IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 26 January 2023, accepted 17 February 2023, date of publication 27 February 2023, date of current version 6 March 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3249469

RESEARCH ARTICLE

VCG-Based Auction for Incentivized Energy Trading in Electric Vehicle Enabled Microgrids

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This work was supported in part by the Engineering and Physical Sciences Research Council (EPSRC) Impact Acceleration Accounts (IAA) (Green secure and privacy aware wireless networks for sustainable future connected and autonomous systems) under Grant EP/X525856/1.

ABSTRACT Under vehicle-to-grid (V2G) concept, electric vehicles (EVs) can be deployed to meet additional energy demand of critical load (CL) in a microgrid. In this article, an incentivized energy trading approach is introduced to study the interaction between EVs and CL. EV mobility and battery degradation are studied to ensure they do not deter EV participation. Bidder satisfaction is introduced which allows EV owners to enforce their energy trading conditions. EV-CL association and discharging scheduling are considered in a two-phase model. In the first phase, EV-CL association is modeled as a single auction to determine the winning bids and corresponding payments. Successful bidders are determined by solving a mixed integer non-linear programming (MINLP) problem, while Vickery-Clarke-Groves (VCG) payment rule is applied to pay the auction winners. In the second phase, EV discharging scheduling determines the operating cost and discharging power of associated EVs at each time slot. Simulation results show that the proposed approach achieves comparable performance with reference schemes and guarantees bidder satisfaction. Theoretical analysis on economic properties of truthfulness and individual rationality are verified as well.

INDEX TERMS Auction, electric vehicle, electric vehicle as a service (EVaaS), energy trading, incentivized, microgrid, Vickrey–Clarke–Groves (VCG).

I. INTRODUCTION

Due to global concerns on climate change, electric vehicles (EVs) could play a key role towards unlocking future sustainable energy systems. Under the vehicle-to-grid (V2G) concept, EVs do not only act as loads but also feed stored energy back to the grid [1]. The application of EVs as loads, energy storage systems and energy resources under the active distribution grid is reviewed in [2]. EVs can be deployed individually or as part of an aggregation in EV-enabled microgrids [3]. In the later, EVs are grouped by an aggregator to create a sizeable capacity for the microgrid [4]. Traditionally, EVs are managed under a centralized system where the grid manager is assumed to have full information and control over participating EVs. However, these approaches are not scalable considering the large number of physically distant EVs, and impractical due to the unwillingness of EV owners to share their private information. Hence, it is important to investigate distributed approaches which enable scalability and consider the interests of EV owners. Incentivizing energy trading in distributed EV-enabled microgrids is both desirable and challenging.

A. BACKGROUND

To address this challenge, economic incentive approaches are often applied to depict the behaviour of trading entities [5]. Here, trading entities are motivated to participate in the market via monetary incentives [6]. Auction is a promising mechanism used to capture the interactions between sellers

The associate editor coordinating the review of this manuscript and approving it for publication was Ahmed Mohamed.

and buyers in decentralized markets [7]. Auctions can be categorized according to the market design. Auctions in which at least one side of the market consists of a single buyer or seller are single auctions, while two-sided markets in which multiple sellers and buyers may be making bids and offers simultaneously are called double auctions.

Some recent works have applied auction mechanism to EV-enabled energy scheduling management [8], [9], [10]. A multi-round auction is designed in [8] for EV charging in decentralized environments and a dynamic charging scheduling algorithm is presented. In [9], a double auction mechanism is designed for energy scheduling management where discharging EVs trade energy with either the grid or charging EVs, and a new price adjustment strategy is proposed. A two-sided market made up of EV drivers and charger owners is cleared by a price-based double auction in [10]. Several factors such as EV driver preferences and charger location are considered in the allocation and scheduling process. It is generally assumed that bidders voluntarily represent their true valuation. However, bidders could misrepresent their valuations in order to maximize their utility. Vickrey-Clarke-Groves (VCG) mechanism is effective in ensuring the properties of incentive compatibility [11]. In VCG mechanism, bidding truthfully is a weakly dominant strategy, so there is no incentive for bidders to misrepresent their valuations.

Several recent works have applied VCG mechanism to a wide range of EV-enabled energy trading applications. In [12], EVs are incentivized to trade charging/discharging energy in active distribution systems and VCG-based pricing rule is applied to determine the payments EVs should make/receive. In [13], an incentive-based charging mechanism is designed for energy trading between EVs and charging stations, and VCG-based pricing rule is applied to determine the price EVs should pay. Double auction models are considered in [14] where autonomous EVs are incentivized to participate in dynamic energy trading with energy aggregators and two incentive payment schemes are proposed. Multiple buyers and multiple sellers are involved in the auctioning process in these works; therefore, it is not inapplicable in a one-sided market. In [15], two extensions of second price auction mechanisms were applied and studied for EV charging control in smart grids, where EVs are required to declare limited valuation to the auctioneer. This poses implementation difficulties in a market environment that requires entire valuation declaration.

In [16], an online continuous progressive second price-based auction scheme is proposed for EV charging in fast charging reservation systems. In [17], an auction mechanism for V2G systems is proposed and a feedback-based price scheme is designed to incentivize EV participation. An auction mechanism is designed in [18] to stimulate EV discharging in V2G systems. In [19], an auction mechanism is proposed to jointly incentivize discharging EVs and utilize local generation to charge EVs during emergency demand response periods. The incentives from these auction mechanisms may not cover battery degradation incurred during energy trading; hence, EV owners may incur revenue loss if they are not compensated. An auction-based scheme which enables local energy trading among EVs and considers battery wear-out cost is proposed in [20]. A battery degradation model is also presented to depict a practical energy trading environment. However, the scheme employs a naive auction process which does not examine essential economic properties such as truthfulness and individual rationality. The auction models in the literature do not consider EV mobility. Ideally, EVs are distributed within the microgrid and would need to travel from one location to another to supply energy [21].

B. OUR CONTRIBUTIONS

In this article, we introduce an incentivized energy trading approach where physically distant EVs are chosen to balance demand-supply mismatch. In the proposed approach, EVs enforce their conditions to participate in the bidding process such as the minimum and maximum amount of energy they are willing to sell. This ensures EVs are not subjected to unfair trade conditions where winning bidders sell an undesirable amount of energy as it is with centralized systems and protects the battery from deep discharge. The major contributions of this article are as follows.

- We formulate the EV-CL association problem as a single auction and the discharging scheduling optimization problem for EVs distributed within the microgrid. The auction determines the winning bids and the corresponding payments, while the discharging scheduling determines the discharging power of associated EVs for all time intervals.
- A number of practical constraints such as energy demand, power balance and state of charge (SoC) limits are captured in the problem formulation. The approach incentivizes EV owners for losses incurred during EV-CL interaction such as distance traveled, battery degradation and V2G reserve capacity. We introduce bidder satisfaction which allows EV bidders to enforce their energy trading conditions.
- The proposed energy trading model is evaluated in comparative studies with centralized and exiting schemes. Simulations results demonstrate that the model guarantees bidder satisfaction, as well as the economic properties of truthfulness and individual rationality.

II. SYSTEM MODEL

A. SYSTEM DESCRIPTION

Electric vehicle as a service (EVaaS) describes a system where suitable EVs in the microgrid are chosen to exchange energy with CL [3]. The energy trading process between EVs and CL is modeled using a one-sided auction with the aggregator acting as an auctioneer, as shown in Fig. 1. The aggregator coordinates the auction between EVs and CL through dedicated communication networks. Charging stations are utilized as sources for EVs to exchange

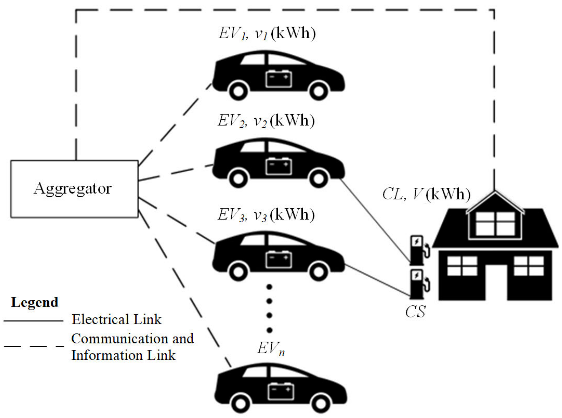

FIGURE 1. One-sided energy market with EVs and CL in a microgrid.

energy with CL. The proposed approach assumes that the discharging rate of EVs are fixed and energy transfer losses in the charging stations are not considered.

B. BATTERY DEGRADATION MODEL

EV battery degradation creates a common concern for EV owners when considering EVaaS participation. Due to natural limitations, the EV battery has a limited amount of charge cycles, where a charge cycle is a complete charge and discharge process. At the end of the estimated number of charge cycles specified by the manufacturer, the battery will start losing capacity and its performance will decrease significantly [22]. Increased charge cycles due to EVaaS participation would accelerate the battery degradation, resulting in revenue loss to the EV owner. The capacity loss and high cost of battery sum up the major financial liabilities of the EV owners and require a compensation [23]. Without assessing the battery degradation cost, it would be challenging to design an incentive mechanism to compensate EV owners [4]. When derived, the battery degradation cost is then counted into the objective function to determine the operating cost of participating EVs [24].

We consider a linear battery model which assumes the number of charge cycles multiplied by the depth of discharge (DoD) corresponds to 1 cycle of 100% DoD, i.e., 5 cycles of 20% DoD as equivalent to 1 cycle of 100% DoD. The DoD of a battery is the inverse of the state of charge (SoC) and can be represented as the SoC subtracted from 100% charge (1−SoC). We can calculate the cost per cycle of a battery as a fraction of the battery capital cost and the number of charge circles [25]. The cost per cycle b^{pc} of a battery and total degradation cost C^{deg} can be expressed as

$$b^{pc} = \frac{C^{bat}}{L_c}, \tag{1}$$

$$C^{deg} = b^{pc} \cdot SoC, \tag{2}$$

where C^{bat} is the battery capital cost in British Pounds (£) and L_c is the number of charges cycles. The linear estimation for capacity degradation of battery energy storage could render non-negligible (explicit and implicit) errors. Taking these factors into consideration, it is impractical to use a linear model to represent battery degradation cost. However, we can take the linear estimation as a reference model to benchmark the performance of the other models.

DoD is an important factor in charge cycle estimation because the relationship between different DoD cycles and equivalent 100% DoD cycles is not linear [26]. For every DoD level, the value of the battery lifetime throughput L_T, measured in kWh, can be expressed as

$$L_T = L_c \cdot v^{cap} \cdot DoD, \tag{3}$$

where v^{cap} is the battery capacity and DoD is the DoD for which L_c was determined [27]. Based on the relationship between DoD and charge cycle, the battery degradation cost per kWh b^d can be expressed as

$$b^d = \frac{C^{bat}}{L_T}. \tag{4}$$

For an EV to participate in EVaaS energy trade, sufficient energy has to be stored in the battery. The energy stored in the battery could be self-generated or purchased. Based on this, the EV incurs a charge cost C^{ch}. From the charge cost, the valuation of energy unit can be expressed as

$$\bar{\mu} = \frac{C^{ch}}{v^{avail}}, \tag{5}$$

where v^{avail} is the available energy in the EV battery. For EV to avoid making financial losses, the discharge cost should cover the charge cost and compensate battery degradation. This can be expressed as

$$C^{dis} \geq C^{ch} + C^{deg}. \tag{6}$$

This ensures battery related liabilities do not become financial burden to EV owners.

C. DESIGN TARGETS

In this article, key properties of the VCG mechanism such as truthfulness and individual rationality, as well as bidder satisfaction, are main targets. Hence, the proposed auction mechanism should be designed to achieve the following properties.

1) TRUTHFULNESS

An auction is truthful or incentive-compatible if participating EVs achieve maximum utility by revealing the true value of the energy stored in their batteries. In other words, the bid submitted by participating EVs equal their private valuation, i.e., $\mu = \bar{\mu}$, where μ is the energy unit bid and $\bar{\mu}$ is the valuation of energy unit. This property ensures that EVs cannot improve their utility by either bidding lower or higher than their true valuations; thus, preventing market manipulations.

2) INDIVIDUAL RATIONALITY

An auction is individually rational if the utility of participating EVs is nonnegative whether they win or lose, i.e., $U \geq 0$, where U is the utility of EV. This property guarantees that no auction winner is paid less than what it bids; thus, ensuring EVs will not be worse off after EVaaS participation.

3) BIDDER SATISFACTION

An auction is satisfactory if participating EVs can enforce their energy trading conditions. This property guarantees that no bidder will be subjected to sell an undesirable amount of energy; thus, ensuring that the accepted bid volume from auction winners is within desirable limits, i.e., $v^{min} \leq v \leq v^{max}$, where v is the desirable amount of tradable energy, v^{min} and v^{max} are the lower and upper bonds, respectively.

III. VCG-BASED AUCTION FOR EV-CL ASSOCIATION

We consider an auction model for EV-CL association. Let $i = \{1, 2, \ldots, N\}$ denote a set of EVs within the microgrid which are available to participate in EVaaS operation. The auction starts with the CL announcing its energy demand, total energy demand time period and location information to the aggregator which acts as an auctioneer. The auctioneer distributes a request for energy with the CL information to EVs within the microgrid. The ith EV sends a four-tuple bid $b_i = (d_i, \mu_i, v_i^{min}, v_i^{max})$ to the auctioneer, where d_i denotes the estimated transportation distance between the ith EV and CL, in km; μ_i denotes energy unit cost of the ith EV, measured in British Pounds (£) per kWh; v_i^{min} denotes the minimum tradeable energy of the ith EV, in kWh; v_i^{max} denotes the maximum tradeable energy of the ith EV, in kWh. The auctioneer then determines the winning bids and the corresponding payments. The auction process is carried out in two stages: winner determination stage and price determination stage. The auction winner is derived in the winner determination stage and the payment to the auction winner is actualised in the price determination stage.

A. WINNER DETERMINATION

Considering the winner determination problem is an optimization problem with binary and continuous variables and nonlinear functions in the objective function and constraints, we formulate it as a mixed integer non-linear programming (MINLP) problem. Let α_i denote the binary variable, where $\alpha_i = 1$ if the ith EV wins the auction and 0 otherwise. The objective is to minimize the energy cost of EVs balancing CL demand, provided the energy stored in the EV batteries is sufficient. The energy cost includes the transportation cost of EVs from its current location to the CL. For EVs to exchange energy with CL, they would have to transport the energy to the CL location. The auction is conducted few hours before the actual delivery, like the day-ahead energy market where auction takes place a day in advance. This allows sufficient travel time for EVs. Energy is consumed during transportation and this needs to be accounted for.

Algorithm 1 Winner and Price Determination

Input: $N, b_i = (d_i, \mu_i, v_i^{min}, v_i^{max}), V, \alpha_i = 0$
Output: $\alpha_i = 1, v_i, \rho_i$ **Winner Determination**

Make a list of CL and EVs within the Area.
Calculate the required energy for transportation of EVs $v_i^{trans} = e_{cr}d_i$.
Sort μ_i in non-descending order.
Initialise: $C_V = 0$
while list of CL to EVs is not empty **do**
  Find EV-CL association with the least energy cost in (7).
  if $v_i^{min} \leq v_i + v_i^{trans} \leq v_i^{max}$ and $C_V + v_i = V$ **then**
    Update $\alpha_i = 1$ and $C_V = C_V + v_i$
  else
    break
  end if
end while **Price Determination**
Calculate the energy cost without the ith EV C_k.
Calculate the energy cost with the ith EV C_k^*.
Compute payment ρ_i for the ith EV based on (8).
return α_i, v_i, ρ_i

The energy consumption of driving EV is influenced by several factors such as road topology, driving patterns, traffic, weather conditions, etc., [28]. These factors would determine the consumed SoC, transportation cost and EV arrival time and need to be studied towards practical implementation. In this article, we assume an average energy consumption rate of 0.2 kWh per kilometre distance driven. Hence, the required energy for transportation of the ith EV v_i^{trans} can be expressed as the average consumption rate multiplied by the distance between the ith EV and CL, i.e., $v_i^{trans} = e_{cr}d_i$. The winner determination problem can be formulated as follows

$$\min_{\alpha_i, v_i} \sum_{i=1}^{N} \mu_i (v_i + v_i^{trans}) \alpha_i \tag{7}$$

Subject to

$$\sum_{i=1}^{N} v_i \alpha_i = V \tag{7a}$$

$$v_i^{min} \leq v_i + v_i^{trans} \leq v_i^{max} \tag{7b}$$

Constraint (7a) ensures the energy from auction winners v_i equals the CL energy demand V. Constraint (7b) ensures that the requested energy is within the limits of the ith EV.

B. PRICE DETERMINATION

In VCG mechanism, we determine the payment of each EV based on the harm it causes to other participants. From the winner determination stage, the energy cost of the ith EV is represented by C_i, which is the cost of per kWh energy multiplied by the requested energy ($C_i = \mu_i(v_i + v_i^{trans})$). The payment made to the ith EV can be calculated as

$$\rho_i = \underbrace{\sum_{k \neq i} C_k}_{\text{without } i\text{th EV}} - \underbrace{\sum_{k \neq i} C_k^*}_{\text{with } i\text{th EV}}. \tag{8}$$

In (8) k serves as an iterative factor which iterates through all the values excluding the ith EV, $*$ is the set of winning bidders chosen in (7). The left part of the equation represents the total energy cost for other participants when the ith EV is not participating, while the right part represents the total energy cost for the other participants when the ith EV participates. Thus, the ith EV does not get any payment if it is not the winning bidder.

The utility of each EV is the difference between its valuation and final payment (after price determination). The utility of the ith EV is calculated as follows

$$U_i = \rho_i - C_i. \tag{9}$$

While the winning bidders from the winner determination stage are guaranteed to make profit, the utility of the losing bidders is 0, i.e., $U_i > 0$ if $\alpha_i = 1$ and $U_i = 0$ if $\alpha_i = 0$.

Market manipulation can lead to a lack of trust in the fairness of the market. VCG mechanism elicits truthful revelation. EV Bidders cannot improve their utility by either bidding lower or higher than their true valuation, as utility is determined by the bids of others. By preventing market manipulations, VCG mechanism ensures fairity, thereby motivating more EVs to participate in EVaaS.

C. AUCTION ALGORITHM

We develop an algorithm that finds the successful bidders and corresponding payment to the auction winners. The proposed strategy is effective in selecting EVs with minimum energy cost. The algorithm starts with computing N EVs and their four-tuple bids b_i. The CL energy demand V is also obtained. The transportation distance of the ith EV d_i is used to compute the required energy for transportation of the ith EV $v_i^{trans} = e_{cr} d_i$. The EVs are sorted in non-decreasing order of their energy unit cost, i.e., $\mu_1 \leq \mu_2 \leq \ldots \leq \mu_N$. A counter for CL energy demand C_V is initialized. Out of the list of EV to CL links, find EV-CL association with the lowest energy cost. The tradeable energy of the ith EV is verified such that $v_i^{min} \leq v_i + v_i^{trans} \leq v_i^{max}$. The energy balance constraint (7a) is then verified such that $C_V + v_i = V$. If all requirements are satisfied, the decision variable is modified as $\alpha = 1$ and the counter is updated accordingly. The process repeats until the list ends or the resources ends that can be tracked using the counter. VCG payment rule is applied to determine the payment of the ith EV. The energy cost without the ith EV C_k and with the ith EV C_k^* is derived. This is then used to compute the payment to the auction winners ρ_i. The procedure is summarized in Algorithm 1.

As mentioned earlier in section II, bidder satisfaction is a key design feature of the proposed auction mechanism. By applying constraint (7b) in the algorithm, winning bidders (EV owners) do not experience any inconveniences beyond their acceptable levels. In other words, this constraint protects bidders from unfair trade conditions, which is common in centralized models where the aggregator finds the optimal solution at the expense of participating EVs.

IV. ENERGY EXCHANGE SCHEDULING FOR EV-CL ASSOCIATION

A. EV MODELING

EV battery capacity indicates the maximum amount of energy that can be extracted from the battery in a single discharge. We define the SoC of the EV battery as the ratio of the available energy to the battery capacity. The SoC of the ith EV can be mathematically represented as

$$SoC_i = \frac{v_i^{avail}}{v_i^{cap}}, \tag{10}$$

where v_i^{avail} is the available energy of the ith EV and v_i^{cap} is the battery capacity of the ith EV. To prolong the life of the EV battery and protect it from degradation, deep discharge should be avoided. After discharging, the remaining energy should cover the energy requirements for battery protection and EV transportation. The maximum tradeable energy v_i^{max} included in the bid ensures that the battery is protected from discharging beyond its user-specified minimum SoC. Based on the accepted amount of energy v_i derived from Algorithm 1, the minimum SoC of the ith EV can be mathematically represented as

$$SoC_i^{min} = \frac{v_i^{avail} - (v_i + v_i^{trans})}{v_i^{cap}}. \tag{11}$$

B. CL MODELING

A load profile is a representation of the energy usage of a consumer, showing the demand variation over a period of time. The load profile of the CL is essential to determining the discharging power of EVs at each time slot. The load behaviour is influenced by several factors such as time, day, weather condition, season, economic factors and random effect. The CL power demand can be forecasted using techniques such as regression method, time-series method, fuzzy logic, neutral networks and similar day approach [29], [30]. In this article, we adopt the similar day approach to estimate the CL power demand at each time slot by averaging the power demand of the same time slot from historical data with similar characteristics (e.g., day of week, weather, etc.). The estimated CL power demand can be expressed as

$$D_t = \frac{1}{M} \sum_{m=1}^{M} \widehat{D}_{m,t} + \Delta D, \tag{12}$$

$$\Delta D = \widehat{D}_t - \tilde{D}_t, \tag{13}$$

where M is the number of data points selected, $D_{m,t}$ is the measurement obtained in the mth similar day at time slot t, ΔD is the bias caused by the forecasting errors, $\widehat{D}_t$ is the actual observed CL power demand at time slot t and $\tilde{D}_t$ is the forecasted CL power demand at time slot t.

We can calculate the CL energy demand as the sum of the CL power demand over a time period, where the total time period T is divided into time slots such that the interval length is given by $\Delta t = 1$ h. The CL energy demand can be mathematically represented as

$$V = \sum_{t=1}^{T} D_t. \tag{14}$$

C. EV DISCHARGING SCHEDULING

We consider the discharging schedule of the auction winners α_i derived in (7). Since the auction takes place few hours in advance, we assume the farthest EV will arrive at the CL location, plug in and be available ahead of the discharging schedule. The scheduling for discharging of EVs is an operating cost minimization problem to determine the best schedule for discharging EVs to supply power to CL at each time slot. Let T indicate the total scheduling intervals, while t defines the value of each parameter or variable at any time instant. We can calculate the operating cost as the sum of the energy, transportation and battery degradation costs. The EV discharging scheduling problem can be formulated as follows

$$\min_{P_i} \quad \sum_{i=1}^{N}\sum_{t=1}^{T} \rho_i P_{i,t} + \sum_{i=1}^{N}\sum_{t=1}^{T} b_i^d P_{i,t} \tag{15}$$

Subject to

$$\sum_{i=1}^{N} P_{i,t} = D_t \tag{15a}$$

$$P_i^{min} \leq P_{i,t} \leq P_i^{max} \tag{15b}$$

$$SoC_{i,t} = SoC_{i,t-1} - \frac{P_{i,t}/\eta^{dis} \times \Delta t}{v_i^{cap}} \tag{15c}$$

$$SoC_i^{min} \leq SoC_{i,t} \leq SoC_i^{max} \tag{15d}$$

The first term of (15) represents the energy cost, and the second term represents the battery degradation cost. Constraint (15a) is the power balance equation which ensures that power from discharging EVs at time slot t equals the CL power demand D_t at time slot t. We assume that the associated EVs have much more discharging power than the CL power demand. Constraint (15b) ensures that the discharging power at time slot t is within the limits of the ith EV, where P_i^{min} and P_i^{max} are the minimum and maximum discharging power of the ith EV, respectively. Constraint (15c) indicates the SoC of the ith EV at time slot t, where η^{dis} is the discharging efficiency and Δt is the length of a single time interval. Constraint (15d) ensures that the SoC at time slot t is within the limits of the ith EV for the protection of battery, where SoC_i^{min} and SoC_i^{max} are the minimum and maximum SoC of the ith EV battery, respectively. Considering the objective function and constraints in problem (15) are linear, the problem is solved using off-the-shelf solvers like CPLEX.

The operating cost in (15) is formulated for markets that pay for energy and compensation for battery loss, and the revenue is the sum these payments. For V2G reserves, revenue is derived from an additional source called capacity payment. This payment is for the maximum capacity contracted for the time duration, whether EVs discharge power or not [27]. The capacity payment is simply the opportunity cost and time cost for EV owners to abandon the use of EVs and participate in the V2G reserve [31]. The capacity payment can be express as

$$\rho^c = \sum_{t=1}^{T} p^{cap} \cdot P_t^{avail}, \tag{16}$$

where p^{cap} denotes the capacity price in British Pounds (£) per kW-h, P_t^{avail} denotes the contracted capacity available in kW at time slot t and T indicates the time the EV is plugged-in and available, in hours. It is to be noted that the capacity price unit, £/kW-h, means £ per kW capacity available during 1 h (whether used or not), and should not be confused with energy price unit, £/kWh.

We can calculate the operating cost of V2G reserves as the sum of the capacity price, energy cost and battery degradation costs. The discharging scheduling for V2G reserves can be formulated as follows

$$\begin{aligned} \min_{P_i} \quad & \sum_{i=1}^{N}\sum_{t=1}^{T} p_i^{cap} P_{i,t}^{avail} + \sum_{i=1}^{N}\sum_{t=1}^{T} \rho_i P_{i,t} \\ & + \sum_{i=1}^{N}\sum_{t=1}^{T} b_i^d P_{i,t} \\ & \text{subject to: (15a) - (15d).} \end{aligned} \tag{17}$$

The capacity payment for V2G reserves is paid only if associated EVs are plugged into the charge points of the CL during the scheduled period.

V. NUMERICAL RESULTS AND DISCUSSIONS

We consider a microgrid where the CL is seeking to buy energy from EVs with surplus energy. The number of participating EVs is Poisson distributed with an average density λ [32]. Based on the retail price of the Nissan Leaf replacement battery pack [33], battery cost of £5,000 is assigned to EVs. We consider an EV battery with 2,000 charge cycles at 100% DOD. Energy demand of the CL is uniformly chosen from [40 220] kWh. Energy unit cost of EVs is randomly distributed over [0.07 0.35] £/kWh. Minimum available energy in the range of [8 12] kWh and maximum available energy in the range of [18 25] kWh are randomly generated for EVs. The data of the EVs and CL and necessary parameters are passed to the algorithms to find the successful bidders and their corresponding payment, and then schedule discharging EVs accordingly. All simulations were performed using MATLAB.

Fig. 2 shows the data set description for the similar day profile of the CL used in the study. The CL model introduced earlier in section IV is used to estimate the CL demand and analyse the proposed energy trading approach. The estimated CL power demand at each time slot is based on similar day approach. The forecasted CL power demand is the average power demand of the same time slot from historical data with similar characteristics. We considered the following characteristics: day of the week, weather,

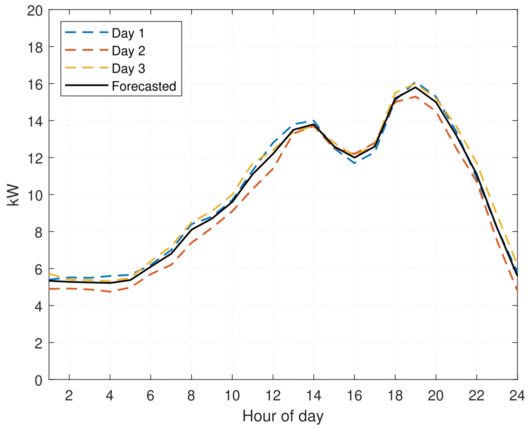

FIGURE 2. Similar day load profile of CL.

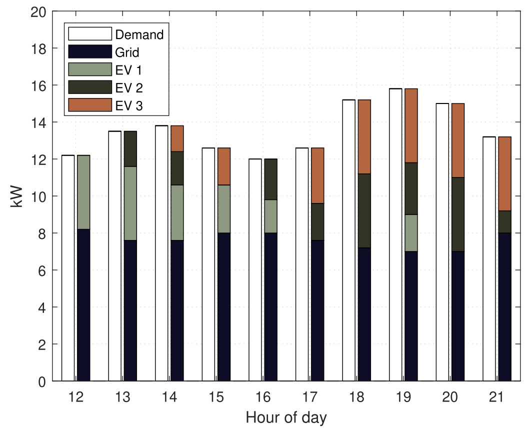

FIGURE 3. Discharging schedule of EVs to fulfil CL demand.

maximum/minimum temperature. We selected the three most similar days and used the average to forecast the CL power demand of 24 scheduling intervals.

Fig. 3 shows the discharging schedule for EV-CL association. This illustrates a real-world scenario where the base load demand is met by regular supply from the grid or on-site generation and supply from V2G reserve is required to meet peak demand. Based on the forecasted CL power demand, the discharging power of associated EVs are scheduled to satisfy the hourly demand of the CL. The fast discharging rates of EV batteries can help to increase the supply and limit the need to use high-priced peak generators. By balancing the peak demand with supply from V2G reserve, V2G can help reduce energy costs in the microgrid. Fig. 4 shows the effect of the proposed battery degradation compensation paid to EV owners. It is observed that in every scenario without compensation EV owners make a significant loss. Without the battery degradation compensation, EV owners will always incur financial losses during EV-CL interaction, regardless of the incentives received from the pricing scheme. This may not motivate the EV owners to participate in EVaaS. By adding the monetary equivalent of battery losses to the charge cost, battery related liabilities are compensated. This demonstrates

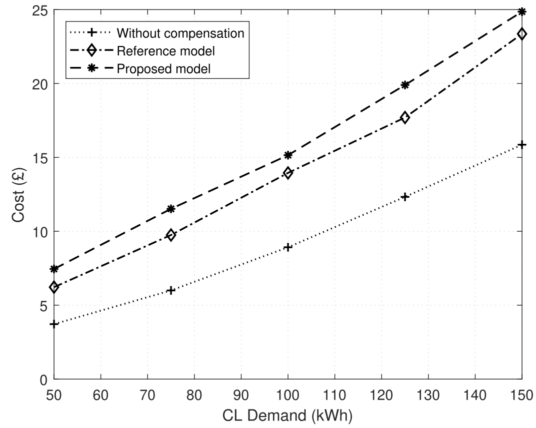

FIGURE 4. Compensation for battery degradation during EV-CL interaction.

that in the absence of battery degradation compensation, EVaaS participation is not profitable for EV owners.

We evaluate the performances of the proposed allocation scheme (7) with the centralized scheme in [34] and single bidding mechanism in [17]. In order to minimize the energy cost for the CL, [34] and [17] subject EVs to sell an undesirable amount of energy. The single bidding approach formulated in [17] is similar to our proposed allocation scheme. However, our allocation scheme is formulated as a MINLP problem where the tradeable energy is a continuous variable bounded by minimum and maximum discharging energy limits for each EV, while [17] considers only a binary variable for their integer linear programming (ILP) problem. We consider [17] as our reference scheme and use it to study the performance of our proposed allocation scheme. Different scenarios were considered in Fig. 5 with respect to CL demand, and for each scenario, the total bids of the auction winners are computed under the different allocation schemes. Our proposed allocation scheme outperforms the reference scheme in every scenario. As expected, the centralized scheme would typically give a better performance than a distributed scheme; however, our proposed allocation scheme follows the centralized scheme closely in each scenario and ensures auction winners sell a reasonable amount of energy.

Fig. 6 shows the bids and final payment made to EVs for different densities of EV distribution. For a CL demand of 60 kWh, λ is uniformly chosen from [0.1 0.9]. Payments obtained for λ in [0.1 0.3], [0.4 0.6] and [0.7 0.9] are averaged to form the low, medium and high EV distribution densities, respectively. The low density represents areas with a low number of EVs (e.g., rural areas), the high density represents areas with a high number of EVs (e.g., urban areas) and the medium density represents areas in-between the rural and urban areas. It is observed that the total payment to the auction winners decreases with an increase in EV distribution density. This can be attributed to the number of EVs participating in the auction. When there are less EVs, the cost gap between progressive lower bids is higher compared to a scenario that has more EVs. When more EVs join the auction, the cost for

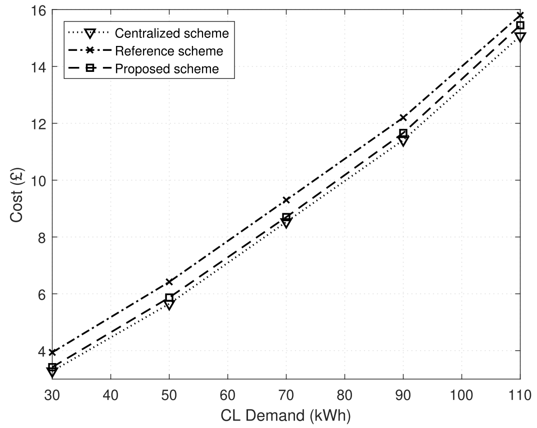

FIGURE 5. Bids of auction winners under different schemes.

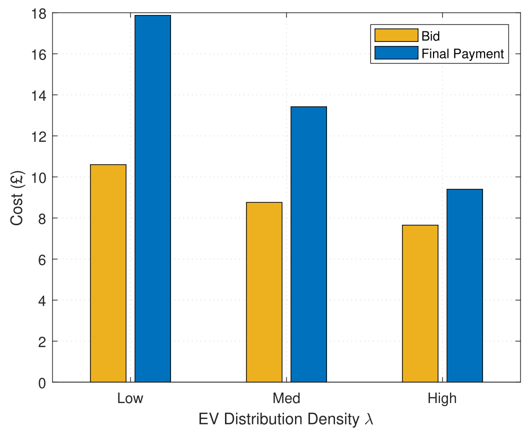

FIGURE 6. Payments of auction winners versus EV distribution density.

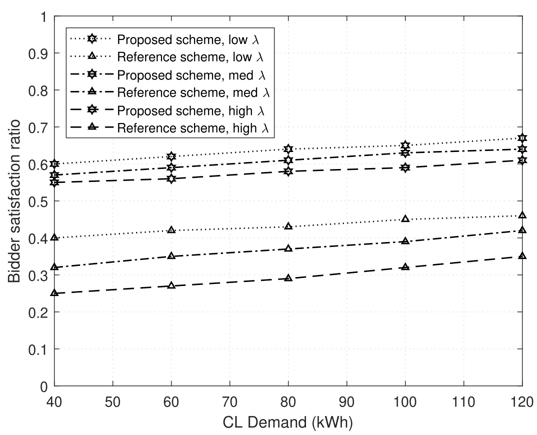

FIGURE 7. Performance on bidder satisfaction.

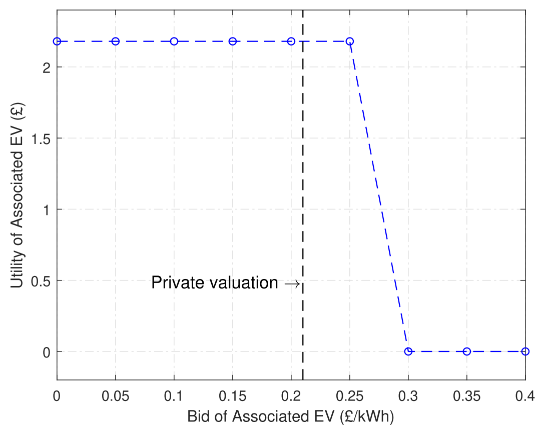

FIGURE 8. Performance on truthfulness.

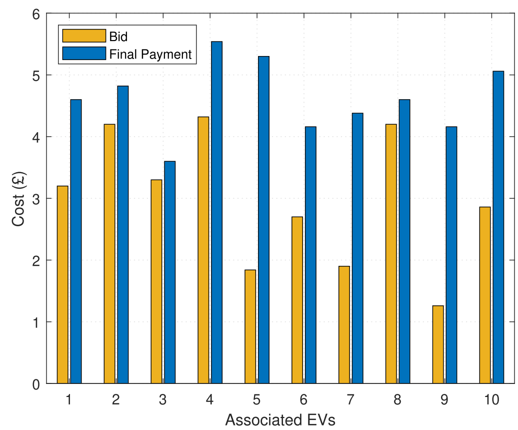

FIGURE 9. Performance on individual rationality.

the CL decreases due to the increased competition between participating EVs. This demonstrates that EVaaS will benefit the EVs more in rural areas, while the CL will save cost in urban areas.

To evaluate the performance on bidder satisfaction, we introduce the bidder satisfaction ratio metric. The bidder satisfaction ratio is defined as the ratio of the amount of energy that the bidder sells in the auction to their maximum tradeable energy. We assume that all bidders want to sell their maximum tradeable energy; thus, we average the satisfaction ratio of successful bidders that are not able to sell their maximum tradeable energy. Fig. 7 shows the bidder satisfaction ratio across the different EV distribution densities with respect to CL demand, where 0.5 is the satisfactory level. It can be observed that the bidder satisfaction ratio in our proposed scheme is above satisfactory level and outperforms the reference scheme in every scenario. While the auction in the reference scheme [17] aims at the minimization of energy cost of the CL. This means that the auction in the reference scheme is carried out at the expense of the bidders, which is responsible for the bidder satisfaction ratio falling below satisfactory level.

We evaluate the performance of the proposed VCG-based auction for EV-CL association on truthfulness and individual rationality. Fig. 8 shows the performance on guaranteeing the truthfulness of bidders. We study the changes in utility under conditions of a random EV submitting untruthful bids and its private valuation. When the EV increases its bid to £0.29/kWh, its loses the auction and its utility is 0. This shows that the EV cannot improve its utility by misrepresenting its valuation, thus protecting the fairness and efficiency of the trade.

Fig. 9 shows the performance on guaranteeing individual rationality of bidders. For a CL of 200 kWh, the submitted bids of the auction winners, as well as their corresponding payments, are presented. It can be observed that the final payments to auction winners is no less than their bids, which means every auction winner has a nonnegative utility. Overall, the proposed mechanism verifies the theoretical analysis on truthfulness and individual rationality and better incentivizes participating EVs.

VI. CONCLUSION

This paper has presented an incentivized energy trading approach to analyse the interaction between EVs and CL in a microgrid. In addition to the VCG payment to auction winners, the approach compensates EV owners for losses incurred during EV-CL interaction such as distance traveled, battery degradation and V2G reserve capacity. By allowing bidders enforce their energy trading requirements, EVs are protected from unfair trade conditions, which is common in centralized models where the aggregator finds the optimal solution at the expense of participating EVs. The energy trading model was applied in a scenario where supply from EVs is required to meet peak demand. Simulation results reveal that our proposed approach achieves a performance which is comparable to those given by reference schemes, guarantees bidder satisfaction and validates theoretical analysis on economic properties of truthfulness and individual rationality. In future work, we will consider a double auction environment where multiple EVs and multiple CLs compete to sell and buy energy, respectively. This two-sided market allows CLs to submit their bids (buy orders) and EVs to submit their asks (sell orders) to the auctioneer. The auctioneer then matches the orders to find the most efficient allocation and decides who trades and at what prices.

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