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A Bayesian Game based Bidding Scheme for Mobile Charging Services in IoEV

Linfeng Liu, *Member, IEEE*, Zhipeng Zhang, Jia Xu, *Senior Member, IEEE*, and Ping Wang, *Fellow, IEEE*

***Abstract*—Due to the low cost and agile service provision, mobile charging stations (MCSs) have been deployed to complement fixed charging stations (FCSs). In the Internet of Electric Vehicles (IoEV) with MCSs, a major concern is to enhance the charging efficiency of MCSs. The charging efficiency of MCSs can be improved by prolonging the charging durations of MCSs, i.e., MCSs should undertake the charging tasks as more as possible, which can increase the charging profits of MCSs and reduce the charging expenses of IEVs (EVs with insufficient electricity). Besides, EVs and MCSs are selfish in terms of charging expenses and charging profits, respectively. In this paper, we propose a Bayesian game based Bidding Scheme for Mobile Charging enabled Electric Vehicles (BBS-MCEV). In BBS-MCEV, each IEV first calculates the maximum charging price (MCP) according to the potential expense if charged by nearby FCSs, and then the optimal charging price (OCP) is determined by the Bayesian game model. Each MCS accepts the charging request with the largest charging profit. Extensive simulations and comparisons demonstrate the superior performance of our proposed BBS-MCEV, i.e., with the Bayesian game model, IEVs can rationally bid for the mobile charging services from MCSs, and thus BBS-MCEV can increase the charging profits of MCSs and reduce the charging expenses of IEVs effectively. Besides, a proper tradeoff between the charging profits of MCSs and the charging expenses of IEVs can be achieved.**

***Index Terms*—Internet of Electric Vehicles; mobile charging station; bidding scheme; Bayesian game.**

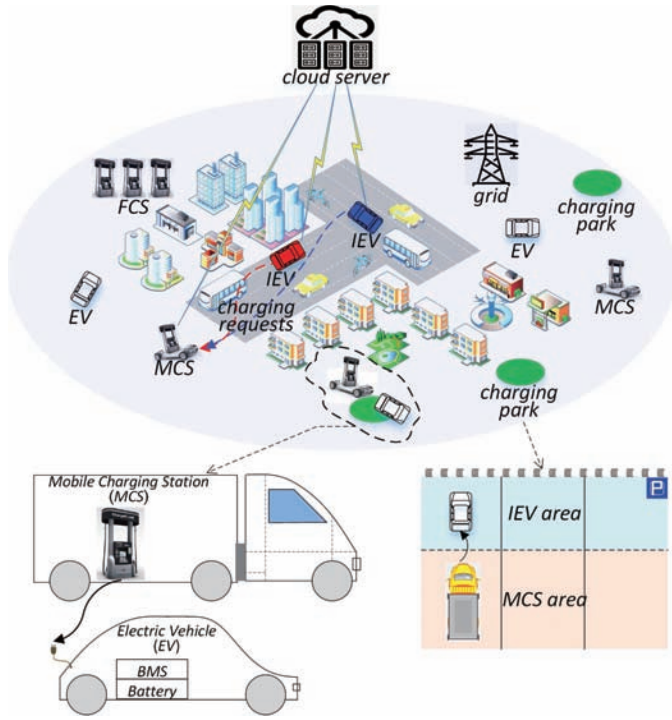

Fig. 1: A mobile charging scenario.

I. Introduction

Electric vehicles (EVs) are automotive vehicles powered by electricity from rechargeable batteries. EVs equipped with wireless communication modules can constitute an Internet of Electric Vehicles (IoEV) [3]. At present, the main charging solutions for EVs include fixed charging stations (FCSs), mobile charging stations (MCSs) [4], [5], and some vehicle-to-vehicle (V2V) charging schemes [6], [7]. Compared with FCSs, MCSs can provide more agile charging services with lower deployment cost, since MCSs do not require deployment sites and can move freely. Generally, several charging parks [8] are arranged for MCSs charging EVs in a city (Fig. 1), and note that the existing parking lots can act as the charging parks.

Some EVs do not have sufficient electricity to sustain their movements to destinations. An EV with insufficient electricity (referred to as an IEV [9]) will make a charging request to a nearby idle MCS when it detects a low battery state. Upon receiving the charging request, the MCS decides whether to charge the IEV at a charging park. In IoEV, FCSs are considered public charging infrastructures and provide a fixed charging price for EVs. On the contrary, MCSs can offer a flexible charging price which could be lower than that of FCSs due to the lower deployment cost of MCSs (the cost for occupying and constructing the deployment sites is not required).

A major concern is to enhance the charging efficiency of MCSs. The charging efficiency of MCSs can be improved by prolonging the charging durations of MCSs, i.e., MCSs should undertake the charging tasks as more as possible. To prolong the charging duration of an MCS, the MCS is inclined to charge the IEVs which require more electricity (the charging duration is longer) and the nearer IEVs (the time spent on moving towards the selected charging parks is shorter). Therefore, the enhancement of the charging efficiency of MCSs is achieved along with the following outcomes: (i) The charging profits of MCSs are increased, because MCSs can obtain more charging profits through

L. Liu, Z. Zhang, and J. Xu are with the School of Computer Science and Technology, Nanjing University of Posts and Telecommunications, Nanjing 210023, China, and also with the Jiangsu Key Laboratory of Big Data Security and Intelligent Processing, Nanjing 210023, China ({liulf,xujia}@njupt.edu.cn, zhangzp0126@foxmail.com).

P. Wang is with the Department of Electrical Engineering and Computer Science, York University, Toronto ON M3J 1P3, Canada (email: pingw@yorku.ca).

charging more IEVs; (*ii*) The charging expenses of IEVs are reduced, because the charging expenses of IEVs paid to MCSs are smaller than those paid to FCSs. The above two metrics (the charging profits of MCSs and the charging expenses of IEVs) can be used to measure the charging efficiency of MCSs.

Moreover, EVs and MCSs are selfish (e.g., EVs belong to different owners, and MCSs are operated by different companies) in terms of charging expenses and charging profits, respectively. With regard to an IEV, if it is charged by an MCS rather than an FCS, then the charging expense can be reduced. Thus, an IEV is willing to slightly raise the charging price when multiple IEVs are competing for the same MCS due to the selfishness of both IEVs and MCSs. Besides, an MCS accepts the charging request with the largest charging profit when it receives multiple charging requests from IEVs simultaneously. Thus, the increase in the charging profits of MCSs is sometimes inconsistent with the decrease in the charging expenses of IEVs.

Apparently, both the charging profits of MCSs and the charging expenses of IEVs are related to the charging price of IEVs. The competitions among IEVs could increase the charging price of IEVs and the charging profits of MCSs. However, the charging expenses of IEVs will not be largely increased if these competitions are rational. Hence, a proper tradeoff between the charging profits of MCSs and the charging expenses of IEVs should be achieved by making IEVs rationally bid the charging price for MCSs.

Motivated by the above considerations, we propose a Bayesian game based Bidding Scheme for Mobile Charging enabled Electric Vehicles (BBS-MCEV), as illustrated in Fig. 2. In BBS-MCEV, each IEV first calculates the maximum charging price (MCP) according to the potential expense if charged by nearby FCSs. Then, the optimal charging price (OCP) is determined by a Bayesian game model and sent to bid for the charging service of an idle MCS. The MCS accepts the charging request with the largest charging profit when several IEVs compete for it. After charging the IEV at a selected charging park, the charging order is uploaded by the MCS to the cloud server to collect information on the required electricity of IEVs (REI). Besides, the cloud server is responsible for periodically updating and releasing the probability distribution of REI.

Obviously, the IEVs requiring more electricity (more electricity purchased from MCSs) or nearer to MCSs (smaller cost for MCSs moving to the selected charging parks) are easier to win the mobile charging services from MCSs, because larger charging profits can be obtained by MCSs for charging these IEVs.

In summary, our proposed BBS-MCEV has the following advantages:

- BBS-MCEV can enhance the charging efficiency of MCSs through a Bayesian game participated by IEVs.
- BBS-MCEV does not require the private information of IEVs (such as the historical routes and the destinations). Hence, the privacy of IEVs can be protected from being revealed.

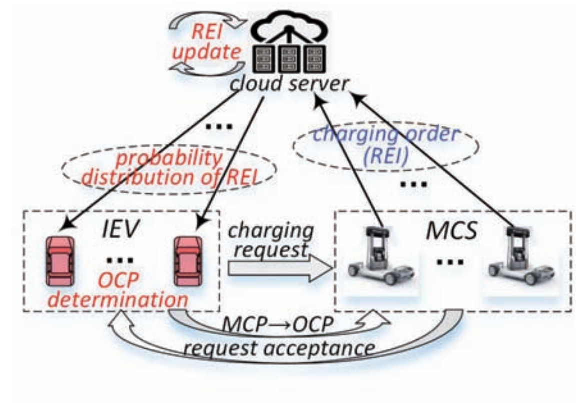

Fig. 2: The framework of BBS-MCEV.

- In BBS-MCEV, each IEV does not learn the bidding information of other bidders (such as their required electricity and urgent levels), and the charging price bid by each IEV is restricted by the potential expense charged by nearby FCSs. Thus, IEVs can rationally bid on the charging price.
- The Bayesian game model adopted in BBS-MCEV can quickly converge to a pure-strategy equilibrium.

The remainder of this paper is organized as follows: Section II briefly surveys some related studies. Section III provides the problem formulation for the bidding problem of IEVs. Section IV proposes the BBS-MCEV. Section V covers some analyses on BBS-MCEV, including the complexity, convergence, and rationality. Simulation results for performance evaluation of BBS-MCEV are reported in Section VI. Finally, Section VII concludes this paper.

II. Related Work

A. Charging with Fixed Charging Stations

In IoEV, the main concerns include the deployment of FCSs and the route schedule of EVs to FCSs. The deployment of FCSs is typically arranged to minimize the deployment cost of FCSs and/or the travel time of EVs. Some relevant research has been conducted, such as [10], [11], [12]. [10] formulates a collaborative planning model to reduce the construction cost of FCSs. In [11], the number of shared electric vehicles that check out from parking stations is predicted based on a random forest algorithm, and the number of FCSs to be deployed is determined by measuring the charging demand of shared electric vehicles. A fuzzy analytical hierarchy process is applied to choose the optimal sites of FCSs. The work [12] aims to propose a multiple criteria decision making approach by the uncertain linguistic multi-objective optimization to determine the most suitable sites for FCSs. For the route schedule of EVs to FCSs, Yang *et al.* propose the multinomial logit-based model and the nested logit-based model [13] to analyze the drivers' charging and route choice behaviors, and extract the differences in the travel behaviors between EVs and gasoline vehicles. Besides, [14] attempts to optimize the route selection and charging/discharging schedule to minimize the total cost of all EVs, and an A^* algorithm is adopted to seek out the K-shortest paths for EVs. [15] considers the charging time optimization for EVs, the EV-FCSs pairing, and the pricing mechanism for FCSs jointly, and a hierarchical game is designed to set the charging price for FCSs and choose the desired FCSs for EVs.

B. Charging with Mobile Charging Stations

Recent years have witnessed the great advantages of M-CS techniques. [16] designs an internet-based information management system to facilitate the communications between CS server, EVs, MCSs, and FCSs. The system helps IEVs to reduce their waiting time when they are queued in fully occupied FCSs. In [17], the user convenience and the expenses of FCSs and MCSs are compared by constructing a mathematical model. To increase the business profits of MCSs, a stochastic optimization model is constructed, and a Lyapunov-based optimization algorithm is designed in [18]. In [19], an intelligent mobile charging control mechanism is designed for EVs by promoting charging reservations (including the service start time, expected charging time, and charging locations). With intelligent charging management, the available mobile chargers are predictable and could be efficiently scheduled for the EVs with large charging demand. To account for the congestion and large waiting queues at public charging stations, [20] provides a novel strategy for routing and scheduling MCSs to charge EVs without the spatio-temporal constraints. The optimization problem of minimizing the charging cost is specially formulated, and the modified saving's heuristic and modified genetic algorithm are given to solve this optimization problem. In [21], the realized peer-to-peer energy trading between EVs and MCSs is used to relieve the overload on FCSs, leverage under-utilized energy resources.

In the above works, the selfishness of MCSs and EVs is neglected. However, in real charging scenarios some IEVs could compete for MCSs, which motivates us to investigate a bidding scheme for the rational competitions among IEVs.

C. Bayesian Game in Electricity Trading

At present, some research has been conducted to apply Bayesian game theory to establish the electricity trading model, such as [22], where a V2V electricity trading scheme based on Bayesian game pricing in blockchain-enabled Internet of vehicles is proposed, and thus the maximum utilities of both sides of electricity transactions can be guaranteed. [23] proposes a V2V and vehicle-to-grid (V2G) electricity trading architecture, and then designs a two-way auction mechanism based on the Bayesian game. In [24], Microgrids Energy Trading Bayesian Game (METBG) model is proposed. Specifically, the microgrids make their decisions as the agents of native users to tackle the bidirectional energy trading. Besides, Liu *et al.* depict a scenario for demand-side management programs to schedule household energy consumption which considers the bidirectional energy trading of plug-in EVs [25], and the energy consumption scheduling among communities with incomplete information can be optimized.

An online continuous PSP-based auction scheme is presented in [26], and this scheme can achieve online energy trading and guarantee that the number of winners is smaller than that of charging piles. In [27], an energy auction is provided to ensure a fair and efficient bidding in the auction. The Bayesian game theory is adopted to enable efficient and cost-effective bidding for each buyer. Likewise, in [28], the problem of frequency-constrained electricity market (FCEM) is proposed in the presence of renewable energy sources and price-maker players. Since the players of FCEM do not know their rivals' objective functions, the problem is modeled by Bayesian game theory, and an optimal generalized Bayesian Nash equilibrium for the FCEM problem can be achieved.

Some valuable insights can be drawn from the above works for exploring the bidding mechanisms. Bayesian game is a game where the players have incomplete information about others, and thus it is suitable for the bidding of IEVs in IoEV, where each IEV typically does not learn about the bidding information of other IEVs competing for the same MCS. To expedite the charging responses and stabilize the charging market, the Bayesian game model adopted for the bidding of IEVs should quickly converge, and the bidding of IEVs must be rational to avoid the unreasonable charging price.

III. Problem Formulation

We first formulate the bidding problem of IEVs. The road network is denoted by $\mathcal{R}$, and the road segments could have different lengths and/or different shapes. The charging parks provide locations for MCSs charging IEVs without affecting the traffic, e.g., the existing parking lots can play the role of charging parks. The set of charging parks is denoted by $\mathcal{P}$. The sets of IEVs, FCSs, and MCSs are denoted by $\mathcal{E}$, $\mathcal{F}$, and $\mathcal{M}$, respectively.

Time is divided into discrete time slots with an equal length of t_s. TABLE I shows the list of main notations.

A. Electric Vehicles and Charging Stations

For an EV v_i, the departure position and the destination are denoted by s_i and d_i, respectively, where $s_i, d_i \in \mathcal{R}$. v_i travels at a speed of $m_s(v_i)$, and c unit of electricity is consumed for travelling through a unit distance. At the t-th time slot, the position and the residual electricity are denoted by $p(v_i)^{(t)}$ and $e(v_i)^{(t)}$, respectively.

If v_i has sufficient electricity to travel from s_i to d_i (i.e., $e(v_i)^{(0)} \geq c \cdot |s_i - d_i|$, where $e(v_i)^{(0)}$ denotes the initial battery electricity of v_i, and $|s_i - d_i|$ denotes the travel distance on the road network from s_i to d_i), and then v_i moves along the shortest route to d_i. Otherwise, v_i makes a charging request to an MCS or an FCS when it detects a low battery state (e.g., $SOC(v_i)^{(t)} \leq \gamma$ at the t-th time slot). For simplifying the problem model and problem analysis, we set the same γ for each EV, because the low battery state is mainly determined by the charging consideration

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TABLE I: Main notations

Parameter	Description
$m_s(v_i)$, $m_s(\psi_j)$	Travel speed of EV v_i (MCS ψ_j)
$e(v_i)^{(t)}$	Residual electricity of EV v_i at the t-th time slot
$SOC(v_i)^{(t)}$	State of charge (SOC) [29] of EV v_i at the t-th time slot
$p(v_i)^{(t)}$, $p(\psi_j)^{(t)}$	Position of EV v_i (MCS ψ_j) at the t-th time slot
$p(\varphi_k)$	Position of FCS φ_k
c	Electricity consumption for an EV travelling through a unit distance
r_d	Dispatching price of an MCS per kilometer
r_f	Price of electricity transferred from FCSs to IEVs
r_0	Price of electricity purchased by MCSs and FCSs from power grid
$r_{max}(v_i, \psi_j, \widetilde{p})$	MCP of IEV v_i bidding for MCS ψ_j (charged at $\widetilde{p}$)
$r(v_i, \psi_j, \widetilde{p})$	OCP of IEV v_i bidding for MCS ψ_j (charged at $\widetilde{p}$)
$t_q(\varphi_k)^{(t)}$	Queuing time for service of FCS φ_k at the t-th time slot
$E_m(v_i, \psi_j, \widetilde{p})$	Extra travel of IEV v_i (charged by MCS ψ_j at $\widetilde{p}$)
$E_m(v_i, \varphi_k)$	Extra travel of EV v_i (charged by FCS φ_k)
$t_w(v_i, \psi_j, \widetilde{p})$	Time of IEV v_i waiting for MCS ψ_j at $\widetilde{p}$
$Delay(v_i, \psi_j, \widetilde{p})$	Extra travel delay of IEV v_i after being charged by MCS ψ_j at $\widetilde{p}$
$Delay(v_i, \varphi_k)$	Extra travel delay of IEV v_i after being charged by FCS φ_k
$Exps(v_i, \psi_j, \widetilde{p})$	Charging expense of IEV v_i paid to MCS ψ_j (charged at $\widetilde{p}$)
$Exps(v_i, \varphi_k)$	Charging expense of IEV v_i paid to FCS φ_k
$Pf(v_i, \psi_j, \widetilde{p})$	Charging profit of MCS ψ_j by charging IEV v_i at $\widetilde{p}$
$Pf(v_i, \varphi_k)$	Charging profit of FCS φ_k by charging IEV v_i
$route(p, p')$	Travel route from position p to position p'

and charging habit of EV drivers, and is quite subjective and difficult to be standardized. Each FCS is allowed to charge multiple IEVs simultaneously because each FCS has multiple charging interfaces, while each MCS is allowed to charge only one IEV simultaneously.

Furthermore, two cases are discussed as follows:

Case A. If an MCS ψ_j accepts the charging request from v_i at the t-th time slot, and then ψ_j and v_i move towards a selected charging park (with the position $\widetilde{p}$). The extra travel undertaken by v_i is expressed as [30]:

$$E_m(v_i, \psi_j, \widetilde{p}) = \left|p(v_i)^{(t)} - \widetilde{p}\right| + |\widetilde{p} - d_i| - \left|p(v_i)^{(t)} - d_i\right|, \tag{1}$$

where $\left|p(v_i)^{(t)} - \widetilde{p}\right| + |\widetilde{p} - d_i|$ denotes the distance of future travel of v_i passing through $\widetilde{p}$, as illustrated in Fig. 3.

Due to the fact that the charging price in the residential zones is much cheap (e.g. when IEVs are charged in the garages of their owners), MCSs are always taken as the emergent charging providers which offer the emergent charging services during the travels of EVs. When ψ_j charges v_i, the amount of electricity transferred from ψ_j to v_i is calculated as the insufficient electricity of v_i for supporting the future travel to the destination d_i: $\triangle e(v_i, \psi_j) = c \cdot \{|s_i - d_i| + E_m(v_i, \psi_j, \widetilde{p})\} - e(v_i)^{(0)}$.

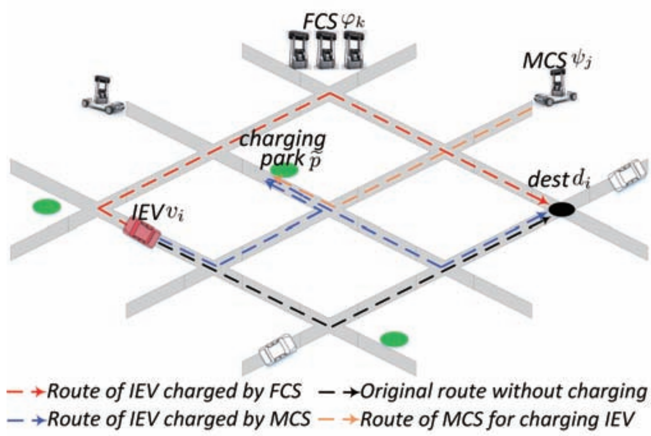

Fig. 3: Different routes of an IEV charged by an MCS or an FCS.

The charging expense of v_i paid to ψ_j is expressed as:

$$Exps(v_i, \psi_j, \widetilde{p}) = r(v_i, \psi_j, \widetilde{p}) \cdot \triangle e(v_i, \psi_j) + r_d \cdot \left|p(\psi_j)^{(t)} - \widetilde{p}\right|, \tag{2}$$

where $r(v_i, \psi_j, \widetilde{p})$ denotes the charging price that v_i bids for ψ_j (the charging position is $\widetilde{p}$), and thus $r(v_i, \psi_j, \widetilde{p}) \cdot \triangle e(v_i, \psi_j)$ denotes the expense for electricity transfers. $r_d \cdot \left|p(\psi_j)^{(t)} - \widetilde{p}\right|$ denotes the dispatching expense for ψ_j travelling to $\widetilde{p}$. Besides, the charging park (charging position) is selected by minimizing the charging expense of v_i.

Thus, the charging profit of ψ_j by charging v_i can be calculated by:

$$Pf(v_i, \psi_j, \widetilde{p}) = \{r(v_i, \psi_j, \widetilde{p}) - r_0\} \cdot \triangle e(v_i, \psi_j), \tag{3}$$

where r_0 denotes the price of electricity purchased by MCSs and FCSs from power grid.

Case B. If v_i decides to be charged by an FCS φ_k at the t-th time slot, then v_i moves towards φ_k for the future charging (Fig. 3). Likewise, the extra travel undertaken by v_i is expressed as:

$$E_m(v_i, \varphi_k) = \left|p(v_i)^{(t)} - p(\varphi_k)\right| + |p(\varphi_k) - d_i| - \left|p(v_i)^{(t)} - d_i\right|. \tag{4}$$

The amount of electricity transferred from φ_k to v_i is obtained by: $\triangle e(v_i, \varphi_k) = c \cdot \{|s_i - d_i| + E_m(v_i, \varphi_k)\} - e(v_i)^{(0)}$.

Similarly, $Exps(v_i, \varphi_k)$ and $Pf(v_i, \varphi_k)$ are expressed as: $Exps(v_i, \varphi_k) = r_f \cdot \triangle e(v_i, \varphi_k)$, and $Pf(v_i, \varphi_k) = (r_f - r_0) \cdot \triangle e(v_i, \varphi_k)$, where r_f denotes the price of electricity transferred from FCSs to IEVs.

B. Objective Functions

In IoEV with FCSs and MCSs, due to the low cost of MCSs, our problem objective is to enhance the charging efficiency of MCSs as much as possible. Recall that the enhancement of the charging efficiency of MCSs can be measured by the charging profits of MCSs and the charging expenses of IEVs, and the problem objective is formally presented as follows:

$$\begin{cases} \max \ \sum_{\psi_j \in \mathcal{M}} Profit(\psi_j), \\ \min \ \sum_{v_i \in \mathcal{E}} \ Expense(v_i), \end{cases} \tag{5}$$

where $Profit(\psi_j)$ denotes the total charging profits earned by MCS ψ_j, and $Expense(v_i)$ denotes the charging expense of IEV v_i paid to an MCS or an FCS.

Typically, the number of MCSs in IoEV is small, and multiple IEVs could compete for the same MCSs. To enhance the charging efficiency of MCSs, the mobile charging services provided by MCSs should be appropriately assigned to IEVs, implying that it is very vital for IEVs to compete for MCSs through rationally bidding the charging price to MCSs.

IV. Bayesian Game based Bidding Scheme for Mobile Charging enabled Electric Vehicles

A. Stages of BBS-MCEV

In this section, we first provide the flowchart of BBS-MCEV in Fig. 4. Fig. 4 illustrates that BBS-MCEV is comprised of five stages: RCP Calculation, Request Making, Bidding, Decision Making, and Updating. Even though BBS-MCEV consists of five stages, the Bayesian game process occurs only in ***Stage*** C, which is a static game of incomplete information.

To streamline the coordination of the bidding of IEVs, the time synchronization is required to control the start and the end of each time slot among IEVs, idle MCSs, FCSs, and cloud server. The time synchronization can be realized by some existing time synchronization methods for vehicular networks (e.g., GNSS-based time synchronization [31], ABTS [32]).

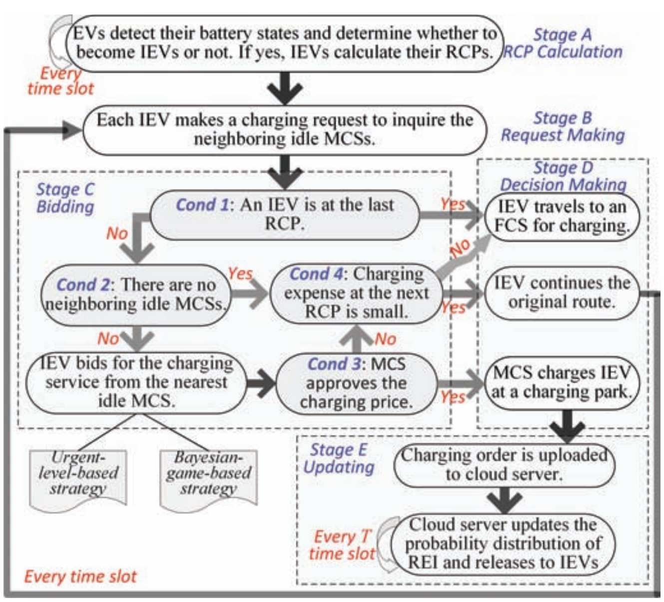

Fig. 4: Flowchart of BBS-MCEV.

Stage A. *RCP Calculation: IEVs calculate route-changing positions*. At the start of each time slot (suppose the t-th time slot), for each EV v_i, if v_i detects a low battery state (e.g., $SOC(v_i)^{(t)} \le \gamma$), v_i should judge whether the residual electricity can support the future travel by the following inequality: $e(v_i)^{(t)} \ge c \cdot \left|p(v_i)^{(t)} - d_i\right|$. If the residual electricity of v_i cannot support the future travel, then v_i turns into an IEV.

When there are no MCSs nearby, each IEV could select one of the neighboring FCSs to charge itself. An example is given in Fig. 5, where there are three FCSs (φ_1, φ_2, and φ_3) around an IEV v_i, the original route of v_i to the destination d_i is marked in blue, and three routes for the charging services of φ_1, φ_2, and φ_3 are marked in red.

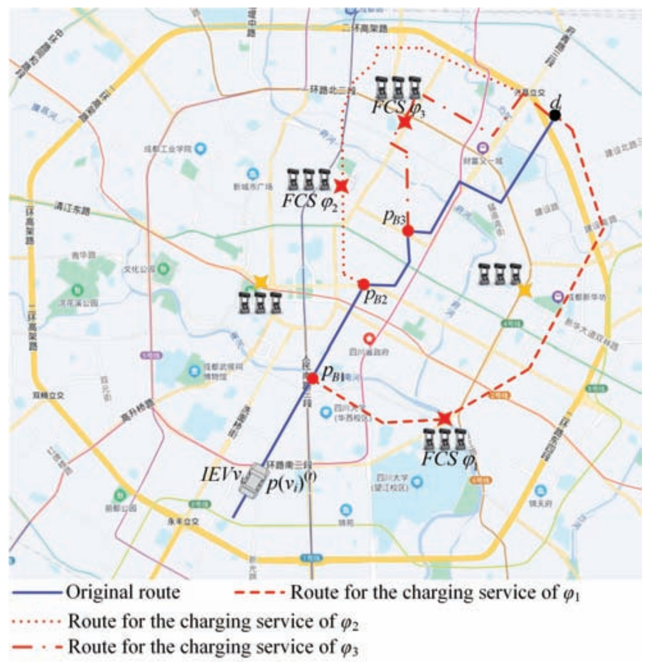

Fig. 5: Routes for the charging services of FCSs.

Specifically, each route to an FCS is with the shortest extra travel, and the route-changing positions (RCPs) for FCSs φ_1, φ_2, and φ_3 are denoted by p_{B1}, p_{B2}, and p_{B3}, respectively. For example, the RCP p_{B1} should be selected from $route\left(p(v_i)^{(t)}, d_i\right)$ (i.e., $p_{B1} \in route\left(p(v_i)^{(t)}, d_i\right)$). p_{B1} and the corresponding FCS φ_1 are obtained by the following formula:

$$\begin{aligned} &\arg \min_{\widetilde{p} \in route\left(p(v_i)^{(t)}, d_i\right)} \left\{ |\widetilde{p} - p(\varphi_k)| + |p(\varphi_k) - d_i| \right\}, \\ &\qquad s.t. \quad c \cdot \left|p(v_i)^{(t)} - p(\varphi_k)\right| \le e(v_i)^{(t)}, \end{aligned} \tag{6}$$

where $c \cdot \left|p(v_i)^{(t)} - p(\varphi_k)\right| \le e(v_i)^{(t)}$ indicates that the residual electricity of v_i should sustain the travel to FCS $p(\varphi_k)$.

Likewise, p_{B2} and p_{B3} are then selected from $route\left(p_{B1}, d_i\right)$ and $route\left(p_{B2}, d_i\right)$, respectively.

Stage B. *Request Making: IEVs make charging requests to MCSs*. Each IEV v_i makes a charging request by broadcasting a $request\_msg$ message (including the current position of v_i). After receiving the $request\_msg$ from v_i, each neighboring idle MCS sends a $reply\_msg$

message (including the current position of the MCS) to v_i.

Stage C. *Bidding: IEVs bid for idle MCSs*. For each IEV v_i, if it has received at least one $reply\_msg$ and it is not at the last RCP, then it bids for the mobile charging service from the nearest idle MCS (suppose ψ_j). The MCP is calculated by v_i and sent to ψ_j, and then ψ_j sends back the average of all MCPs received from IEVs.

Based on the probability distribution of REI and the average MCP, v_i can calculate the OCP and send bid to ψ_j. The details of the two bidding strategies are provided in Section IV.B.

Stage D. *Decision Making: IEVs make charging decisions*. When each IEV v_i has arrived at the current RCP $p_{_{Bk}}$, v_i makes a charging decision according to the following three cases:

- If the charging price bid by v_i is approved by ψ_j (ψ_j accepts the charging request of v_i), an $approve\_msg$ message is sent to inform v_i of the acceptance. Then, v_i and ψ_j travel towards the selected charging park for charging.
- If $p_{_{Bk}}$ is the last RCP of v_i, then v_i travels to FCS φ_k for charging.
- If the charging price bid by v_i is not approved by ψ_j, and $p_{_{Bk}}$ is not the last RCP of v_i, then v_i decides to travel towards FCS φ_k for charging or continue the original route (travel towards the next RCP $p_{_{Bk+1}}$) by the inequality (7):

$$Exps(v_i, \varphi_{k+1}) < \frac{Exps(v_i, \varphi_k)}{\alpha + (1-\alpha) \cdot \frac{U(v_i)^{(t)}}{K}}, \tag{7}$$

  where α is a preset parameter. When (7) is satisfied, v_i travels towards the next RCP $p_{_{Bk+1}}$; Otherwise, v_i travels towards FCS φ_k.

In (7), $U(v_i)^{(t)}$ denotes the urgent level of v_i at the t-th time slot. The charging urgency of an IEV is measured by state of charge (SOC) and is divided into K levels. For an IEV v_i, if $SOC(v_i)^{(t)}$ falls into the interval $\left(\frac{K-\kappa}{K} \cdot \gamma, \frac{K-\kappa+1}{K} \cdot \gamma\right)$, then $U(v_i)^{(t)} = \kappa$.

Stage E. *Updating: Cloud server updates probability distribution of REI*. After charging v_i, ψ_j uploads the charging order to the cloud server. Every T time slots, the cloud server updates the probability distribution of REI and releases to IEVs.

B. Bidding Strategies of IEVs

The bidding strategies of IEVs can be designed from two viewpoints: (i) The charging urgency of an IEV indicates how urgently the IEV should be charged, and an IEV with a higher urgent level is prone to bid a higher charging price; (ii) The competitions for MCSs compel IEVs to rationally bid their charging price, and a Bayesian game model can properly formulate the competitions and make IEVs rationally bid their charging price. To this end, two bidding strategies are given as follows.

Strategy A: *Urgent-level-based strategy*. Suppose the approaching RCP of v_i is $p_{_{Bk}}$ (the corresponding FCS is φ_k), and the nearest idle MCS is ψ_j. Then, the MCP of v_i is calculated by:

$$r_{max}(v_i, \psi_j, \widetilde{p}) = \frac{Exps(v_i, \varphi_k) - r_d \cdot \left| p(\psi_j)^{(t)} - \widetilde{p} \right|}{\triangle e(v_i, \psi_j)}. \tag{8}$$

Note that the charging price bid by an IEV will not be larger than the MCP, which tallies with one of the objective functions (the minimization of charging expenses of IEVs). In (8), $\widetilde{p}$ denotes the position of the charging park which is selected by minimizing the charging expense of v_i:

$$\begin{aligned} \widetilde{p} = \arg\min_{\widehat{p} \in \mathcal{P}} \; & Exps(v_i, \psi_j, \widehat{p}), \\ s.t. \quad & c \cdot \left| p(v_i)^{(t)} - \widehat{p} \right| \le e(v_i)^{(t)}. \end{aligned} \tag{9}$$

Then, the OCP of v_i is determined by the urgent level:

$$r(v_i, \psi_j, \widetilde{p}) = r_{_0} + \{ r_{max}(v_i, \psi_j, \widetilde{p}) - r_{_0} \} \cdot \frac{U(v_i)^{(t)}}{K}, \tag{10}$$

which indicates the basic thought the urgent-level-based strategy. The urgent-level-based strategy is specially tailored to reflect the charging inclination of drivers. As the residual electricity of an IEV decreases, the urgent level increases, also promoting a rise in the bidding price that the IEV is willing to offer.

Strategy B: *Bayesian-game-based strategy*. Multiple IEVs could compete for the mobile charging service from an MCS, and only one IEV can be served by the MCS, implying that the charging price of only one IEV (providing the largest charging profit) can be approved by the MCS. Naturally, the issue of competitions among IEVs arises, and thus a Bayesian-game-based strategy is proposed for the bidding of IEVs. Firstly, the sequence chart of the Bayesian-game-based strategy is depicted in Fig. 6. Note that an IEV participating in a bidding game requires some communications among IEVs, idle MCSs, FCSs, and cloud server. These steps can be completed in a time slot. When an IEV urgently requires the charging, and if it does not encounter any available MCSs, or the broken communication links impede the IEV from participating in the bidding game, it will opt to be charged by a nearest FCS upon reaching the last RCP. This mechanism ensures that the IEV can be successfully charged in the worst case.

Suppose there are n IEVs competing for MCS ψ_j. The Bayesian game is represented by a five-tuple $< \mathcal{N}, \theta, \mathcal{A}, \Omega, \mathcal{F}(\cdot,\cdot) >$, where

- $\mathcal{N}$ denotes the set of bidders, and $\mathcal{N} = \{v_1, \cdots, v_i, \cdots, v_n\}$;
- $\theta = \{\theta_1, \cdots, \theta_i, \cdots, \theta_n\}$, where θ_i denotes the type of the bidder v_i;
- $\mathcal{A} = \{\mathcal{A}_1, \cdots, \mathcal{A}_i, \cdots, \mathcal{A}_n\}$, where $\mathcal{A}_i$ denotes the action set of the bidder v_i;
- $\Omega = \{\Omega_1, \cdots, \Omega_i, \cdots, \Omega_n\}$, where Ω_i denotes the belief of the bidder v_i with respect to the uncertainty over the other bidders' types;

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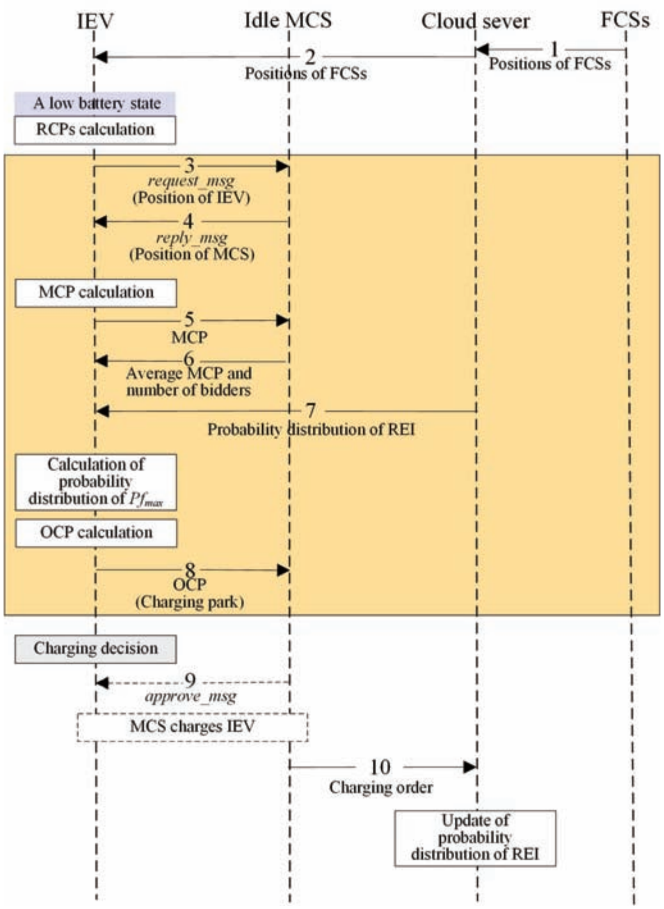


Fig. 6: Sequence chart of Bayesian-game-based strategy.

- $\mathcal{F}(\cdot,\cdot)$ denotes the expected utility function.

With regard to an idle MCS, it typically approves the IEV which can provide the largest charging profit and the charging profit is determined by two factors: the amount of electricity transferred to the IEV, and the charging price bid by the IEV.

The type of the bidder v_i is represented by the maximum charging profit of MCS ψ_j by charging v_i at $\widetilde{p}$, i.e., $\theta_i = Pf_{max}(v_i,\psi_j,\widetilde{p}) = \{r_{max}(v_i,\psi_j,\widetilde{p}) - r_0\} \cdot \triangle e(v_i,\psi_j)$.

The action set is defined as the potential charging profit, e.g., $\mathcal{A}_i = \{Pf(v_i,\psi_j,\widetilde{p}) : 0 \le Pf(v_i,\psi_j,\widetilde{p}) \le Pf_{max}(v_i,\psi_j,\widetilde{p})\}$.

Ω_i is expressed by a probability distribution function for inferring other bidders' types (a probability distribution function of the maximum charging profits of MCSs), i.e., $\Omega_i = Pro(\theta_{-i}|\theta_i)$, where $\theta_{-i} = (\theta_1,\cdots,\theta_{i-1},\theta_{i+1},\cdots,\theta_n)$. This probability distribution function can be derived by the probability distribution function of REI and the average of MCPs of all bidders.

Recall that the amount of required electricity of an IEV v_i is written as: $\triangle e(v_i,\psi_j) = c\cdot\{|s_i - d_i| + E_m(v_i,\psi_j,\widetilde{p})\} - e(v_i)^{(0)}$. We can obtain the probability distribution of REI from the historical charging orders of MCSs. Generally, the probability distribution of daily travel distance of EVs is of lognormal type, with zero probability of occurrence of all negative distances [33].

To simplify the description, we take dis, e_0, and $\triangle e$ to denote the travel distance, initial battery electricity, and required electricity, respectively. The probability density function of dis is expressed as:

$$f(dis) = \frac{1}{dis\cdot\sqrt{2\pi}\cdot\delta_1}\cdot\exp\left\{-\frac{(\ln dis-\mu_1)^2}{2\delta_1^2}\right\}, \quad (11)$$

where μ_1 and δ_1 denote the mean and the standard deviation of $\ln dis$, respectively. Suppose the initial battery electricity of EVs (typically related to the battery state of health of EVs) obeys a Gaussian distribution $N(\mu_2,\delta_2^2)$ [34], where Gaussian process regression is introduced and verified for forecasting the battery state of health. Then, the probability density function of the initial battery electricity is expressed as:

$$f(e_0) = \frac{1}{\sqrt{2\pi}\cdot\delta_2}\cdot\exp\left\{-\frac{(e_0-\mu_2)^2}{2\delta_2^2}\right\}. \quad (12)$$

Typically, γ (the preset low battery state) is small, and the extra travel undertaken by an IEV is very short due to the restriction of residual electricity. Thus, we can obtain Lemma 1.

Lemma 1: The probability density function of $\triangle e$ is approximatively written as: $f(\triangle e) = \int_0^{+\infty}\frac{\exp\left\{-\frac{(\ln x-\mu_1-\ln c)^2}{2\delta_1^2}-\frac{(\triangle e-x+\mu_2)^2}{2\delta_2^2}\right\}}{2\pi\cdot\delta_1\cdot\delta_2\cdot x}\mathrm{d}x$.

Proof: Let $c\cdot dis = x$, $-e_0 = y$, and $\triangle e = z$, which yields that:

$$\begin{cases} \ln x \sim N(\mu_1+\ln c,\delta_1^2), \\ y \sim N(-\mu_2,\delta_2^2). \end{cases}$$

We have that:

$$\begin{cases} f_X(x) = \frac{1}{x\cdot\sqrt{2\pi}\cdot\delta_1}\cdot\exp\left\{-\frac{(\ln x-\mu_1-\ln c)^2}{2\delta_1^2}\right\}, \\ f_Y(y) = \frac{1}{\sqrt{2\pi}\cdot\delta_2}\cdot\exp\left\{-\frac{(y+\mu_2)^2}{2\delta_2^2}\right\}. \end{cases}$$

Approximatively, $z = x + y$. Besides, x and y are independent of each other, and we can obtain that:

$$f_Z(z) = \int_{-\infty}^{+\infty} f_X(x)\cdot f_Y(z-x)\mathrm{d}x \equiv f_X * f_Y,$$

which can be further rewritten as:

$$\begin{aligned} f_Z(z) &= \int_0^{+\infty}\frac{\exp\left\{-\frac{(\ln x-\mu_1-\ln c)^2}{2\delta_1^2}\right\}}{x\cdot\sqrt{2\pi}\cdot\delta_1}\cdot\frac{\exp\left\{-\frac{(z-x+\mu_2)^2}{2\delta_2^2}\right\}}{\sqrt{2\pi}\cdot\delta_2}\mathrm{d}x \\ &= \int_0^{+\infty}\frac{\exp\left\{-\frac{(\ln x-\mu_1-\ln c)^2}{2\delta_1^2}-\frac{(z-x+\mu_2)^2}{2\delta_2^2}\right\}}{2\pi\cdot\delta_1\cdot\delta_2\cdot x}\mathrm{d}x. \quad \square \end{aligned}$$

The plot shape of $f(\triangle e)$ is exhibited by Fig. 7.

The cumulative distribution function regarding the maximum charging profits of MCSs (belief function) can be expressed as:

$$F(Pf_{max}) = \int_0^{\frac{Pf_{max}}{r_{max}-r_0}} f(\triangle e)\mathrm{d}\triangle e, \quad (13)$$

where r_{max} denotes the average of the MCPs of all IEVs.

If the charging profit of ψ_j earned by charging v_i is larger than that by charging other IEVs, v_i can win the mobile charging service of ψ_j, and then the utility of v_i is written

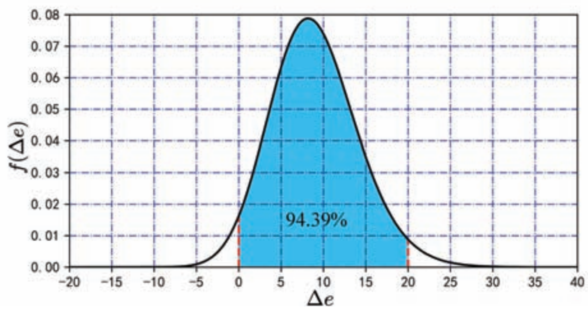


Fig. 7: Probability density function of $\triangle e$ ($\mu_1 = 2.8$, $\delta_1 = 0.2$, $\mu_2 = 12$, $\delta_2 = 3$, and $c = 1.25$).

as $Exps(v_i, \varphi_k) - Exps(v_i, \psi_j, \widetilde{p})$; Otherwise, the utility of v_i is equal to 0. Therefore, the utility of v_i is expressed as:

$$B(v_i) = \begin{cases} 0, \text{if } Pf(v_i, \psi_j, \widetilde{p}) < \max_{v_i' \in \mathcal{N}, i' \neq i} Pf(v_i', \psi_j, \widetilde{p}'), \\ Exps(v_i, \varphi_k) - Exps(v_i, \psi_j, \widetilde{p}), \text{ otherwise,} \end{cases} \tag{14}$$

where

$$\begin{aligned} &Exps(v_i, \varphi_k) - Exps(v_i, \psi_j, \widetilde{p}) \\ &\quad = \begin{array}{l} \{r_{max}(v_i, \psi_j, \widetilde{p}) - r_0\} \cdot \triangle e(v_i, \psi_j) \\ - \{r(v_i, \psi_j, \widetilde{p}) - r_0\} \cdot \triangle e(v_i, \psi_j) \end{array} \\ &\quad = Pf_{max}(v_i, \psi_j, \widetilde{p}) - Pf(v_i, \psi_j, \widetilde{p}). \end{aligned} \tag{15}$$

Then, the expected utility function of v_i is written as:

$$\begin{aligned} \mathcal{F}(\theta_i, a_i) = &\{Pf_{max}(v_i, \psi_j, \widetilde{p}) - Pf(v_i, \psi_j, \widetilde{p})\} \\ &\cdot Pro\left(Pf(v_i, \psi_j, \widetilde{p}) > \max_{v_{i'} \in \mathcal{N}, i' \neq i} Pf(v_{i'}, \psi_j, \widetilde{p}')\right), \end{aligned} \tag{16}$$

where $Pro\left(Pf(v_i, \psi_j, \widetilde{p}) > \max_{v_{i'} \in \mathcal{N}, i' \neq i} Pf(v_{i'}, \psi_j, \widetilde{p}')\right)$ denotes the probability of $Pf(v_i, \psi_j, \widetilde{p}) > \max_{v_{i'} \in \mathcal{N}, i' \neq i} Pf(v_{i'}, \psi_j, \widetilde{p}')$, and the detailed expression will be given in Section V.

Based on the above analysis, the optimal action of an IEV v_i is determined by the following strategy function:

$$a(\theta_i) = \frac{\int_0^{\theta_i} x \cdot G'(x) \mathrm{d}x}{G(\theta_i)}, \tag{17}$$

where $G'(x)$ is the first order derivative of $G(x)$, and $G(\theta_i) = F(\theta_i)^{n-1}$, where n denotes the number of competitors. To reduce the computational efficiency of (17), we find the optimal action (charging price) by traversing the discrete values falling into the value interval $[r_0, r_{max}]$ (with the step size of 0.01).

Accordingly, the OCP of v_i bidding for ψ_j is calculated by $\frac{a(\theta_i)}{\triangle e(v_i, \psi_j)} + r_0$. By this strategy function, a symmetric pure strategy Nash equilibrium can be achieved, as proven by Proposition 2.

An example of BBS-MCEV is provided in Fig. 8, where an EV v_i starts its travel from the departure position to the destination. At the t-th time slot, v_i detects a low battery state and turns into an IEV. During each time slot, the local time of v_i is synchronized, and v_i calculates the RCPs. After the t-th time slot, in each of the following time slots, v_i has the option to either make a charging request to nearby idle MCSs or travel to the nearest FCS. If v_i makes a charging request to an idle MCS ψ_j, then it engages in a Bayesian game. If v_i becomes the winner of the Bayesian game, then it proceeds to the selected charging park for charging; Otherwise, the aforementioned steps will be repeated in the following time slots. When v_i reaches the last RCP without receiving any charging approvals from idle MCSs, it travels to the last FCS for charging. This situation could arise due to the previous bidding failures in the Bayesian game, the absence of idle MCSs, or the broken communication links.

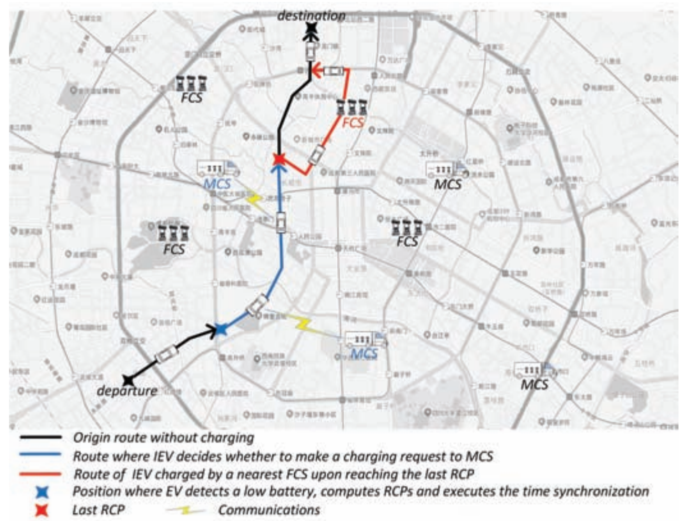


Fig. 8: An example of BBS-MCEV.

V. Theoretical Analysis of BBS-MCEV

A. Complexity of BBS-MCEV

Suppose the numbers of IEVs, MCSs, and FCSs are denoted by N, M, and F, respectively.

In *Stage B*, each IEV broadcasts a $request\_msg$ message to neighboring idle MCSs. After receiving the $request\_msg$ message, each neighboring idle MCS sends back a $reply\_msg$ message, which implies that the number of message exchanges is $\mathrm{O}(M \cdot N)$ in the worst case. In *Stage C*, each IEV would bid for an idle MCS, and the number of message exchanges is at most $\mathrm{O}(N)$. In *Stage D*, the number of $approve\_msg$ messages is up to $\mathrm{O}(M)$. In *Stage E*, an MCS would upload the charging order after charging an IEV, and the cloud server would release the updated probability distribution of REI to IEVs, which results in $\mathrm{O}(M + N)$ communications. Thus, the communication complexity of BBS-MCEV is of $\mathrm{O}(M \cdot N)$.

With regard to the computational complexity, in *Stage A*, each IEV calculates their RCPs, and an IEV has at most F RCPs, therefore the amount of computations in *Stage A* is $\mathrm{O}(F \cdot N)$. In *Stage C*, IEVs bid for idle MCSs, and each IEV would calculate MCP and OCP; hence, the computational complexity of *Stage C* is $\mathrm{O}(N)$. In *Stage D*, IEVs make charging decisions, and each IEV would decide whether to travel towards an FCS for the future charging, and the worst computational complexity is up to $\mathrm{O}(F \cdot N)$. Likewise, the charging orders regarding IEVs would be uploaded to the cloud server for updating the probability distribution of REI, and the computational complexity of $Stage\ E$ is $\mathrm{O}(N)$. Therefore, the computational complexity of BBS-MCEV is of $\mathrm{O}(F \cdot N)$.

B. Some Properties of Bayesian Game Model in BBS-MCEV

Proposition 1 proves that the strategy function provided in (17) enables each bidder to adopt the optimal action.

Proposition 1: The strategy function $a(\theta_i) = \frac{\int_0^{\theta_i} x \cdot G'(x)\mathrm{d}x}{G(\theta_i)}$ enables each bidder to adopt the optimal action.

Proof: For a bidder v_i, when $\theta_i > 0$, the strategy function $a(\theta_i)$ is incremental and differentiable [35] (which is proven by Lemma 2), and there exists an inverse function $a^{-1}(\cdot)$. Let $a_{i'} = a(\theta_{i'})$, we can obtain that:

$$\begin{aligned} Pro\left(a_i > \max_{v_{i'} \in \mathcal{N}, i' \neq i} a_{i'}\right) &= Pro\left(a_i > a\left(\max_{v_{i'} \in \mathcal{N}, i' \neq i} \theta_{i'}\right)\right) \\ &= Pro\left(a^{-1}(a_i) > \max_{v_{i'} \in \mathcal{N}, i' \neq i} \theta_{i'}\right). \end{aligned} \tag{18}$$

For any $v_{i'}$ ($v_{i'} \in \mathcal{N}$), the bidder v_i considers that the type of the bidder $v_{i'}$ obeys the probability distribution function $F(\theta_{i'})$. Therefore, we have that:

$$\begin{aligned} Pro\left(a_i > \max_{v_{i'} \in \mathcal{N}, i' \neq i} a_{i'}\right) &= \prod_{v_{i'} \in \mathcal{N}, i' \neq i} Pro\left(a^{-1}(a_i) > \theta_{i'}\right) \\ &= F(a^{-1}(a_i))^{n-1}. \end{aligned} \tag{19}$$

Let $F(a^{-1}(a_i))^{n-1} = G(a^{-1}(a_i))$ and $G'(a^{-1}(a_i)) = g(a^{-1}(a_i))$, we have that:

$$\mathcal{F}(\theta_i, a_i) = (\theta_i - a_i) \cdot G(a^{-1}(a_i)). \tag{20}$$

The optimal action can be obtained when the first order derivative of $\mathcal{F}(\theta_i, a_i)$ with respect to a_i is equal to 0 ($\frac{\partial \mathcal{F}(\theta_i, a_i)}{\partial a_i} = 0$), i.e.,

$$\frac{g(a^{-1}(a_i)) \cdot (\theta_i - a_i)}{a'(a^{-1}(a_i))} - G(a^{-1}(a_i)) = 0, \tag{21}$$

where $G(a^{-1}(a_i)) = G(\theta_i)$, and thus we obtain that $a(\theta_i) = \frac{\int_0^{\theta_i} x \cdot g(x)\mathrm{d}x}{G(\theta_i)}$. □

Lemma 2: The strategy function $a(\theta_i)$ is incremental and differentiable.

Proof: Evidently, we have that:

$$a'(\theta_i) = \frac{\theta_i \cdot g(\theta_i) \cdot G(\theta_i) - g(\theta_i) \cdot \int_0^{\theta_i} x \cdot g(x)\mathrm{d}x}{G(\theta_i)^2}, \tag{22}$$

which indicates that $a(\theta_i)$ is differentiable.

We let $Q(\theta_i) = \theta_i \cdot G(\theta_i) - \int_0^{\theta_i} x \cdot g(x)\mathrm{d}x$, and then we have:

$$\begin{cases} Q(0) = 0, \\ Q'(\theta_i) = G(\theta_i) > 0, \text{where } \theta_i > 0, \end{cases} \tag{23}$$

which implies that there is $Q(\theta_i) > Q(0)$ when $\theta_i > 0$, and thus $a'(\theta_i) > 0$, i.e., $a(\theta_i)$ is incremental. □

Moreover, the convergence of the proposed Bayesian game model in BBS-MCEV is proven by Proposition 2.

Proposition 2: A symmetric pure strategy Nash equilibrium can be achieved by the Bayesian game model.

Proof: Suppose the action of the bidder v_i (with the type θ_i) is $\widetilde{a}_i$ rather than the optimal action a_i, and there is $a(\widetilde{\theta}_i) = \widetilde{a}_i$. Then, the expected utility of v_i is expressed as:

$$\begin{aligned} \mathcal{F}(\theta_i, \widetilde{a}_i) &= \mathcal{F}(\theta_i, a(\widetilde{\theta}_i)) = Pro\left(\widetilde{a}_i > \max_{v_{i'} \in \mathcal{N}, i' \neq i} a_{i'}\right) \cdot (\theta_i - \widetilde{a}_i) \\ &= G(\widetilde{\theta}_i) \cdot \left\{\theta_i - a(\widetilde{\theta}_i)\right\} = G(\widetilde{\theta}_i) \cdot \theta_i - \int_0^{\widetilde{\theta}_i} x \cdot g(x)\mathrm{d}x \\ &= G(\widetilde{\theta}_i) \cdot \theta_i - \left\{G(\widetilde{\theta}_i) \cdot \widetilde{\theta}_i - \int_0^{\widetilde{\theta}_i} G(x)\mathrm{d}x\right\}. \end{aligned} \tag{24}$$

When the bidder v_i adopts the action a_i, the expected utility of v_i is $\mathcal{F}(\theta_i, a_i) = \int_0^{\theta_i} G(x)\mathrm{d}x$. Hence,

$$\mathcal{F}(\theta_i, a_i) - \mathcal{F}(\theta_i, \widetilde{a}_i) = \int_{\widetilde{\theta}_i}^{\theta_i} G(x)\mathrm{d}x - G(\widetilde{\theta}_i) \cdot (\theta_i - \widetilde{\theta}_i). \tag{25}$$

Besides, $G(x)$ is monotonically incremental and satisfies the following equation set:

$$\begin{cases} G(0) = 0, \\ \lim_{x \to +\infty} G(x) = \beta \quad (0 < \beta < 1). \end{cases} \tag{26}$$

The value of $\{\mathcal{F}(\theta_i, a_i) - \mathcal{F}(\theta_i, \widetilde{a}_i)\}$ is illustrated in Fig. 9, and the following two cases are discussed:

- When $\theta_i > \widetilde{\theta}_i$, $\mathcal{F}(\theta_i, a_i) - \mathcal{F}(\theta_i, \widetilde{a}_i) = \int_{\widetilde{\theta}_i}^{\theta_i} G(x)\mathrm{d}x - G(\widetilde{\theta}_i) \cdot (\theta_i - \widetilde{\theta}_i) > 0$;
- When $\theta_i < \widetilde{\theta}_i$, $\mathcal{F}(\theta_i, a_i) - \mathcal{F}(\theta_i, \widetilde{a}_i) = G(\widetilde{\theta}_i) \cdot (\widetilde{\theta}_i - \theta_i) - \int_{\theta_i}^{\widetilde{\theta}_i} G(x)\mathrm{d}x > 0$. Therefore, when $\theta_i \neq \widetilde{\theta}_i$, we have $\mathcal{F}(\theta_i, a_i) > \mathcal{F}(\theta_i, \widetilde{a}_i)$, indicating that a symmetric pure strategy Nash equilibrium can be achieved by the proposed Bayesian game model. □

Corollary 1: $a(\theta_i)$ is the conditional expectation of the variable $\max_{v_{i'} \in \mathcal{N}, i' \neq i} \theta_{i'}$.

Proof: According to Lemma 2, for any two bidders v_i and $v_{i'}$, if $\theta_i > \theta_{i'}$, then we have $a(\theta_i) > a(\theta_{i'})$, which implies that the charging price of v_i is approved by ψ_j more preferentially than that of $v_{i'}$.

$G(\theta_i)$ denotes the probability distribution function of $\max_{v_{i'} \in \mathcal{N}, i' \neq i} \theta_{i'}$, and the conditional expectation of $\max_{v_{i'} \in \mathcal{N}, i' \neq i} \theta_{i'}$ with respect to $\max_{v_{i'} \in \mathcal{N}, i' \neq i} \theta_{i'} < \theta_i$ is expressed as:

$$\mathbb{E}\left\{\max_{v_{i'} \in \mathcal{N}, i' \neq i} \theta_{i'} \,\middle|\, \max_{v_{i'} \in \mathcal{N}, i' \neq i} \theta_{i'} < \theta_i\right\} = \frac{\int_0^{\theta_i} x \cdot g(x)\mathrm{d}x}{G(\theta_i)}, \tag{27}$$

which yields that:

$$a(\theta_i) = \mathbb{E}\left\{\max_{v_{i'} \in \mathcal{N}, i' \neq i} \theta_{i'} \,\middle|\, \max_{v_{i'} \in \mathcal{N}, i' \neq i} \theta_{i'} < \theta_i\right\}, \tag{28}$$

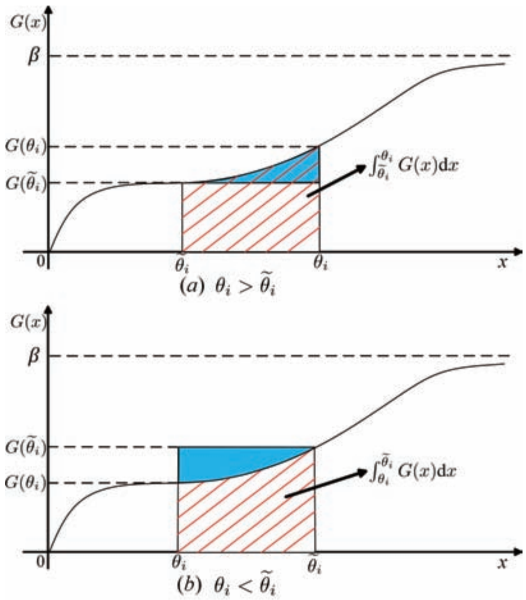


Fig. 9: Value of $\{\mathcal{F}(\theta_i, a_i) - \mathcal{F}(\theta_i, \widetilde{a}_i)\}$.

and $a(\theta_i)$ denotes the conditional expectation of the variable $\max_{v_{i'} \in \mathcal{N}, i' \neq i} \theta_{i'}$ whose value falls into the interval $[0, \theta_i]$. □

Note that the conclusion of Corollary 1 can validate the rationality of our proposed Bayesian game model.

VI. Performance Evaluations

In this section, we provide comprehensive performance evaluations of our proposed BBS-MCEV, along with comparisons with other strategies. The simulations are conducted on a real dataset comprised of taxis' trajectories [36] in Chengdu city, China. In this dataset, there are about 10,000 taxis, and their trajectories were produced during the period from Oct. 1, 2018 to Oct. 31, 2018. Each trajectory point is represented by a set of time stamp, latitude, longitude, and taxi ID. The total number of trajectory points in the dataset is about 11 million.

The trajectories of N taxis are randomly selected to simulate the movements of N IEVs. Besides, F FCSs and P charging parks are randomly deployed in the map, and the deployment of FCSs and charging parks in Qingyang district is shown in Fig. 10.

We develop a simulator using Python language, and the simulation results are averaged over 500 runs. The main parameter settings are given in TABLE II. Note that the charging speed of MCSs can reach that of FCSs by equipping DCFCs (Direct Current Fast Chargers) [37].

A. Number of IEVs and Impact of Number of Charging Interfaces

We first observe the variation of the number of IEVs among 3,000 EVs, and the number of IEVs is mainly affected by the parameters μ_r, δ_r, and c.

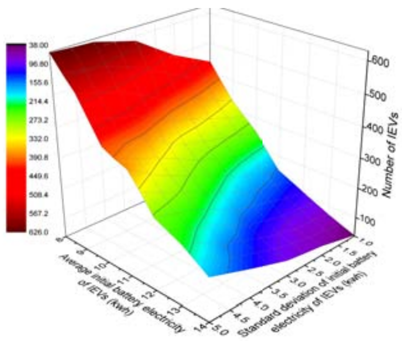
Fig. 10: Delpoyment of FCSs and charging parks in Qingyang district, Chengdu city.

TABLE II: Simulation parameters

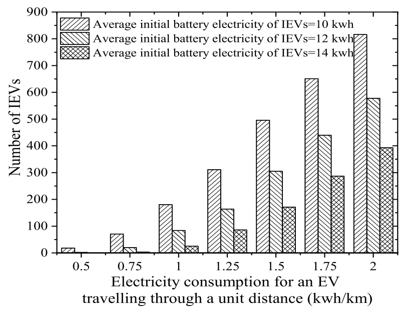
Parameter	Description	Value
N	Number of IEVs	400
M	Number of MCSs	30
F	Number of FCSs	30
P	Number of charging parks	50
t_s	Length of each time slot	60 s
m_s	Travel speed of each EV and each MCS	8.33 m/s
c	Electricity consumption for an EV travelling through a unit distance	1.25 kwh/km
r_d	Dispatching price of an MCS per kilometer	1.5
r_f	Price of electricity transferred from FCSs to EVs	3
r_0	Price of electricity purchased by MCSs and FCSs from power grid	1.5
ν	Charging speed of each MCS and each FCS	50 kw
μ_r	Average initial battery electricity of EVs	12 kwh
δ_r	Standard deviation of initial battery electricity of EVs	3 kwh
γ	Low battery state for an IEV making a charging request	5 kwh
α	A preset parameter in (7)	0.8
K	Number of urgent levels	10

Fig. 11(a) illustrates the impacts of μ_r and δ_r on the number of IEVs. The number of IEVs decreases as μ_r grows. This is because μ_r denotes the average initial battery electricity of EVs, and thus a larger μ_r implies that more EVs have enough electricity to complete their travels. Likewise, the growth of δ_r leads to an augment in the number of IEVs. In Fig. 11(b), the impact of c on the number of IEVs is observed. When μ_r and δ_r are fixed, the number of IEVs increases with the growth of c. The reason for this phenomenon is that the amount of electricity required by EVs to support their travels increases as c grows.

Fig. 12(b) indicates that the average charging expense of IEVs is reduced when each MCS (and FCS) has more charging interfaces. However, in Fig. 12(a), the total charging profits of MCSs are first increased and then decreased with the increase of the number of charging interfaces, and the reasons are as follows: When the number of charging interfaces is few, the charging profits of MCSs are increased

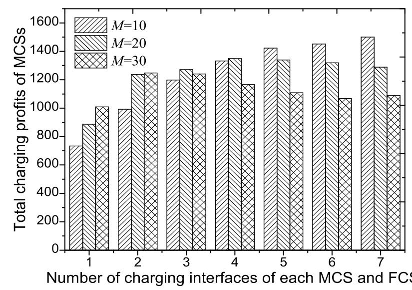


(a) Number of IEVs vs. μ_r and δ_r

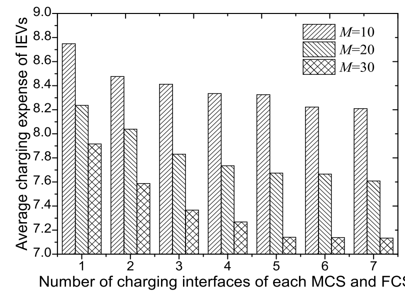


(b) Number of IEVs vs. μ_r and c

Fig. 11: Number of IEVs.



(a) Total charging profits of MCSs vs. number of charging interfaces



(b) Average charging expense of IEVs vs. number of charging interfaces

Fig. 12: Impact of number of charging interfaces.

with the increase of the number of charging interfaces because more IEVs can be charged; When the number of charging interfaces is large, the charging profits of MCSs are slightly decreased with the increase of the number of charging interfaces, because the extra travel distance of IEVs is shortened.

B. Average Charging Expense of IEVs

In Fig. 13(a), the average charging expense of IEVs increases with the increase of IEVs' number, due to the following two reasons: (i) With the increase of IEVs' number, more IEVs are charged by FCSs rather than MCSs, which increases the charging expenses of IEVs. (ii) When more IEVs compete for idle MCSs, IEVs could raise their charging price. Besides, the average charging expense of IEVs decreases when there are more MCSs deployed on the road network, since more IEVs can reduce their charging expenses through obtaining the mobile charging services from MCSs.

Fig. 13(b) shows that the curve with a larger P (the number of charging parks) is lower than that with a smaller P, because better charging positions shortening the extra travels of IEVs can be selected when there are more available charging parks. Likewise, the average charging expense of IEVs decreases with the growth of F (the number of FCSs), and the reason is that the charging expenses of IEVs can be reduced by providing more charging facilities (more FCSs or MCSs).

As shown in Fig. 13(c), the average charging expense cuts down gradually with the increase of μ_r, because less electricity is required by IEVs when they have more initial battery electricity. Besides, the average expense of IEVs is decreased with the increase of γ, due to the fact that IEVs make charging requests earlier when γ becomes larger, and hence IEVs are easier to be charged by MCSs, because there could be more RCPs on the uncompleted routes, and IEVs have more chances to be charged by MCSs.

Moreover, Fig. 13(d) illustrates the impacts of α and K on the average charging expense of IEVs. Two observations are obtained: (i) The average charging expense of IEVs decreases slightly with the increase of α. α reflects the willingness of IEVs to travel towards the next RCPs. With a smaller α, IEVs are prone to travel towards the next RCPs where FCSs could require higher charging expenses. (ii) The number of urgent levels does not have an obvious effect on the average charging expense of IEVs, indicating that the charging price of IEVs is almost independent of the number of urgent levels when K is not very small.

C. Charging Profits of MCSs and FCSs

The charging efficiency of MCSs and FCSs can be reflected by their charging profits, and this simulation observes the charging profits of MCSs and FCSs.

As depicted in Fig. 14, both the total charging profits of MCSs and the total charging profits of FCSs are reduced with the increase of M or F, which is attributed to the fact that a larger M or a larger F indicates that IEVs are easier to be charged by the charging facilities (MCSs or FCSs). Thus, the extra travel distance of IEVs is shortened

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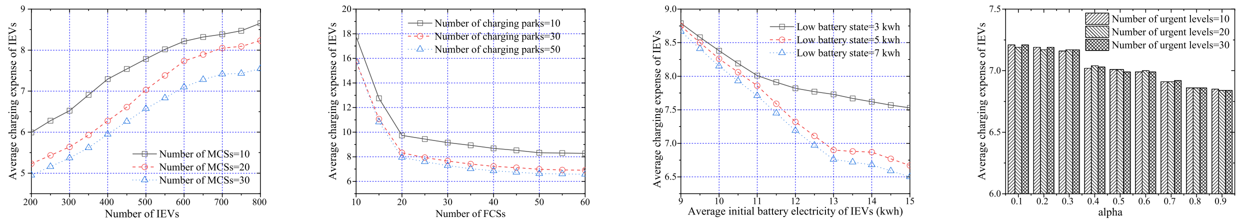
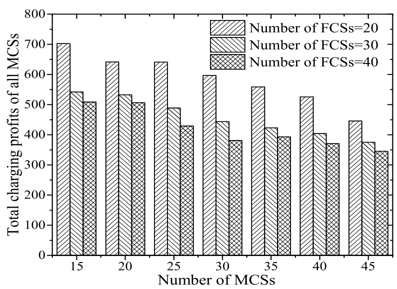


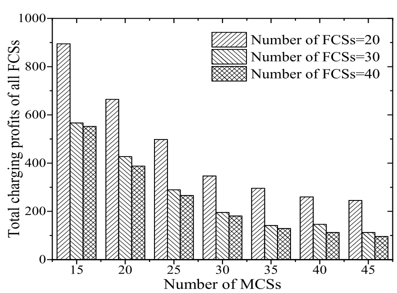
(a) Average charging expense of IEVs vs. N and M (b) Average charging expense of IEVs vs. F and P (c) Average charging expense of IEVs vs. μ_r and γ (d) Average charging expense of IEVs vs. α and K

Fig. 13: Average charging expense of IEVs.

(Fig. 16), which accordingly reduces the amount of electricity required by IEVs (REI) and the total charging profits of these charging facilities.



(a) Total charging profits of MCSs vs. M and F

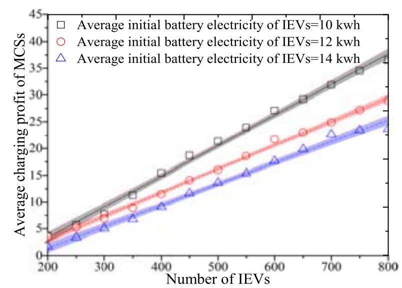


(b) Total charging profits of FCSs vs. M and F

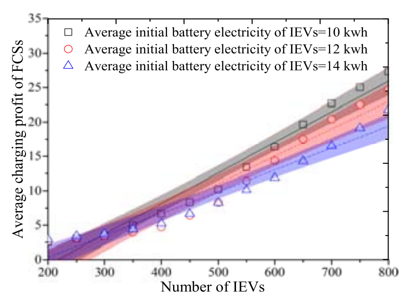
Fig. 14: Total charging profits of MCSs and FCSs.

In Fig. 15(a), the average charging profit of MCSs increases with the increase of N or the decrease of μ_r. A larger N implies that there are more IEVs, and MCSs can accept the charging requests of IEVs which provide larger charging profits. Besides, REI is raised with the decrease of μ_r, and thus more charging profits could be earned by MCSs.

Likewise, the average charging profit of FCSs increases with the increase of N (Fig. 15(b)). However, the curve with a smaller μ_r is lower than that with a larger one when $N < 400$, and the reason is that when IEVs are sparsely deployed on the road network, the IEVs with more initial battery electricity are inclined to move towards the later RCPs and are more likely to be charged by FCSs. When N is large enough, the curve with a smaller μ_r is higher than that with a larger one, and the gap between the curves is gradually enlarged with the continuous increase of N.



(a) Average charging profit of MCSs vs. N and μ_r



(b) Average charging profit of FCSs vs. N and μ_r

Fig. 15: Average charging profits of MCSs and FCSs.

D. Extra Travel Distance and Extra Travel Delay of IEVs

The results regarding the average extra travel distance of IEVs are provided in Fig. 16. The average extra travel distance of IEVs is shortened with the increase of M or F, since more charging facilities can charge IEVs more timely once IEVs make charging requests.

With regard to an IEV v_i, if v_i is charged by an MCS ψ_j at the charging position $\widetilde{p}$, then the extra travel delay of

v_i is calculated by:

$$\begin{aligned} &Delay(v_i,\psi_j,\widetilde{p}) = \frac{E_m(v_i,\psi_j,\widetilde{p})}{m_s(v_i)} + t_w(v_i,\psi_j,\widetilde{p}) \\ &= \frac{E_m(v_i,\psi_j,\widetilde{p})}{m_s(v_i)} + \begin{cases} 0, & \text{if } \frac{|p(v_i)^{(t)}-\widetilde{p}|}{m_s(v_i)} \geq \frac{|p(\psi_j)^{(t)}-\widetilde{p}|}{m_s(\psi_j)}, \\ \frac{|p(\psi_j)^{(t)}-\widetilde{p}|}{m_s(\psi_j)} - \frac{|p(v_i)^{(t)}-\widetilde{p}|}{m_s(v_i)}, & \text{otherwise,} \end{cases} \end{aligned} \tag{29}$$

which indicates that the extra travel delay of v_i includes two parts: (i) The delay consumed for the extra travel of v_i; (ii) The delay of IEV waiting for MCS ψ_j (v_i arrives at the charging position $\widetilde{p}$ before ψ_j).

If v_i is charged by an FCS φ_k, then the extra travel delay of v_i is expressed as:

$$\begin{aligned} &Delay(v_i,\varphi_k) = \\ &\frac{E_m(v_i,\varphi_k)}{m_s(v_i)} + \begin{cases} 0, & \text{if } t_q(\varphi_k)^{(t)} \leq \frac{|p(v_i)^{(t)}-p(\varphi_k)|}{m_s(v_i)}, \\ t_q(\varphi_k)^{(t)} - \frac{|p(v_i)^{(t)}-p(\varphi_k)|}{m_s(v_i)}, & \text{otherwise.} \end{cases} \end{aligned} \tag{30}$$

Fig. 17(a) shows that the average extra travel delay of IEVs is reduced with the increase of M or F. Besides, when MCSs and FCSs can charge IEVs more rapidly, or MCSs and IEVs move faster, the average extra travel delay of IEVs is reduced as well (Fig. 17(b)).

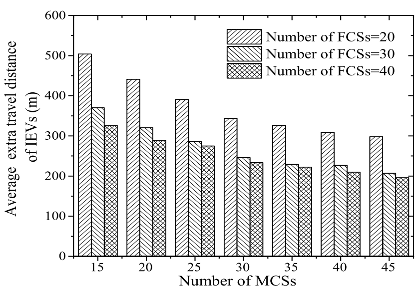
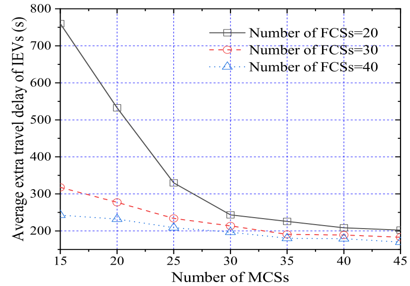
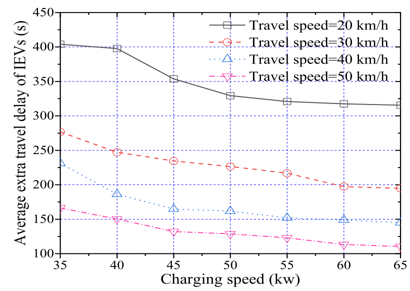


Fig. 16: Average extra travel distance of IEVs.



(a) Average extra travel delay vs. M and K



(b) Average extra travel delay vs. ν and m_s

Fig. 17: Average extra travel delay of IEVs.

E. Comparisons among Different Strategies

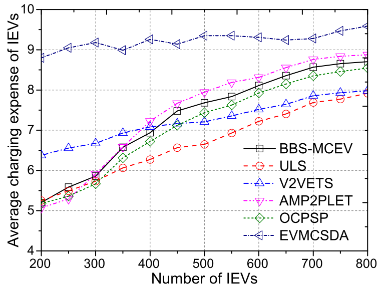
To further verify the merits of BBS-MCEV, we compare BBS-MCEV with other related strategies, such as ULS (Urgent-Level-based Strategy, as introduced in Section IV.B), V2VETS (Vehicle-to-Vehicle Electricity Trading Scheme [22]), AMP2PLET (Auction Mechanism for P2P Local Energy Trading [27]), OCPSP (Online Continuous PSP-based auction scheme [26]), and EVMCSDA [16]. The methods of V2VETS, AMP2PLET, OCPSP, and EVMCSDA have been introduced in Section II. These strategies are compared in terms of the average charging expense of IEVs, average charging profit of MCSs, charging loss, average extra travel distance of IEVs, and average extra travel delay of IEVs. These simulation results are given in Fig. 18.

In Fig. 18(a), the average charging expense of our proposed BBS-MCEV is larger than those of ULS and V2VETS, due to the fact that ULS does not consider the selfishness of EVs and MCSs, and V2VETS does not consider the competitions among IEVs, and thereby the charging price of IEVs is not affected by the number of competitors. Besides, the average charging expense of BBS-MCEV is slightly larger than that of OCPSP. Although BBS-MCEV cannot achieve the best results in terms of the average charging expense, it outperforms other strategies especially in terms of the average charging profit of MCSs (Fig. 18(b)), the proportion of IEVs charged by MCSs (Fig. 18(c)), and the charging loss (Fig. 18(d)). The average charging expense of EVMCSDA is the largest among these strategies, because EVMCSDA provides a dispatch algorithm to facilitate the MCS requests from fully occupied FCSs or from IEVs outside FCSs, i.e., MCSs are only taken as the emergent charging solution when FCSs are busy or unavailable.

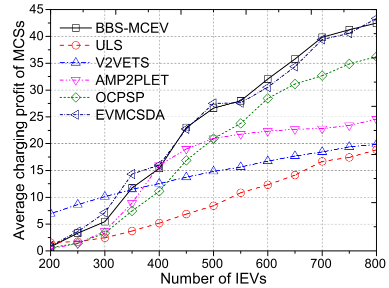
Fig. 18(b) indicates that the average charging profit obtained by BBS-MCEV is much larger than others when the number of IEVs is large enough ($N > 400$), because in BBS-MCEV IEVs rationally bid for the mobile charging services from MCSs, and MCSs accept the charging requests with the largest charging profits.

Moreover, as shown in Fig. 18(c), the proportion of IEVs charged by MCSs of BBS-MCEV is larger than others, which demonstrates that the bidding mechanism adopted in BBS-MCEV can differentiate the situations of IEVs and make more IEVs be charged by MCSs, and these results also verify that IEVs can bid their charging price rationally.

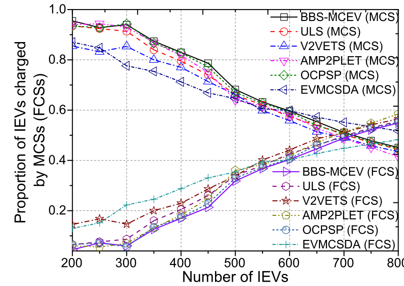
Specially, to measure the tradeoff between the charging profits of MCSs and the charging expenses of IEVs, we



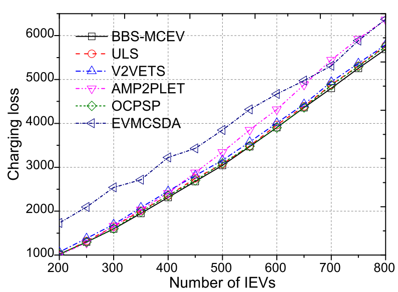
(a) Average charging expense of IEVs



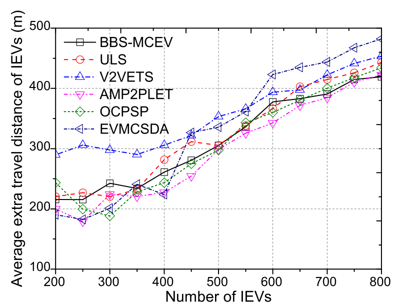
(b) Average charging profit of MCSs



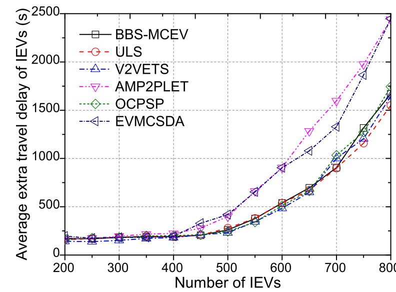
(c) Proportion of IEVs charged by MCSs (FCSs)



(d) Charging loss



(e) Average extra travel distance of IEVs



(f) Average extra travel delay of IEVs

Fig. 18: Comparisons among different strategies.

introduce a new index termed charging loss, which is calculated as: $\sum_{v_i \in \mathcal{E}} Expense(v_i) - \sum_{\psi_j \in \mathcal{M}} Profit(\psi_j)$. Naturally, the charging loss should be minimized as much as possible. Fig. 18(d) indicates that BBS-MCEV achieves a preferable tradeoff between the charging profits of MCSs and the charging expenses of IEVs. The reason is that BBS-MCEV attempts to enhance the charging efficiency of MCSs by the competitions among IEVs, and the charging price of IEVs is determined by jointly considering the residual electricity of IEVs, the deployment of FCSs, the positions of MCSs, and the competitions of nearby IEVs. Besides, in Fig. 18(e) and Fig. 18(f), the curves of different strategies are close to each other.

VII. Conclusion

We have studied the bidding problem of IEVs in the IoEV, and a Bayesian game based Bidding Scheme for Mobile Charging enabled Electric Vehicles (BBS-MCEV) has been proposed. In BBS-MCEV, each IEV first calculates the maximum charging price according to the potential expense if charged by nearby FCSs, and then the optimal charging price is decided by a Bayesian game model. Besides, each idle MCS accepts the charging request with the largest charging profit. The Bayesian game model adopted in BBS-MCEV has been proven to quickly converge to a pure-strategy equilibrium. BBS-MCEV increases the charging profits of MCSs and reduces the charging expenses of IEVs effectively, and it can achieve a proper tradeoff between the charging profits of MCSs and the charging expenses of IEVs. BBS-MCEV is suitable for the practical charging scenarios where MCSs and IEVs are selfish, and IEVs should rationally bid for the mobile charging services with incomplete information about other IEVs.

In real charging scenarios, the route schedule of IEVs is vital for enhancing the charging efficiency of MCSs, e.g., the over-competitions for local mobile charging services can be avoided by carefully scheduling the routes of IEVs. In addition, the battery capacity of MCSs is also limited, and some MCSs could be temporarily offline due to the lack of electricity. These MCSs should be recharged by the power grid, therefore the charging price bid by IEVs should be related to the residual electricity of MCSs. Moreover, the delay caused by the road conditions (e.g., traffic jams) should be counted into the extra travel delay of IEVs. In the situation that each MCS has multiple charging interfaces, the bidding mechanism in our proposed BBS-MCEV should take into account the assignment rescheduling of MCSs.

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Author Biography

Linfeng Liu received the B. S. and Ph. D. degrees in computer science from the Southeast University, Nanjing, China, in 2003 and 2008, respectively. At present, he is a Professor in the School of Computer Science and Technology, Nanjing University of Posts and Telecommunications, China. His main research interests include the areas of vehicular ad hoc networks, wireless sensor networks and multi-hop mobile wireless networks. He has published more than 80 peer-reviewed papers in some technical journals or conference proceedings, such as IEEE TMC, IEEE TPDS, IEEE TIFS, IEEE TITS, IEEE TVT, IEEE TSC, ACM TAAS, ACM TOIT, Computer Networks, Elsevier JPDC. He has served as the TPC member of Globecom, ICONIP, VTC, WCSP.

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Zhipeng Zhang received the B. S. degree in computer science from the Nanjing University of Posts and Telecommunications in 2021. At present, he is a master student of Nanjing University of Posts and Telecommunications. His current research interest includes the areas of Internet of electric vehicles and vehicular ad-hoc networks.

Jia Xu received the Ph. D. Degree in School of Computer Science and Engineering from Nanjing University of Science and Technology, Jiangsu, China, in 2010. He is currently a professor in Jiangsu Key Laboratory of Big Data Security and Intelligent Processing at Nanjing University of Posts and Telecommunications. His main research interests include crowdsourcing, edge computing and wireless sensor networks. Prof. Xu has served as the PC Co-Chair of SciSec 2019, Organizing Chair of ISKE 2017, TPC member of Globecom, ICC, MASS, ICNC, EDGE, and has served as the Publicity Co-Chair of SciSec 2021.

Ping Wang received her Bachelor and Master degrees from Huazhong University of Science and Technology, in 1994 and 1997, respectively, and her PhD degree from the University of Waterloo, Canada, in 2008, all in electrical and computer engineering. She joined York University as an Associate Professor in August 2018. Prior to that, she worked with Nanyang Technological University, Singapore, from 2008 to July 2018. Her research interests are mainly in wireless communication networks, cloud computing and the Internet of Things. Her scholarly works have been widely disseminated through top-ranked IEEE journals/conferences and received the Best Paper Awards from IEEE Wireless Communications and Networking Conference (WCNC) in 2012 and 2020, from IEEE Communication Society: Green Communications & Computing Technical Committee in 2018, and from IEEE International Conference on Communications (ICC) in 2007. She is a Fellow of the IEEE and a Distinguished Lecturer of the IEEE Vehicular Technology Society.