User Behavior-based Spatial Charging Coordination of EV Fleet

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***Abstract*—User behavior has attracted growing attention recent years in electric vehicles (EVs) charging coordination problems. This paper proposes a spatial EV fleet charging coordination system considering charging station distribution and user behavior. Firstly, the configuration of the coordination system is introduced and private information protection is highlighted in this system. Traffic uncertainty model, charging station charging pole schedule algorithm (CPSA) and EV mobility model are designed to reflect the spatial interaction of the system. Then, an user behavior based EV coordination algorithm is proposed to maximize upcoming EV user's satisfaction level. Detailed simulation results are presented to verify the effectiveness of proposed EV coordination system. It shows that this system increases EV user's satisfaction level in charging coordination process and spatially shifts the overload of charging stations.**

***Index Terms*—spatial charging coordination, user behavior, mobility uncertainty, electric vehicle (EV), charging station**

I. Introduction

Electric vehicles (EVs) have been widely promoted worldwide, and expected to consistently increase rapidly in coming decades [1]. However, due to the low energy density of battery, EV users face the problem that they need to charge their EVs frequently and have to bear longer charge time than traditional vehicles. This may influence user's travel plan and decrease user's satisfaction level. Besides, due to the high charging power load of EV, disorderly charging will increase load burden on power grid and the power system may break down [2]. So, it is important to schedule EV charging not only for charging service quality of users, but also for proper operation of power suppliers and charging stations (CSs).

EV charging coordination can be divided into two domains, temporal coordination problem and spatial coordination problem [3]. For temporal charing problem, the EVs here are considered to be existing in their charging sites, stations, and plugged in for charging. The aim here is to distribute the EV charging load over time, i.e., shift the charging load to different time like in [4] and [5]. For spatial charing problem, the EVs here are out of the charging sites and seeking to select a proper one among them for charging. The aim here is to distribute the EV charging load over location, i.e., shift the charging load to different locations like in [6] and [7].

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Spatial coordination addressed importance in the mobility of EVs. A potential charging hot spot may happen when many EVs select the same charing station and move toward it [8]. A previous work [9] proposed the charing station reservation algorithm based on the expected arrival time of EV, however, traffic condition increases the uncertainty of EV's arrival time to CS, making fluctuation in the reservation system. Some works like [6] and [8]use information updated approach to dynamically planning best CS based on current situation.

Users' satisfaction level is important in spatial coordination problem because users have their unique trip planning and preferences. However it is still the main trend to treat EV users to have homogeneous response in EV coordination problems [4]. EV users have unique charging and driving behaviors in real world, and their preferences to charging coordination criteria like minimum distance or waiting time can influence satisfaction level of charging service. It is becoming important to consider the unique user behaviors in EV coordination problem to realize a refined energy management [10] [11].

In this paper, we propose a user behavior-based spatial charging coordination system for EV Fleet. The main contributions are listed as follows:

- The proposed spatial EV charging coordination system considers selection among multiple CSs. Private information protection is ensured in this system. A simulation platform is built to model mobility uncertainty and verify coordination performance.
- This work considers various users' preferences in terms of criteria like travel time, travel distance, and waiting time. Spatial coordination is combined with users' unique travel plans, which will maximum user's satisfaction level in charging service.

The remainder of this paper is organized as follows. In Section II, we present the System configuration and model, followed by Section III in which we introduce EV coordination algorithm including user behavior based criterion. Simulation results and analysis are evaluated in Section IV, followed by the conclusion made in Section V.

II. System configuration and modelling

A. System configuration

The purposed EV charging coordination system considers the interaction among EVs, CSs, coordination information center (CIC), traffic network and power grid as shown in Fig. 1. CIC is a platform that provide navigation service for EVs and work as an agent to share information between EVs and CSs. Navigation service can be performed securely by means of navigation service provider. EVs are divided into three states: upcoming EVs, namely EVs that have charging need and are traveling on road, waiting EVs, namely EVs that already arrived at CS but are still waiting for charging, and charging EVs, namely EVs that are charging in CS. The CS selection for upcoming EVs is according to a user behavior based CS selection algorithm that is further illustrated in chapter III. CS has limited power capacity, which influences the maximum number of charging poles at different times in one day, namely capacity profile. Based on this capacity profile, charging poles are arranged according to Charging Poles Schedule Algorithm (CPSA) that is further illustrated in section II.C.

The proposed EV charging coordination system works as the following steps. Power grid will announce power constrain for each CS before a day based on historical data, then CS will calculate its capacity profile. For upcoming EVs, firstly they send their location and SoC information to CIC as shown in step 1. Then based on traffic data and available CSs' location, CIC will provide navigation service and send navigation information including travel distance and travel time to EVs as shown in step 2. At the same time, CIC will also send anonymous expected arrival time and required SoC information to candidate CSs. Expected waiting time is queried and send back to CIC and then send to upcoming EVs as shown in step 3. Then user behavior based CS selection is performed based on travel distance, travel time and waiting time as shown in step 4. This procedure is carried out periodically to keep track of the dynamic variation of traffic network, upcoming EV states and CS states. When EVs arrive at selected CS, direct information change is available between EVs and CS, then charging coordination is performed by means of CPSA as shown in step 5.

Private information protection is highlighted here when EV and CS are spatially separated. Only anonymous information of upcoming EVs like arrival time and required SoC and public information of CSs like CS location and waiting time query result are shared between EVs and CSs. Private information like location and user behavior of upcoming EVs and operational information like number of EVs in CS are protected. when EVs arrive at CS, EVs and CS can change information locally, and hence their private information is also protected.

The model of traffic uncertainty, CS and EV are introduced as follows.

B. Traffic Uncertainty Model

Fig. 2 shows a simplified model of geographical system with meshed road network. EV will follow the segments of

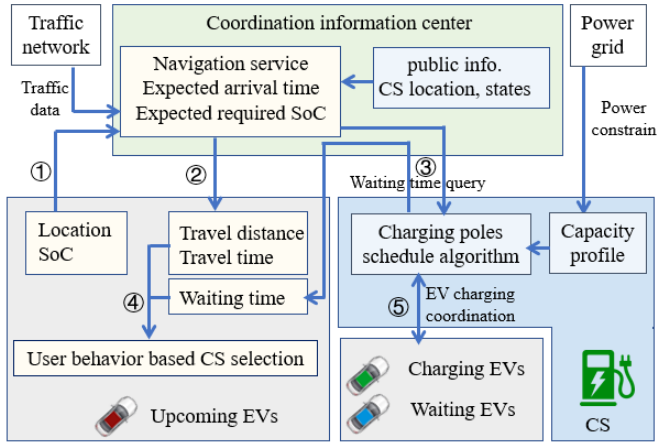


Fig. 1. The proposed EV coordination system

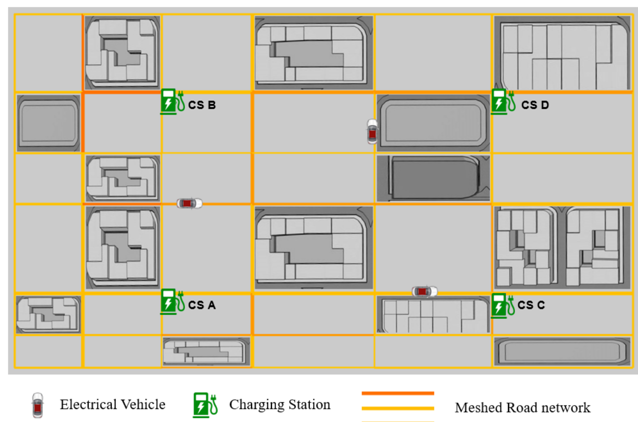


Fig. 2. Illustration of meshed road network

roads when travels in this area. The width of these segments represents the road condition while the color represents traffic condition. The average speed on each segment $v$is determined by (1).

$$v = \overline{V} \times E_t^i \times E_r^i \tag{1}$$

where $\overline{V}$ is the maximum speed limit in urban area. E_t^i is coefficient of traffic jam degree and E_r^i is the coefficient of road condition, they are all range from [0,1], which will decrease the actual speed. Due to the uncertainty of traffic, E_t^i will change following Possion distribution.

C. Charging Station Model

CSs are assumed to locate in the some junctions of roads and hence can be reached from any initial location on road. CSs are assigned power constrain $p_{c,t}$ by power grid. We assume each charging pole has constant charging power p_c, then the maximum available pole M_t at any time can be calculated according to (2).

$$M_t = \lfloor p_{c,t}/p_c \rfloor \tag{2}$$

The current number of charging EV in CS is m_t. When EV arrives at CS, it will charge immediately at a constant power p_c if there are available charging poles $(m_t < M_t)$. Otherwise it will wait in a waiting queue with current queue length n_t and maximum capacity N, when some EV finish charging and leave available charging poles, EVs in the waiting queue will charge following the first come first serve rules.

In this paper, charging schedule is based on CPSA, and it is divided into two phase as illustrated in Algorithm 1 and 2. In EV arrival phase, EV has arrived at selected CS. EV will be assigned to the earliest available pole according to its arrival time t_r and required SoC based on line 1 to 4. Where T_i^{free} is the earliest free time in pole i, T_i^{shift} is maximum pole number shift time for pole i, T_p is candidate starting charing time set for EV. The earliest candidate starting charing time t_p that satisfies pole constrain will be assigned to this EV. In EV query phase, EV hasn't selected CS or hasn't arrived at CS. EV needs to query expected waiting time in CS for decision. Based on line 1 to 6, EV is virtually scheduled in the waiting queue and the expected waiting time is calculated.

Algorithm 1 CPSA EV arrival phase

Require: $t_r, requiredSoC$
1: $T_p \leftarrow [T_i^{free}, T_i^{shift}]$ for i in total poles
2: Rank T_p in Ascending order
3: **for** t_p in T_p **do**
4:     Virtually append new EV at t_p
5:     **if** $m < M$ **then**
6:         Arrange EV to poles, Update poles, Return
7:     **end if**
8: **end for**
9: Refuse EV, Return

Algorithm 2 CPSA EV query phase

Require: $t_r, requiredSoC$
1: $T_p \leftarrow [T_i^{free}, T_i^{shift}]$ for i in total poles
2: Rank T_p in Ascending order
3: **for** t_p in T_p **do**
4:     Virtually append new EV at t_p
5:     **if** $m < M$ **then**
6:         Expected waiting time $\leftarrow (t_p - t_r)$
7:         Return expected waiting time
8:     **end if**
9: **end for**
10: Refuse EV, Return

By CPSA, early arrival EVs will keep their charing power in the presence of later arrival EVs. This is more fair for early arrival EV users comparing with the vary power method in [6], where the charging power of early arrival EVs may decrease due to later arrived EVs. Besides, CPSA provides a flexible way in practice considering traffic mobility uncertainty. The periodically update mechanism will keep waiting time updated for CS selection decisions.

D. EV Model

EV model including its location, speed, SoC dynamic and navigation model, the main features of EV are explained as follows:

1) EV SoC Dynamic: Based on EV driving and charging states, two different models to calculate SoC dynamic are used here:

- EV driving model for calculation of SoC is derived as follows. The EV dynamical power related to speed can be approximated by quadratic form [12]:

$$P_{total} = C_1 v^2 + C_2 v + C_3 \tag{3}$$

  where C_1, C_2, C_3 are positive numbers. Then the SoC consumption when EV is driving can be expressed by:

$$SoC_{present} = SoC_{previous} - P_{total}\Delta t / C_{battery} \tag{4}$$

- EV charging model for calculation of SoC is derived based on the charging energy:

$$SoC_{present} = SoC_{previous} + \eta P_{charge}\Delta t / C_{battery} \tag{5}$$

  where η is power conversion efficiency.

2) EV mobility navigation: EV mobility refers to EV daily travel activities. EV has a charging demand when its SoC is low (e.g., lower than 0.3), and it has to be charged to continue its travel. EV needs to choose a proper CS to travel to it, and to recharge itself. When EV is fully charged in CS, it will continue to travel to its planned destination. The above EV travel mobility divid can be represented by the following flowchart in Fig. 3.

III. User Behavior Based CS Selection

A. Selection Criteria of candidate CSs

As EV travels and loses energy, it needs to be charged to be able to continue traveling. EV users can decide which CS to choose and hence the satisfaction level of users will be more important in Spatial Coordination Problem. EV travel distance, EV travel time and EV waiting time are used to measure the satisfaction level of users, and they are introduced as follows.

1) EV travel distance to CS: This reflects an energy consumption reservation of EV users. The distance form EV number n to CS i is expressed by $d_{n,i}$, and it can be calculated by shortest distance route.

2) EV travel time to CS: This reflects the traffic convenience of EV and it is influenced by the mobility uncertainty. EV travel time from EV number n to CS i is expressed by $t_{n,i}^r$, and it can be calculated by the sum of travel times in each segment of selected route.

3) EV waiting time in CS: This reflects the available capacity of CS and can influence the anxiety of EV charging process. The expected waiting time for EV number n in CS i is expressed by $t_{n,i}^w$, and it can be calculated by CPSA proposed in section II.

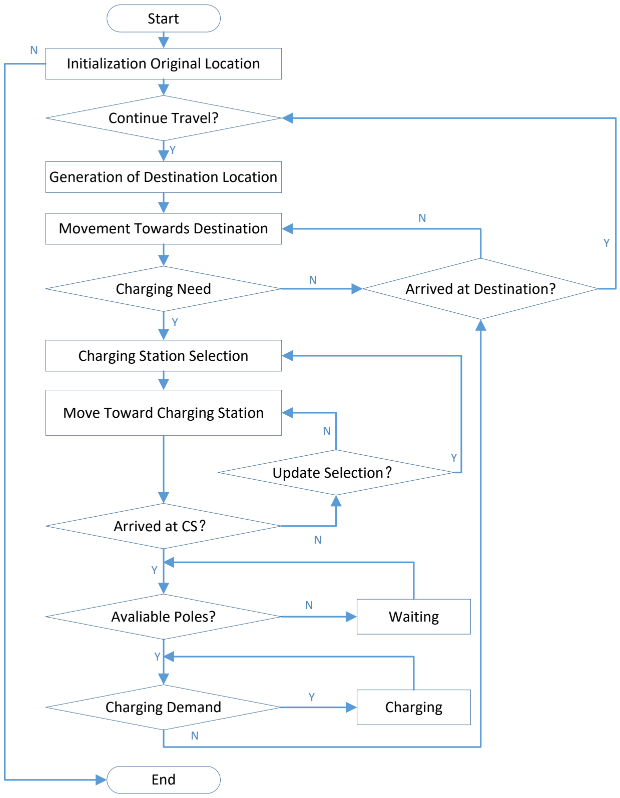


Fig. 3. EV navigation model

B. User Behavior Based CS Selection Model

The concern of user behavior based selection is to select the proper CS for charging EV and get maximum satisfaction level based on information on location and traffic conditions. Thus, after considering the geographical distribution of the CS locations, EV user will select only one CS. This CS selection decision can be represented by a binary value $x_{n,i}$ as below (6)

$$x_{n,i} = \begin{cases} 0, & EV_n \text{ does not select } CS_i \\ 1, & EV_n \text{ selects } CS_i \end{cases} \tag{6}$$

where i is the index of the CS out of the existing number N_{cs} and n indicates for the EV out of the existing number N_{ev}.

Travel distance, travel time, waiting time are normalized and used as the criterion for users' satisfaction level (7).

$$W_{n,i} = \omega_1 \frac{d_{n,i} - \underline{d_n}}{\overline{d_n} - \underline{d_n}} + \omega_2 \frac{t^r_{n,i} - \underline{t^r_n}}{\overline{t^r_n} - \underline{t^r_n}} + \omega_3 \frac{t^w_{n,i} - \underline{t^w_n}}{\overline{t^w_n} - \underline{t^w_n}} \tag{7}$$

$$F_n = 1 - \sum_{i=1}^{N_{cs}} x_{n,i} W_{n,i} \tag{8}$$

where $\overline{d_n}$, $\underline{d_n}$, $\overline{t^r_n}$, $\underline{t^r_n}$, $\overline{t^w_n}$, and $\underline{t^w_n}$ are the maximum and minimum values of travel distance, travel time and waiting time in CSs respectively. Then the satisfaction level of EV user n can be expressed by (8). We assume EV user n will select and travel to the CS that maximizes his/her satisfaction level. (7) expresses criteria in a normalized form so that these criteria can be added together to measure users' satisfaction level. And $\omega_1, \omega_2, \omega_3$ are weight factors that represent the degree of sensitivity among energy consumption reservation , traffic convenience on mobility uncertainty and anxiety on charging process. For normalization purposes and to constrain the behavior range it is assumed that $\omega_1 + \omega_2 + \omega_3 = 1$. Different weight combinations reflect different EV user's behavior.

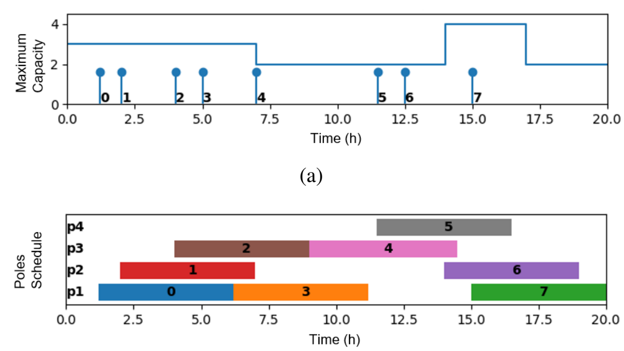
IV. Simulation Results and Analysis

The simulation is carried out on animation based platform programed by python. Firstly, charging poles schedule result in a single CS is presented to show the effectiveness of CPSA. Then a cases study is simulated to show the performance of proposed EV coordination system.

A. EV coordination in single CS

The example CS is assumed to have 4 charging poles. Due to power constrain, the maximum available poles in a period that last 20 hours is shown in Fig. 4 (a). 8 EVs arrival this CS during this period and their arrival order and arrival time at CS are marked on time axis. EV will be assigned to a charging pole and charge if there is available charging pole according to EV arrival phase in CPSA. Charging pole schedule result is shown in Fig. 4 (b). Color bars and numbers represent that some EV is charging at a specific charging pole (P1, P2, P3 or P4) in the time interval that a bar cover.

The result shows that EV (0, 1, 2, 5, 7) charge immediately when they arrive at the CS, and EV (3, 4, 7) will wait until there is available charging poles. The total number of charging poles used at any time is within the constrain of maximum available poles, namely the capacity in CS.



(a)

(b)

Fig. 4. Charging poles schedule result. (a) EV arrival time and maximum capacity of CS. (b) Sequential charging poles schedule arrangement.

B. EV coordination in multiple CSs

We assume the studied geographical area is a 7Km×4Km rectangular area with four CSs and meshed road network as shown in Fig. 2. EVs are assumed to travel in this geographical area like taxi fleet and will not leave this area. Besides, we assume that the four CS inside this area will not accept EVs that are not considered in this coordination system. 80 EVs are generated following the navigation model in section III.A. EV users are equally divided into 5 groups in terms of their preference to travel time, waiting time, and distance as shown in TABLE 1. The preference here stands for the combination of three weight factors $\omega_1/\omega_2/\omega_3$ mentioned in section III.B.

TABLE I
FIVE DRIVER GROUPS AND THEIR PREFERENCES

Groups	Driver type	Preference
1	Travel distance sensitivity drivers	1/0/0
2	Travel time sensitivity drivers	0/1/0
3	Waiting time sensitivity drivers	0/0/1
4	Time sensitivity drivers	0/0.5/0.5
5	Distance and time moderate drivers	0.4/0.3/0.3

Power constrain for each CS is taken from [6], which is set in one day between 6:00 and 22:00 considering power distribution and grid load. EV battery capacity is assumed to be 30kWh. When EV is running on road, its power consumption has quadratic form with parameter C_1, C_2, C_3 scaled and taken from [12]. When EV charge in CS, it will charge at 25kW constant power with conversion efficiency η equals to 0.96.

Power constrain for each CS and actual charging power with and without CPSA in one day is shown in Fig. 5. It can be seen that in CS A form 14:00 to 18:00, the available power is in shortage (green curve), the power schedule result without CPSA result in overload (blue curve), while the power schedule result with CPSA can avoid overload by shifting EVs to other CSs which have more available power (orange curve).

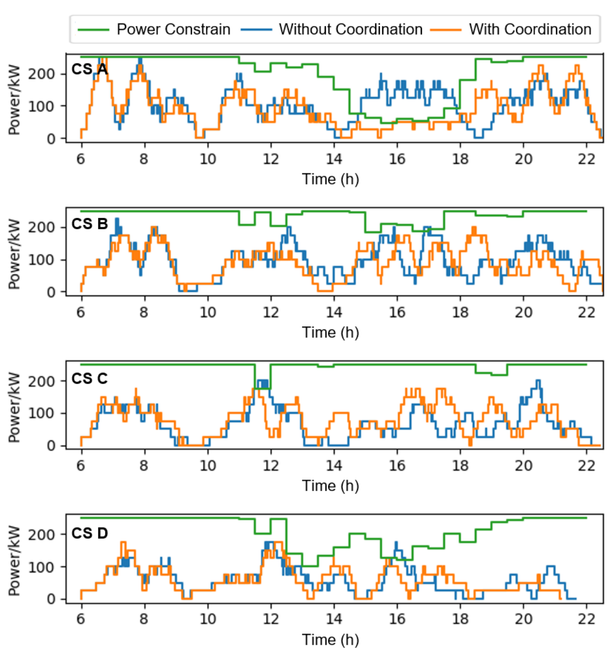


Fig. 5. Power constrain and actual power in each CS with/ without pole schedule

The waiting EV number in CSs with or without coordination are compared in Fig. 6. Without coordination means upcoming EV users will simply choose the nearest CS, while with coordination means EV users will choose CS according to user based coordination algorithm proposed in section III.B. The result shows that in the case without coordination, there is a large number of EVs waiting in CS A due to limit power constrain form 14:00 to 18:00. However in the case with coordination, the waiting EV number in CS A decreases and is shifted to CS B.

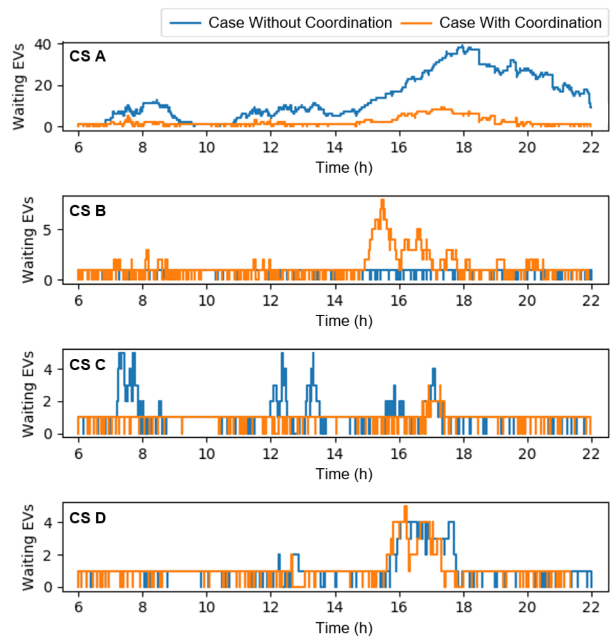
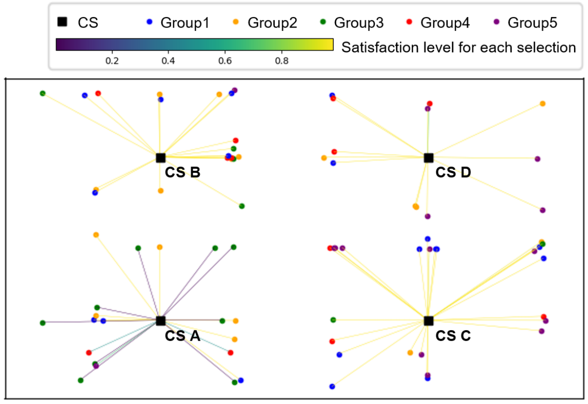


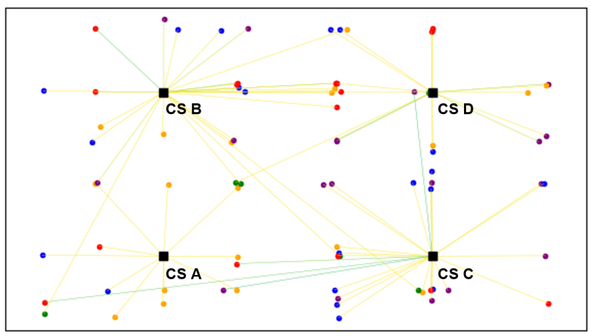
Fig. 6. Waiting EV number in each CS with/ without coordination

Different groups of user's satisfaction level in spatial domain are shown in Fig. 7. Black squares represent four CSs that locate in this studied geographical area, and dots represent location of EVs when they make their first CS selection decision. Different colors of dots represent different groups of EVs that have unique preference. The line that connect dot and square represents the CS selected by this EV, and the color of the line represents satisfaction level of this selection based on (8) and (7). In order to show these lines clearly, only selections happen from 15:00 to 17:00 in the case study is shown here. Note that EV is traveling on meshed road network and will only make decision at cross node. a small vibration is added to their location so that these dots won't overlap. In Fig. 8 (a), EV always chose nearest CS, and it shows that for group3(green dots) near CS A, they have low satisfaction level because CS A has long waiting time during this period. In Fig. 8 (b), EV will choose CS based on preference and try to maximum their satisfaction level. It shows that some EVs that belong to group 3,4 or 5 will travel further to charge in some CSs that have shorter waiting time. Hence the overall satisfaction level is increased.

In order to compare satisfaction level in a whole day,



(a)



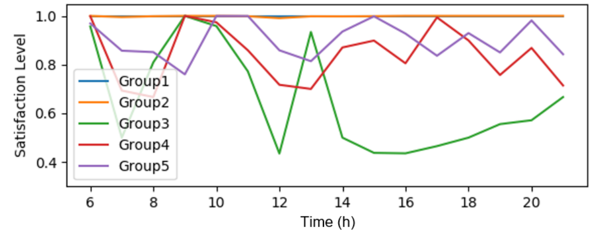
(b)

Fig. 7. Compassion of satisfaction level of different groups in spatial domain. (a) Without coordination. (b) With coordination.

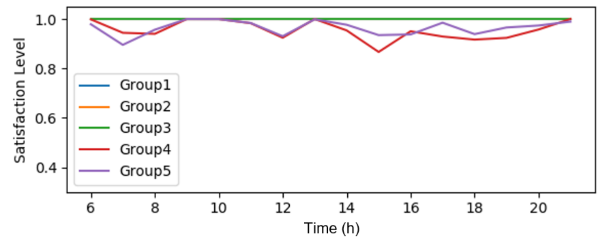
Satisfaction level of different groups of EV users in time domain is shown in Fig. 8. For group 1 users, the minimum distance CS selection is the same in cases with or without coordination, so their satisfaction level don't change much. For other groups, satisfaction level of different group of users have increased due to the behavior based EV coordination algorithm. In average, the satisfaction level has increased from 88% to 98%.

V. Conclusion

In this paper, a spatial EV coordination system is proposed considering user's behavior and distribution of CSs. a coordination information center is introduced in this system to guarantee private information protection. Traffic uncertainty, CS and EV are modeled considering mobility factors. User behavior based CS selection model is proposed to maximize upcoming EV user's satisfaction level. EV users will choose the CS based on their preference to travel distance, travel time and waiting time in CS. EV coordination simulation in single CS and multiple CSs are present to show the effectiveness of purposed coordination system. The results show that the proposed coordination system increases EV user's satisfaction level in charging coordination process and spatially shifts the overload of charging stations. In future work, more detailed constrains when EV arrive at the CSs will be considered, such as price for electricity, power limit for CSs.



(a)



(b)

Fig. 8. Compassion of satisfaction level of different groups in temporal domain. (a) Without coordination. (b) With coordination.

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