Congestion Probability Balanced Electric Vehicle Charging Strategy in Smart Grid

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Abstract. In this paper, a coordinated charging strategy CCCS (Charging Congestion probability based Charging Strategy) is proposed, which considers the congestion probabilities of the charging stations (CSs), the charging costs of the electric vehicles (EVs), the distance between EV and charging station and EV users' satisfactions. The coordinated charging issue is formulated as a convex optimization problem, which can be solved to get the distributed charging algorithms, based on which the communication system is further proposed. In order to illustrate the performance, we put forward three benchmarks. In the simulation, we combine the power grid i.e. MATPOWER and the charging module together to build the simulation platform. Simulation results show that CCCS performs well in terms of balancing the congestion probabilities, reducing charging costs, and mitigating the impacts on the power grid voltage.

Keywords: Congestion probability · Charging cost · Voltage level · Electric vehicle · Smart grid

1 Introduction

In recent years, EV charging strategy is an important issue in smart grid [1]. The EV charging strategy mainly contains two categories: centralized charging strategy and decentralized charging strategy [2].

In the centralized category, a lot of EVs' information is collected by a central unit, which considers many constraints to make the comprehensive charging decisions. A.S. Masoum et al. [3] proposed an online fuzzy coordination algorithm (OL-FCA) for the EV charging, which aims at reducing the total cost of energy generation and associated grid losses. In [4], a novel method for EV charging was put forward, which considers the power grid constrains, the voltage as well as the power to avoid the distribution grid

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congestion while satisfying the charging requirements. A GVs (gridable vehicles) concept was defined by Ahmed Yousuf Saber et al. [5], who also proposed an optimization EV charging algorithm combining the V2G (vehicle-to-grid) technology to reduce the cost and emissions of UC (unit commitment). In order to minimize the grid operation cost while considering the EVs' random charging behaviours, the stochastic security-constrained unit commitment model is adopted [6]. In [7], the coordinated charging of minimize distribution system losses is studied. A two-stage strategy is proposed in [8]. In the strategy, the electricity price and demand at first by the control center, and then the control center purchases the energy from the market, and dispatches it to each EVs.

The centralized strategies have the ability to solve the optimization problems precisely, but they need a lot of computing resources to process the massive EV charging request. In order to mitigate the computational burden for large-scale EV charging, the decentralized charging strategies become more and more popular in recent years. In the decentralized charging strategy, each participant has the ability to compute the optimal decision and communicate with other participants. Every participant's decision will be finally stable, and the whole EV charging strategy will be in an equilibrium state.

In [9], a non-cooperative Stackelberg game is used for the EV charging. In the game, smart gird is a leader which provides the price at first, and the EVs are followers who decide their charging strategies according to the price. In [10], a non-cooperative game is adopted to formulate the parking-lot EV charging problem. In order to solve the coupled constraint problem, the Rosen-Nash normalized equilibrium is utilized in the game model. Julian de Hoog et al. [11] took advantages of a market mechanism to allocate the charging capacity to ensure the network stability. For the purpose of processing the large population and dynamic EV arrivals, the authors in [12] proposed a local scheduling scheme, which divides the EVs into different groups and the charging decision is determined based on the group information. In [13], in order to minimize the charging cost, Yijia Cao et al. put forward an optimized charging model, which considered the SOC curve and TOU price. In regarding with the security problems, Chao-Kai Wen et al. in [14] proposed a distributed charging strategy, which only requires the EV demand rather than the private information for protecting the users privacy.

A lot of research work is mainly related with the charging cost, security, price curve and distributed generation et al. In [15], the authors believed that the congestion management is an important issue in smart grid. They summarized that the congestion management is used to manage and control the charging EVs, so as to minimize queue at the charging station. According to their survey, only two papers are related with they defined congestion management. The two papers are about finding the minimum congestion travel routings. Islam Safak Bayram also studied the congestion management problem in [16], where they brought forward a control mechanism to avoid congestion at busy charging station, but the authors did not consider the congestion probabilities balance among different charging stations.

In this paper, we propose a distributed charging strategy CCCS, which focuses on balancing the congestion probabilities among different charging stations, and meanwhile the charging costs, traveling distances to the charging station as well as the users' satisfactions are all considered. The rest of this paper is organized as follows. Section 2 introduces the system model as well as the charging algorithm of CCCS. In Sect. 3, the performance of CCCS is evaluated. Conclusions and future work are presented in Sect. 4.

2 Mathematical Model of CCCS

2.1 Utility Function of Charging Station

Every charging station has the maximum charging power *Pmax*, which is deter-mined by the following equation:

$$P_j^{max} = P_k^{max} - P_k^{basic} \tag{1}$$

Where P_k^{max} the is the maximum allowed power of the electricity bus k, which the charging station j connects to. The P_k^{basic} is the basic load consumed by other entities, such as buildings, equipment, et al. In this paper, we assume each CS connects to only one bus node.

Each charging station also has different charging piles in different time slots, which is defined as follows:

$$N_j^{pile} = \frac{P_j^{max}}{P^{charging}} \tag{2}$$

Where $P^{charging}$ is the charging power of EV, and we assume it is a constant. In order to express conveniently, we omit the annotations of time slot on every variable.

Because of the finite charging piles in each charging station, we further define a congestion probability to represent the charging congestion:

$$Con_j = \begin{cases} \frac{N_j - N_j^{pile}}{N_j}, & \text{if} \quad N_j > N_j^{pile} \\ 0, & \text{if} \quad N_j \le N_j^{pile} \end{cases} \tag{3}$$

Where N_j is the number of EVs that willing to charge at the charging station j. In order to introduce the proportion of the available charging piles in charging station j, we define the following indicator:

$$Ava_j = \begin{cases} \frac{N_j^{pile} - N_j}{N_j^{pile}}, & \text{if} \quad N_j^{pile} > N_j \\ 0, & \text{if} \quad N_j^{pile} \le N_j \end{cases} \tag{4}$$

The utility function of charging station j is defined as:

$$U(L_j) = p_j L_j - a(L_j)^2 - bL_j - c \tag{5}$$

Where L_j is the charging load of charging station j, and p_j is the charging price. Besides a, b, and c are constants for all the charging stations in this paper. $P_j L_j$ denotes the income of charging, and $a(L_j)^2 + bL_j + c$ denotes the cost for generating L_j electricity quantity of power grid. Equation (5) can be proved as a convex function.

2.2 Utility Function of Electric Vehicle

Every EV i has a coordinate (cx_i, cy_i), destination coordinate (cx_i^{des}, cy_i^{des}) and distance d_i^j to charging station j whose coordinate is $(cx_j, cy_i) \cdot d_i^j$ is:

$$d_i^j = \sqrt{(cx_i - cx_j)^2 + (cx_i - cx_j)^2} \tag{6}$$

The convex utility function is defined as:

$$U(x_i) = \alpha_j(r \ln(\omega x_i) - p_j x_i - p^{last} d_i^j \beta + C) \tag{7}$$

Where r, ω and β are constants, and β is the constant coefficient of converting the distance 1 km into the electricity quantity 1 MWh. p^{last} is the charging price of the latest time slot, and we assume it is a constant for simplicity. p_j is the charging price of this time slot of charging station j, and its initial value is p^{last} C is a big positive constant for ensuring the value of U (xi) is positive. αj is a probability related factor, which is defined as follows:

$$\alpha_j = (m + Ava_j)(m - C\,on_j) \tag{8}$$

Where m is a constant. In the actual environment, the electricity charging quantity of EV is limited to a range $[x_i^{min}, x_i^{max}]$, the boundary values of which are defined as follows:

$$x_i^{min} = \begin{cases} \beta d_j^{des} & \text{if } \beta d_j^{des} < (0.8 - SOC_i)Cap_i, \\ (0.8 - SOC_i)Cap_i, & \text{else} \end{cases} \tag{9}$$

$$x_i^{max} = (0.8 - SOC_i)Cap_i \tag{10}$$

$$d_j^{des} = \sqrt{(cx_j - cx_i^{des})^2 + (cy_j - cy_i^{des})^2} \tag{11}$$

Where $SOCi$ the is the state of charge (SOC) of EV i, which belongs to the interval (0, 1). In order to avoid the overcharge, we set the maximum SOC is 0.8. Cap_i is the battery capacity of EV i, which is a constant for all EVs. d_j^{des} is the distance between charging station j and the destination of the EV i.

2.3 Optimization Problem

We define the following optimization model for the maximum social utility:

$$
\begin{aligned}
& maximize \sum_{j=1}^{M}\left(U(L_j)+\sum_{i=1}^{N_j}U(x_i)\right) \\
& s.t.\, L_j=\sum_{i=1}^{N_j}x_i
\end{aligned}
\tag{12}
$$

Where M is the charging station number. The solution of problem (12) is also the solution of the follow problem:

$$
\begin{aligned}
& maximize \left(U(L_j)+\sum_{i=1}^{N_j}U(x_i)\right) \\
& s.t.\, L_j=\sum_{i=1}^{N_j}x_i
\end{aligned}
\tag{13}
$$

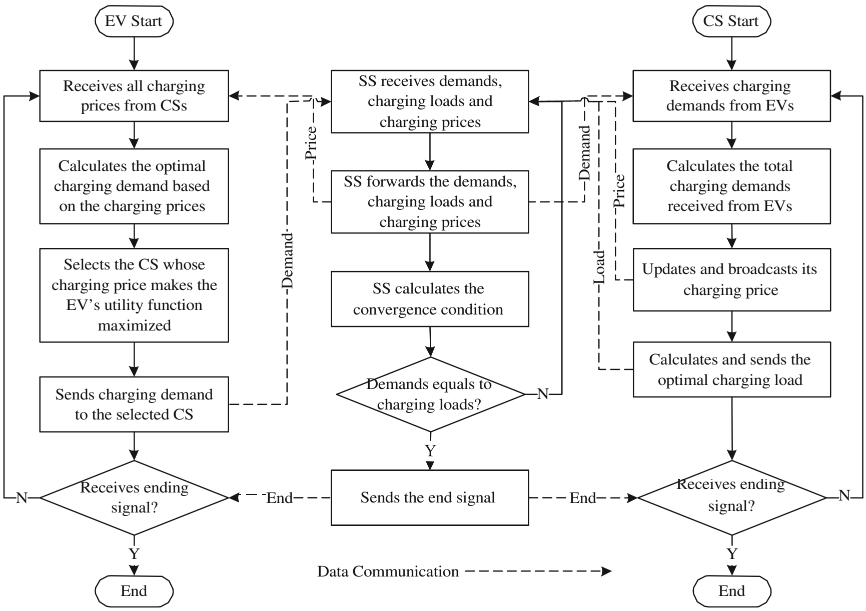


Fig. 1. The flowchart of communication system

Problem (13) can be solved by the convex theory, and after using the dual decomposition to the dual problem of the (13)'s Lagrangian function [17] the sub-optimization strategies can be obtained for both EV and CS. Based on the strategies of EV and CS, we further propose a coordinated charging communication system, shown in Fig. 1. As for the ending signal, we define the following inequality to represent the ending condition:

$$convergence = \frac{\sqrt{\sum_{j=1}^{M}\left(L_j^* - \sum_{i=1}^{N_j} x_i^*\right)^2}}{\sum_{j=1}^{M}\sum_{i=1}^{N_j} x_i^*} < \sigma \tag{14}$$

Where $\sqrt{\sum_{j=1}^{M}\left(L_j^* - \sum_{i=1}^{N_j} x_i^*\right)^2}$ means the standard deviation between the optimal charging demands of EVs and charging loads of CSs. $\sum_{j=1}^{M}\sum_{i=1}^{N_j} x_i^*$ means all the optimal charging demands. σ is a very small positive value.

3 Simulation

3.1 Environment Setting

In the simulation, we have developed a platform, which combines the MATPOWER [18] and the charging module together. We use the MATPOWER to calculate the power flow for the node voltage verification. The charging module is developed based on the Java environment.

The basic load is obtained from [19], and we have adjusted the load data in proportion manner to adapt the simulation scenes. The basic load is divided into several parts and dispatched to every charging station. The EVs are randomly distributed in a square area with the side length as 100,000 m. There are 20 charging stations randomly located in this area. We assume each charging station connects to only one electricity bus node. The IEEE 30-bus power grid is used for simulation, and its parameter values are the same as that in [18]. The maximum allowed power of each bus node is defined as the same values in MATPOWER case30 testing file. The necessary parameters' values are assigned in Table 1.

3.2 Comparison Strategies

We define three benchmarks: CCS (Congestion based Charging Strategy), DCS (Distance based Charging Strategy) and COSTCS (COST based Charging Strategy).

In the CCS, the utility function of CS is the same as that of CCCS. But the utility function of EV is different:

$$U(x_i) = \alpha_j \tag{15}$$

Table 1. Parameter settings

Parameter name	Assigned value	Remarks
Area side length	100,000 m	–
CS Number (M)	20	–
EV Number	2000	–
$p^{charging}$	0.048 MW	Fast charging power (ref [16])
a	0.01	–
b	0.8	–
c	0.5	–
r	2.0	–
ω	25.0	–
β	0.0002	1 km consumes 0.0002MWh (ref [1])
m	5.0	–
C	10000	Big enough positive value
Cap_i	0.024 MWh	The same value for EVs (ref [1])
p^{last}	2.0	Initial price for every CS
σ	0.002	For ending iteration process

According to (15), the x_i^* is an arbitrary value, and we fix it as x_i^{min}. In the DCS, the utility function of EV is:

$$U(x_i) = -d_i^j/1000 + C \tag{16}$$

The value of x_i^* is also fixed as x_i^{min}. In the COSTCS, the utility function of EV is:

$$U(x_i) = -p_j x_i - p^{last} d_i^j \beta + C \tag{17}$$

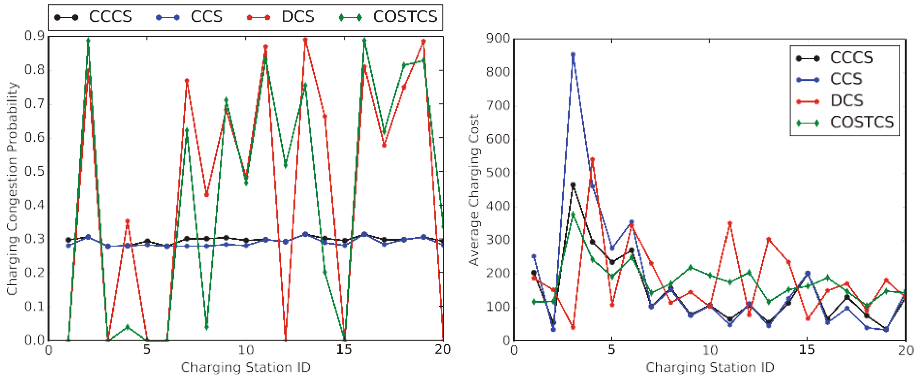
Because it is a linear function, the x_i^* is also fixed as x_i^{min}.

3.3 Charging Congestion Probability and Charging Cost

In this sub section, we simulate the four algorithms in one time slot. The parameters values are shown in Table 1. The charging congestion probability and average charging cost are simulated, and the results are shown in Fig. 2.

In Fig. 2(a), because the curves of the CCCS and CCS are the most flatten, the charging congestion probabilities of CSs are almost equal to each other. So, CCCS and CCS have the best performance in terms of charging congestion probability. Meanwhile, the DCS and COSTCS do not have the ability to balance the charging congestion probability among charging stations. The main reason is that DCS and COSTCS do not consider the charging congestion probability in their utility functions of EV.

In Fig. 2(b), the COSTCS has the best performance of the average charging cost, which is because the COSTCS only considers the charging cost in its utility function.



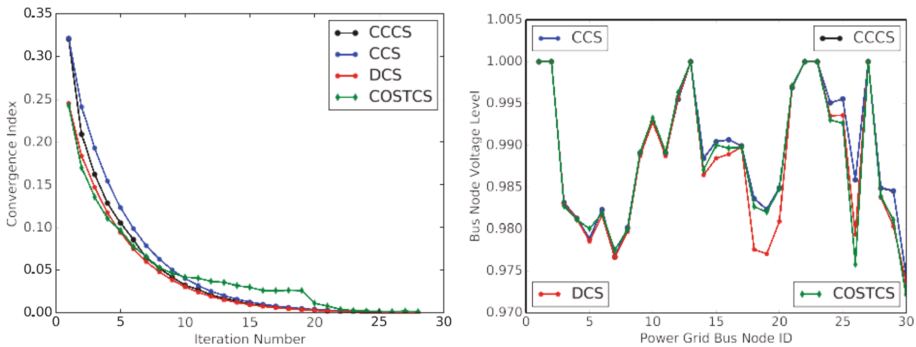
(a) (b)

Fig. 2. The charging congestion probability and average charging cost of different CSs

The CCS has the worst performance in terms of the average charging cost, because it only considers the charging congestion probability. Both the CCCS and DCS have the moderate performance as they have partly considered the charging cost in their utility functions.

3.4 Convergence and Bus Node Voltage

In this sub section, the parameters are the same as that of 4.3. Simulation results are shown in Fig. 3. The Bus node minimum voltage level is set as 0.95. When the Bus voltage is simulated, we let all the charging demands from EVs are injected into the power grid at the same time.



(a) (b)

Fig. 3. The convergence performance and influences to the power grid voltage

In the Fig. 3(a), the convergence index is defined in (14). As shown in Fig. 3(a), all the algorithms are convergent in 30 iterations, which means all the four algorithms are convergent and each charging station has satisfied the charging demand of EVs.

In the Fig. 3(b), we let all the charging demands are injected into Bus at the same time. We find that the voltage levels of DCS and COSTCS are very low at some bus node, which is because the EVs in these charging strategies are not considering the charging congestion probability, which results into the unbalanced charging power distribution. The voltage performances of CCCS and CCS are much better than that of the other two.

According to the voltage level results, we know that the charging congestion probability is an important factor for the power grid, and it can avoid the unbalanced charging demand among different charging stations.

4 Conclusion

In this paper, we propose an EV charging strategy CCCS, which considers the charging congestion probability, charging cost, distance and users' satisfactions in the utility function. The charging station utility and EV utility are combined together to formulate a social welfare maximizing convex problem. Simulation results show that the CCCS performs well in terms of balancing the charging congestion probabilities among charging stations and reducing charging costs. Most importantly, this paper presents that the charging congestion probability is an important factor to balance the charging demand among different charging stations.

In the future, we will focus on the uncertainly to the EV charging strategy, such as the distributed resources integration. Besides, the implement of the EV charging algorithms is also an important issue, where each participant executes distributed algorithm, and how to make them execute algorithms in synchronous manner is essential. Besides, there are many other factors should be considered, such as the transportation conditions, communication data loss etc.

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