Matching Theory based Travel Plan Aware Charging Algorithms in V2G Smart Grid Networks

Ming Zeng*, Supeng Leng*, Jianhua He†, Yan Zhang‡ and Guanhua Qiao*

* University of Electronic Science and Technology of China, China

†Aston University, UK

‡Simula Research Laboratory, Norway

Corresponding author email: spleng@uestc.edu.cn

***Abstract*—The frequency, time and places of charging have large impact on the Quality of Experience (QoE) of EV drivers. It is critical to design effective EV charging scheduling system to improve the QoE of EV drivers. In order to improve EV charging QoE and utilization of CSs, we develop an innovative travel plan aware charging scheduling scheme for moving EVs to be charged at Charging Stations (CS). In the design of the proposed charging scheduling scheme for moving EVs, the travel routes of EVs and the utility of CSs are taken into consideration. The assignment of EVs to CSs is modeled as a two-sided many-to-one matching game with the objective of maximizing the system utility which reflects the satisfactory degrees of EVs and the profits of CSs. A Stable Matching Algorithm (SMA) is proposed to seek stable matching between charging EVs and CSs. Furthermore, an improved Learning based On-LiNe scheduling Algorithm (LONA) is proposed to be executed by each CS in a distributed manner. The performance gain of the average system utility by the SMA is up to 38.2% comparing to the Random Charging Scheduling (RCS) algorithm, and 4.67% comparing to Only utility of Electric Vehicle Concerned (OEVC) scheme. The effectiveness of the proposed SMA and LONA is also demonstrated by simulations in terms of the satisfactory ratio of charging EVs and the the convergence speed of iteration.**

***Index Terms*—vehicle-to-grid; traveling plan aware; stable matching; on-line scheduling**

I. Introduction

Vehicle-to-Grid (V2G) system, as a component of smart grid, holds large potentials to reduce the peak-to-average ratio of the electric grid load and balance the electricity supply and the demand through coordinated Electric Vehicle (EV) charging and EV electricity feedback. However, driving range and charging of EVs are key concerns when people choose either EV or gasoline cars. The short driving range of EVs, long charging time and shortage of Charging Stations (CSs) are among the major reasons that put people off EVs. How to effectively improve the Quality of Experience (QoE) of EV drivers (such as by deploying more CSs and improve CS utilization) is one of the big challenges faced by the V2G industry.

Extensive works have been reported on coordinated EV charging in V2G system, attempting to optimize the Peak-to-Average Ratio (PAR) of the electric grid load and minimize the cost of EV users. In [1], a novel two-stage EV charging mechanism is designed to reduce the energy cost and PAR of the power grid with highly fluctuant renewable energy as a significant portion of the power resources. Reference [2] proposes an Integer Linear Programming (ILP) based optimization technique to minimize the peak hourly load by scheduling household appliances and a sizable number of EV vehicles connected to the grid. Microgrid is utilized to be a promising component in the future smart grid to balance the demand and supply in the work [3]. In [4], a predictive control based method is developed to design a dynamic charging and mode switching strategy to optimize the driving cost of all-electric mode and gasoline-only mode EVs. Reference [5] proposed a stochastic dynamic programming based method to reduce average charging costs of EVs. Reference [6] studies an intelligent energy management approach for a solar powered EV charging station with energy storage to reduce impacts of the EV charging system on utility grids in terms of peak power demand and energy exchange, reduce grid system losses, and benefit the charging station owner through the time-of-use rate plans. Reference [7] changes the charging time of each EV to minimize the fluctuation of the total load curve. In [8], a novel hierarchical charge control framework based on the Benders decomposition is proposed for large populations of EVs to minimize the grid operation cost and improve the unit operating efficiency. Reference [9] proposes a distributed EV coordination mechanism which utilizes the flexibility of EV demand the electricity feedback capability to minimize the load variance of the power grid. Reference [10] surveys the incentive-based energy trading mechanism in the smart grid, and proposes a contract-based electricity trading scheme.

However, the reported scheduling algorightms are not EV centric and they require network-level coordination. The mobility and QoE of EV users has been ignored in the design of the charging scheduling algorithms. In this paper, we propose a travel plan aware EV charging scheduling scheme for moving EVs charging at CSs. In the travel plan aware EV charging scheduling scheme, we not only consider the benefits of CS as a part of the optimization objective, but also treat the QoE of EV charging with high importance. We incorporate EV travel plans into the charging scheduling scheme, so that EVs can be properly assigned to the CSs located along their travel routes. Due to extra time and electricity consumption, EV users do not need to make detours to charge which brings inconvenience and extra costs. The optimization problem for EV charging scheduling at CSs is formulated under the matching theory and a Stable Matching

Algorithm (SMA) with low complexity algorithm is developed to solve the problem. Moreover, a Learning-based On-liNe charging scheduling Algorithm (LONA) is proposed to further reduce the iteration number of algorithm execution in a real time scheduling scenario. Extensive simulations demonstrate the effectiveness of the proposed SMA and LONA in terms of improving QoE of EV drivers and maximizing the system utility. Iteration numbers of algorithm execution with SMA and LONA are also discussed.

The main contributions of this paper are

- The travel plan aware EV charging scheduling problem is formulated as a many-to-one matching model with two-sided preference following the matching theory framework.
- A stable matching algorithm is developed to solve the problem with tractable complexity, and a learning based on-line scheduling algorithm is designed to reduce iteration number of algorithm execution in a real time scheduling scenario.

The remainder of this paper is organized as follows. In Section II, we present the system model. Terminologies in matching theory and the proposed SMA and LONA are introduced in Section III. Simulation results are presented and discussed in Section IV. Finally, Section V concludes the paper.

II. System Model

Shortage of CSs and excessively long charging service time are among the major complains of EV drivers. It is expected that there will be more CSs distributed ubiquitously in the cities but with limited capacity. The CSs can only provide a limited number of charging outlets for simultaneous EV charging, i.e., the number of in-charging EVs at one CS at any given time cannot exceed the number of charging outlets of the CS. To improve the user charging experience, assignment of charging opportunities at the CSs should exploit the EV travel routes and preferences. The idea can be illustrated by an example shown in Fig. 1. With a given travel plan for EV 1, it will prefer to use CS 1, 2 and 4, while CSs 3 and 4 are desirable for EV 2.

In this section, we will first describe the system model, then present the SMA, which determines the charging stations with the consideration of travel plans and preferred CSs of EVs. The aim of charging scheduling problem in mobile scenario is to maximize the total utility of CSs and EVs, and meanwhile improve the satisfaction ratio of charging EVs. Based on the SMA, a stable assignment to CSs to EV charging can be obtained.

There are N CSs in total in an given investigated urban area in a set of CSs denoted by $\mathcal{N}$. Each CS is labeled by index $i, i \in \{1, 2, ..., N\}$ and has K_i charging outlets for EV charging. The charging rate of each outlet is assumed to be the same and fixed. There are M EVs making charging requests from a set of EVs denoted by $\mathcal{M}$, traveling through the investigated area. The EVs are indexed by variable $j, j \in \{1, 2, ..., M\}$. We assume that the battery capacity of EV is limited, and the

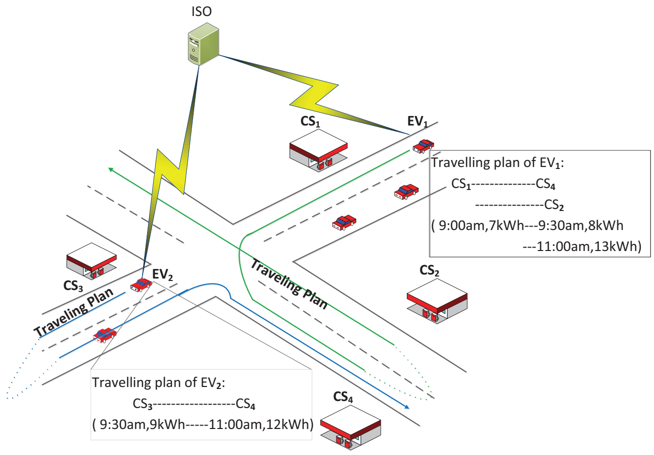

Fig. 1: Traveling plan-aware charging scheduling in the mobile scenario

maximum amount of electricity requested by an EV (say j) is denoted by Q_j^{max}. For tractability, the unit price of electricity purchased at each CS is assumed to be the same. Given the preference and constraints of the charging EVs, we need to find a optimal CS allocation scheme, such that requirement of each EV can be satisfied.

The main idea of the travel plan aware scheduling scheme is to assign requesting EVs to CSs close to their travel routes and within the driving distance using the remaining State Of Charge (SOC) of EV batteries. In addition, the EV drivers should specify their preferred latest charging start time t_j according to their travel plan. The amount of electricity that an CS can offer will affect the QoE of EV charging . An EV may run into the risk that the amount of electricity supply from the assigned CS assigned to the EV is insufficient. It then may run out of electricity before reaching the next available CS and need to charge more often unnecessarily.

We assume Ω to be a $N \times M$ allocation matrix with element $a_{ij} = \{0, 1\}$, where $i \in \{1, 2, ..., N\}$ and $j \in \{1, 2, ..., M\}$. An element $a_{ij} = 1$ means the jth EV is assigned to the ith CS and otherwise $a_{ij} = 0$. One charging EV is assigned to one and only one CS, while CS i can service at most K_i EVs simultaneously. Thus, we have two constraints, i.e.,

$$\sum_{i=1}^{N} a_{ij} \leq 1 \tag{1}$$

$$\sum_{j=1}^{M} a_{ij} \leq K_i \tag{2}$$

To quantify the QoE of EV charging, in this paper we propose to use a simple utility function. Let $UE_{i,j}$ denote the utility for EV j to charge at CS i, $j \in \mathcal{M}$ and $i \in \mathcal{N}$, which is computed by:

$$UE_{i,j} = Q_j^i - d_j^i * R_j - C(t_j^i) \tag{3}$$

where Q_j^i is the amount of electricity CS i can sell to EV j,

d_j^i is the distance of EV j to and back from CS i away from the EV's travel route, R_j is the electricity consumption rate of EV j, and t_j^i represents the arriving time of EV j at CS i. It can be observed that the utility $UE_{i,j}$ higher if CS i could offer more electricity, and CS i is not far away from EV j travel route. $C(.)$ function is a step function representing the cost due to delay. It is probable that charging EV j will arrive at CS j later than its expected time t_j due to road congestion or other factors. If t_j^i is later than t_j, $C(t_j^i) = C$ where C is a constant, otherwise $C(t_j^i) = 0$. It is reasonable to assume that charging EVs are Incentive Rational (IR), if $UE_{i,j}$ is negative, EV j will not charge at the CS i, which gives the following constraints,

$$a_{ij}UE_{i,j} > 0, \forall i \in \mathcal{N}, j \in \mathcal{M} \tag{4}$$

$$Q_j^i \leq Q_j^{max}, \forall i \in \mathcal{N}, j \in \mathcal{M} \tag{5}$$

Let $UC_{i,j}$ denote the utility for CS i to offer charging opportunity to EV j, $j \in \mathcal{M}$ and $i \in \mathcal{N}$, which is computed by

$$UC_{i,j} = pQ_j^i \tag{6}$$

where p is the unit price of electricity that CS i charges EV j. Since the unit price of electricity charged by CSs to each EV is the same, to achieve higher utility, CS i prefers to be allocated to EVs demanding for more electricity. Thus,

$$UC_{i,j} > UC_{i,j'}, for\ Q_j^i > Q_{j'}^i \tag{7}$$

Following the above notations, we set the objective of the system to maximize the utilities of both charging EVs and CSs, with a configurable parameter β as a weight to adjust the impact of charing EVs and CSs, i.e.,

$$\max_{a_{ij}} \sum_{i\in\mathcal{N}}\sum_{j\in\mathcal{M}} a_{ij}UE_{i,j} + \beta \sum_{j\in\mathcal{M}}\sum_{i\in\mathcal{N}} a_{ij}UC_{i,j} \tag{8}$$

Thus, the optimization problem for the EV charging scheduling problem is formulated as

$$\max_{a_{ij}} \sum_{i\in\mathcal{N}}\sum_{j\in\mathcal{M}} a_{ij}UE_{i,j} + \beta \sum_{j\in\mathcal{M}}\sum_{i\in\mathcal{N}} a_{ij}UC_{i,j} \tag{9}$$

$$s.t. \sum_{i=1}^{N} a_{ij} \leq 1, \sum_{j=1}^{M} a_{ij} \leq K_i, a_{ij} = \{0,1\} \tag{10}$$

$$Q_j^i \leq Q_j^{max}, \forall i \in \mathcal{N}, j \in \mathcal{M} \tag{11}$$

$$a_{ij}UE_{i,j} > 0, \forall i \in \mathcal{N}, j \in \mathcal{M} \tag{12}$$

It can be found that the computational complexity of the optimization problem expressed by Equations (9)-(12) increase exponentially with the numbers of CSs and charging EVs. In the next section, we model the optimization problem as a many-to-one matching problem in matching theory [11] and develop computational efficient algorithms to solve the scheduling problem .

III. Travel Plan Aware Charging Scheduling Schemes

In this section, the travel plan aware scheduling problem for EV charging is modeled as a many-to-one matching game. We first introduce the basic terminology in matching theory, then describe the proposed Stable Matching Algorithm (SMA). Last but not least, a Learning based On-Line Algorithm (LONA) applied in on-line scenario is proposed to further reduce the iteration number of algorithm execution.

A. Basic Terminologies in Matching Theory

Definition 1: Matching

A many-to-one *matching* Φ in the instance of EV charging scheduling is an assignment such that

- each EV is assigned to at most one CS in Ω, i.e., $\Phi(EV_j) \in \mathcal{N} \bigcup \{\varnothing\}$, and $|\Phi(EV_j)| = \{0,1\}$,
- each CS is assigned to at most K_i EVs in Ω, i.e., $\Phi(CS_i) \in \mathcal{M} \bigcup \{\varnothing\}$, and $|\Phi(CS_i)| = \{0,1,...,K_i\}$, where $\Phi(EV_j)$ denotes the CS that is assigned to EV j, and $\Phi(CS_i)$ denotes the set of EVs that ares assigned to CS i.

Definition 2: Preference List

Each EV $j \in \mathcal{M}$ ranks a subset of CSs in $\mathcal{N}$ in strict descending order according to the utility function defined in Equation (3) giving rise to its *preference list* $\mathbf{PL}_j$.

Definition 3: Stable Matching

A matching Φ is *stable* if and only if there are no two EVs j and j', $\forall j, j' \in \mathcal{M}$ that $\Phi(j)_j \prec \Phi(j')$ and $\Phi(j')_{j'} \prec \Phi(j)$ [8], where $\Phi(j)_j \prec \Phi(j')$ means EV j prefers CS assigned to EV j' to its assignment $\Phi(j)$, and so does EV j'.

B. Stable Matching Algorithm (SMA)

Gale and Shapely have proposed the well-known acceptance deferring algorithm in [9] to solve the two-sided one-to-one matching problem with tractable complexity. The classic algorithm is extended to the many-to-one matching problem for moving EV to charged at CSs and we propose the SMA to find the stable matching between charging EVs and CSs with consideration of travel plans of EVs. The matching process is illustrated in Algorithm 1 and explained as follows.

First, each EV calculates the utilities it can achieve with charging at each CS in the set $\mathcal{M}$. Then, the CSs with positive utilities for the EVs are included in the corresponding *preference lists* (shown as $\mathbf{PList}$ in Algorithm 1) of EVs in descending orders. Each EV first proposes to its favorite CS in the preference list. After receiving proposals from all EVs, each CS checks if the number of proposals exceeds the number of its available interfaces. If CS i does not receive excessive charging requests, it will accept all, and cache the tentatively accepted charging requests of this iteration into the *in-suspend list of CS i* (shown as $\mathbf{SupList_i}$ in Algorithm 1), which is initially empty. Otherwise, CS i will choose K_i EVs which request most amounts of electricity and cache them, and reject the others. EV $j, j \in \mathcal{M}$ add the CS rejecting its charging request to the Reject List (shown as $\mathbf{RejList_j}$ in Algorithm 1), which is initially empty.

Algorithm 1 SMA: Stable Matching Algorithm for travel plan aware EV charging scheduling problem

Initialization:

Q_j^i; d_i^j; R_j; t_j^i; C; K_i; $\mathbf{RejList}_j = \varnothing$; $\mathbf{SupList}_i = \varnothing$

$Construct$ $\mathbf{PList}_j$ $according\ to\ Equation$ (3);
for all $EV_j, j \in \mathcal{M} \setminus \bigcup_{i=1}^{N} \mathbf{SupList}_i$ **do**
  $\mathbf{PROPOSE}_i = \varnothing$;
  $Propose\ to\ the\ favorite\ CS\ i \in \mathbf{PList}_j \setminus \mathbf{RejList}_j$;
  $Update$ $\mathbf{PROPOSE}_i$;
  if $length(\mathbf{PROPOSE}_i) + length(\mathbf{SupList}_i) < K_i$ **then**
    $\mathbf{SupList}_i = \mathbf{SupList}_i \bigcup \mathbf{PROPOSE}_i$;
  else
    $\mathbf{SupList}_i = \mathbf{K_i^{most}} \subset (\mathbf{SupList}_i \bigcup \mathbf{PROPOSE}_i)$;
    $Reject\ others$;
    $Update$ $\mathbf{RejList}_j$;
  end if
  if $\bigcup_{i=1}^{N} \mathbf{SupList}_i == \mathcal{M} || \mathbf{RejList}_j == \mathbf{PList}_j, \forall j \in \mathcal{M} \setminus \bigcup_{i=1}^{N} \mathbf{SupList}_i$ **then**
    break;
  else
    continue;
  end if
end for

Output:

$\mathbf{SupList}_i, \forall i \in \mathcal{N}$

In the next iteration, EVs which have been rejected propose to the highest ranked CSs in their preference list which are not requested in the previous rounds of assignment. Then the requested CSs check again whether the total number of new coming proposals and EVs in-suspense exceed the number of available interfaces. Similar actions are taken to choose EVs to update the $\mathbf{SupList_i}$ of each CS. The iterations go on until all the charging EVs are in the in-suspense lists of all CSs or EVs which are not suspended by any CSs have been rejected by all CSs in their preference lists. The detailed matching process is illustrated in Algorithm 1.

C. Learning based On-liNe Algorithm (LONA)

As shown in Algorithm 1, the proposed SMA assumes in each iteration the charging requests from different EVs proposed to the same CS are received at the same time, which can be true if there are intensive charging requests and the intervals between the arrival time of two charging requests can be negligible, otherwise EVs have to wait until other charging requests proposed to the same CS arrive. In addition, CSs will inform EVs immediately if their charging requests are rejected in each iteration, but the acceptance of EV charging requests will be published until the whole algorithm terminates. Although the SMA has tractable complexity, the charging demand response delay for a specific EV could be long due to the low arrival rate of charging requests and iteration times of the algorithm, which decreases the QoE of the EV. Thus, the proposed SMA is more suitable for conducting off-line. In this subsection, we propose a Learning based On-liNe charging scheduling Algorithm (LONA) which can be executed by each CS in distributed manner. The main idea of the proposed LONA is that through learning from previous received charging requests, each CS decides whether the amount of electricity demanded by the arriving charging request is large enough to maximize its utility. Acceptance or rejection of one charging request is decided immediately by comparing the amount of electricity demanded by the arriving charging request with the threshold amount of electricity set by the CS according to the previous received charging requests. Hence, the travel plan aware charging can be on-line scheduling through the proposed LONA. The utility of CS will be guaranteed as sufficient charging requests are received by the CS, then the CS can pick up the large enough amount of electricity demanded through learning from previous charging requests. The detailed learning process is illustrated in Algorithm 2, where θ_i is the initial threshold amount of electricity for CS i to decide whether accept the first received charging request, and α_i is a weighting parameter determining the impact of previous charging request and the arriving charging request on the threshold amount of electricity of CS i.

Algorithm 2 LONA: Learning based On-liNe charging scheduling Algorithm

Input:

$Charging\ requests\ of\ EV\ j\ proposed\ to\ CSs\ according\ to\ the\ sequence\ in$ $\mathbf{PList}_j, \forall j \in \mathcal{M}$

Initialization:

$K_i; \theta_i, \alpha_i, K_i^{accept} = 0\ \forall i \in \mathcal{N}$

if $K_i^{accept} < K_i\ and\ Q_j^i \geq \theta_i$ **then**
  $Charging\ request\ of\ EV\ j\ is\ accepted\ by\ EV\ i$;
  $K_i^{accept} = K_i^{accept} + 1$;
  $\theta_i = \alpha_i \theta_i + (1 - \alpha_i) Q_j^i$;
else
  $Reject\ Charging\ request\ of\ EV\ j$;
  $\theta_i = \alpha_i \theta_i + (1 - \alpha_i) Q_j^i$;
end if

IV. Performance Evaluation

Simulations are conducted to evaluate the performance of the proposed SMA and LONA for travel plan aware EV charging scheduling problem.

We investigate a $50km \times 50km$ district with 10 CSs randomly distributed in the investigated area. Four types of charging EVs are considered, and their electricity consumption rates can be found in [12]. Each CS is assumed to have 10 charging outlets. The distance between each EV and each CS is uniformly distributed in $(0, 30]km$. The amount of electricity demanded by EV is uniformly distributed in $[10, 20]kWh$. The probability that an EV may arrive at the CS later than the expected time is set to be 0.2, and the delay cost constant

C is set to be 100. In LONA, θ_i and α_i is initialized to be $15kWh$ and 0.5, respectively. Simulation parameters are summarized in Table I. We compare the performance of our proposed SMA and LONA algorithms with the basic Random Charging Scheduling (RCS) scheme as well as a slightly simplified version of the SMA algorithm–Only utility of EV Concerned (OEVC) scheme. The RCS scheme assigns CSs to EVs randomly. In the OEVC scheme, only utilities of EVs are considered during the allocation process while the utilities of CSs are not taken into account.

TABLE I: Simulation Parameters

Notation	Implication	Value(Distribution)
N	Number of CSs	10
K_i	Number of Interfaces of CS i	10
Q_j^i	Amount of Electricity Needed	$U[10,20](kWh)$
d_j^i	Distance from EV j to CS i	$U(0,30](km)$
R_j	Electricity Consumption Rate	randomly choose from (0.121,0.15,0.16,0.21) (kWh/km)
$p(t_j^i > t_j)$	Probability of Delay	0.2
C	Delay Cost	100
β	Weighting Parameter in SMA	1
α_i	Weighting Parameter in LONA	0.5
θ_i	Initial Threshold Amount of Electricity	15(kWh)

In Fig. 2, we show average system utilities for EV charging at CSs with the proposed SMA, LONA and the RCS and OEVC algorithms. It can be observed that the proposed SMA has the highest average system utility among the four algorithms. The performance gain of the average system utility by the SMA is up to 38.2% comparing to the RCS algorithm, and 4.67% comparing to OEVC scheme when the number of charging requests is more than the total number of outlets of all CSs. When EV charing demand is unsaturated, the average system utility of algorithms SMA and OEVC are almost the same. That can be explained by that when charging demand is less, almost every charging request can be satisfied. However, when there are substantially large number of charging requests, the proposed SMA gives priority to charging request demanding for more electricity which improves the utilities of CSs and increases the average system utility. The average system utility of LONA increases with the increasing number of charging EVs, and is very close to that of SMA when number of EVs achieve 160. This is because as the number of charging EVs increase, CSs with the LONA can make better choice on charging EVs through learning from previous received charging requests and properly reject some charging requests demanding for less electricity and reserve limited number of charging outlets for charging requests demanding for more electricity in the future.

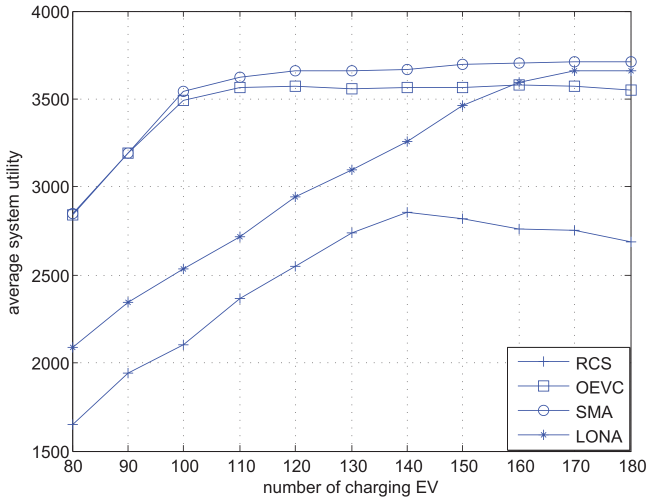

Fig. 2: Average system utility under different schemes

In Fig. 3, we show the satisfactory ratio evolution with scheduling algorithms SMA, LONA, RCS and OEVC with increasing number of charging EVs. The satisfactory ratio is defined as the percentage of EV charging requests being accepted over the total number of EVs. Since the number of CS outlets determines the capacity of each CS, when the number of charging EVs is more than the aggregated capacity of all CSs, satisfaction ratios with the four scheduling algorithms all decrease. However, when there are sufficient CS outlets, both SMA and OEVC can give 100% satisfactory ratio, which is higher than the RCS scheme. The performance of the proposed LONA on satisfactory ratio of EVs is the worst when the number of charging EVs is small, and decrease to the same low level with the other three algorithm when the number of charging EVs reaches 150. This can be explained that in the proposed LONA, making correct acceptance choice need to learn from the history information in previous charging requests. When the LONA is exploring the threshold amount of electricity, charging requests demanding for less electricity than the threshold amount are rejected, thus the number of accepted charging requests decrease. However, when sufficient charging requests are received in the LONA, the number of accepted charging requests equals to that in the other three algorithms and satisfactory ratios are the same with the four algorithm when the number of charging EVs is large.

Fig. 4 shows the average number of iterations when applying the proposed SMA and LONA. Since the proposed LONA is an on-line algorithm and no iteration conducted in the algorithm, we set the number of iteration with LONA always to be 1. For SMA, Fig. 4 shows the largest average numbers of iterations emerge when the number of charging EVs is close to the capacity of all CSs. The average number of iterations is small, either when the number of charging EVs is much smaller than the capacity of all CSs or is much larger

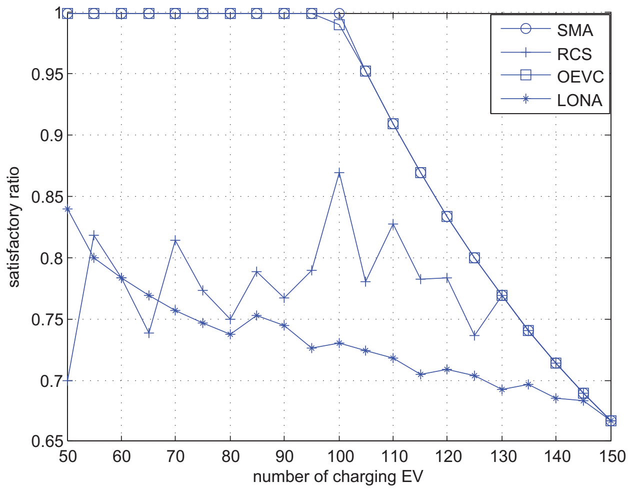

Fig. 3: Satisfactory ratio under different schemes

than the CS capacity. This is because when the number of charging EVs is much smaller than the capacity of all CSs, shortly all the charging EVs are in the in-suspense lists of all CSs, and the proposed SMA terminates. Meanwhile, when the number of charging EVs is much larger than the capacity of all CSs, it is easy to satisfy the condition that EVs which are not suspended by any CSs have been rejected by all CSs in their preference lists, then the proposed SMA terminates. Moreover, Fig. 4 compares the largest average numbers of iterations for different numbers of charging EVs $M = 100$, $M = 150$, and $M = 300$. The largest average number of iterations is expected to increase with the number of charging EVs as shown in Fig. 4.

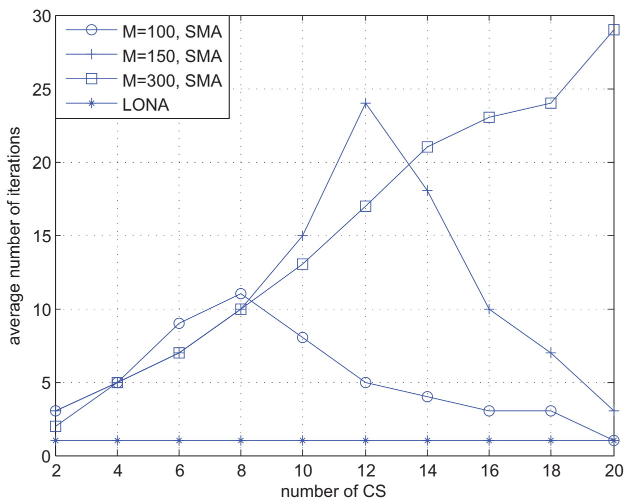

Fig. 4: Average number of iterations with the proposed SMA and LONA vs N with $K_i = 10$ for charging requests from different number of EVs $M = 100$, $M = 150$ and $M = 300$ denoting light charging demand and heavy charging demand.

V. Conclusion

The capability of driving range and charging is still major concern for EV drivers which impedes the development of V2G system. In this paper, we develop the travel plan aware scheduling scheme for EV charging to improve QoE of EV drivers. Matching theory is applied to maximize the system utility of EVs and CSs. The travel plan aware charging scheduling problem is formulated as a many-to-one matching problem with two-sided preference. Both off-line (i.e. SMA) algorithm and on-line (i.e. LONA) algorithm are proposed, which can be implemented in centralized and distributed manner, respectively. Simulation results show the proposed SMA can largely improve the system utility and satisfactory ratio of charging EVs. The proposed LONA can achieve high system utility through learning from large number of charging requests, and apply to on-line scheduling scenario.

Acknowledgment

This work was supported by the National Natural Science Foundation of China under Grant (No. 61374189).

References

[1] R. Wang, P. Wang and G. Xiao, "Two-stage Mechanism for Massive Electric Vehicle Charging Involving Renewable Energy", *IEEE Transactions on Vehicular Technology*, vol. 99, no. 99, pp. 1-13, January 2016.

[2] H. Sherif, Z. Zhu and S. Lambotharan, "An Optimization Framework for Home Demand Side Management Incorporating Electric Vehicles", *IEEE Innovative Smart Grid Technologies-asia*, May 2014.

[3] Y. Huang and S. Mao, "On Quality of Usage Provisioning for Electricity Scheduling in Microgrids", *IEEE Systems Journal*, vol. 8, no. 2, pp. 619-628, June 2014.

[4] N. Korolko and Z. Sahinoglu, "Robust Optimization of EV Charging Schedules in Unregulated Electricity Markets", *IEEE Transaction on Smart Grid*, vol. 99, no. 99, pp. 1-9, September 2015.

[5] L. Rao and J. Yao, "SmartCar: Smart Charging and Driving Control for Electric Vehicles in the Smart Grid", *IEEE Global Communications Conference (GLOBECOM)*, December 2014.

[6] H. Zhao and A. Burke, "An intelligent solar powered battery buffered EV charging station with solar electricity forecasting and EV charging load projection functions", *IEEE International Electric Vehicle Conference (IEVC)*, December 2014.

[7] Y. Liu, Q. Li, S. Tao and X. Xiao, "Coordinated EV charging and its application in distribution networks", *International Conference on Technological Advances in Electrical, Electronics and Computer Engineering (TAEECE)*, May 2013.

[8] C. Shao, X. Wang, X. Wang,C. Du and B. Wang, "Hierarchical Charge Control of Large Populations of EVs", *IEEE Transactions on Smart Grid*, vol. 7, no. 2, pp. 1147-1155, February 2016.

[9] E. L. Karfopoulos and N. D. Hatziargyriou, "Distributed Coordination of Electric Vehicles Providing V2G Services", *IEEE Transactions on Power Systems*, vol. 31, no. 1, pp. 329-338, February 2015.

[10] K. Zhang, Y. Mao, S. Leng, S. Maharjan, Y. Zhang, A. Vinel and M. Jonsson, "Incentive-driven energy trading in the smart grid", *IEEE Access*, vol. 4, no. 1, pp. 1243-1257, April 2016.

[11] A. E. Roth, "The college admissions problem is not equivalent to the marriage problem", *Journal of Economic Theory*, vol. 36, no. 2, pp. 277-288, March 1985.

[12] M. Zeng, S. Leng and Y. Zhang, "Power Charging and Discharging Scheduling for V2G Networks in the Smart Grid", *IEEE International Conference on Communications (ICC) Workshops*, June 2013.