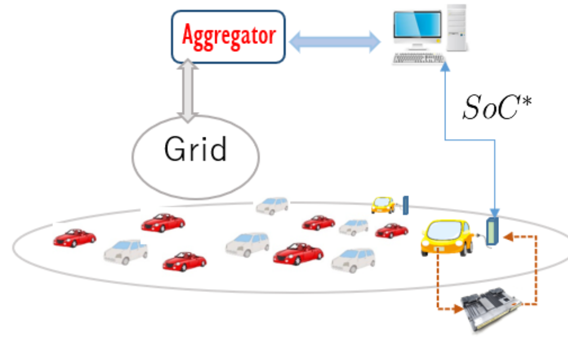

Fig 1 Concept of the parking-based EV collective charging

charging model that will be employed throughout the paper. The charging rate of vehicle i is denoted by $u_i(t)$. The amount of electric energy stored in the battery of vehicle i at time t is denoted by $x_i(t) \in [0,1]$, quantified in energy units. In this way, $x_i(t) = 0$ means the battery is empty, $x_i(t) = 1$ means the battery is fully charged.

In this paper, it is assumed that all the dynamic of each vehicle' s SoC is identical, which is described as the following stochastic differential equations:

$$dx_i(t) = u_i(t)dt + \sigma(t)dw_i(t), \quad 1 \le i \le N, \quad (1)$$

where $w_i(t)$ is the standard independent Brownian motion which represents the instability of the charging process and the modeling error. $\sigma > 0$ is a given weight factor that determines how much the volatility affect the determinate dynamics.

We assume the agent i's initial SoC $x_i(0), 1 \le i \le N$ is random, distributed according to some known probability density function (pdf) ξ_0. In addition, we denote the population average SoC by

$$\bar{x}(t) = \lim_{N \to +\infty} \sum_{i=1}^{N} \frac{x_i(t)}{N}.$$

2.3. Problem formulation

This paper focuses on the optimal charging coordination for large-scale electric vehicles (EVs) in the charging station with balance of following three parts: (1) Average SoC of the collective EVs gradually filled up to a satisfactory level. (2) To achieve the SoC consensus at the average SoC, in other words, every SoC of EVs is not far away from the average SoC. (3) To minimize the electric energy consumption under the satisfaction of the object of (1) and (2). To the end, the SoCs of the large-scale vehicles should reach consensus at the given desired value.

Thus, we use a more formal mathematics expression to describe the above three requirement parts:

Each vehicle i is aimed to determine the charging rate

$u_i(t)$ that minimize its own total cost J_i. That is,

$$J_i(u_i, u_{-i}) = E\int_0^{\infty} e^{-\rho t}[q_t^2(x_i(t)-z)^2 + u_i(t)^2]d\,t$$

where u_{-i} denotes the charging inputs of the complementary set of EVs i.e. $u_{-i} = \{u_j,\ j \neq i,\ 1 \leq j \leq N\}$. The value of z is a direction assigned to each EV in the population and each EV's deviation from this direction is penalized by the deviation penalty coefficient q_t. Integral controller embedded in mean-target deviation coefficient q_t is calculated as the following integrated error signal:

$$q_t = \int_0^t (\bar{x}(s) - y)ds + K, \tag{2}$$

where K is positive weight factors and y is the mean target.

The justification for the above cost function is that by pointing individual EV's SoC towards what is considered as the maximum value z, it dictates a global increase in their individual SoCs. This pressure for increase persists as long as the differential between the mean SoC and the mean target y is high. The role of the integral controller is to automatically compute the right level of penalty coefficient q_t which, in the steady state, should maintain the mean population SoC at y. Since $x_i(t) = 1$ means the individual EV's battery is fully charged, we usually set the value of z to 1.

3. PROPOSED APPROACH

In this section, to solve the problem formulated above, we expand the system to a three-dimension augmented system, then the policy iteration algorithm is employed to derive the decentralized charging control law for individual EV.

3.1. Augmented system

Taking the average of both sides of equation (1) and let $N \to +\infty$, we have:

$$\begin{cases} \dfrac{d\bar{x}}{dt} = \bar{u}(t) \\ \bar{x}(0) = \overline{x_0} \end{cases} \tag{3}$$

Also, we can write the dynamic of q_t from equation (2)

$$\begin{cases} \dfrac{dq_t}{dt} = \lambda(\bar{x}(t) - y) \\ \quad q_t(0) = K \end{cases} \tag{4}$$

By putting the dynamics of x_i, $\bar{x}$ and q_t together, the augmented system state $X_i = col(x_i, \bar{x}, q_t)$. In this way, the augmented system can be described as follows:

$$dX_i = [A(t,X_i) + B(t,X_i)u_i]dt + Cdw_i$$

where

$$A(t,X_i) = \begin{bmatrix} 0 \\ \bar{u}(t) \\ \bar{x}(t) - y \end{bmatrix},\ B(t,X_i) = \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}, C(t,X_i) = \begin{bmatrix} \sigma(t) \\ 0 \\ 0 \end{bmatrix}.$$

We suppose that the controller of each EV is a liner state feedback control law and has a uniform form, assume the optimal control law is

$$u_i = \eta(t, x_i, \bar{x}),$$

then by using the linear property of the control input, we have

$$\bar{u} = \frac{1}{N}\sum_{i=1}^{N}\eta(t, x_i, \bar{x}) = \eta\left(t, \frac{1}{N}\sum_{i=1}^{N} x_i\,, \bar{x}\right) = \eta(t, \bar{x}, \bar{x}).$$

According to Bellman's principle of optimality, the Hamilton–Jacobi–Bellman (HJB) equation is

$$\rho V_i(t,X_i) = \min_u\{q_t^2(x_i(t)-z)^2 + u_i(t)^2 + \frac{\partial V_i}{\partial t} + \left(\frac{\partial V_i}{\partial X_i}\right)^T [A(t,X_i) + B(t,X_i)u_i(t)]\} + \frac{1}{2}\mathrm{Tr}\left(C^T\frac{\partial^2 V_i}{\partial X_i^2}C\right).$$

Thus, the optimal control can be represented by

$$u_i^* = -\frac{B(t,X_i)}{2}\frac{\partial V_i}{\partial X_i}.$$

Throughout this paper, we assume that the value function $V_i(u_i, x_i)$ has the following quadratic form

$$V_i(t,X_i) = p(t,\bar{x},q_t)x_i^2 + s(t,\bar{x},q_t)x_i + m(t,\bar{x},q_t).$$

Substituting above $V_i(t,X_i)$ into HJB equation, then grouping the terms multiplied by x_i^2 and x_i we have the following three equations:

$$\frac{\partial p}{\partial t} + q_t^2 + p - 2p^2 - \left(p\bar{x} + \frac{s}{2}\right)\frac{\partial p}{\partial \bar{x}} + (\bar{x}-y)\frac{\partial p}{\partial q_t} - \rho p = 0 \tag{5}$$

$$\frac{\partial s}{\partial t} - 2zq_t^2 - ps - \left(p\bar{x} + \frac{s}{2}\right)\frac{\partial s}{\partial \bar{x}} + (\bar{x}-y)\frac{\partial s}{\partial q_t} - \rho s = 0 \tag{6}$$

$$\frac{\partial \mathrm{m}}{\partial \mathrm{t}} + q_t^2 z^2 - \frac{s^{\,2}}{4} - \left(p\bar{x} + \frac{s}{2}\right)\frac{\partial m}{\partial \bar{x}} + (\bar{x}-y)\frac{\partial m}{\partial q_t} + 2p\sigma^2 - \rho m = 0 \tag{7}$$

3.2. Policy iteration algorithm

Since it is difficult to analytically obtain the optimal solution satisfying the optimal conditions in (5), (6) and (7), the policy iteration method is employed to deal with the problem. Here, the main task is to arbitrarily give an initial control policy and set the convergence criterion ξ, then the optimal control inputs can be updated through following policy iteration algorithm showing in Fig 2. step by step. After a finite number of policies, $|u_i^{(j)} - u_i^{(j-1)}| < \xi$, that means this process must converge to an optimal policy, in other words, the algorithm has found the optimal control. It is obvious that optimal charging control satisfying the optimal conditions.

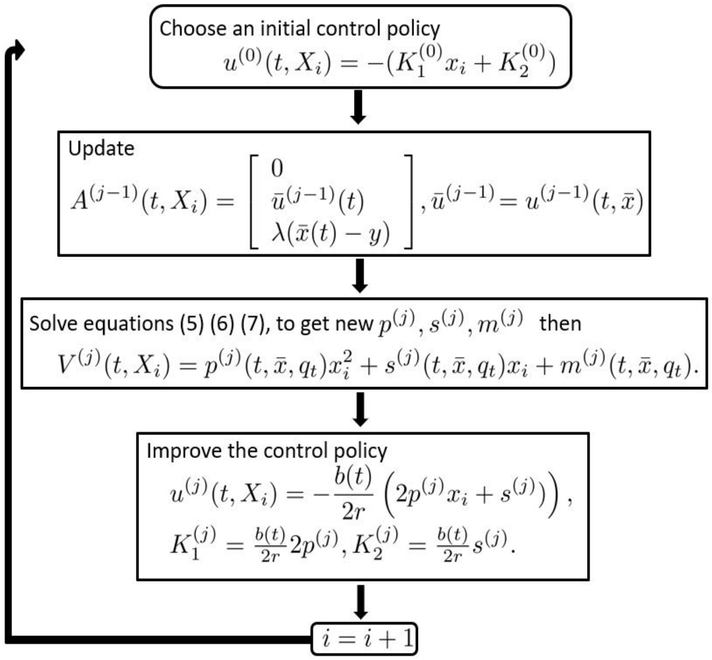

Fig 2 Flowchart of the proposed numerical method

It is shown that the optimal charging power is only dependent on the individual state variable SoC. Thus, the proposed real-time MFG-based optimal charging control for large-scale EVs is decentralized.

4. SIMULATION RESULTS

In this section, the simulation validations of collective control problem for a parking-based large-scaled EVs are conducted to show the effectiveness of the above proposed approach.

For our simulation experiments we simulate a population of 1000 EVs. We consider a uniform population of vehicles adopt the charging model as given in equation (1). The initial SOCs of the EVs are drawn from a Uniform distribution $U(0.1, 0.4)$. That means the initial average SOC $\bar{x}(0) = 0.25$. The basic physical parameters used in the simulation are listed in Table. 1.

Table. 1.

Parameters	Value
K	1.5
ρ	0.01
$\sigma(t)$	0.01
$x_i(0)$	$U(0.1, 0.4)$
z	1
y	0.7

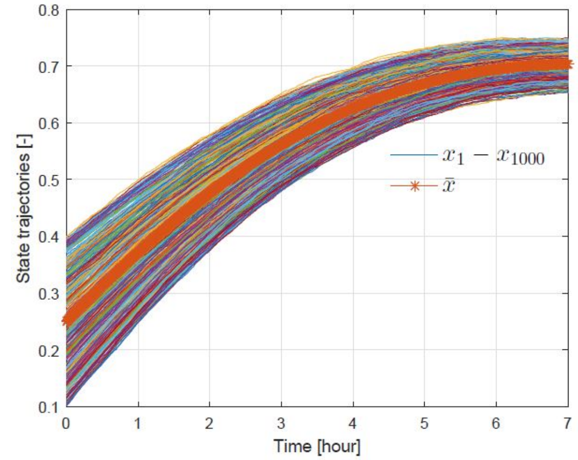

Fig 3 The evolution of SoCs and $\bar{x}$

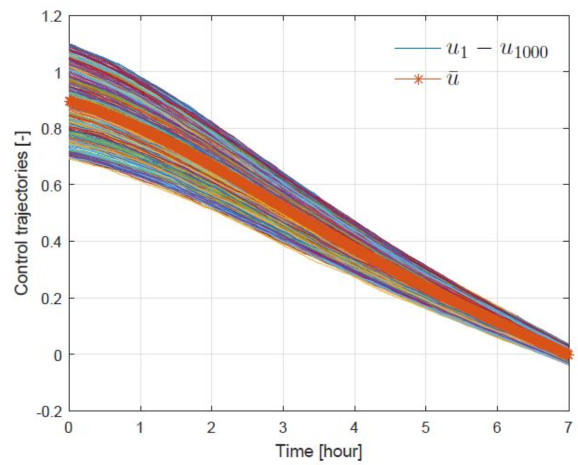

Fig 4 The evolution of charging rates and $\bar{u}$

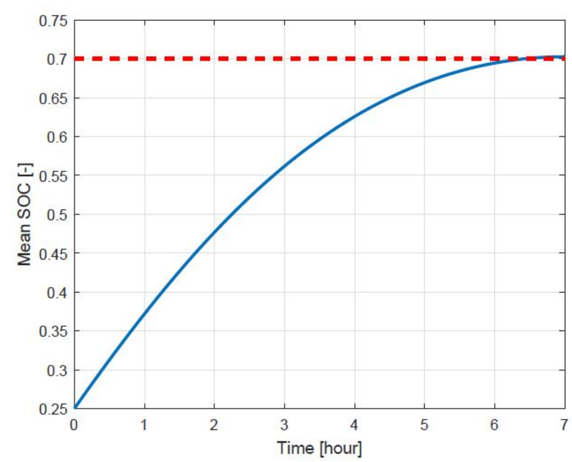

Fig 5 The evolution of mean SoC

Fig. 3 shows the trajectories of vehicles' SoC and the thick orange line is the average of SoC, Which are generated by the augmented system and policy iteration approach proposed in Section 4. It can be seen that the average of SoC of the collective EVs is gradually filled up and finally stabilized at the satisfactory level 0.7 within 7 hours. Individual EV's SoC consensus at the average SoC.

Fig. 4 shows the evolution of charging rates and the thick orange line is the average charging rate. It shown that the charging power is decreasing, and finally become zero when the average of SoC reach the satisfactory level.

Fig. 5 shows the evolution of mean SoC, it clearly shows average of SoC from low level 0.25 gradually filled to the preset value.

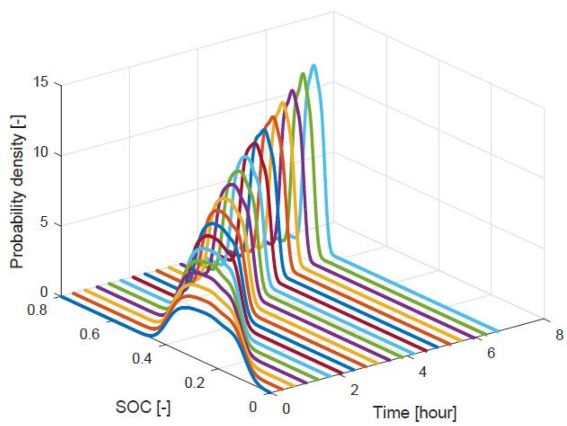

Fig 6 The evolution of probability densities of SoCs

Fig. 6 shows the evolution of probability densities of SoCs from the beginning to the end. It can be seen that the curve of probability density function getting narrower and narrower over time. That also means individual EV's SoC consensus at the average SoC, every SoC of EVs g gets closer and closer from the average SoC. All the Figs we show here demonstrate the proposed decentralized optimal charging strategy for parking-based large-scale EVs is effective for the three goals which formulated in Section 2.

5. CONCLUSION

This paper focuses on the collective control problem for a parking-based large-scaled EVs. Under mean-field game theory, the problem model that balancing between the collective charging behavior and the charging level of each EV is established. Next, a three-dimension augmented system and the policy iteration algorithm is employed to derive the decentralized charging control law for individual EV. A simulation validation is employed to examine the effective of the charging strategy we designed.

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