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Towards Double Auction for Assisting Electric Vehicles Demand Response in Smart Grid*

Donghe Li[1], Qingyu Yang[1,2], Wei Yu[3], Dou An[1] and Xinyu Yang[1]

Abstract— **In the smart grid, the online double auction scheme is useful to ensure energy trading between Electric Vehicles (EVs) that have surplus or insufficient energy. In this paper we present a new online double auction scheme, which enables multi-unit energy trading among EVs. Particularly, EVs that have surplus and insufficient energy act as sellers and buyers, while the MicroGrid Center Controller (MGCC) is responsible for maximizing the market social welfare by matching buyers and sellers. We conduct a theoretical analysis and show that our proposed scheme achieves the desired economic properties. Through extensive performance evaluation, our experimental results show that our scheme can not only achieve good performance with respect to social welfare, EVs' satisfaction ratio, efficiency ratio, and computational overhead, but also help the power system shift peak load and save charging costs to the EV owners.**

I. INTRODUCTION

The smart grid is a typical energy-based cyber-physical system [1], [2], which integrates information communication technologies into the power grid. Particulary, Microgrids (MGs), as small-scale power grid systems, are integrated in the smart grid, aiming to deal with energy management issues and the integration of intermittent renewable energy resources [3], [4]. Nonetheless, the growth rate of power generating capacity cannot keep up with the growth in load demands [5]. As a consequence, demand response [6] plays a key role in helping balance supply and growing demand in MGs. For instance, utilizing various incentives (real-time pricing, time-of use pricing, and others), demand response tends to induce the consumers to change their electricity consumption behavior, temporarily shifting or reducing load from peak hours to off-peak hours, reducing operation cost, and leading to more reliable operation [7].

As Electric Vehicles (EVs) are connected to MGs, they can be utilized as flexible storage devices to benefit demand response, and enhance the functionalities of MGs [8]. Thus, a number of EVs can be aggregated and used to balance between demand and supply. EVs are willing to charge when the electricity is low or discharge energy back to the grid and other EVs when the electricity is high, via V2G (Vehicle-to-Grid) and V2V technologies [9]. The feasibility of using the V2V technology has been studied, showing that the charging and discharging speed of EVs could be greatly improved by the supercharger [10], and the transmission lose could also quite small. Notice that existing charging schemes focused on the maximizing utility in MGs level (e.g., optimal demand response, and optimal energy utilization). Unfortunately, these schemes could sacrifice individual utilities of EVs, which is private and voluntary, leading to the performance dissatisfaction of EVs. To address this issue, we need to design an effective scheme for EVs to voluntarily aid in demand response.

To this end, utilizing the auction mechanism to address EV demand response problem through V2V technology could provide a viable solution, because it satisfies the EVs utility requirements (valuation) through bidding process, while avoiding line losses between EV and MGs when discharging [11]. In the recent past, there have been a number of research efforts on the design of auction schemes in the smart grid [12], [13], [14]. Nonetheless, the existing works cannot directly and efficiently solve the scenario that we consider in this paper. In addition to the auction scheme that should work online, the auction scheme should allow the multi-unit trading and induce EVs to truthfully inform their bids and asks to maximize social welfare. Thus, in this paper, we develop an effective online double auction scheme to address the EV demand response in MGs.

The main contributions of this paper can be summarized as follows:

First, we consider how to deal with the demand response problem, as well as to reduce the EVs' operational cost in the MGs, both of which are important components in the smart grid. To address these issues, we propose a new EV market model in MG through V2V technology, in which the EV owners as the auction participants could freely access and depart the auction market, as well as freely bid. This designed market will be triggered whenever there exist both EVs that are able to sell surplus energy, and EVs that are able to purchase energy to offset their deficit, simultaneously.

Second, we present a new online double auction scheme to determine the winning EV in the auction market by solving the social welfare maximization problem. In our scheme, we consider the EVs that desire to discharge their surplus energy as sellers, and the EVs that desire to meet their insufficient energy as buyers. In addition, our propose scheme satisfies several economic properties, including individual rationality,

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[1]School of Electronic and Information Engineering, Xi'an Jiaotong University, China. Emails: lidonghe@stu.xjtu.edu.cn, adkaka.an@gmail.com, yxyphd@mail.xjtu.edu.cn

[2]SKLMSE lab, Xi'an Jiaotong University, China. Email: yangqingyu@mail.xjtu.edu.cn

[3]Department of Computer and Information Sciences, Towson University, USA. Email: wyu@towson.edu

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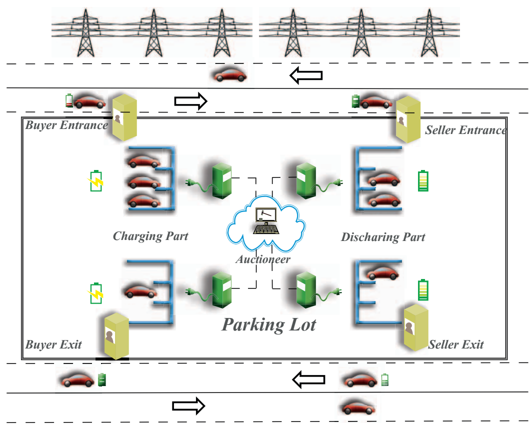

Fig. 1: System Model

weak budget balance, incentive compatibility, and computational efficiency.

Third, we have conducted extensive performance evaluation in a MG with a number of EVs participating in the auction market. Our experimental results show that our scheme could provide good performance with respect to the total cost of EV owners, peak load shifting, social welfare, EVs' satisfaction ratio, and computing time. Meanwhile, we have carried out the sensitivity analysis to investigate the impact on the performance raised by the key parameters (the scale of EV and waiting patience). Our experimental results demonstrate that our scheme, as an online arithmetic, compared with the offline linear programming, achieves a higher winning rate as well.

The remainder of this paper is organized as follows: In Section II, we propose the system model. In Section III, we present the problem formalization and the desired properties of our auction scheme. In Section IV, we present our online double auction scheme in detail. In Section V, we show the theoretical analysis and prove that our online double auction scheme satisfies several properties. In Section VI, we show performance evaluation results. Finally, we conclude this paper in Section VII.

II. System Model

In this paper, we consider that an auction market model in the smart grid, which consists of electricity users (e.g., EV owners) and MicroGrid Center Controller (MGCC). The energy transmission among EVs are realized via V2V technology. The detailed system model is illustrated in Fig. 1. In the auction system, EVs act as buyers and sellers. For instance, to enable EVs trade freely and participate in demand response, the parking lot acts as a trading platform which allows buyer EVs charge from seller EVs as well as charge from the main grid.

In addition, EVs have incentive to participate in the auction process and therefore benefit from the following aspects. First, the owners of EVs are able to arrange their own charging/discharing schedules actively, instead of being managed by the power system passively. Second, considering real-time pricing in the power grid, those EV owners who participate in the auction market can have substantial benefits, including discharging in the daytime with economic gain due to a higher price and charging at a potentially lower price in the auction market, in comparison with the likely higher market price direct from the high voltage power grid, etc.

In our system, EVs that have surplus energy act as sellers, while EVs that have insufficient energy act as buyers, and the MGCC acts as the auctioneer. In particular, when an EV enters the auction market, he or she provides his or her bid to the MGCC, which consists of arrival time, departure time, supply and demand volume, and valuation. It is worth noting that neither buyers, nor sellers, have the knowledge of each others information. The auctioneer then uses the bids of buyers and sellers at the current time to determine the winners of the auction in terms of social welfare maximization. Again, the operation of our online double auction has the following benefit, meaning that buyers and sellers are allowed to enter and leave the auction market at any time, and the online double auction auctioneer makes allocation and payment decisions based on the current bids without knowing future bids and decision sequences.

TABLE I: Notations

Symbols	Descriptions
M, T	The sets of EVs and time slots
a_i, d_i	Arrival and departure time of EV i
v_i	Valuation of EV i for per unit electricity
q_i	Demand and supply capacity of EV i
ω	Waiting patience of EVs
α_i	Actual type of EV i
α^t	The bids and asks before and at time slot t
$\overline{\alpha_i}$	The type misreported by EV i at time slot t
${A_i}^t(\alpha^t)$	Allocation for EV i at time slot t
${P_i}^t(\alpha^t)$	Unit electricity price of EV i at time slot t
$U_i(\alpha_i)$	Utility of EV i with the report type of α_i
C^t	The available EV sets at time slot t
SW^t, BW^t	The sets of winning EVs at time slot t
${z_i}^t(\alpha^t)$	Key price at t with the report type of α^t

III. Problem Formalization

In the following, we first introduce the notations and assumptions in our auction model and then the problem formalization. The list of key notations in this paper can be found in Table I.

Notations and assumptions: (i) We consider the time to be slotted as integer set T. Denote all EVs as set M, in which buyers and sellers come from sets B and S.

(ii) For EV $i \in M$, its bidding information can be expressed as $\alpha_i = (a_i, d_i, v_i, q_i)$. In which, a_i, d_i represent its arrival/departure time, v_i is its valuation of per unit (kWh) electricity, and q_i denotes its supply/demand electrical energy. For valuation v_i, the positive number represents that EV i is a buyer, while the negative number represents it is a seller. In addition, α_i is a private information.

(iii) Denote ω as the maximum waiting time.

(iv) We define false bidding information that is misreported by the EV i as $\overline{\alpha_i} = (a_i, d_i, v_i, q_i)$.

(v) The transaction results of auction can be expressed as: ${A_i}^t(\alpha^t), {P_i}^t(\alpha^t) | t \in T, i \in M$, where ${A_i}^t(\alpha^t)$ and ${P_i}^t(\alpha^t)$ denote the trading volume and the payment/reimbursement of EV i during the period of t, respectively. For ${P_i}^t(\alpha^t)$, positive represents buyers and negative represents sellers.

Before formalizing the online double auction problem, two main definitions are given as follows:

Definition 1 (Utility). The differences between EV i's bid and the actual payment or remuneration are defined as the utility of EV i, and can be expressed as follows:

$$U_i(\alpha_i) = \sum_{t \in T} (v_i - {P_i}^t(\alpha^t)){A_i}^t(\alpha^t). \tag{1}$$

Obviously, both the sellers and buyers are seeking the maximum utilities to obtain their greatest benefits.

Definition 2 (Social Welfare). Social welfare is denoted as the sum of utilities for both buyers and sellers and the profit of the auctioneer.

Thus, in the case where the EVs' bidding is truthful, designing an effective online double auction scheme is equivalent to solving the problem of **Social Welfare Maximization (SWM)** as following:

$$\max : \sum_{i \in M} U_i(\alpha_i) + \sum_{t \in T, i \in M} {P_i}^t(\alpha^t){A_i}^t(\alpha^t), \tag{2}$$

$$s.t. \sum_{i \in M} {A_i}^t(\alpha^t) = 0 \qquad \forall t \in T,$$

$$\sum_{t \in [a_i, d_i]} {A_i}^t(\alpha^t) \le q_i \quad \forall i \in M,$$

$$0 \le {A_i}^t(\alpha^t) \le A_{limit} \quad \forall i \in M, \forall t \in T.$$

Here, the first constraint ensures the energy balance at any time. The second constraint ensures that the transaction volume of every EV should not exceed the capacity of their demand or supply. The third constraint shows that the allocation of every EV is positive, which ensures that the transaction occurs with realistic significance.

IV. Our Approach

In this section, we introduce the detail of our online double auction scheme. First, we introduce the workflow of our scheme. Then, we introduce the key components such as winner determination rule and allocation rule.

A. Workflow

Before introducing our online double auction scheme, we define the following two important definitions.

Definition 3 (Key Price). Key price is referred to as a terminal price that determines whether EVs win in the auction. It is independent with the type of individual EVs and the EV's type after time slot t.

Definition 4 (Available EV). For EV i, if the following constraints are satisfied, $t \in [a_i, d_i]$, $q_i > \sum_{t' \in [a_i, t-1]} {A_i}^{t'}(\alpha^{t'})$ and $v_i > \max_{\gamma \in \{\max\{d_i - \lambda, 0\}, \ldots, t-1\}} \{{z_i}^\gamma(\alpha^\gamma)\}$, then EV i is the available EVs at time slot t, which is allowed to trade in this time slot.

Algorithm 1: Online Double Auction Scheme

Input: Buyers set B, sellers set S, and each EV i's type α_i.
Output: The payment rule ${P_i}^t(\alpha^t)$ and the allocation rule ${A_i}^t(\alpha^t)$

for $t = 1$ *to* T **do**
  Compute the key price ${z_i}^t$ for B and S;
  for $i = 1$ *to* M **do**
    if $a_i \le t \le d_i$ *and* $q_i \ne 0$ *and* $v_i > \max_{\gamma \in \{\max\{d_i - \lambda, 0\}, \ldots, t-1\}} \{{z_i}^\gamma(\alpha^\gamma)\}$ **then**
      Update the available EV sets $C^t \leftarrow i$;
    else
      The EV is not the available EV;
    end
    if $v_i > {z_i}^t$ **then**
      $BW^t \leftarrow i \in B$, $SW^t \leftarrow i \in S$;
      Payment rule: ${P_i}^t(\alpha^t) \leftarrow \max_{\gamma \in \{\max\{d_i - \lambda, 0\}, \ldots, t\}} \{{z_i}^\gamma(\alpha^\gamma)\}$;
      Allocation rule: ${A_i}^t(\alpha^t)$;
      Update $q_i \leftarrow q_i - {A_i}^t(\alpha^t)$;
    else
      The EV is not able to win the bid;
    end
  end
end
return Payment ${P_i}^t(\alpha^t)$ and allocation ${A_i}^t(\alpha^t)$.

In this paper, our goal is to design an effective online auction scheme to help the auctioneer solve the social welfare maximization problem. The workflow of our proposed online double auction scheme is listed as follows:

Step 1 (Initialization): At the beginning of the auction, the auctioneer needs to initialize the variables, $t = 0$, ${A_i}^t(\alpha^t) = 0$, ${P_i}^t(\alpha^t) = 0$, the bids and asks of EVs are saved as α^t, and EVs that arrive at the time slot $t = 0$ are denoted as available EV sets $C^t = \{i | i \in M, a_i = 0\}$.

Step 2 (Winner Determination): At the time slot t, the auctioneer should first compute key price ${z_i}^t(\alpha^t)$. Then, the auctioneer would determine the winners though the key price. The key price rule and determination rule would be introduced in the Section IV-B.

Step 3 (Payment Rule): The payment and reimbursement of winning buyers and sellers for per kWh electricity are computed:

$${P_i}^t(\alpha^t) = \max_{\gamma \in \{\max\{d_i - \lambda, 0\}, \ldots, t\}} \{{z_i}^\gamma(\alpha^\gamma)\}. \tag{3}$$

Step 4 (Allocation Rule): In this step, the auctioneer computes the detailed energy allocation of winning EVs by the allocation rule, which will be introduced in Section IV-C.

Step 5 (Update): The auctioneer updates the time slot $t = t + 1$, and the demand or supply capacity of each EV as $q_i = q_i - {A_i}^t(\alpha^t)$. In addition, the set of available EV set is updated as

$$C^t = \{i | i \in M, t \in [a_i, d_i], v_i > \max\{{z_i}^\gamma(\alpha^\gamma)\}, q_i \ne 0\}. \tag{4}$$

Then, repeating the procedure from Step 2 to Step 6.

The detailed procedure of the online double auction scheme is shown in Algorithm 1.

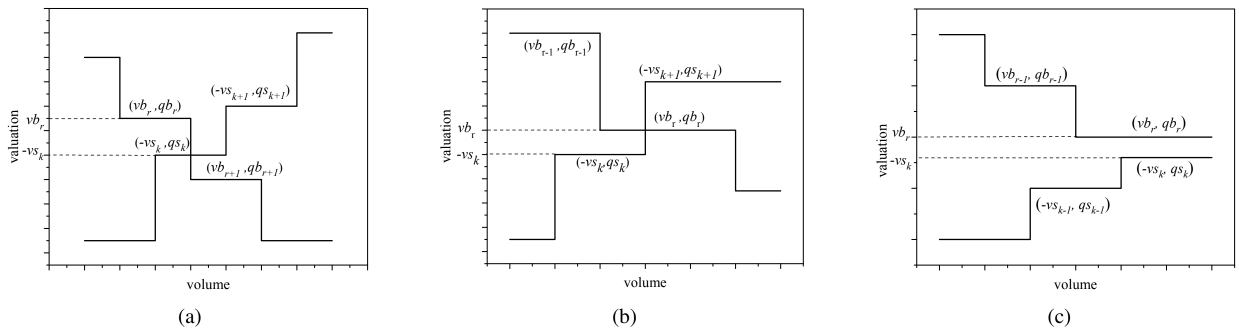

Fig. 2: Key Price

B. Winner Determination Rule

The key price is to help determine the winner and the payment. Thus, in winner determination rule, we first need to compute the key price. Nonetheless, the existing winner determination price rule such as Macfee price scheme [15] is to solve the problem in single unit trading.

Thus, in our auction scheme, we enhance a key price scheme to solve the multi-unit trading as follows:

First, recording the valuation and demand/supply of buyers and sellers as (vb_i, qb_i) and (vs_i, qs_i). Then, the auctioneer arranges the buyers' valuation vb_i in accordance in descending order, and the absolute value of sellers valuation $-vs_i$ in accordance with ascending order.

Second, we plot the demand qs_i of sellers in accordance with the valuation vs_i in descending order. Similarly, plotting the supply qb_i of buyers in accordance with the valuation vb_i in ascending order at the same picture. We consider the following three conditions stated in Fig. 2-a, Fig. 2-b, and Fig. 2-c. It easy to observe that the difference between the three figures is the location of the intersection. In each cases, as shown in Fig. 2, we would have two prices, which are vb_r and vs_k, respectively. They are defined as the key price of buyers and sellers in this time slot: ${z_i}^t(\alpha^t) = vb_r, i \in B$, ${z_i}^t(\alpha^t) = vs_k, i \in S$, respectively.

Finally, at the time slot t, the available EVs are able to win the bids if, and only if, their valuations are larger than the key price: $v_i > {z_i}^t(\alpha^t)$. Then, the auctioneer will update the winning sellers at time slot t as SW^t, as well as the winning buyers as BW^t.

C. Allocation Rule

In our auction scheme, the allocation rule plays a key role in ensuring the balance of the demand and supply. We now introduce the allocation rule in Step 5 of subsection IV-A.

First of all, we would ensure the possibility of charging process. Thus, when the demand and supply volume q_i is larger than the charging speed limit A_{limit}, we set $q_i = A_{limit}$. Then, we denote the difference between the total demand volume of winning buyers and the total supply volume of winning sellers to be defined as $\Delta^t = \sum_{i \in BW^t} q_i - \sum_{i \in SW^t} q_i$. We introduce the allocation rule to make sure the material balance in the following three cases.

Case A. When $\Delta^t = 0$, the allocation of all the winning EVs is determined by ${A_i}^t(\alpha^t) = q_i$.

Case B. When $\Delta^t > 0$, we know that the demand volume of winning buyers is larger than the supply volume of winning sellers, it means that we need to scarify the demand volume of buyers. For fairness, we should make sure that every winning buyers would obtain the same state of charge (SOC), the relevant proof will be detailed in next section. Thus, the SOC of buyer denote as: $SOC_t = \sum_{i \in SW^t} q_i / \sum_{i \in BW^t} q_i$. For sellers, the allocation is ${A_i}^t(\alpha^t) = q_i$. For buyers, the allocation is ${A_i}^t(\alpha^t) = SOC_t \cdot q_i$.

Case C. When $\Delta^t < 0$, the allocation is as the same as the above case.

Obviously, our allocation rule ensures that the trading volume at each time is balanced.

V. Theoretical Analysis

As a fair and feasible auction scheme, it needs to satisfy several economic properties, including incentive compatibility, individual rationality, weak budget balance, and computational efficiency. We now give the definition of the properties and conduct theoretical analysis to prove that our scheme satisfies these properties. Due to the space limit, the proofs are brief.

Definition 5 (Individual Rationality). If for a given EV $i \in M$, there exist: $\sum_{t \in T} (v_i - {P_i}^t(\alpha^t)){A_i}^t(\alpha^t) \geq 0$. Then, the online double auction scheme achieves individual rationality. This property ensures that each EV earns non-negative profit in the designed auction process.

Proof. For those winners, their allocation would not be less than zero, and their payment is determined by the key price. Nonetheless, the key price is smaller than the valuation: $v_i > c_i$. Thus, the utilities for winners would not less than zero. For those EVs who do not wins, their utilities denote as zero. In conclusion, the EVs would earn non-negative profit in the auction scheme. ∎

Definition 6 (Weak Budget Balance). If for any given EV $i \in M$, there exist: $\sum_{t \in T} ({A_i}^t(\alpha^t){P_i}^t(\alpha^t)) \geq 0$. Then, the online double auction scheme satisfies the weak budget balance. This property ensures the auctioneer does not need to inject money to keep the auction working.

Proof. For those winners, the payment of buyers would not be smaller than sellers': $\sum_{i \in BW^t} {P_i}^t(\alpha^t) + \sum_{i \in SW^t} {P_i}^t(\alpha^t) \geq 0$. Due to the material balance, we know that the profit of auctioneer is not less than 0: $\sum {P_i}^t(\alpha^t){A_i}^t(\alpha^t) \geq 0$. For those EVs who do not win, the auctioneer would not obtain any profit from them. Thus, our auction scheme satisfies the weak budget balance. ■

Definition 7 (Incentive Compatibility). If for a given EV $i \in M$, there exist: $U_i(\alpha_i) \geq \sum_{t \in T} (v_i - {P_i}^t(\overline{\alpha^t})){A_i}^t(\overline{\alpha^t})$. Then, the double auction scheme satisfies the incentive compatibility. In other words, the incentive compatibility ensures that EVs obtain the maximum social welfare if and only if they report their true types. The property of incentive compatibility is also denoted as truthful.

Proof. Due to the allocation rule is fair for all EVs win the bids, we just consider the impact of false bidding information on winner determination. We would explain the property in the following two cases.

Case A. When EVs misreport their valuation. Due to the key price rule and payment rule, the valuation of each EV would only decide whether they win the bids instead of the payment. For those EVs who had won the auction, if they misreport a valuation that is bigger than key price, they would also win the bids, the utility would remain unchanged. If they misreport a valuation that is smaller than the key price, they would miss the auction, utility would reduce to zero. For those EVs who do not won the auction, if they misreport a bigger valuation to win the bid, their utility would become negative, since the payment (key price) is larger than their true valuation. Thus, in this case, the EVs would not increase their utility by misreporting the valuation.

Case B. When the EVs misreport their arrving/departure time. Due to the actual situation, they would misreport a smaller time period. Thus, they may lose the trading opportunity and the utility would not increase.

To summarize, the EVs would not increase their utility by misreporting their biding information. ■

Definition 8 (Computational Efficiency). The computational efficiency indicates that the optimal allocation in the scheme can be obtained in polynomial time. This property shows the feasibility of our scheme in practical use.

Proof. We can observe from Algorithm 1 that the time complexity in each time slot is $O(2M)$. Thus, in T time slots, the overall time complexity of our scheme is $O(2TM)$, it is quite efficient for an auction scheme. ■

VI. Performance Evaluation

In this section, we present the performance evaluation to demonstrate the effectiveness of our proposed online double auction scheme.

To evaluate the effectiveness of the proposed scheme, we conducted experiments in a microgrid [16] with several EVs on MATLAB. In our simulation, we denote time slot t as 20 mins, so that one day can be expressed as $T = 72$. We assume demand and supply of each EV is uniformly distributed from 0 to 40. In our simulation, the arrival times of EVs follows the Poisson distribution by $P(X = k) = \frac{\lambda^k}{k!} e^{-\lambda}$, where λ is the arrival rate of the EVs, and we set λ to 20. We denote the valuation of the buyers and sellers uniformly distributed from 0 to 0.15 \$kWh based on the real electricity price [13]. All experiments were conducted on a computer with 3.3 GHz Intel Core i5-4590 CPU and 8 G RAM. In the following, we evaluate the performance of our approach with respect to demand response and EV charging costs.

Demand Response. Fig. 3 illustrates the results of the peak-load shifting in the power grid utilizing our auction scheme. We can observe from this figure that the peak load is significantly decreased in this scenario. Thus, we can conclude that our auction scheme is helpful in maintaining the stable operation of power grid.

EV charging cost. From EV owners' viewpoint, the most concerning problem is whether they can reduce charging cost in the auction market. Fig. 4 illustrates the EVs charging costs with and without the auction scheme. Here, the charging cost with auction is defined as the payment rule in Section IV-A, and the charging cost without the auction is defined as $\sum_{t \in T, i \in BW^t} {A_i}^t(\alpha^t) Price(t)$, where $Price(t)$ represents the real time electrical price. Our findings show that the EVs costs of the proposed auction scheme is significantly less than the cost without auction. As a result, the proposed auction scheme has enough appeal to the EV owners.

In addition, to evaluate the effectiveness of our online double auction scheme, we consider the following metrics: (i) **Social welfare**, (ii) **EVs' satisfaction ratio**, which is referred to as the proportion of the winners to the total EVs, and (iii) **Efficiency ratio,** which is referred to as the satisfaction ratio between our online double auction scheme and the optimal solution derived by directly solving the offline social welfare maximization problem 2. We have also evaluated the pivotal factors that could affect the effectiveness of online double auction scheme, including (i) the number of EVs, and (ii) waiting patience ω.

Social welfare *vs.* the number of EVs and waiting patience: We can observe from Fig. 5 that social welfare also has a significant growth with the increase in both the number of EVs, and the waiting patience. When the number of EVs is fixed and the waiting patience increases, the growth of the social welfare will slow, and finally converge at a waiting patience of 15. This is because that the EV owners will have more time to stay in the auction market with the growth of waiting patience, thus providing more opportunities for to win the bids.

EVs satisfaction ratio *vs.* the number of EVs and waiting patience: In Fig. 6, the EVs satisfaction ratio has the same trend as the social welfare, and the reason is also the same.

Efficiency ratio *vs.* the number of EVs and waiting patience: From Fig. 7, we can observe that the efficiency ratio grows as the waiting patience increases. The reason is that, when solving the social welfare maximization problem offline, the auctioneer will meet the EVs' demand as much as possible, and EV satisfaction ratio is fixed. Thus, when the waiting patience increases, the EV satisfaction ratio in our online double auction scheme will increase too. As a result, the efficiency ratio will increase. In addition, with the growth of the number of EVs, the EV satisfaction ratio by the

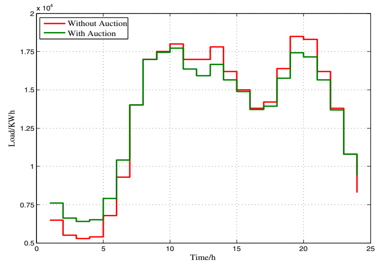

Fig. 3: Load curve of power grid

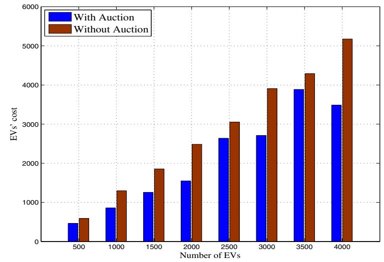

Fig. 4: EVs' cost

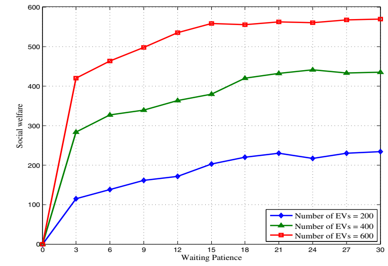

Fig. 5: Social welfare

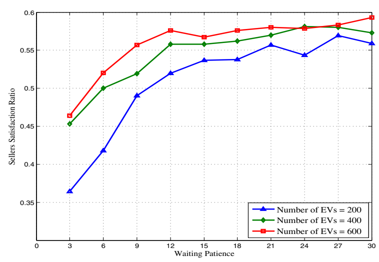

Fig. 6: EVs' satisfaction ratio

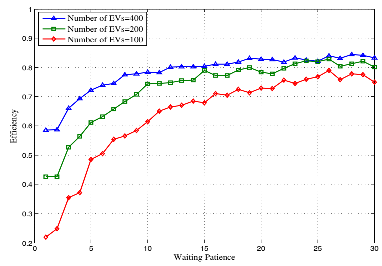

Fig. 7: Efficiency ratio

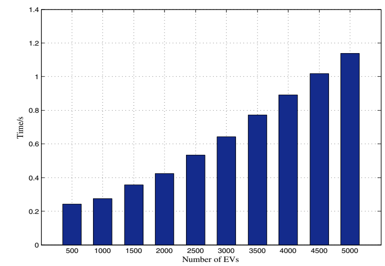

Fig. 8: Computational overhead

offline linear programming and online auction will increase simultaneously. Nonetheless, the increase of EV satisfaction ratio in the online approach is even greater, because there will be more opportunities to match the bids for the EVs as the number of EVs increases. We can observe that the efficiency ratio achieves 85 %, which validates that our scheme is very effective as an online approach.

Computation overhead: To validate the computational efficiency, we show the computation time of our scheme with respect to the number of EVs range from 500 to 5000. As shown in Fig. 8, the time consumption increases with the number of EVs. Particularly, when there are 5000 EVs, the time consumption is less than 1.2 s, which is highly acceptable.

VII. Conclusion

In this paper, we have addressed the issue of EV demand response in the smart grid with MGs, and have presented a novel online double auction scheme for optimal energy trading among energy surplus and deficit EVs. Theoretical analysis has demonstrated that our scheme satisfies economic properties (individual rationality, weak budget balance, incentive compatibility, and computational efficiency). The extensive experiments based on a MG with EVs, have shown that our scheme is helpful in shifting peak load for the grid, as well as reducing the charging cost for EVs. In addition, our proposed auction scheme achieves a good performance with respect to social welfare, seller and buyer satisfaction ratio, efficiency ratio, and computational efficiency.

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